The price elasticity of demand for prescription drugs: An exploration of demand in different settings

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Abstract

Health systems in most high-income countries provide protection against the financial risks associated with ill health on a broadly universal basis, although many impose measures that lower financial protection, for example, by offering a limited package of benefits or requiring beneficiaries to pay part of the cost of health care at the point of use. This last measure, known as cost sharing or user charges, is a policy tool applied mainly to raise revenue for the health system and to enhance efficiency. The neo-classical economic argument for user fees posits that moral hazard exists in health insurance markets, and user fees help combat this "overconsumption" of care. The simultaneous policy argument is that cost sharing reduces unnecessary consumption of prescription drugs, which leads to both expenditure reductions and health improvements.

While literature investigating these cost sharing arguments exists, there are still unanswered questions as many of the papers are outdated, others only focus on specific populations, and there are methodological issues surrounding some studies. As estimates vary widely between studies, a methodological approach that obtains an "adjusted" or "composite" price elasticity from the literature by pooling the existing estimates would provide a broad measure of elasticity. Updated estimates of the price elasticity of demand for the general population, the elderly, and low-income individuals in the United States would also be useful for American policymakers given recent changes to public and private insurance coverage. The calculation of estimates for elderly Americans also provides a useful backdrop for comparing estimates from the elderly in British Columbia, Canada. There is a need for economic and policy discussions related to economic efficiency, policy arguments for efficiency in user fees, and equity in the literature.

We contribute to filling these gaps by estimating the price elasticity of demand in three main settings: a collection of elasticity estimates from the existing literature, the American population, and the older population in British Columbia, Canada. Based on our results, we determine that the price elasticity of demand is relatively low in all of these settings, even among the low-income group and the general population. Our adjusted price elasticity estimate is an insignificant -0.16, while the elasticity estimates from the American analyses range from an insignificant -0.11 for the elderly to -0.25 for the general population. We obtain an estimate of –0.30 for the elderly in British Columbia. Overall, the sensitivity to user fees depends on the institutional setting, the level of cost sharing, the specific subpopulation examined, and other factors.

The implications of these relatively low estimates can be viewed from both an economics and policy perspective. While cost sharing leads to greater efficiency when we define efficiency in a neo-classical economic sense, from a policy perspective user fees may negatively affect beneficiaries' health and equity. The implication is that policymakers should set transparent policy goals and openly discuss whether any detrimental effects of cost sharing are considered acceptable from a policy standpoint.

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Abbreviations

2SLS – Two-Stage Least Squares
AFDC - Aid to Families with Dependent Children
AHRQ - Agency for Healthcare Research and Quality
BC – British Columbia
BC-CPI - British Columbia Consumer Price Index
BCHC - British Columbia Health Coalition
BCLHD – British Columbia Linked Health Database
CA-CPI - Canadian Consumer Price Index
CAPI - Computer-assisted personal interviewing
CCPA - Canadian Centre for Policy Alternatives
CDC – Centers for Disease Control
CDN – Canadian (used to refer to currency)
CMS – Centers for Medicare and Medicaid Services
DHHS - Department of Health and Human Services
DPC - Disability Policy Collaboration
DRA - Deficit Reduction Act
DTCA - Direct-to-consumer advertising
FAMP - Federal Medical Assistance Percentage
FE – Fixed effects regression
FFS – Fee for service
FPL – Federal Poverty Level
GMM – Generalized method of moments (estimator)
H2RA - Histamine-2 receptor antagonist
HC - Household Component (of MEPS)
HMO – Health Maintenance Organization
HRET - Health Research and Educational Trust
HSA - Health Savings Account
KFF – Kaiser Family Foundation
LTC – Long-term Care
MCBS - Medicare Current Beneficiary Survey
MEPS – Medical Expenditure Panel Survey
MPC - Medical Provider Component (of MEPS)
MRA – Meta-regression analysis
MSP - Medical Services Plan
NAMCS - National Ambulatory Medical Care Survey
NPS - National Pharmaceuticals Strategy
NSAID - Non-steroidal anti-inflammatory drug
OLS – Ordinary least squares
OOP – Out-of-pocket
PBM – Pharmacy Benefit Manager
PPO - Preferred provider organization

POS - Point of service plan
PSID - Panel Study of Income Dynamics
RE – Random effects regression
RP – Reference pricing
SCHIP – State Children's Health Insurance Program
SID – Supplier-induced demand
SS – Sample selection
US – United States
US-CPI – United States Consumer Price Index
USVA – US Department of Veterans Affairs
VIF - Variance Inflation Factor

Glossary

Adverse selection – a situation in which individuals are able to purchase insurance at rates which are below actuarially fair rates, because information known to them is not available to insurers

Asymmetric information – a situation in which the parties on opposite sides of a transaction have differing amounts of relevant information

Autocorrelation (serial correlation) – a situation where the value of the disturbance term is not determined independently of its values in all other observations

Coinsurance - shared risk between a consumer and the insurance company where the company insures only a fixed percentage of the consumer's medical expenditures

Co-payment - shared risk between a consumer and the insurance company where the company insures only a set amount of the consumer's medical expenditures

Deductible – a clause in an insurance policy that relieves the insurance company of responsibility to pay the initial amount of medical expenditures up to a stated amount

Discount rate - the highest interest rate an individual could earn through savings

Equity - equal access to health care for those in need of medical care.

Endogeneity – when there is correlation between the error term and at least one of the covariates in the model, often caused by omitted variables.

Expenditure elasticity of demand – the percentage change in total expenditures brought about by a one percentage change in the price of the good or service.

Health care efficiency - an allocation of resources that maximizes health gain, where health gain is measured in a standardized manner (for instance, through years of life lost or quality-adjusted life years).

Heterogeneity – the existence of differences in the characteristics of individuals within the sample

Indirect utility function- takes the value of the maximum utility that can be achieved by spending the consumer's budget on the consumption goods with prices p.

Insurance - a contract between individuals or entities concerned about potential future losses and an insurance company that involves a promise of reimbursement or in-kind

payments in the case of a loss paid to the insured individuals or companies in return for prepayments to the insurance company.

Kaldorian (or Hicks-Kaldor) principle – a reallocation of resources is a social improvement if the gainers from the change sufficiently value their gain so that they could, at least in principle, bribe the losers from the reallocation into accepting that move, even if the bribe is not actually paid.

Moral hazard - the risk that the presence of a contract will influence the behavior of one or more parties. Typically arises in insurance contracts where agents have disincentives to take measures that would reduce the amount of care demanded.

Multi-tier formularies – typically contain two or three tiers; the first tier consists of generic drugs with the lowest co-payment; the second and third tiers generally comprise brand-name drugs, which can be split into preferred and non-preferred drugs in the three-tier formularies where the preferred brand-name drugs have a lower co-payment than the non-preferred drugs.

Pareto efficiency - an allocation of resources that cannot be changed to make one individual better off without simultaneously making another feel worse off.

Price elasticity of demand – the percentage change in the quantity demanded brought about by a one percentage change in the price of the good or service.

Principle of the law of large numbers – in repeated, independent trials with the same probability p of success in each trial, the chance that the percentage of successes differs from p by more than a fixed positive amount, $a>0$, converges to zero as the number of trials goes to infinity for every positive a.

Reference pricing system - the maximum price for a group of equal or similar drugs that the insurer will reimburse the user. If the user chooses a drug that costs more than the reference price, he or she must pay the difference.

Risk – uncertainty about possible states of the world.

Sample selection – the inability to determine whether the zero consumption represents a true choice of no consumption.

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Chapter 1: Introduction

1.1. Thesis background and scope

In most high-income countries there is generally universal protection against the financial risks associated with ill health, although many health systems impose measures that lower financial protection; for instance, by limiting coverage of medical benefits or forcing beneficiaries to cover part of the health care cost at the point of use. This last measure, known as demand-side cost sharing or user fees or charges, is a policy tool generally employed to raise revenue for the health system and to enhance efficiency. The revenue-raising motive is more common in low-income countries as it may be driven by the need to generate private sources of funding where public sources are insufficient or to contain public spending by shifting some of the prescription drug expenditure burden to individuals. Theoretically, the third-party payer can shift the saved funds to more cost-effective areas of the health care system. Meanwhile, the efficiency motive is meant to negate the third-party payment-related problem of ex-post moral hazard and to guide patients towards more cost-effective care and patterns of health care use.

As illustrated in Table 1.1, demand-side cost sharing exists in various forms and may be applied to any type of health service. An important note is that although cost sharing can be applied at the patient or provider level, any time we refer to cost sharing in this dissertation, the implicit reference is for demand-side cost sharing and not supply-side cost sharing.

While there is significant variation in the extent to which user charges are applied to physician visits and inpatient care among OECD countries, almost all oblige health insurance recipients to pay user fees for prescription drugs[1]. Yet, the types of cost sharing, the burden placed on users, and the exempt populations differ by country. The universality of prescription charges reflects anxiety about the rapid rate at which pharmaceutical budgets have grown over time, particularly because pharmaceutical expenditures as a percentage of total health expenditures have generally been rising faster than inflation over the past decade in a number of the wealthiest countries (OECD, 2005). However, many of these countries required cost sharing for prescription drugs before rising drug budgets became a pressing policy matter, suggesting that a belief in demand-cost sharing as a primary policy tool was widespread at the time.

In the late 1960s Arrow (1968) and Pauly (1968) were instrumental in forwarding the theoretical arguments for cost sharing in medical services. Further papers that implicitly or explicitly used neo-classical theory as the basis for empirical tests of moral hazard were soon published by Feldstein (1970; 1971), Newhouse and Phelps (1974); Phelps and Newhouse (1972), and Rosett and Huang (1973), among others. In fact, the neo-classical economic arguments in favor of cost sharing appear to have influenced health care policy since the 1970s because cost sharing has become an

[1] For example, there is no cost sharing for prescription drugs in Wales, and at the time of this writing, Scotland is considering a similar proposal.

entrenched part of the various health insurance systems in the United States (Nyman, 2004). Traditional economic theory posits that individuals shielded from the full cost of health care through insurance provided by a national health service, sickness fund, or private health plan will use health services beyond the point at which the marginal benefits of use outweigh the marginal costs (Pauly, 1968). This behavior creates a welfare loss as scarce resources might be better spent on other goods and services[2]. The premise behind cost sharing is that when the patient faces out-of-pocket payments for health care, he is inclined to reduce his additional consumption

Table 1.1. Direct and indirect forms of cost sharing for prescription drugs and their incentives

Form	Definition	Incentives
Direct		
Co-payment	The user pays a fixed fee (flat rate) per item or service unit.	Patient may decrease volume of drugs consumed or decrease the number of prescriptions filled while increasing the size of each prescription. Patient has no incentive to consume cheaper alternative medications unless co-payments are lower for these medications.
Co-insurance	The user pays a fixed proportion of the total cost.	Patient may decrease volume of drugs consumed and may only request a larger pack size if this produces savings. Patient has an incentive to consume cheaper therapeutic medications.
Deductible	The user bears a fixed quantity of total prescription costs; deductibles can apply to specific cases or to a period of time.	When patient is not close to the deductible level, he may decrease the volume of drugs consumed and/or switch to cheaper therapeutic alternatives. As he nears the deductible limit, he has an incentive to consume more drugs and more expensive drugs to exceed the deductible.
Indirect		
Reference pricing (RP)	A reference price refers to the maximum price for a group of equal or similar drugs that the insurer will reimburse the user. If the user chooses a drug that costs more than the reference price, he or she must pay the difference.	Patient is likely to decrease his or her consumption of drugs that are priced above the reference price and switch to alternative drugs priced at or below the reference price.
Multi-tier formularies	Typically, these formularies contain two or three tiers. The first tier consists of generic drugs, which have the lowest co-payment. The second and third tiers generally comprise brand-name drugs, which can be split into preferred and non-preferred drugs in the three-tier formularies. The preferred brand-name drugs have a lower co-payment than the non-preferred drugs. Multi-tier formularies are most commonly used in the United States.	Patient has an incentive to switch from brand-name medications to generic medications and from non-preferred medications to preferred medications.

Although cost sharing became an important part of the health care system in America, other developed countries have been more reluctant to shift such a large burden of costs to patients (Cutler, 2002b). European nations, Canada, Australia, and New Zealand all seem to have strived for more of a balance between reducing moral hazard

[2] Moral hazard may also lead to higher premiums.

without significantly reducing equity[3]. Interestingly, there is relatively little demand-side cost sharing for health care services in developed countries outside of the United States, but as mentioned previously, virtually all developed health systems impose user fees on prescription drugs (Saltman and Figueras, 1998). Although it is unclear why this is the case, the fact that prescription drug coverage is less generous than core medical care across the board in the developed world implies that, at least when cost sharing provisions were first enacted, there was a general consensus regarding the necessity of prescription drugs. However, significant exclusions from prescription charges are prevalent (Saltman and Figueras, 1998), usually for children, older people, and low-income groups, indicating that policymakers were still concerned that significant user fees for prescription drugs would adversely affect certain populations.

While user fees for all types of medical care are still prevalent in the United States, and prescription charges are common in the developed world, the arguments regarding cost sharing in the health care sector have shifted since the original neo-classical theory was presented. Rice (1992) and Nyman (1999), for instance, have suggested that the neo-classical theory is inherently flawed, particularly in relation to health insurance. Both present alternate theories for health care demand and hypothesize that moral hazard is less of a problem than previously predicted. Economists like Culyer and Evans (1996) and Reinhardt (1992) have instead argued that although the neo-classical economic theory is sound, the theory is only of limited application to health care policymakers because they have other policy goals in mind. In particular, health policymakers are concerned with maximizing societal health, maintaining or improving equity, and remaining within a budget constraint. User fees can have varying effects on each of these policy goals, although the effects depend crucially on the design of the cost sharing system.

There is a significant body of literature investigating the link between cost sharing for prescription drugs, the demand for treatment, and health. The initial concentration in the literature was from the perspective of neo-classical theory and the focus was on determining whether a moral hazard effect existed. The most influential studies regarding cost sharing have used data from the RAND Health Insurance Experiment, which was conducted in the late 1970s and early 1980s and used an experimental design (Rice and Morrison, 1994). Non-elderly participants were randomly assigned to 0 percent, 25 percent, 50 percent, and 95 percent coinsurance plans, and their use of medical services was tracked over a number of years. Even today, the findings from the RAND regarding prescription drugs and other health services are widely cited as elasticity benchmarks in the literature, despite the fact that it has been over 25 years since the experiment was conducted. Meanwhile, later papers focused on specific groups within the population to examine whether some were more adversely affected by cost sharing. More recent papers also focused on newer forms of cost sharing such as reference pricing and tiered co-payment systems. Overall, the literature has been

[3] A full discussion of equity, including a definition and the relationship between equity and cost sharing, is given in Chapter 8. However, it is worth mentioning here that we take equal access for equal need as the working definition of equity in this chapter. Because the burden of cost sharing typically falls on the poor and heavy users of health care (unless these groups are given sufficient exemptions), many argue that cost sharing reduces equity.

overwhelmingly empirical in nature and has established that cost sharing leads to a lower volume of prescription drugs for all populations considered. The elasticity of demand for cost sharing is typically less than one, indicating that consumers are not very responsive to changes in price.

Given the discussion above, there are a number of reasons for delving deeper into this area. One of the most important reasons is that price elasticity estimates are of interest to policymakers, as these estimates shed some light on the economic efficiency, "health care efficiency"[4], and equity concerns. If those who are the most medically needy, for instance the poor and the elderly, are still sensitive to out-of-pocket price changes, cost sharing may have a detrimental effect on health. In terms of equity, cost sharing that is applied across the board is clearly inequitable. But even if cost sharing differs between different population groups, the mechanism may still be inequitable. For instance, the wealthiest of the elderly are sometimes well protected from user fees even though they can more easily afford their prescription medications. The lack of economic or policy discussions of these considerations in the literature highlights the need for this dialogue.

Since the RAND experiment there have been developments in econometric methodology, which allow the researcher to test whether different specifications are more appropriate to model the demand for prescription drugs. Despite these novel techniques, few researchers in the area of prescription drugs have taken advantage of econometric models that simultaneously account for panel data, endogeneity, and other data characteristics. Thus, the application of newer methodology to the problem is an interesting prospect.

From a policy perspective most economists have focused on the Pareto efficiency[5] effects of moral hazard and the relationship to the elasticity of demand, but health care policy typically encompasses additional goals such as health care efficiency and equity. There is a clear need for a broader discussion of demand-side cost sharing that considers not only the economic perspective but also other aspects of the health policy perspective.

Although the literature has reached broad conclusions regarding the influence of cost sharing on the general population, there are still a number of unanswered questions. One problem is that price elasticity estimates tend to vary widely from one study to the next, partially depending on the country being analyzed, the group of individuals considered, the time frame of the study, and the statistical techniques employed. As such, there is a need to statistically obtain an "adjusted" or "composite" elasticity estimate that accounts for heterogeneity between studies, giving policymakers and economists a benchmark price elasticity value for developed countries that can be used for individual country and subpopulation elasticity comparisons.

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[4] Although this distinction is not always made explicitly, economic arguments for efficiency are typically based on Pareto efficiency, while health care arguments for efficiency are more concerned with maximizing population health. Pareto efficiency will be defined and discussed in Chapter 2, while health care efficiency and equity and the differences between economic efficiency, health care efficiency, and equity will be explained in greater detail in Chapter 8.

[5] For example, see Ellis and McGuire (1993), Pauly (1974), or Zeckhauser (1970).

Given the wide range of existing estimates, there is still a need for a more robust statistical analysis. Some studies did not account for potential sample selection, which can occur when the decision not to purchase any drugs in a given year may not be a true consumption choice. While the decision to obtain health insurance that offers prescription drugs may be endogenous to the number of prescription drugs consumed[6], few studies that considered individuals with privately purchased health insurance accounted for this potential endogeneity. Finally, when longitudinal data are available, the application of panel data regression techniques provides certain advantages, particularly, the ability to account for omitted variable bias. The failure to account for some or all of these factors in non-experimental settings may have led to biased estimates that subsequently misinform policy responses. Thus, to highlight the contribution of price to the consumption of prescription drugs and inform policymakers and insurance companies about the sensitivity of consumers to price changes, a robust price elasticity estimate is needed.

Another missing piece is how prescription drug cost sharing influences the elderly population, a prevalent user group of prescriptions. Few studies have calculated price elasticity values for this population. The existing estimates are either for subsets of the elderly (individuals living in one region, those without employer-sponsored insurance or Medicaid, or those with a specific ailment), or only capture recent drug consumption. It would be useful to compare price elasticity values between the elderly and the general and low-income populations. It would also be informative to compare elasticity values of the elderly between the US and Canada and to hypothesize why estimates might differ between the two countries.

This thesis aims to address these specific gaps. In doing so we analyze three different datasets: one constructed from the existing price elasticity values from the literature, one of the population in the United States, and one of the older population in British Columbia (BC), Canada. The populations of the US and BC are comparable in that both are similar in terms of demographic and socioeconomic characteristics and culture. Yet, their health insurance systems are widely divergent because America relies more on public insurance for the poor and elderly and private or no insurance for the rest of the population, while British Columbia provides universal health insurance coverage for most health services. Even a broad comparison of these two systems would provide a deeper understanding of the fundamental relationships between cost sharing, socioeconomic and demographic characteristics, and the demand for prescription drugs, as well as highlighting health system differences that may be amenable to policy initiatives.

Our findings indicate that the price elasticity of demand is relatively low, even among the low-income group and the general population. Our "adjusted" price elasticity estimate for non-aggregate data is a non-significant –0.156, while the elasticity estimates from the American analyses range from -0.108 (though not significant) for the elderly to -0.250 for the general population. We obtain an estimate of –0.295 for

[6] Endogeneity may also arise if the co-payment is computed from total out-of-pocket expenditures and total prescription drugs purchased; in a situation where there are deductibles mixed with co-payments/coinsurance and out-of-pocket limits, there is a non-linear price schedule.

the elderly in British Columbia. Overall, the sensitivity to user fees varies depending on the institutional setting, the level of cost sharing, the specific population examined, and other factors.

1.2. Background on cost sharing in the United States and British Columbia

Before discussing the research aims and objectives and providing an outline of the organization of the thesis, it is useful to set the context of health care in the United States and British Columbia. The United States and Canada have followed divergent paths with respect to health coverage beginning in the mid-1960s when both created their own unique brands of public coverage. In 1965 the US Federal government established Medicaid to provide coverage for low-income groups, and in 1966 they established Medicare to provide coverage for the elderly (CMS, 2005a). Employer-sponsored insurance was already a significant source of coverage for the working population, and the government chose to leave this coverage in place rather than extending public coverage to the entire population.

In contrast to the United States, Canada went down the route of universal health insurance coverage for core medical services beginning in 1966 with the Medical Care Act (Grootendorst, 2002). Prescription drug coverage was left to the territories and provinces, and all have enacted public drug coverage for the low-income and elderly groups. Although the Commission on the Future of Health Care in Canada (Romanow, 2002) recommended in a widely cited report that prescription drug coverage be integrated into core health services in Canada to ensure appropriate utilization, the Canadian government has not taken action on this recommendation.

These two different paths have also influenced the uptake of cost sharing provisions within each country. In the United States competition between insurers is assumed to be more efficient than a single purchaser system, and even within government-financed health care, policymakers have introduced competition between insurers. Around 15 percent of the US population is uninsured, but many of the current administration's proposals for extending coverage involve tax credits or deductions (Cogan et al., 2005) or health savings accounts (Cannon and Tanner, 2005), both of which are more market-oriented ideas. There seems to be a theme throughout time among a significant (or at least powerful) group that neo-classical/market-oriented economics can determine the health care system that is best for society. This belief is reflected in the attitude among some policymakers towards the uninsured[7] and the argument that moral hazard is prevalent and should be dampened (Jost, 2007) as reflected in recent provisions allowing Medicaid to charge higher co-payments and the significant cost sharing requirements enacted in Medicare Part D. Thus, the prevalence of cost sharing provisions within both public and private coverage is not only based on a desire to limit drug expenditures, but also on an assumption that the

[7] Specifically, some researchers and policymakers argue that health care resources should be allocated according to ability to pay and thus other concepts such as need are irrelevant (Jost, 2007). It is important to note that this is generally an agenda associated with certain right-wing groups in the country.

lessons from economics regarding moral hazard should be applied to the health system to benefit society.

In Canada some economists and policymakers have tried to inject economic arguments into government policy, but they have generally been less successful as Canadians strongly support equity, fairness, and solidarity (Romanow, 2002). Concerns about equity and health maximization have typically outweighed the economic arguments, at least for what Canada defines as core health services. Yet, in the area of prescription drugs, there is significant cost sharing across the country, with private financing making up about 46 percent of total drug expenditures in 2005 (CIHI, 2006). The real objective of these policies for prescription drugs may be to contain prescription drug expenditures by shifting a significant portion of the burden to patients. Policymakers in British Columbia do seem concerned with preserving access and equity, though, as low-income groups have always faced lower user fees than residents who are non-elderly. Moreover, the government of British Columbia enacted Fair PharmaCare in 2003, which bases prescription charges on income.

1.3. Thesis research objective and aims

This research has three primary aims: (i) to use previous price elasticity estimates from the literature and run a meta-regression to calculate a standardized estimate of the price elasticity of demand for prescription drugs across multiple countries and settings, (ii) to empirically test the hypotheses regarding the effect of cost sharing on drug utilization that stem from the neo-classical economic theory of insurance, and (iii) to discuss the economic and policy implications of the results. The first aim, as well as providing an aggregate quantitative estimate of price elasticity, also sets a baseline against which newer estimates can be compared. The intent of the second aim is to determine whether user fees reduce the quantity demanded of prescription drugs in the United States and British Columbia, Canada. This also permits us to investigate whether certain individuals are more adversely affected by increases in out-of-pocket fees and allows us to broadly compare drug consumption among the elderly in these two countries.

While a large body of literature that investigates the relationship between cost sharing and demand for prescription drugs exists, this dissertation contributes to the literature by (i) utilizing an econometric model which accounts for unobserved heterogeneity, sample selection, and the potential endogeneity of the co-payment, (ii) considering the impact of user fees on access to prescription drugs for both the entire population and various groups within the population, (iii) calculating the price elasticity of demand for prescription drugs for both the United States and British Columbia, (iv) using the most recent datasets available, and (v) drawing policy implications for each of the considered regions and for society as a whole.

The research involves empirical estimation on three datasets. We construct one of the datasets by pulling relevant information from the prescription drug cost sharing literature. Studies which reported price elasticity estimates or which reported enough information for us to calculate a price elasticity estimate by hand were chosen.

Contextual information was pulled from each paper and inputted into the database. The second dataset includes a sample of non-institutionalized individuals from the United States. The third database provides information on elderly beneficiaries in British Columbia, Canada. Different statistical techniques are employed for each dataset depending on the objective of the analysis, the information available in the dataset, and the nature of health insurance coverage for the studied population.

The hypotheses that we intend to test are context specific. For the meta-regression analysis, which is more an extension of the literature review, we are primarily interested in obtaining a composite price elasticity value and quantifying the study-specific factors that determine this estimate. Based on these two uses of the meta-regression, the main hypotheses that we aim to test are:

H1a: The price elasticity of demand for prescription drugs is less than one

H1b: The price elasticity of demand for prescription drugs is greater than zero

H1c: The quality of the medium within which the elasticity estimate was published influences the elasticity estimate

H1d: The characteristics of the study within which the elasticity estimate was published affect the elasticity estimate

H1e: The institutional setting of the data that generated the elasticity estimate affects the estimate

This thesis also aims to test hypotheses related to prescription drug cost sharing in two regional contexts. The main hypotheses regarding user fees in the United States and British Columbia, Canada are:

H2a: As out-of-pocket prices for prescription drugs increase, quantity demanded decreases

H2b: When patients do not face the full cost of prescriptions, the price elasticity of demand for prescription drugs is greater than zero

By considering these hypotheses, we can explore estimates within and between different contexts and draw broad economic and policy conclusions regarding cost sharing for prescription drugs. Moreover, based on these hypotheses, we formulate the

main research questions for each studied region in Chapters 6 and 7. The specific research questions, however, differ between the United States and British Columbia because of the unique institutional and demographic characteristics of each area and the availability of data.

1.4. Organization of the thesis

The dissertation is comprised of nine chapters, including this introduction. In Chapter 2 we present the neo-classical economic theory of insurance and the economic literature that has followed this traditional theory. The primary focus of the chapter is on the moral hazard effect of insurance and the associated welfare loss. Not only has the concept of moral hazard shaped cost sharing policy in the United States, but because *ex post* moral hazard is prevalent in all health systems, there has been a contentious debate over the implementation of user fees in some countries such as Canada. As the traditional economic theory has been an impetus for empirical literature and for policy change in the United States, we provide the neo-classical framework as a means of setting the context. There are a number of critiques of the traditional economic theory, and those critiques are useful for highlighting the shortcomings of the economic arguments in the context of policy. Despite these criticisms, the neo-classical theory provides a valuable framework for predicting and estimating consumer behavior in the face of higher prices.

Chapter 3 then offers an overview of the literature that has covered cost sharing for medical services. This chapter provides a brief outline of studies that have considered cost sharing for medical services in general, inpatient services, and physician services. The intent is to place the prescription drug elasticity estimates in the context of price elasticity estimates from other sectors of health care. As prescription drug cost sharing is the focus of this thesis, significantly more attention in the chapter is given to the related literature. The section on cost sharing for prescription drugs also considers how various supply- and demand-side explanatory variables concurrently affect demand. To indicate why we chose to focus on the particular research questions and the specific settings, Chapter 3 also includes information regarding the limitations of existing studies and existing empirical gaps.

Chapter 4 is an extension of Chapter 3 in that it statistically summarizes the various price elasticity estimates from the literature using a meta-regression analysis. The result is that we obtain a "composite" or "adjusted" elasticity estimate. A meta-regression analysis requires that the researcher pull selected information from relevant studies, including information regarding the quality of the study, the institutional setting of the paper, and the dataset used for the analysis. This information is then put together in a database, and the researcher uses an econometric model to obtain a composite price elasticity estimate. In addition, a meta-regression analysis provides information on the study-specific characteristics, such as the standard error, that have a significant influence on the elasticity estimate. The adjusted elasticity estimate is particularly important for this thesis in that it gives us a baseline comparator for the estimates that we obtain for the United States and British Columbia.

Another gap highlighted in the literature review is the need for updated price elasticity estimates from the United States, comparisons of different populations (based on age and income) within one country, and general comparisons of elasticity estimates between two similar countries. Chapters 5, 6, and 7 are all related to these aspects of the dissertation. Chapter 5 begins by setting the policy context and offering a detailed overview of health insurance and prescription drug insurance coverage in the United States and British Columbia. Not only does the description of each health care system provide some motivation for the specific econometric model chosen for each setting, but the policy background also sets the scene for later policy analysis in Chapter 8 based on the results of the empirical work.

Chapter 6 provides an econometric estimation of the relationship between cost sharing and the demand for prescription drugs in the United States. We employ the Medical Expenditure Panel Survey, an unbalanced rotating panel dataset covering the years 1996 to 2004. The analysis considers the adult population and more vulnerable populations, such as the elderly and low-income individuals. The chapter then calculates price elasticities of demand for each of these population groups. Important demographic, socioeconomic, and health-related explanatory variables are included in the model as covariates, and the econometric specification accounts for unobserved heterogeneity, sample selection, and endogeneity.

Chapter 7 focuses on British Columbia for price elasticity estimates. The analysis employs the British Columbia Linked Health Database, a panel covering all recipients of PharmaCare drug coverage in the province. Because we are unable to determine whether non-elderly recipients of public drug coverage in British Columbia simultaneously have private drug coverage, the analysis is restricted to the elderly. The model includes important demographic, socioeconomic, and health-related explanatory variables, and the specification considers the non-linearity of the dependent variable and unobserved heterogeneity.

Chapter 8 provides a comparison and policy discussion of the results. The chapter broadly compares the results from the United States and British Columbia, offering insight into why the estimates might differ between the two areas. As the original motivation of cost sharing was to dampen the moral hazard effect of insurance, we then provide a discussion of our elasticity results from a neo-classical economic perspective. However, policymakers are often concerned with goals that may be unrelated to economic efficiency, and we also consider the meaning of the elasticity estimates in terms of equity and health care efficiency. This leads to a broad set of policy implications for developed health systems and then a narrower set of policy implications for the American and British Columbian health care systems.

Finally, Chapter 9 wraps up the dissertation by reviewing the other eight chapters in the thesis. Chapter 9 also provides some direction for future research related to the question put forward in this thesis. In particular, some of the suggested research extends the work of this thesis. Another avenue of research involves work that is related to cost sharing for prescription drugs but involves different questions than the ones put forward in this dissertation.

Chapter 2: The theory of health insurance

2.1. Introduction

As explained in Chapter 1, the neo-classical theory of insurance[1] underlies many of the empirical models in the literature that have been used to estimate the price elasticity of demand for prescription drugs. It is important to present the insurance theory as the theory motivates our empirical specifications for the United States and British Columbia. Although the literature on insurance market failure encompasses a number of issues, including asymmetric information, the conditions necessary for an insurance market to function, and industrial organization, among others, this chapter is not intended to be a textbook overview of all these aspects of insurance. Instead, the chapter is meant to highlight the characteristics of insurance, mainly moral hazard and adverse selection (to some extent), that determine the level of cost sharing individuals face for prescription drugs. We refer the reader to texts such as Cutler and Zeckhauser (2000) and Zweifel and Breyer (1997) for more detailed explanations of insurance theory.

The focus of this chapter is primarily on moral hazard rather than adverse selection because of a large body of theoretical and empirical literature related to moral hazard, which has influenced demand-side cost sharing decisions in the United States and sparked a fierce debate on user fees in other countries such as Canada[2]. The existence of this debate highlights the fact that moral hazard is persistent in all health systems, whether the systems are based on social or private insurance or a tax-based regime. Recent theoretical developments that extend our conceptual understanding of the traditional neo-classical theory of moral hazard add another perspective to the debate. Generally, this chapter draws upon references such as Cutler and Zeckhauser (2000), Folland et al. (1997), Pauly (1968), Rothschild and Stiglitz (1976), and Zweifel and Breyer (1997) for the fundamental explanations of insurance theory.

We begin our discussion with a basic competitive model that introduces insurance in the absence of asymmetric information. The model describes how consumers maximize their expected utility from the purchase of insurance subject to the zero profit constraint of insurance companies. However, in reality, various distortions occur once the insurance market has evolved. For example, consumers are likely to have more information about their likelihood of falling ill (Folland et al., 1997), and high-risk individuals have an incentive to hide their true risk type to avoid paying higher premiums. This inevitable existence of heterogeneity in the health insurance market changes the equilibrium outcome, and we briefly discuss this situation. Another type of asymmetric information is moral hazard where the existence of insurance either induces consumers to alter their likelihood of falling ill (*ex ante*

[1] Another possibility is to approach the elasticity of demand for prescription drugs from the Grossman (1972) human capital model of demand perspective. However, our primary concern in this thesis is examining the moral hazard effect of insurance and whether it is significant. The Grossman model is more relevant for determining the importance of other factors like age that influence the individual's production of his own health.

[2] Another reason to focus on moral hazard is that we did not have premium information in our data (which would have permitted empirical investigation of adverse selection).

moral hazard) or to increase their consumption of medical care (*ex post* moral hazard) (Zweifel and Breyer, 1997). As *ex post* moral hazard has been the main focus of the literature and an important determinant of health policy since Pauly's (1968) pivotal article, we focus on this aspect of moral hazard in the chapter. There has also been debate within the health economics literature over the extent to which *ex post* moral hazard exists and the applicability of the neo-classical model. Given this debate, we provide a discussion of this literature and the implications for this dissertation. An important note regarding this chapter is that we provide the basic mathematical models and conceptual descriptions, but more detailed information is available in Appendix A.

The organization of the chapter is as follows: Section 2.2 provides a general discussion of the insurance purchase where we assume symmetric information. This is followed by a relaxation of the symmetric information assumption in Section 2.3; this section briefly discusses adverse selection and provides a more detailed explanation of *ex post* moral hazard. Section 2.4 then goes over the alternative theories and models regarding moral hazard, and Section 2.5 relates the theory to the subsequent analyses in Chapters 6 and 7. Section 2.6 offers concluding remarks.

2.2. A general approach to specifying the insurance purchase

Before we discuss moral hazard, which is the main focus of this chapter, it is important to clarify the insurance purchase decision. The purpose of health insurance is to reduce the variability in income that occurs because medical spending is unpredictable. By pooling a large number of individuals, insurance companies can reduce the variability of insured individuals' incomes because of the principle of the law of large numbers (Pauly, 1968). We begin by discussing the demand side of the market, then we present the conditions for the supply of insurance, and finally we discuss equilibrium in the insurance market.

2.2.1. The demand for insurance contracts

In this section, we first derive the individual's expected utility when he is uninsured, and we then compare this outcome with his expected utility when he purchases insurance. For simplicity, assume that there are only two states of the world: sickness and health. With probability π the individual falls ill, and he faces an exogenous loss m, the amount of medical spending required to restore him to good health. His income that period[3] is W, and without insurance his utility is $u(W-m)$. With probability $1-\pi$ he remains healthy, incurring no losses, and his utility is $u(W)$. The uninsured individual's expected utility is thus:

$$EU_{unins} = \pi * u[W-m] + (1-\pi) * u[W] \qquad (2.1).$$

Assume he now has the option of purchasing health insurance, and in the event of illness, the insurance company pays him a pre-determined amount I. If the insured

[3] We assume that illness has no effect on his earnings.

individual finds himself in poor health, his wealth is: $y^s = W - \beta - m + I$, where β is the insurance premium. If he remains in good health, his disposable income is $y^h = W - \beta$. Letting $\varepsilon = I - \beta$ the vector $\Omega = (\beta, \varepsilon)$ describes the health insurance contract. Thus, his expected utility is:

$$EU_{ins} = \pi * u[W - \beta - m + I] + (1 - \pi) * u[W - \beta] \qquad (2.2).$$

Whether the individual chooses to purchase insurance depends on the contract: if either the premium is too high or the payout is too low, such that his expected utility is lower than the utility associated with being uninsured, he will forego insurance.

2.2.2. The supply of insurance contracts

Given that the individual chooses to insure based on his expected utility of wealth, the task is now to resolve how insurance companies decide which contracts should be offered on the market and which customers should be allowed to purchase specific contracts. Unlike the risk-averse purchasers, insurance companies are assumed to be risk-neutral and concerned only with expected profits. The market is competitive, and insurance firms are willing and able to sell any number of contracts they believe will make an expected profit. To simplify the analysis we assume that there are no loading costs. The profit q for a contract Ω that is associated with a probability π of ill health is:

$$q(\pi, \Omega) = \pi * (\beta - I) + (1 - \pi) * \beta \qquad (2.3).$$

The first term represents the insurance company's loss if the consumer falls ill because the company must make a payout. The second term is the profit if the individual remains healthy. Because the market is perfectly competitive, $q(\pi, \Omega) = 0$. Solving equation (2.3) for $q(\pi, \Omega) = 0$ yields the optimal insurance premium:

$$\beta = \pi * I \qquad (2.4).$$

This is the actuarially-fair premium and equals the probability of illness multiplied by the generosity of insurance coverage. We can thus see that better information regarding the risk level of the consumer allows the insurance company to offer a premium closer to the break-even level.

2.2.3. Equilibrium in the insurance market

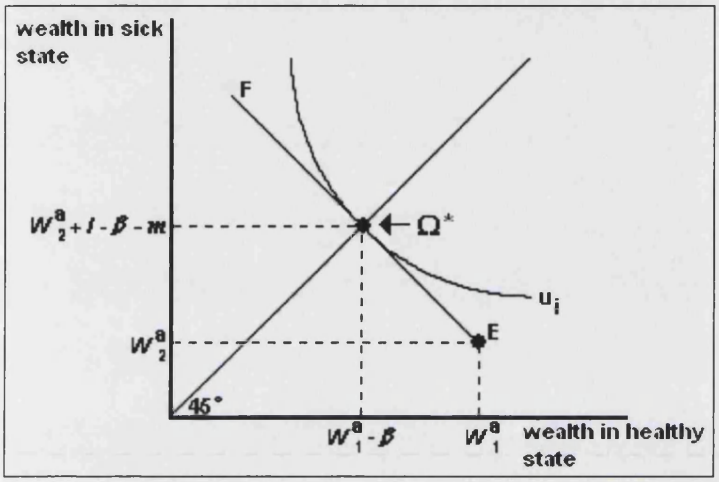
The equilibrium set of contracts can be determined based on the given supply- and demand-side equations for health insurance. An important assumption regarding the competitive insurance market is that consumers can only buy one insurance contract, implying that insurance companies control the prices and quantities of contracts[4]. We also assume that all consumers have the same probability of illness. The competitive equilibrium set of contracts is determined by maximizing consumers' expected

[4] For a defense of this assumption, see Rothschild and Stiglitz (1976).

utilities under insurance subject to firms' zero profit constraints (Rothschild and Stiglitz, 1976).

The equilibrium of supply and demand is illustrated in Figure 2.1, where the horizontal axis represents the consumer's income when he is in good health, and the vertical axis represents his income when he is ill.

Figure 2.1. Equilibrium with identical customers



The point E with the coordinates (W_1^a, W_2^a) in Figure 2.1 represents the amount of wealth that the individual has when he is uninsured, and the indifference curve in the diagram is derived from the function in equation (2.1). When the individual purchases an insurance contract Ω, he moves from point E to the point $(W_1^a - \beta, W_2^a + I - \beta - m)$, represented by Ω^* in Figure 2.1.

The line EF, termed the fair-odds line, represents the set of all policies that provide insurance companies with zero profits (Rothschild and Stiglitz, 1976). With identical customers the equilibrium policy Ω^* is at the point of tangency between the indifference curves and the fair-odds line. Additionally, the 45°-line indicates all points where the consumer will have equal income in both states of the world. Since consumers are risk averse, the equilibrium policy Ω^* is also located at the intersection of the 45°-line and the fair-odds line.

Mathematically, we can solve for the optimal insurance policy that the individual should purchase under these conditions. The consumer will maximize his utility of wealth in the insured state by considering the possible insurance payouts that he could receive in the event of illness (Rothschild and Stiglitz, 1976). The result is that the insurance payout must equal his medical losses such that $I = m$, indicating that if insurance is actuarially fair, the optimal policy for a risk averse individual is full

insurance. He does have the option of foregoing insurance altogether, so he will only purchase insurance if $EU_{ins} \geq EU_{uins}$. A derivation of this result is available in Appendix A.1.

2.3. Insurance and asymmetric information

The previous model of equilibrium in the health insurance market assumed that symmetric information exists. In reality, insurers and consumers are likely to possess different levels of information, and there is often a cost to bridging the information gap. Analyzing this phenomenon is important to this dissertation because the existence of asymmetric information is likely to affect the insurance contracts offered on the market and consumption once insurance has been purchased. Moral hazard and adverse selection are two such types of asymmetric information that frequently arise in insurance markets. These problems occur when three conditions take place in the market: (a) there is a risk, (b) there is a contract that implicitly or explicitly transfers this risk from one agent (or group of agents) to another agent (or group), and (3) the parties to the contract have different information about the relevant states of nature (Loubergé, 1991). Since the focus of this dissertation is on moral hazard, we only provide a brief overview of adverse selection in this chapter.

2.3.1. Asymmetric information and adverse selection

One form of information asymmetry, adverse selection, occurs when consumers have more information than insurers about their expected level of health, and insurers cannot easily distinguish between individuals who belong to different risk classes. If plans could charge premiums based on individuals' expected costs, the market would efficiently sort consumers into plans that reflected their expected costs (Cutler and Zeckhauser, 2000; Rothschild and Stiglitz, 1976). The problem is that high-risk individuals prefer to obtain generous insurance[5] without paying higher premiums and often attempt to mask their true risk profiles as a result. Even in the absence of information asymmetries, determining an individual's risk profile is difficult due to technology constraints, and charging someone a higher premium simply because he is sickly may also be considered socially unacceptable (Cutler and Zeckhauser, 2000)[6]. As mentioned above because the focus of this dissertation is on quantifying the moral hazard effect of insurance through the price elasticity of demand, we only provide a brief overview of adverse selection in this section. A general understanding of adverse selection is important, though, because the existence of adverse selection in the American setting has an important influence both on the insurance contracts offered on the market and on the contracts chosen by consumers. This has implications for the

[5] Generous insurance refers to lower cost sharing requirements and fewer restrictions on covered services.

[6] One option is for insurance companies to charge an average premium, but this entails low-risk individuals paying more than their actuarially fair premiums and high-risk customers paying less. Generous plans will attract disproportionate amounts of ill individuals, moderate plans will attract a larger number of healthier individuals (Arrow, 1985; Cutler and Zeckhauser, 2000), and some low-risk individuals may decide to forego insurance altogether. To cover the costs of insuring against higher risks, generous plans will have to charge higher premiums than moderate plans (Rothschild and Stiglitz, 1976).

econometric specification chosen, a consideration that is detailed in Section 2.5. More in-depth mathematical and diagrammatical representations of adverse selection and the insurance purchase are available in Appendix A.2.

Where there are consumers with different risk types and those consumers do not reveal their risk profiles to insurers, there is no pooling equilibrium insurance contract (Rothschild and Stiglitz, 1976). If equilibrium does occur in the market (see Appendix A.2 for the necessary condition), then it will be a separating equilibrium where high-risk persons have complete health insurance coverage and low-risk individuals only have partial insurance coverage.

In terms of the relationship between this theory and cost sharing, when there is a heterogeneous population and consumers choose not to reveal their risk type, there will be differing insurance contracts offered on the market. High-risk individuals will choose the complete insurance package and thus face minimal user fees and extensive coverage of health services, including prescription drugs. Lower-risk consumers, however, may choose contracts that do not include prescription drug coverage or may involve significant out-of-pocket requirements for prescription drugs and other health services.

2.3.2. Asymmetric information and moral hazard

Once individuals are sorted into insurance plans, another form of asymmetric information, moral hazard or hidden action, arises (Arrow, 1963; Pauly, 1968; Pauly, 1974; Zeckhauser, 1970). This phenomenon occurs when the existence of a contract between the consumer and the insurer causes the consumer to alter his behaviour in such as way that may change his probability of falling ill (*ex ante* moral hazard) and/or his expected cost of illness (*ex post* moral hazard). Both *ex post* and *ex ante* moral hazard are phenomena that occur whenever there is insurance, whether the insurance coverage is public or private.

Ex ante moral hazard occurs when the purchase of insurance reduces the individual's incentive to engage in preventative effort (self-protection), potentially altering his probability of falling ill. *Ex ante* moral hazard would not be a problem if the insurer was able to observe the level of preventative effort undertaken because the insurer could impose an insurance premium that was inversely related to the individual's level of preventative effort (Zweifel and Breuer, 2005; Zweifel and Breyer, 1997). Because this is not the case in reality, insurers offer different insurance contracts to induce patients to either engage in more preventative effort or pay higher premiums. As *ex ante* moral hazard has been a less important factor in shaping health policy and because we do not have data on preventative effort or premiums (which would allow us to consider *ex ante* moral hazard), we do not provide any further information on this type of moral hazard.

Another variant of moral hazard, *ex post* moral hazard, occurs because individuals with insurance face lower marginal prices for medical care than they would in a free market without insurance, and there is an inevitable increase in the consumption of

health care (Pauly, 1968). *Ex post* moral hazard is a problem because the insurer cannot always determine the marginal benefit of medical care, and even if it could, monitoring each purchase is too costly. There is further uncertainty because medical technology is not advanced enough for medical practitioners to always determine the value of treatment. According to the neo-classical economic theory, the presence of this information asymmetry leads to over-consumption of medical care, creating a welfare loss (Feldstein, 1973) because the resources spent on health care could be put towards other goods and services with marginal benefits that outweigh the marginal costs.

An additional problem with moral hazard is that it conflicts with risk-spreading goals (Zeckhauser, 1970). Insurance companies are forced to trade off the benefits of risk spreading against the costs of moral hazard that arise from more generous insurance by transferring risk to insured individuals. This risk transfer takes the form of higher demand-side cost sharing or gaps in medical coverage.

There is also a third type of moral hazard: supplier-induced demand (SID). Although there is not an agreed upon definition for SID, one definition posits that SID is demand that exists beyond the amount that a well-informed patient would have chosen (Donaldson and Gerard, 1993), and this excess demand is caused by provider moral hazard. Not only are doctors sometimes shielded from the true costs of medical care, but there is also asymmetric information between the doctor and the patient and the doctor and the third-party payer. Another definition indicates that SID occurs when the physician provides medical care for the patient that is contrary to his interpretation of the best interest of the patient (McGuire, 2000). Thus, in both definitions, the physician uses his hidden information to create demand; for instance, by ordering additional unnecessary tests for the patient or requiring the patient to make additional office visits. Although this is an important aspect of moral hazard, supplier-induced demand will not be considered in this research because we are concerned with how the existence of demand-side cost sharing influences patients rather than the factors that are motivating moral hazard.

The aim of the next section is to provide a brief discussion of *ex post* moral hazard in insurance markets. The subsequent analysis follows from work completed by other researchers (Pauly, 1968; Zeckhauser, 1970; Pauly, 1974; Cutler and Zeckhauser, 2000). The models introduced in this section are an extension of the basic insurance model with a risk-averse utility maximizing individual facing two states of the world: sickness and health. The section does not provide mathematical derivations, but more in-depth presentations are available in Appendix A.3.

Ex post moral hazard

By definition *ex post* moral hazard occurs because more generous insurance coverage increases the amount of care that the individual consumes in his sick state. If the insurer could observe the insured's health status, then the optimal insurance would be a lump-sum payout to the individual in the event of illness (Zweifel and Breuer, 2005; Zweifel and Breyer, 1997; Zweifel and Manning, 2000). The insured individual could

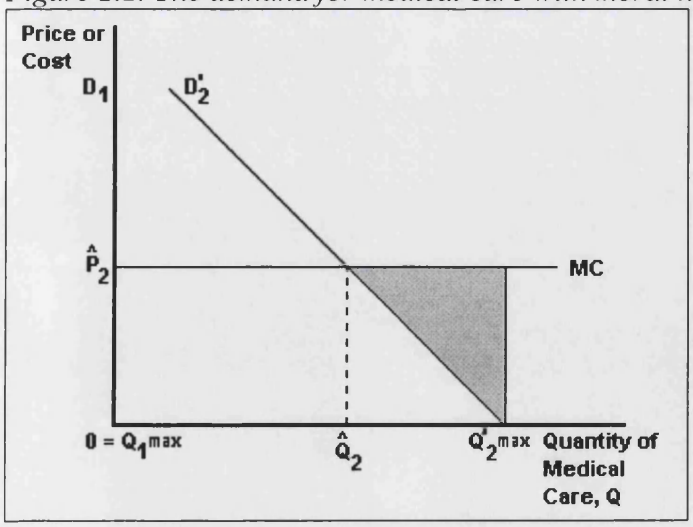
then choose his own amount of treatment, although he would have no incentive to over-consume medical care because his payout is fixed and related to his health status. There is evidence that real-world insurance plans consider the individual's health status (Blomqvist, 1997). For example, some health insurance plans refuse to cover pre-existing conditions for a period of time, while the provisions for dental coverage are often different than the provisions for other types of coverage. Nevertheless, there is still uncertainty surrounding the individual's health status, and resolving this uncertainty is costly. Thus, the subsequent analysis will consider the situation where the insurer can only observe health expenditures rather than health status.

We first approach the analysis of *ex post* moral hazard through the traditional diagram, and then we provide a brief description of the utility maximizing mathematical approach. A more detailed mathematical derivation of this approach is provided in Appendix A.3.

The traditional method of considering moral hazard is one put forth by Pauly (1968). Because demand curves are downward sloping, the insured consumer increases the quantity of medical care consumed when he purchases insurance. This is because insurance lowers the marginal cost of care, where full insurance corresponds to a price of zero for medical care. This situation is illustrated in Figure 2.2.

The individual in this diagram faces two states of the world: in one state, he becomes ill with probability π, and in the other state he remains healthy and incurs no medical expenses. His demand for medical care in the unhealthy state is represented by the line, $D_2^{'}$, and his demand in the healthy state is represented by the inelastic curve D_1 (which corresponds with the vertical axis). In the unhealthy state the quantity demanded of medical care is not only dependent on price but also other factors such as income, preferences, and morbidity (Pauly, 1968).

Figure 2.2. The demand for medical care with moral hazard



If the patient was uninsured, his consumption decision would be represented by $(\hat{P}_2, \hat{Q}_2)$. Assuming that the price of medical care is one ($\hat{P}_2 = 1$), the expected value of his medical care expenses is:

$$m = \pi * \hat{Q}_2 * 1 + (1 - \pi) * 0 * 1 = \pi * \hat{Q}_2 \qquad (2.5).$$

His other choice is to purchase insurance and pay a premium of:

$$\beta_{mh} = \pi * Q_2^{'} max \qquad (2.6).$$

The value of β_{mh} is greater than the premium the individual would pay if moral hazard were nonexistent[7].

Thus, the premium for medical insurance has two components: the pure cost of protection against risk and the extra resource cost due to moral hazard. This additional consumption of medical care beyond the equilibrium quantity demanded in the presence of no insurance could create a net welfare loss. The extent of this welfare loss may differ between consumers depending on their individual demand curves and levels of risk aversion. Thus, from an actuarial standpoint some events may not be insurable for certain individuals (Pauly, 1968), for example if the individual is extremely risk averse. The implication is that the optimal level of insurance is individual-specific, and the responsiveness to cost sharing is likely to differ between broad population groups such as the elderly and low-income groups. However, it is often assumed that groups of individuals share the same risks and risk preferences for insurance, allowing insurers to offer insurance at the group level.

This situation can also be approached using utility-maximizing equations. Total medical expenditures m can be broken into two components: price ρ and quantity Q. To simplify the analysis we normalize the price of medical care to one such that the quantity of health care consumed can be represented by m (as $m = Q^*1$). The consumer has a choice between consuming the homogenous health good m and other goods y.

At the beginning of the period, the individual does not know whether he will be sick or healthy during the period. If he falls ill, his disposable income is:

$$y^s = W - \beta - m + I \qquad (2.7),$$

but if he remains healthy, his budget constraint becomes:

$$y^h = W - \beta \qquad (2.8).$$

[7] If there was no moral hazard, the premium would be based on consumption at point $\hat{Q}_2$.

Further assume that medical services are valuable to the individual when he falls ill but useless when he is healthy. As a result, he has two different utility functions for each state of the world: $u^s\lfloor m, y^s \rfloor$ and $u^h\lfloor m, y^h \rfloor$.
There is likely to be uncertainty surrounding the individual's health status, such that the insurance company can observe the individual's medical expenditures but not his health status. This means that the insurance company must use medical expenditures as a proxy for health status such that $I = I(m)$. Although the insurer has multiple options for shifting some of the costs to the individual, for simplicity we only consider the existence of a constant coinsurance rate c $(0 \leq c \leq 1)$, which depends on medical expenses. By including the coinsurance rate, the insurance payout can be expressed as:

$$I(m) = (1-c)^* m \qquad (2.9),$$

indicating that the consumer bears some proportion of his medical expenses.

The analysis begins with the consumer choosing the quantity of medical care that maximizes his expected utility in the sick state, $u^s\lfloor m, y^s \rfloor$ (Zweifel and Breyer, 1997). He then determines the relationship between medical expenditures and the coinsurance rate by maximizing the result with respect to his medical expenditures and the coinsurance rate. The conclusion from this exercise is that decreasing the coinsurance rate increases his demand for medical care in the event of illness (Zweifel and Breyer, 1997).

Once the consumer has determined his optimal choice of medical care based on an exogenous coinsurance rate, he enters the second stage where he finds the value of c that maximizes his expected utility. He takes into account the possibilities of being ill or healthy and the fact that his premium depends on the coinsurance rate as pointed out in equation (2.9). The result is that the optimal rate of coinsurance is positive, and as the probability of falling ill rises, the optimal coinsurance rate rises (Zweifel and Breyer, 1997).

The existence of *ex post* moral hazard affects the types of insurance contracts offered and the individual's utility maximizing levels of insurance coverage and cost sharing. When there is *ex post* moral hazard, full coverage is suboptimal if the presence of insurance leads the utility-maximizing individual to increase his medical expenditures in the sick state. Choosing an insurance contract with a coinsurance requirement is advantageous to the individual because he gives himself an incentive to be more cost-conscious. As a result, he faces a lower premium than if he were to consume up to the point of satiation.

Ex post moral hazard and efficiency

Given the existence of asymmetric information, one concern in the economic literature is the most efficient level of insurance coverage that can be achieved. Within the literature efficiency is most commonly defined as Pareto efficiency

(Reinhardt, 1992), which is an allocation of resources that cannot be changed to make one individual better off without simultaneously making another feel worse off (Reinhardt, 1992).

One avenue of research on efficiency is the calculation of the net welfare effect of health insurance. Evidence indicates that there would be a net welfare gain if individuals bore more risk and the price of medical care was lower (Blomqvist, 1997; Feldman and Dowd, 1991; 1993; Feldstein, 1973); in other words, a more efficient outcome would be somewhere in between no insurance and full insurance coverage.

Based on the assumption that excess health insurance gives rise to a welfare loss, researchers have attempted to determine the most efficient level of cost sharing (Blomqvist, 1997; Zeckhauser, 1970), but there is disagreement over the optimal level. Some evidence indicates that the optimal situation is one of cost sharing that is non-linear in expenditure (Blomqvist, 1997; Zeckhauser, 1970) and that the most efficient level of cost sharing may be relatively low (Blomqvist, 1997). Others suggest that cost sharing should be higher, even up to the 45 percent rate (Manning and Marquis, 1996). Another option that has been suggested is to charge higher user fees to patients that choose high-cost treatment and lower user fees to patients that choose low-cost treatments (Chernew et al., 2000), although this applies only to the case of severe, observable illnesses.

2.4. Alternative theories and models regarding *ex post* moral hazard

There are, however, economists who argue that the neo-classical economic theory incorrectly measures the welfare loss of excess insurance. Given that one justification for demand-side cost sharing is to reduce supposed over-consumption of medical care when there is full insurance, it is important to outline the alternatives to the traditional model.

Rice (1992; 1993) argues that the demand curve for medical care does not accurately reflect individual utilities, mainly because consumers do not cut back on services of the least marginal benefit to them first when faced with user fees. To refute the neo-classical model for moral hazard, he cites evidence from the Lohr et al. (1986) study, which found that patients reduced their consumption of both necessary and unnecessary medical services when faced with cost sharing. Possible reasons for this anomaly are that patients may have insufficient information and experience to make their own health care choices and that medical practitioners may not provide optimal care given their own objectives (Rice, 1992). The alternative definition of welfare loss that he offers is more useful for policymakers in that it considers the necessity of health care services; that is, he argues that a welfare loss occurs when medically unnecessary health care is provided (Rice, 1992). Thus, insurance can influence this alternative definition of welfare loss in two ways: (1) by lowering the price of care and improving access to health services, and (2) influencing provider incentives to provide appropriate care[8].

[8] For instance, insurance companies may carry out drug utilization reviews.

Nyman (1999) argues that the findings from Lohr et al. (1986) are consistent with neo-classical economic theory. Instead of the analysis put forward by Rice (1992), where rational and informed consumers rank their medical care by effectiveness, Nyman (1999) presents an alternative interpretation of the Lohr et al. (1986) results. When faced with two different medical procedures or goods of varying effectiveness[9], consumers demand more of the most effective procedure at any given price. For instance, given the extensive literature on the benefit of statins (La Rosa et al., 1999), we should not be surprised if patients facing an equal co-payment for statins and fibrates demand more statins than fibrates. Nonetheless, higher cost sharing will still cause patients to reduce their consumption of both effective and non-effective care, as predicted by the inverse relationship between the out-of-pocket price and the quantity demanded.

Although Nyman (1999) contends that it is still possible to use the demand curve to measure the value of health care procedures, he argues that Pauly's (1968) moral hazard framework needs modification. Pauly (1968) assumes that patients' health care purchases are unresponsive to income, but the empirical findings that income elasticities are positive and significant implies that Pauly's assumption does not hold for health care demand. By relaxing Pauly's assumption, Nyman (1999) instead contends that part of the increase in quantity demanded due to full insurance is because of an income transfer from the healthy insured group to the unhealthy insured individual, and part of the consumption increase is due to a decrease in the out-of-pocket price of care. The amount of income transferred to the ill patient is positively related to the probability of illness, and this increased level of income in turn determines the amount of medical care consumed by the ill patient. This income effect of insurance should not be included as part of the net welfare loss calculation because the income gain for the unhealthy insured patient equals the income loss from the healthy insured consumers.

Nyman's (1999) alternative net welfare loss calculation takes into account the gain from the consumer transferring risk to the insurer, the welfare loss of insurance due to the price effect on consumption, and other gains from insurance not mentioned in the neo-classical theory. The neo-classical estimates of the risk-bearing gain are based on the expected utility theory (Von Neumann and Morgenstern, 1947), which can only apply to medical expenses that would have occurred in the absence of insurance, and therefore existing estimates of the values of risk-bearing based on total medical expenditures overestimate the true value. Despite the lower predicted value of risk-bearing under his framework, Nyman purports that other aspects of insurance add value. In particular, insurance allows access to medical services that the uninsured would be unable to afford. Because new health care technologies such as medicines for the treatment of kidney failure or end-stage renal disease are effective but also vastly more expensive than other alternatives (Bunker et al., 1994), this is a welfare gain. An additional aspect of health insurance is that it increases consumption of medical care that is affordable to the uninsured group, and it increases consumption of other goods and services in the ill state (through the income transfer). Given that

[9] Nyman (1999) also assumes that the effectiveness of procedures is known and that patients value higher effectiveness.

consumers purchase insurance because the expected value of income with insurance exceeds the expected value of the premium foregone in the present state (Zweifel and Breyer, 1997), the transfer from the healthy to the unhealthy is a societal gain (Nyman, 1999). By incorporating the smaller gain from risk-bearing along with the gain from improved access to affordable medical care and other consumption in the ill state, the net welfare loss of insurance from Nyman (1999) is likely to be smaller than the conventional welfare loss put forward by Pauly (1968).

Blomqvist (2001), while arguing that Nyman's criticisms of the traditional model are correct, claims that the biases inherent in the traditional model that Nyman discusses are not necessarily significant. Blomqvist's argument relates to the fact that most health care analyses of the welfare loss of insurance are concerned with evaluating insurance at the margin rather than the entire welfare loss. As a result, Nyman's framework is less useful except for the situation where the researcher is considering the gain of changing from no insurance to insurance. First, Blomqvist (2001) indicates that because health insurers have recognized that flat coinsurance rates for all medical services, including catastrophic expenses, are less efficient, most insurance plans provide better coverage for large expenses. The implication is that purchasing more generous insurance may have little or no effect on affordability, and thus this aspect of insurance (affordability) not considered in the traditional model may be less of a bias than Nyman indicates. Second, because health insurance plans are designed to limit catastrophic spending, the relevant individual budget share devoted to out-of-pocket health expenditures is generally lower than Nyman estimates. The result is that the elasticity estimates from the empirical literature, particularly the RAND study, are less biased than Nyman claims. Thus, because of this and another technicality that Blomqvist mentions[10], Nyman's (1999) framework underestimates the welfare loss of health insurance.

One issue with Blomqvist's criticism of Nyman's affordability bias is that affordability may differ vastly from low-income to high-income consumers. In particular, health plan deductibles have been increasing significantly since the beginning of this century, and the average deductible in a family employer-sponsored plan ranges from $751 per family in health maintenance organizations to $3511 in Health Savings Accounts (KFF/HRET, 2006). Furthermore, the KFF/HRET survey indicates that 51 percent of individuals in employer-sponsored plans face cost sharing for inpatient services in addition to the deductible, and about half of this group faces a coinsurance rate. This suggests that insurance companies have not moved away from coinsurance rates and high cost sharing for high-cost and possibly necessary services, implying that affordability may be a significant issue for many insured individuals. The fact that non-group insurance is less generous than employer-sponsored insurance suggests that affordability is likely an even greater issue among this group of the insured. A further related consideration is that a low-income individual may find it more difficult to devote 3 percent of his income to health than a high-income individual, as other consumption goods, such as housing and food comprise a larger

[10] Nyman (1999) takes the relevant budget share for his revised elasticity estimates as the share of each family's total spending on medical care, but Blomqvist argues that the relevant budget share should be the share of each family's out-of-pocket spending on health care.

portion of the low-income individual's budget. In fact, out-of-pocket limits for private health insurance are unrelated to income (although they were in the RAND experiment, which Blomqvist uses as his example). Around 22 percent of workers with employer-sponsored insurance have no limits on out-of-pocket spending. Of the workers that do face annual maximums, these limits may not include spending on certain services such as prescription drugs or spending below a deductible, effectively increasing the annual out-of-pocket limit. Thus, particularly for poor individuals ineligible for public coverage, more generous insurance coverage may improve affordability.

2.5. Economic theory, the research hypothesis, and the econometric model

The neo-classical theory of insurance and moral hazard and the extended theories of moral hazard provide some indication of expected results for the empirical analysis. Ideally, a dataset would contain information related to the insurance contracts: the premiums, cost sharing requirements, and any exclusions. Few datasets contain this information, though, and most datasets with medical utilization information only contain variables related to user fees. Nonetheless, the theory of insurance and adverse selection indicates that the level of cost sharing is affected by the insurer's inability to fully assess consumers' risk profiles, leading to multiple insurance contracts that are each meant to attract a different risk profile.

The importance of the adverse selection discussion is not to suggest a theoretical basis to test for adverse selection as our data are not rich enough to permit this. Instead, the discussion indicates that in a private market, adverse selection may contribute to issues of endogeneity. This issue is relevant in a place such as the United States where a large proportion of the population chooses between various prescription drug insurance options (or chooses between health plans offering varying levels of prescription drug coverage). Thus, the insurance contracts offered on the market to counteract adverse selection along with the consumer's expected prescription drug consumption in the period may influence the generosity of insurance coverage chosen, i.e. the level of the prescription drug co-payment. It is important to note that other factors may contribute to an endogeneity bias; for instance, the inability to measure consumption expectations or past consumption and the non-linearity of the price schedule, and it may be impossible to disentangle the sources of endogeneity. Nonetheless, the theory of adverse selection and the confirmation of its existence in the literature imply a need for us to empirically test for endogeneity.

Adverse selection is less of an issue in public insurance markets, and it has no bearing on cost sharing requirements in public systems such as those in Canada. As a result, any estimations that we carry out on samples in countries with universal prescription drug coverage need not account for endogeneity related to the consumption expectations or adverse selection.

In contrast to adverse selection, *ex post* moral hazard affects cost sharing within both the private and public insurance markets. Although there are a few competing theories of moral hazard, as discussed earlier in this chapter, this fact does not change the

nature of our empirical analysis, although it does influence the interpretation of the elasticity results. Specifically, the various theories yield different policy implications, and we will discuss these in Chapter 8.

In terms of the empirical analysis, the neo-classical economic theory and Nyman's (1999) extension provide a useful framework. The implication of Rice (1992), however, is that the demand curve for medical care is not an accurate representation of preferences. Because of the criticisms of Rice's model discussed in Section 2.4, we feel that the demand curve is still a useful measure of preferences. We choose not to account for Rice's framework in our empirical analysis. Both Pauly (1968) and Nyman (1999) confirm that the demand curve is downward sloping and that holding all other measures constant, the price elasticity of demand measures consumer responsiveness to changes in out-of-pocket prices. These other measures are the traditional determinants of demand, such as income, consumer preferences for prescription drugs, and the prices of substitute and complement goods and services. Thus, regression analysis considers these other demand determinants as covariates in the model.

Preferences for prescription drugs can encompass a variety of factors as mentioned in Section 2.3.2. One issue is the patient's perceived need for prescription medications. Age, for example, is likely to determine whether the patient feels that his illnesses are pressing enough to merit prescription treatment. Older people generally face more medical conditions, may be more risk averse as adverse outcomes can be more detrimental to their health, may perceive a shorter time horizon within which to improve their health, and may believe that substitutes for prescription drugs such as lifestyle changes are less appealing. Similarly, illness is also important as this influences the need for medical care and the perceptions of pharmaceutical treatment (based on the seriousness of the illness, noticeable symptoms, and the perceived effectiveness of the relevant medication). Other perceptions such as those regarding the riskiness of foregoing medical treatment, the safety profile of prescribed medicines, and general preferences for medical care and pharmaceutical treatment may also be important predictors of pharmaceutical demand.
Unfortunately, due to data limitations researchers are rarely ever able to control for all variables that influence the demand for health care. Yet, failing to account for important predictors can lead to omitted variable bias (Baltagi, 2002), indicating that a panel data framework is needed to capture the effect of unobserved variables. Another important empirical issue that economic theory highlights is the correlation between the variables that proxy the determinants of demand. For example, age partially reflects the need for medical care, particularly because older people typically suffer from more morbidities than their younger cohorts. The same is true for income as there is a positive correlation between income and better health (Macinko et al., 2003). The implication is that regression analysis is necessary to hold the effect of covariates constant and to test for interaction effects. As a result, our strategy for estimating the elasticity of demand for prescription drugs is based on econometric methodology.

One interesting implication of using regression analysis is that we may capture some of the income effect of insurance that Nyman (1999) discusses, although in practice it is impossible to determine if this is the case given the limitations of the dataset. Specifically, if we use income net of health expenses not including premiums, this partially represents disposable income and is held constant in the regression. An increase in disposable income could either reflect an increase in income or a decrease in out-of-pocket expenses, either due to more generous insurance coverage, lower medical consumption, or consumption of less expensive medical care. Nonetheless, because we cannot determine what care the consumer would have consumed in the absence of insurance in order to estimate Nyman's welfare effect of insurance, it is beyond the scope of this thesis to empirically examine this theory.

2.6. Conclusion

This chapter has covered the neo-classical economic theory of insurance and some of the extensions within the health care arena. The primary focus has been on the moral hazard effect of insurance and the importance of theory in providing a basis for our analysis.

Assuming no asymmetric information in the market, we determined that the optimal insurance contract for the consumer is one of full insurance. However, the assumption of symmetric information is restrictive given the reality in the market. By relaxing this assumption, we determine that adverse selection and moral hazard are two characteristics of the insurance market. The existence of adverse selection leads to a separating equilibrium (if equilibrium occurs) with high-risk individuals purchasing more generous insurance coverage than low-risk individuals. Moral hazard means that the consumer alters his behavior because of the insurance purchase. *Ex post* moral hazard means that the consumer increases the quantity of health care that he demands when he has insurance coverage, leading to higher premiums for all of the insured and a potential welfare loss. This welfare loss has been a subject of debate within the literature; some researchers have argued over the size of this welfare loss given the traditional theory, and other authors have argued that the traditional economic theory leads to an incorrect calculation of this welfare effect.

The implication of this insurance discussion is that it provides a useful framework for empirically estimating the price elasticity of demand. Specifically, the theory provides insight into the magnitude of the elasticity estimates we should expect to find in the prescription drug market given different settings. As Pauly (1968) pointed out, the optimal level of insurance differs between individuals, and thus we would expect the responsiveness to price to differ between various groups of the population. Furthermore, the theory of insurance highlights the factors that influence the demand for prescription drugs as the demand curve in the moral hazard analysis is dependent upon individual incomes, preferences for prescription drugs, and levels of illness. As the neo-classical theory of moral hazard spawned a large body of empirical research on cost sharing and the demand for medical care, including prescription drugs, this chapter is a natural precursor to the next chapter which covers the empirical literature on user fees.

Chapter 3: Cost sharing literature review

3.1. Introduction

As the seminal papers from Arrow (1968) and Pauly (1968) sparked a large body of literature that attempted to quantify the moral hazard effect of insurance, a natural extension of insurance theory is a chapter providing an overview of the empirical literature. The intent of this chapter is thus to provide a basic overview of this literature, with a primary focus on cost sharing for prescription drugs. Since Pauly (1968), who posited that price elasticities should differ between various types of medical care depending on factors such as risk aversion and the randomness of medical events, research on user fees has generally been divided between different types of medical care. The main areas that researchers have studied are medical care in general, inpatient services, physician and outpatient care, and prescription drugs. Many of the original papers were from authors such as Davis and Russell (1972), Feldstein (1971; 1977), Newhouse and Phelps (1976), and Phelps and Newhouse (1974). By the end of the 1970s, interest in the area had increased, and the RAND experiment was a large scale effort intended to provide insight into user fees. In fact, it appears that the considerable research in the area influenced US health care policy (Nyman, 2004) given the importance of user fees in public and private insurance that now dates back over 30 years.

While the focus of this dissertation is on prescription drugs, it is important to provide an overview of the literature on cost sharing and other forms of medical care. This puts the prescription drug literature in the context of the medical care literature, allowing us to make general statements about whether reactions to prescription drug cost sharing differ from reactions to cost sharing for other medical services. This contextualization is important for policy, as cost sharing for prescription drugs has traditionally been higher than for other medical services, but there may not be a clear justification for this distinction. By comparing prescription drugs with other medical services, we can comment on these differences in out-of-pocket burdens from a policy perspective (in Chapter 8).

Although a small body of published literature and working papers that have conducted literature reviews on cost sharing for prescription drugs exists (Gerdtham and Johannesson, 1996; Gleason et al., 2005; Hitiris, 2000; Hurley and Arbuthnot-Johnson, 1991; Huttin, 1994; Lexchin and Grootendorst, 2004; Rice and Matsuoka, 2004; Thomson and Mossialos, 2004), there is a need to review the subject with our specific research questions in mind. Most of these review papers have only looked at specific populations such as vulnerable groups or have only considered a small subset of the literature, such as studies from the US and the UK or the main papers in the area. However, we are particularly interested in the existing gaps in the literature related to the price elasticity of demand, and thus there is a need to comprehensively cover all of the papers that have considered this outcome variable. In addition to covering all papers in the area published in English, the literature review includes a number of papers published in other languages. Furthermore, to better understand the relationship between cost sharing and various outcomes, it is first necessary to

investigate the impact of cost sharing on medical services in general. This provides a basis for comparison and offers some insight into whether responses to the prices of prescription drugs are different than responses to the prices of other types of medical care.

The organization of the chapter is as follows: Section 3.2 outlines the search strategy that was utilized to identify relevant papers in the literature. To provide a general idea of the findings related to the literature on cost sharing for other medical services, Section 3.3 offers a basic literature review of cost sharing for medical services in general, hospital services, and physician services, and the main focus is on the volume of services obtained and the price elasticity of demand. Abbreviated literature reviews of other outcome variables such as expenditures and health care are available in Appendix B, and more study-specific information is also provided in Appendix B. Section 3.4 then offers a comprehensive overview of the literature on cost sharing for prescription drugs with a focus on the volume of prescriptions obtained and the price elasticity of demand. Again, additional literature reviews of other outcome variables and more detailed information regarding the study samples, methods, approaches, findings, and limitations is available in Appendix B. Meanwhile, Section 3.5 discusses the main limitations that can occur with analyses, while Section 3.6 identifies some of the gaps in the literature related to the price elasticity of demand for prescription drugs and explains how this dissertation will contribute to the area. Finally, Section 3.7 wraps up the findings and discussion from this chapter.

3.2. Search strategy

A number of strategies were used to identify papers related to cost sharing for the various types of medical services. The search was limited to articles detailing cost sharing in developed countries, as developing countries may have different reasons for implementing user charges. In addition to the standard forms of cost sharing, the search included papers that analyzed the impact of insurance on medical care, hospital, physician, and prescription drug utilization. We did not limit our collection to studies that used regression techniques as we were interested in determining the adjusted and unadjusted effects of cost sharing on demand.

An important note is that because the primary focus of this dissertation is on cost sharing for prescription drugs, the literature search for that specific topic is comprehensive. However, the literature search for papers related to medical, inpatient, and physician services is not intended to be comprehensive; it is only intended to provide an overview of the main papers in the literature.

Cutler's (2002c) literature review of cost sharing for medical services, Nyman's (2003) review of relevant cost sharing articles, and a number of other previously performed literature reviews of cost sharing for medical services and prescription drugs (Hitiris, 2000; Hurley and Arbuthnot-Johnson, 1991; Huttin, 1994; Lexchin and Grootendorst, 1999; Lexchin and Grootendorst, 2004; Rice and Morrison, 1994; Smith and Kirking, 1992; Thomson and Mossialos, 2004) all served as the basis for

the literature search. We electronically traced forward in time the articles from these literature reviews by looking for studies that cited these articles. Additional searches were run on the Internet and relevant databases such as PubMed, EconLit, Blackwell's Synergy, and Ingenta with combinations of the keywords listed in Table 3.1.

Table 3.1. Keywords used to search for relevant literature

Main keyword(s)	Combined with these keyword(s)
cost sharing	health
user charges	prescription drugs
user fees	medical services
copayments	medical visits
co-payments	hospital services
coinsurance	hospital visits
	inpatient services
	inpatient visits
	physician services
	physician visits
	doctor services
	doctor visits

While we did not require that a paper was published after a certain time period, our search for relevant articles ended in December 2006. In-country experts helped to identify some of the papers in languages other than English, which were then translated by colleagues. Although a number of the papers included in the original literature reviews were related to additional types of medical services, such as dental services, specific preventative services, and others, these articles were catalogued but no attempts were made to find additional ones in these categories.

We use tables to summarise our main findings and cite references, using the text for more detailed discussion. As a measure of quality, the tables specify the type of study carried out, the type of data analyzed, and the techniques used for analysis. Some studies are experimental (ES), some are based on a natural experiment (NS), and others are observational (OS). Data analysis is cross-sectional (CD), time-series (TD), panel (time-series, cross-sectional or longitudinal) (PD)[1], or survival analysis (SA).

[1] While time-series data can also be classified as aggregate or macroeconomic data, cross-sectional and panel data can be classified as non-aggregate or microeconomic data. Aggregate data is defined as data collected at the macroeconomic level such that individual-specific or household-specific information is not identifiable.

As most researchers used large datasets, we do not include information on sample size. The majority of studies used regression techniques to analyze data (R), but some reported descriptive statistics alone (NR). We do not go beyond this in assessing the quality of the research we review, mainly because efforts to determine the most appropriate method of analysis for each study depend on the study's objectives and sample characteristics. In general, however, results did not vary based on study characteristics.

3.3. Literature review of cost sharing for medical care, inpatient services, and physician services

For comparability purposes it is useful to obtain an idea of the literature on cost sharing for medical services in general. As mentioned in the introduction to this chapter, since Pauly (1968) posited that elasticity values should differ between various types of medical care, the literature has fragmented along these lines. A comparison of these different elasticity estimates is useful for researchers and policymakers in that it leads to a natural discussion of why these estimates might differ. An in-depth discussion of the utility of comparisons between prescription drug elasticities and medical care elasticities is beyond the scope of this chapter, but more attention is given to this topic in Chapter 8.

The literature on cost sharing for medical services, inpatient services, and physician visits covers a number of dependent variables, including the number of services purchased, the elasticity, expenditures, and health. Because this dissertation is focused on the moral hazard effect of insurance (albeit prescription drug insurance), this section focuses on outcomes relevant to our research questions: the volume of medical services and the price elasticity of demand. A literature review of studies related to the other outcome variables is available in Appendix B. We begin by discussing the literature that has considered all medical services in Sections 3.3.1 and 3.3.2, and later we cover the literature that has looked at inpatient and physician services specifically. Inpatient care is covered in Sections 3.3.3 and 3.3.4, while physician and outpatient care is covered in Sections 3.3.5 and 3.3.6.

3.3.1. Medical care: the effect of cost sharing on volume

Given the economic theory of moral hazard, a relevant question that has been addressed in the empirical literature is whether insurance coverage leads to consumption of medical services beyond the no insurance equilibrium. As the law of demand predicts a negative relationship, the empirical methods for examining this question have been based on quantifying the relationship between the out-of-pocket price and the number of services purchased.

This relationship has been investigated at various levels of aggregation, mainly using individual-level, household-level, and time-series data. Most of the studies focused on the United States, but country investigated a Swedish population. The literature has considered various subpopulations such as individuals of all ages, children, adults, the

non-elderly, the elderly, pregnant women, low-income individuals, and persons with HIV. A summary of the findings is presented in Table 3.2.

Virtually all studies found that cost sharing, whether it was through a co-payment, a coinsurance rate, or some other type of system, had a negative effect on the total number of medical services purchased. Approaching the question from another angle, researchers also determined that having insurance coverage increased the number of services obtained as compared with the no insurance equilibrium. Interestingly, Wolfson et al. (1982) found no relationship between user fees and the use of medical services among crippled children in one US state. It is possible that a crippled child is less likely to reduce his use of medical services because he suffers from a debilitating condition. Additionally, medical decisions for children are made by guardians who may be less inclined to risk the child's health by foregoing medical services.

Table 3.2. Medical care: cost sharing and the volume of medical services

Variable	Volume	Studies
Co-payment	-	**Elofsson et al.** (1998) [SW, OS, CD, R]
Co-payment	0	**Wolfson et al.** (1982) [US, NS, TD, R]
Coinsurance	-	**Lohr et al.** (1986) [US, ES, CD, R]; **Manning et al.** (1981) [US, ES, CD, R]; **Manning et al.** (1987) [US, ES, CD, R]; **Manning and Marquis** (1996) [US, ES, CD, R]; **Scitovsky and Snyder** (1972) [US, NS, CD, NR]; **Scitovsky and McCall** (1977) [US, NS, CD, NR]
Mixed system	-	**Rosett and Huang** (1973) [US, OS, CD, R]
Insurance coverage		
Primary (vs. none)	+	**Overpeck and Kotch** (1995) [US, OS, CD, R]; **Spillman** (1992) [US, OS, CD, R]

Country: SW = Sweden; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model; TD = time-series model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

3.3.2. Medicare care: the price elasticity of demand

Quantifying how various magnitudes of changes in cost sharing for medical services is useful as it provides a clearer picture of cause and effect. However, comparability across papers can be difficult because of different measurement units. The price elasticity of demand[2] is a unitless measure that allows us to measure consumers'

[2] Although there are various types of elasticity estimates, the three main types are: price elasticity, expenditure elasticity, and income elasticity. The price elasticity measures the percentage change in the total number of drugs consumed that is associated with a one percent change in the out-of-pocket price, and is usually considered a reflection of the uncompensated demand curve. The expenditure elasticity measures the percentage change in total prescription drug expenditures that is associated with a one percent change in the out-of-pocket price, and is typically considered a reflection of the compensated demand curve. Meanwhile, the income elasticity measures a change in prescription drug consumption associated with a change in income.

sensitivity to price along the demand curve. The most common methods of calculating elasticities are: (i) arc elasticity methods, which measure the percentage change in price and quantity between two points on the demand curve, (ii) point elasticity methods, which measure the elasticity at a particular point on the demand curve, usually the mean, and (iii) constant elasticity methods, which often use log-log regressions and assume that elasticity is constant along the demand curve (Phelps, 1997).

Table 3.3 summarizes the price elasticity results from the literature. All of the articles used cross-sectional data from the United States to compute the elasticity.

Table 3.3. Medical care: the price elasticity of demand

Author (Year)	Type of cost sharing	Price elasticity
Manning et al. (1981) [US, ES, CD, R]	Coinsurance	-0.20
Manning et al. (1987) [US, ES, CD, R]	Coinsurance	-0.14 to -0.10
Manning and Marquis (1996) [US, ES, CD, R]	Coinsurance	-0.18
Rosett and Huang (1973) [US, OS, CD, R]	Mixed system	-1.50 to -0.35

Country: US = United States
Type of study: ES = experimental study; OS = observational study
Type of model used for analysis: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques

Comparing the elasticity estimates from various studies is difficult because of the different datasets employed, the various subpopulations studied, and the different price ranges considered. Nonetheless, we can reach broad conclusions regarding the price elasticity, particularly considering that most analyses found that the demand for medical services was inelastic, although the price elasticity estimates ranged from -1.50 to -0.10. The largest elasticity estimate (-1.50) was likely due to the authors' specification of the co-payment (Rosett and Huang, 1973) because they assumed that the patient covered 80 percent of his medical care expenses, indicating that the respondents in their study were being measured at higher points on the demand curve.

3.3.3. Inpatient care: the effect of cost sharing on volume

While investigating the relationship between cost sharing and general medical services offers insight into the impact of cost sharing on the health system, there is also the question of whether price sensitivity varies by types of medical care. For example, perhaps user fees lead individuals to decrease the use of physician visits but have little impact on hospital visits, which may be more related to need rather than prevention. In Sections 3.3.3 and 3.3.4 we cover cost sharing for inpatient care, while in Sections 3.3.5 and 3.3.6 we discuss user fees for physician and outpatient care.

Table 3.4. Inpatient and emergency room care: cost sharing and the number of admissions and length of stay

Variable	Number of admissions	Length of stay	Studies
Co-payment	-	N/A	**Ahlamaa-Tuompo et al.** (1998a) [FI, NS, CD/PD, R]; **Ahlamaa-Tuompo et al.** (1998b) [FI, NS, CD/PD, R]; **Roemer et al.** (1975) [US, ES, CD, NR]; **Selby et al.** (1996) [US, NS, CD, R]
Coinsurance	-	-	**Freiberg and Scutchfield** (1976) [US, OS, CD, R]; **Newhouse** (1993) [US, ES, CD, R]
Coinsurance	-	N/A	**Babazono et al.** (1991) [JP, NS, TD, R]; **Bhattacharya et al.** (1996) [JP, OS, SA, R]; **Kupor et al.** (1995) [JP, OS, CD, R]; **Manning et al.** (1987) [US, ES, CD, R]; **Newhouse** (1993) [US, ES, CD, R]; **O'Grady et al.** (1985) [US, ES, CD, R]; **Phelps and Newhouse** (1974) [US, NS, CD, R]
Coinsurance	N/A	-	**Phelps** (1975) [US, OS, CD, R]
Deductible	-	N/A	**Van Vliet** (2001) [NE, OS, CD, R]
Mixed system	-	-	**Feldstein** (1971) [US, OS, TD, R]; **Feldstein** (1977) [US, OS, CD, R]
Mixed system	-	N/A	**Davis and Russell** (1972) [US, OS, TD, R]; **Greene and Gunselman** (1986) [US, NS, CD, NR]; **McAvinchey and Yannopoulos** (1993) [UK, OS, TD, R]; **Rosenthal** (1964) [US, OS, TD, R]; **Siu et al.** (1986) [US, ES, CD, R]; **Williams** (1966) [US, OS, CD, NR]
Mixed system	0	-	**Hill and Veney** (1970) [US, ES, CD, NR]
Mixed system	0	N/A	**Lewis and Keairnes** (1970) [US, ES, CD, NR]
Mixed system	N/A	-	**Newhouse and Phelps** (1974) [US, OS, CD, R]; **Newhouse and Phelps** (1976) [US, OS, CD, R]; **Rosenthal** (1968) [US, OS, CD, R]; **Scheffler** (1984) [US, NS, CD, R]
Insurance coverage		N/A	
Primary (vs. none)	+	N/A	**Billings and Tiecholz** (1990) [US, OS, CD, NR]; **Blendon et al** (1992) [US, OS, CD, NR]; **Harmon and Nolan** (2001) [IR, OS, CD, R]; **Monheit et al.** (1985) [US, OS, CD, NR]; **Patrick et al.** (1992) [US, OS, CD, R]; **Van der Gaag and Wolfe** (1991) [US, OS, CD, R]
Primary (vs. none)	N/A	+	**Hadley et al.** (1991) [US, OS, CD, R]; **Spillman** (1992) [US, OS, CD, R]; **Young and Cohen** (1991) [US, OS, CD, R]
Primary public (vs. private)	+	+	**Fleishman and Mor** (1993) [US, OS, CD, R]
Primary public (vs. private)	+	N/A	**Hahn** (1994) [US, OS, CD, R]; **Van der Gaag and Wolfe** (1991) [US, OS, CD, R]
Primary public (vs. private)	N/A	+	**Nolan** (1993) [IR, OS, CD, R]
Supplementary (vs. none)	+	N/A	**Holly et al.** (1998) [CH, OS, CD, R]; **McCall et al.** (1991) [US, OS, CD, R]
Supplementary (vs. none)	N/A	+	**Christensen and Shinogle** (1997) [US, OS, CD, R]

Country: BE = Belgium; CH = Switzerland; FI = Finland; IR = Ireland; JP = Japan; NE = the Netherlands; UK = United Kingdom; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model; SA = survival analysis model; TD = time-series model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Cost sharing can influence the volume of hospital services via two main pathways: one possibility is that individuals may visit the hospital less, perhaps choosing to utilize physician services instead. Another possibility is that individuals will still visit the hospital but may leave earlier to recover at home. Table 3.4 provides an overview of the literature that has examined both of these outcome variables.

Across co-payments, coinsurance rates, deductibles, and combinations of these types, cost sharing negatively influenced the number of inpatient and emergency room admissions. Not surprisingly, the existence of insurance had the opposite effect on hospital admissions. However, an interesting finding was that compared with private insurance beneficiaries, public insurance beneficiaries had more inpatient admissions. This result was consistent across the United States and Ireland and was somewhat surprising given that we might expect significant barriers in access to care in these countries. However, publicly insured populations tend to be less healthy on average than privately insured populations, and even in studies that controlled for health status, the cost sharing variable may have picked up some of this need effect.

Hill and Veney (1970) and Lewis and Keairnes (1970) were the only studies that found a link between user fees and the number of admissions, although an interesting observation is that both of these studies were from the same dataset and neither of these studies used regression analysis. The underlying dataset was from one county in Kansas, which is a very rural state, and thus the results may not be applicable to a larger population.

In terms of length of stay, the results for this variable were consistent across all of the countries and the different cost sharing regimes considered. Not only did cost sharing reduce inpatient length of stay, but a number of studies found that the existence of insurance coverage and the type of insurance coverage (whether public or private) mattered. Individuals with public insurance coverage appeared to have longer inpatient stays, although this result could have been due to unmeasured need.

3.3.4. Inpatient care: the price elasticity of demand

Across the United States and the United Kingdom, various studies have used microeconomic and macroeconomic data to calculate the price elasticity of demand for hospital services under cost sharing. Table 3.5 provides a summary of the price elasticity results from the literature, distinguished according to total inpatient visits and length of stay.

Researchers have found a wide range of price elasticity values for inpatient visits, from a low of -0.04 to a high of -0.85. The likely reason for this range is that each study examined a different population and used a different type of data (time series and cross sectional). For instance, McAvinchey and Yannopoulos (1993) separated elasticity values by public and private hospitals. In general, price elasticity values for private care appeared to be larger than for public care, likely because rationing for private care was through cost sharing, while rationing for public care was through waiting lists. We can also see that the time-series estimates were generally higher than

the estimates from cross-sectional datasets, a result that is generally consistent with greater noise in time-series data.

Table 3.5. Inpatient care: the price elasticity of demand

Author (Year)	Type of cost sharing	Elasticity (inpatient visits)	Elasticity (length of stay)
Davis and Russell (1972) [US, OS, TD, R]	Mixed system	-0.46 to -0.32	
Feldstein (1971) [US, OS, TD, R]	Mixed system	-0.74 to -0.21	
Feldstein (1977) [US, OS, CD, R]	Mixed system	-0.24 to -0.04	-0.44 to 0.08
Freiberg and Scutchfield (1976) [US, OS, CD, R]	Coinsurance		-0.07
McAvinchey and Yannopoulos (1993) [UK, OS, TD, R]	Private care, mixed system	-0.68 to -0.29	
McAvinchey and Yannopoulos (1993) [UK, OS, TD, R]	Public care, no cost sharing	-0.85 to -0.79	
Newhouse and Phelps (1974) [US, OS, CD, R]	Mixed system		-0.10
Newhouse and Phelps (1976) [US, OS, CD, R]	Mixed system		-0.06
Newhouse (1993) [US, ES, CD, R]	Coinsurance	-0.31 to -0.17	
Phelps and Newhouse (1974) [US, NS, CD, R]	Coinsurance	-0.05	
Phelps (1975) [US, OS, CD, R]	Coinsurance		-0.03
Rosenthal (1968) [US, OS, CD, R]	Mixed system		-0.70 to 0.44

Country: UK = United Kingdom, US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model; TD = time-series model
Type of statistical analysis used: R = regression techniques

The elasticity estimates for inpatient length of stay were also widely variable with some estimates being positive, although all of the positive estimates were insignificant. In general, most of the estimates were closer to zero when the analysis was not broken down according to specific inpatient procedures. Interestingly, Rosenthal (1968) examined price elasticities across a number of different medical categories, which accounts for the wide range of elasticity values that he obtains. This suggests that other factors such as patients' preferences for inpatient care, the availability of substitutes, perceptions of need for certain types of care, and other unmeasured variables are important determinants of the elasticity.

3.3.5. Physician and outpatient care: the effect of cost sharing on volume

The demand for physician and outpatient services are interesting outcome variables because the physician may be best suited to assessing a patient's health through repeated contact and because the physician can potentially identify health problems early. Yet, the patient is typically the primary decision-maker regarding primary

contact with the physician and may unnecessarily visit the doctor for minor health complaints if the marginal cost is minimal.

Thus, an important question regarding physician and outpatient cost sharing is: do user fees reduce the number of visits? Across a number of different countries, authors have employed various microeconomic and macroeconomic datasets to answer this question. Table 3.6 provides an overview of the literature on this area.

Table 3.6. Physician and outpatient care: cost sharing and the volume of services

Variable	Volume	Studies
Co-payment	-	**Beck** (1974) [CA, NS, CD, R]; **Beck and Horne** (1980) [CA, NS, CD, R]; **Cameron et al. (1988)** [AU, OS, CD, R]; **Cherkin et al.** (1989) [US, NS, CD, NR]; **Cockx and Brasseur** (2003) [BE, NS, PD, R]; **Helms et al.** (1978) [US, NS, CD, R]; **Scott et al.** (2003) [NZ, OS, CD, R]; **Van de Voorde et al.** (2001) [BE, NS, TD, R]
Coinsurance	-	**Babazono et al.** (1991) [JP, NS, TD, R]; **Bhattacharya et al.** (1996) [JP, OS, SA, R]; **Chiappori et al.** (1988) [FR, NS, CD, R]; **Kupor et al.** (1995) [JP, OS, CD, R]; **Newhouse et al.** (1981) [US, ES, CD, R]; **Phelps** (1975) [US, OS, CD, R]; **Shapiro et al.** (1986) [US, ES, CD, R]
Coinsurance	0	**Chiappori et al.** (1988) [FR, NS, CD, R]; **Shapiro et al.** (1986) [US, ES, CD, R]
Mixed system	-	**Barnett et al.** (2000) [NZ, OS, CD, R]; **Colle and Grossman** (1978) [US, OS, CD, R]; **Feldstein** (1970) [US, OS, TD, R]; **Fuchs and Kramer** (1972) [US, OS, TD, R]; **Goldman and Grossman** (1978) [US, OS, CD, R]; **Gribben** (1996) [NZ, OS, CD, R]; **Newhouse and Phelps** (1974) [US, OS, CD, R]; **Newhouse and Phelps** (1976) [US, OS, CD, R]; **Nolan** (1993) [IR, OS, CD, R]; **Scheffler** (1984) [US, NS, CD, R]; **Wedig** (1988) [US, OS, CD, R]
Insurance coverage		
Primary (vs. none)	+	**Blendon et al** (1992) [US, OS, CD, NR]; **Christensen et al.** (1987) [US, OS, CD, R]; **Fleishman and Mor** (1993) [US, OS, CD, R]; **Freeman et al** (1990) [US, OS, CD, NR]; **Grana and Stuart** (1996/1997) [US, OS, CD, R]; **Hahn** (1994) [US, OS, CD, R]; **Link et al.** (1980) [US, OS, CD, R]; **McDonald et al** (1974) [CA, NS, CD, NR]; **Monheit et al.** (1985) [US, OS, CD, NR]; **Patrick et al.** (1992) [US, OS, CD, R]
Primary (vs. none)	0	**Link et al.** (1980) [US, OS, CD, R]
Supplementary coverage (vs. none)	+	**Buchmueller et al.** (2002) [FR, OS, CD, R]; **Buchmueller et al.** (2004) [FR, OS, CD, R]; **McCall et al.** (1991) [US, OS, CD, R]; **Vera-Hernández** (1999) [SP, OS, CD, R]
Public supplementary coverage (vs. none)	+	**Hurd and McGarry** (1997) [US, OS, CD, R]

Country: AU = Australia; BE = Belgium; CA = Canada; CH = Switzerland; FR = France; IR = Ireland; JP = Japan; NE = the Netherlands; NZ = New Zealand; SP = Spain; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Across the various types of cost sharing tools that third-party payers can employ, most studies determined that cost sharing decreased the volume of physician and outpatient services demanded. The existence of some type of insurance coverage increased this volume, whether the insurance was primary or supplementary.

There were a few studies that found no significant relationship between cost sharing and physician or outpatient services for some subgroups or particular types of physician visits. For instance Chiappori et al. (1988) determined that French patients were insensitive to changes in coinsurance for GP office and specialist visits but sensitive to price changes for GP home visits, likely because office visits were a cheaper substitute. Link et al. (1980) also determined that among chronically ill patients, there was no difference in physician visits between those with private insurance and those with no insurance, likely because chronically ill patients view medical care as a necessity. In line with the result from Link et al. (1980), Shapiro et al. (1986) found that cost sharing had no effect on physician visits among patients suffering from serious illnesses.

3.3.6. Physician and out patient care: the price elasticity of demand

Across Belgium, Canada, the Netherlands, and the United States, a number of articles have calculated the price elasticity of demand, and both non-aggregate and aggregate estimates are available. The elasticity results from the literature are listed below in Table 3.7.

In terms of physician visits, almost all of the price elasticity estimates were less than one, ranging from -0.51 to -0.01, indicating that consumers are not particularly responsive to changes in out-of-pocket prices. Phelps (1975) may have obtained an elastic estimate because he calculated this elasticity at the mean co-payment rate. Since some individuals did not have insurance in the sample, these persons would have driven up the mean coinsurance rate, likely causing the elastic estimate. However, Feldstein (1970) obtained positive elasticity values for physician visits, and he argued that because of medical ethics, physicians are constrained in their ability to charge higher prices. To compensate physicians charge lower prices but are selective about which patients they choose to treat. This situation leads to excess demand, and thus the elasticity of demand for physician visits is positive. Colle and Grossman (1978) and Goldman and Grossman (1978) also considered a quality-adjusted price of physician visits and found estimates ranging from -0.04 to -0.03, although their estimates were insignificant. The relatively inelastic price elasticity values indicate that better perceptions of physician quality are correlated with less price sensitivity.

Most price elasticity estimates for outpatient visits were similar to the elasticity estimates for physician visits. In general, the estimates ranged from -0.22 to -0.06. Interestingly, the values from Feldstein (1970) were well above those in other studies, perhaps because Feldstein considered the period of 1948-1966. Medicare and Medicaid were not implemented until 1966 and thus the substantial group of uninsured or underinsured individuals in America during that period may have accounted for the large sensitivity to changes in out-of-pocket prices.

Table 3.7. Physician and outpatient care: the price elasticity of demand

Author (Year)	Type of cost sharing	Elasticity (doctor visits)	Elasticity (outpatient visits)
Cockx and Brasseur (2003) [BE, NS, PD, R]	Co-payment	-0.18 to -0.01	
Colle and Grossman (1978) [US, OS, CD, R]	Mixed system	-0.15 to -0.10	
Feldstein (1970) [US, OS, TD, R]	Mixed system	0.16 to 0.36	-1.05 to -0.90
Fuchs and Kramer (1972) [US, OS, TD, R]	Mixed system	-0.36 to -0.06	
Goldman and Grossman (1978) [US, OS, CD, R]	Mixed system	-0.11 to -0.02	
Manning et al. (1987) [US, ES, CD, R]	Coinsurance		-0.21 to -0.13
Newhouse (1993) [US, ES, CD, R]	Coinsurance		-0.22 to -0.17
Newhouse and Phelps (1974) [US, OS, CD, R]	Mixed system	-0.06	
Newhouse and Phelps (1976) [US, OS, CD, R]	Mixed system	-0.08	
Phelps (1975) [US, OS, CD, R]	Coinsurance	-1.38 to -0.18	
Phelps and Newhouse (1972) [US, NS, CD, NR]	Coinsurance	-0.14 to -0.07	
Phelps and Newhouse (1974) [US, NS, CD, R]	Coinsurance	-0.51 to -0.28	
Scitovsky and Snyder (1972) [US, NS, CD, NR]	Coinsurance	-0.14[a]	-0.06[a]
Van de Voorde et al. (2001) [BE, NS, TD, R]	Co-payment	-0.39 to -0.10	
Wedig (1988) [US, OS, CD, R]	Mixed system	-0.23 to -0.16	

[a]calculated by this author using the arc elasticity formula:

$$e_d = ((Q_2 - Q_1)/(Q_2 + Q_1))((P_2 + P_1)/(P_2 - P_1)).$$

Country: BE = Belgium; CA = Canada; NE = the Netherlands; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

3.3.7. Conclusion on the literature related to cost sharing for medical services, inpatient care, and physician and outpatient care

By summing up the literature on cost sharing for medical services, inpatient care, and physician and outpatient care, we can infer what findings we might expect for prescription drugs. Across the different developed countries, subpopulations, and forms of cost sharing, the results were relatively consistent. That is, higher user fees decreased the volume of health care goods and services obtained. Given this consistent result, we would expect to find the same relationship between prescription charges and the demand for prescription drugs.

Of even more relevance to this thesis, though, is the price elasticity of demand, as we are interested in knowing whether the price elasticity of demand for prescription drugs

falls within the range of elasticities for medical care. Table 3.8 lists the main ranges of price elasticity estimates from the previous sections. Note that we only include the elasticity values for inpatient admissions as patients are less likely to have discretion over the inpatient length of stay.

Table 3.8. Health care: the price elasticity of demand

Outcome variable	Price elasticity
Medical care	-0.20 to -0.10
Inpatient care (admissions)	-0.85 to -0.04
Physician and outpatient care	-0.51 to -0.01

Although the price elasticities of demand for each of the relevant outcome variables appear to be inelastic, there is a wide range of values from the literature. This seems to be due to the different populations considered, the types of medical care services examined, the statistical techniques employed, the time period considered, and a host of other factors. For instance, the elderly are likely to be less sensitive to price changes because they have a shorter time horizon within which to improve their health and because it generally takes more health inputs to improve the well-being of this group (Grossman, 1972). Another example of why estimates might differ is that some authors such as Rosenthal (1968) and Van Vliet (2004) looked at different types of medical care, such as specific types of surgery or GP and specialist care. The implication is that elasticity values might vary between different forms of medical care based on consumer preferences for those types of care, beliefs about utility, consensus in the medical literature on effectiveness, and other factors.

Given that most estimates seem to fall within between -0.30 and -0.04, we might hypothesize that among the general population, the demand for prescription drugs falls within a similar range. Importantly, this hypothesis requires that we look at prescription drugs as an entire class rather than at specific drugs or drug classes, as the price elasticity is likely to vary widely between these classes. A more interesting question is whether the prescription drug elasticity of demand lies near the upper or lower boundaries of this range or whether the elasticity is actually outside this range, as this offers more insight into how consumers value prescription drugs in comparison to other forms of medical care. This consideration is discussed in Chapter 8.

3.4. Literature review of cost sharing for prescription drugs

In contrast to physician visits where the patient is usually the primary decision-maker regarding whether to initiate contact, the patient has less input into the decision to initiate pharmaceutical treatment. The early literature on the subject, however, seemed more interested in establishing whether moral hazard in the area of prescription drugs existed and the extent to which moral hazard was a problem. Most papers have

investigated the impact of specific cost sharing requirements on the demand for prescription drugs, although some have considered how the generosity of insurance influences the uptake of prescriptions. Later studies have moved away from quantifying the relationship between prescription charges and the demand for drugs and have focused more on the ability of patients to correctly value their medications. This literature has thus considered other outcome variables, such as the uptake of essential and non-essential medications and adherence to medicines.

Given the primary research questions in this dissertation, the main focus of this section is on two main outcome variables: the volume of prescription drugs purchased and the price elasticity of demand. However, as alluded to above, the literature has also addressed a number of other topics, for instance the use of essential and non-essential drugs, the use of substitutes and complements, and prescription drug expenditures, among others. To give the reader an idea of these additional topics, we provide tables of the literature and brief explanations of these tables in Appendix B. More comprehensive information on the methodology, results, and limitations of each study is also available in Appendix B.

Within each of the two main outcome variables, the literature related to the volume of prescription drugs purchased and the elasticity of demand is broken into three main groups: the general population, the elderly and chronically ill groups, and the low-income population. Specifically, we would expect the elderly and chronically ill to be the least sensitive to changes in cost sharing. Given the relationship between income and health (as a proxy for need), we also separate the discussion into low-income groups and the general population, as the effect of cost sharing is also likely to differ between these groups. The literature review is further categorized according to the specific form of cost sharing employed (e.g. co-payments or coinsurance).

Furthermore, in the section that covers the volume effect of user fees, we consider various independent variables that have been used in the literature as covariates. These controls are important in that they provide guidance as to what personal and institutional factors are important predictors of the demand for prescription drugs and thus should be included in our empirical analysis if possible.

3.4.1. Prescription drugs: the effect of cost sharing on volume

The relationship between cost sharing for prescription drugs and the volume purchased provides an indication of whether any moral hazard effect exists in the prescription drug market. To get a feel for what has already been published in the literature and what has been found regarding this relationship, we provide the results of the studies that investigated the effect of cost sharing on volume in this section.

Prescription drug user fees: the general population

One place to start is to consider the general effect of cost sharing across the entire population. The volume effect for the general population is useful as a benchmark

against the volume effect among other more vulnerable populations, and Table 3.9 provides an overview of the literature that has focused on the general population.

There generally appears to be a negative relationship between prescription charges and drug use, regardless of the form(s) of cost sharing in place. In most cases insurance coverage had a positive effect on volume, while the existence of a limited (positive) list of prescription drugs qualifying for reimbursement had a negative effect (O'Brien, 1989; Ryan and Birch, 1991).

Table 3.9. Prescription drugs: the effect of cost sharing on volume, the general population

Variable	Volume	Studies
Co-payment	-	**Birch** (1986) [UK, NS, CD, NR]; **Brenna et al.** (1984) [IT, NS, TD, R]; **Cameron et al. (1988)** [AU, OS, CD, R]; **Delnoij et al.** (2000) [NE, NS, CD, R]; **Gardner et al.** (1996) [NZ, OS, CD, NR]; **Harris et al.** (1990) [US, NS, TD, NR]; **Hughes and McGuire** (1995) [US, NS, TD, R]; **Lauterbach et al.** (2000) [DE, OS, CD, R]; **Lavers** (1989) [UK, NS, TD, R]; **Lundberg et al.** (1988) [SW, OS, CD, R]; **McManus et al.** (1996) [AU, NS, TD, R]; **O'Brien** (1989) [US, NS, TD, R]; **Ryan and Birch** (1991) [UK, NS, TD, R]; **Smith and Watson** (1990) [UK, OS, CD, R]
Multi-tier formulary (vs. 1- or 2-tiers)	0	**Motheral and Henderson** (1999) [US, NS, CD, R]
Multi-tier formulary (vs. 1- or 2-tiers)	-	**Fairman et al.** (2003) [US, NS, CD, R]; **Gibson et al.** (2005) [US, NS, PD, R]; **Landsman et al.** (2005) [US, NS, TD, R]; **Motheral and Fairman** (2001) [US, NS, CD, R]
Coinsurance	-	**Foxman et al.** (1987) [US, ES, CD, R]; **Liebowitz et al.** (1985) [US, ES, CD, R]; **Lohr et al.** (1986) [US, ES, CD, NR]; **Puig-Junoy** (1988) [SP, OS, TD, R]; **Steffensen et al.** (1997) [DK, NS, CD, NR]
Deductible	-	**Socialstyrelsen** (1997) [SW, OS, CD, NR]
Mixed system	-	**Anderson et al.** (2006) [SW, NS, TD, R]; **Carrin and Van Dael** (1991) [BE, OS, TD, R]; **Grootendorst and Levine** (2001) [CA, OS, CD, R]; **Smith** (1993) [US, OS, CD, R]; **Van Vliet et al.** (1999) [NE, OS, CD, R]
Mixed system	0	**Anderson et al.** (2006) [SW, NS, TD, R]; **Ong et al.** (2003) [SW, NS, TD, R]
Change from		
co-payment to coinsurance	-	**Van Doorslaer** (1984) [BE, NS, TD, R]
coinsurance to deductible	-	**Friis et al.** (1993) [DK, NS, CD, NR]
Insurance coverage		
Primary (vs. none)	+	**Danzon and Pauly** (2002) [US, OS, CD, NR]
Supplementary (vs. none)	+	**Caussat and Glaude** (1993) [FR, OS, CD, R]; **Greenlick and Darsky** (1968) [CA, OS, CD, NR]; **Weeks** (1973) [US, NS, CD, NR]
Limited list	+	**O'Brien** (1989) [US, NS, TD, R]; **Ryan and Birch** (1991) [UK, NS, TD, R]

Country: AU = Australia; BE = Belgium; CA = Canada; DE = Germany; DK = Denmark; FR = France; IT = Italy; NE = the Netherlands; NZ = New Zealand; SP = Spain; SW = Sweden; UK = United Kingdom; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

A few studies found no relationship between cost sharing and volume. Interestingly, two different Swedish articles (Anderson et al., 2006; Ong et al., 2003) found no effect of increased cost sharing on use, possibly because prescriptions were heavily subsidized, particularly for individuals suffering from chronic diseases (Anderson et al., 2006). Furthermore, other cost sharing changes, such as the introduction of multi-tier formularies, may negatively affect the volume of drugs that become relatively more expensive under these policies but may have little impact on overall volume as patients switch to less expensive medications.

In summary, among the general population there appears to be some sensitivity to changes in out-of-pocket prices, and this sensitivity seems to depend on the country-specific context. For instance, countries with low overall user fees or a large proportion of heavily subsidized individuals may appear to have little sensitivity to user fees on average. This highlights the importance of considering the demographic, cultural, and institutional factors of each country when discussing the policy implications of demand-side cost sharing.

Prescription drug user fees: the older and chronically ill populations

We would expect that compared with the general population, those who are older or chronically ill are less sensitive to out-of-pocket price changes. Both groups require more health care resources to regain good health. The elderly may feel that there are fewer substitutes for prescription drugs, particularly because they may not have the time in which to implement lifestyle changes for health improvements. Meanwhile, the chronically ill may perceive their medications as necessary to survival or well-being and thus be averse to reducing consumption. Table 3.10 provides an overview of the literature related to cost sharing and the use of prescription drugs among those who are older or taking medications for chronic illnesses.

Most of the literature has found a negative relationship between cost sharing and the volume of medications purchased. While a handful of papers found either no relationship or a positive link, all of these studies considered chronically ill populations. For instance, Anderson et al. (2006) examined a group of patients taking medications for some chronic illnesses in Sweden. They found that co-payments only had a negative effect immediately after implementation, but subsequent increases in the co-payment had no effect on consumption. Blais et al. (2001) and Pilote et al. (2002) also investigated a sample of individuals with serious chronic conditions. Their insignificant results implied that individuals with serious chronic conditions may be more willing to forego spending on other goods or services to purchase prescription drugs. Along these lines, Stuart et al. (2000) determined that cost sharing had no effect on a nursing home sample. Not only is this sample likely to be insensitive to price because of the reasons given above, but caretakers may be making the decisions regarding medications on behalf of nursing home residents and thus may feel that the patient's health is their obligation.

Grootendorst and Levine (2001) obtained a small positive correlation between price and volume among older people in Canada, perhaps because public drug coverage for

seniors in Canada is relatively generous, and older people may perceive few substitutes for prescription drugs (Grootendorst and Levine, 2001).

Table 3.10. Prescription drugs: the effect of cost sharing on volume, the elderly and chronically ill

Variable	Volume	Studies
Co-payment	-	**Anessi Pessina** (1997) [IT, OS, TD, R]; **Anis et al.** (2005) [CA, OS, PD, R]; **Balkrishnan et al.** (2001) [US, NS, PD, R]; **Begg** (1984) [UK, OS, CD, NR]; **Gardner et al.** (1997) [US, NS, TD, R]; **Hux et al.** (1997) [CA, NS, CD, R]; **Johnson et al.** (1997a) [US, NS, CD, R]; **Johnson et al.** (1997b) [US, NS, CD, R]; **McManus et al.** (1996) [AU, NS, TD, R]; **Scott et al.** (1990) [US, NS, CD, NR]; **Starmans et al.** (1994) [NE, NS, TD, R]; **Watt et al.** (1992) [NZ, NS, CD, NR]
Co-payment	0	**Soumerai et al.** (1987)[1] [US, NS, TD, R]
Multi-tier formulary (vs. 1- or 2-tiers)	-	**Rector et al.** (2003) [US, OS, CD, R]
Coinsurance	-	**Johnson et al.** (1997a) [US, NS, CD, R]; **Johnson et al.** (1997b) [US, NS, CD, R]
Deductible	-	**Blais et al.** (1999)[1] [CA, NS, TD, R]
Mixed system	-	**Anderson et al.** (2006) [SW, NS, TD, R]; **Carrin and Van Dael**[2] (1991) [BE, OS, TD, R]; **Klick and Stratmann** (2005) [US, OS, CD, R]; **Li et al.** (2006)[1] [CA, NS, PD, R]; **Tamblyn et al.** (2001)[1] [CA, NS, TD, R]
Mixed system	+	**Grootendorst and Levine** (2001) [CA, OS, CD, R]
Mixed system	0	**Anderson et al.** (2006) [SW, NS, TD, R]
Change from		
co-payment to coinsurance	-	**Van Doorslaer** (1984)[1] [BE, NS, TD, R]
co-payment to deductible and coinsurance	-	**Tamblyn et al.** (2001)[1] [CA, NS, TD, R]
coinsurance to deductible and coinsurance	-	**Blais et al.** (2003)[1] [CA, NS, TD, R]
coinsurance to deductible and coinsurance	0	**Blais et al.** (2001) [CA, NS, TD, R]; **Pilote et al.** (2002) [CA, NS, CD, R]
Insurance coverage		
Primary (vs. none)	+	**Artz et al.** (2002) [US, OS, CD, R]; **Coulson and Stuart** (1995) [US, OS, CD, R]; **Fillenbaum et al.** (1993) [US, OS, CD, R]; **Gianfrancesco et al.** (1994) [US, NS, CD, NR]; **Shih** (1999) [US, OS, CD, R]
Primary (vs. none)	0	**Stuart et al.** (2000) [US, OS, CD, R]
Supplementary (vs. none)	+	**Coulson and Stuart** (1995) [US, OS, CD, R]; **Fillenbaum et al.** (1993) [US, OS, CD, R]; **Coulson et al.** (1995) [US, OS, CD, R]; **Davis et al.** (1999) [US, OS, CD, NR]; **Grootendorst et al.** (1997) [CA, OS, CD, R]; **Poisal and Chulis** (2000) [US, OS, CD, NR]; **Poisal and Murray** (2001) [US, OS, CD, NR]; **Stuart et al.** (2000) [US, OS, CD, R]
Prescription limit	-	**Soumerai et al.** (1987)[1] [US, NS, TD, R]; **Soumerai et al.** (1994)[1] [US, NS, TD, R]
Reimbursement limit	-	**Hsu et al.** (2006) [US, OS, PD, R]

[1]sample also includes low-income individuals
Country: AU = Australia; BE = Belgium; CA = Canada; IT = Italy; NE = the Netherlands; NZ = New Zealand; SW = Sweden; UK = United Kingdom; US = United States
Type of study: NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Thus, it appears that in some cases chronic drug users may not be sensitive to changes in their out-of-pocket costs, at least at the levels of cost sharing observed in these studies.

Prescription drug user fees: the low-income population

The relationship between user fees and consumption among the low-income population may be different than among the elderly, chronic users, and the general population. On the one hand, with less disposable income to spend on prescription drugs, low-income individuals may be more likely than other subgroups to reduce consumption when faced with user fees. On the other hand, the experience of the low-income group may tend more toward that of the elderly and the chronically ill because there is a positive relationship between income and good health (Macinko et al., 2003). Moreover, low-income groups in most developed countries, including the United States, generally receive greater subsidies for prescription drugs, and thus empirical studies may measure these groups on a lower portion of the demand curve. To shed more light on these possibilities, Table 3.11 provides an overview of the literature that has examined cost sharing among the low-income group.

Table 3.11. Prescription drugs: the effect of cost sharing on volume, the low-income groups

Variable	Volume	Studies
Co-payment	-	**Begg** (1984) [UK, OS, CD, NR]; **Brian and Gibbens** (1974) [US, ES, CD, NR]; **Lurk et al.** (2004) [US, NS, CD, R]; **Nelson et al.** (1984) [US, OS, TD, R]; **Reeder and Nelson** (1985) [US, NS, TD, R]
Co-payment	0	**Reeder and Nelson** (1985) [US, NS, TD, R]; **Soumerai et al.** (1987)[2] [US, NS, TD, R]
Coinsurance	-	**Martin and McMillan** (1996) [US, NS, TD, R]
Deductible	-	**Blais et al.** (1999)[1] [CA, NS, TD, R]
Mixed system	-	**Carrin and Van Dael**[2] (1991) [BE, OS, TD, R]; **Grootendorst and Levine** (2001) [CA, OS, CD, R]; **Li et al.** (2006)[1,2] [CA, NS, PD, R]; **Tamblyn et al.** (2001)[2] [CA, NS, TD, R]
Change from		
co-payment to coinsurance	-	**Van Doorslaer** (1984)[2] [BE, NS, TD, R]
co-payment to deductible and coinsurance	-	**Tamblyn et al.** (2001)[2] [CA, NS, TD, R]
coinsurance to deductible and coinsurance	-	**Blais et al.** (2003)[1] [CA, NS, TD, R]
Insurance coverage		
Primary (vs. none)	+	**Smith and Garner** (1974) [US, NS, CD, NR]
Supplementary (vs. none)	+	**Grootendorst et al.** (1997) [CA, OS, CD, R]
Prescription limit	-	**Soumerai et al.** (1987)[2] [US, NS, TD, R]; **Soumerai et al.** (1994)[1] [US, NS, TD, R]

[1]sample also includes the chronically ill, [2]sample also includes the elderly
Country: BE = Belgium; CA = Canada; UK = United Kingdom; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

The findings were relatively consistent across the literature; user fees reduced consumption of prescription drugs, regardless of the form of cost sharing employed. Only two papers found no significant relationship between cost sharing and the volume of drugs obtained among the poor (Reeder and Nelson, 1985; Soumerai et al., 1987).

The results from Reeder and Nelson (1985) were varied as they found that the implementation of a $0.50 co-payment led to lower use for some therapeutic groups, but not all therapeutic groups experienced a significant decline (e.g. analgesics and sedatives). Factors such as substitutes for drugs within the therapeutic groups, patients' and physicians' perceptions of the necessity of drugs within these groups, and others may be important reasons for the differences in significance. Soumerai et al. (1987) found that when a limit on the number of prescriptions among the Medicaid population in the US was applied, there was a decrease in drug consumption among this group. However, when the prescription cap was replaced with a $1 co-payment, consumption resumed to the pre-cap levels. The likely reason for this is two-fold: first, there is a psychological effect of receiving better coverage after a reduction in generosity even if the latest coverage is not as generous as the initial coverage (Kahneman and Tversky, 1979). Second, the $1 co-payment was relatively minor and could be waved if the patient was unable to afford that amount.

Overall, it appears that low-income groups are sensitive to price changes, although the degree of this sensitivity is discussed later in this chapter when we look at price elasticity estimates for prescription drugs.

3.4.2. Prescription drugs: the effect of other covariates on volume

While the primary focus of this dissertation is on prescription drug user fees, it is important to control for other factors that may influence the demand for prescription drugs. Otherwise, the prescription charges variable may pick up the effect of these other factors. In line with the Section 3.5.1, we classify the relevant literature according to the population considered: (i) the general population, (ii) the elderly and the chronically ill, and (iii) the low-income group. While the determinants of demand for prescription drugs might be relatively similar across the three populations we consider, the importance of specific factors might differ between populations. For example, age could have a positive effect in the general population but a negative effect within the elderly as the oldest of the elderly may be unable to handle a large cocktail of drugs. As a result, the following section discusses the findings from the literature in light of these potential differences. Because we are interested in the effect of user fees at the individual-level, the discussion of the literature in this section is restricted to studies that have examined cost sharing at the micro-level.

Other determinants of demand for prescription drugs: the general population

As a baseline comparator for other more vulnerable populations, we begin by examining the influence of different determinants on the volume of prescription drugs

obtained among the general population. Table 3.12 provides an overview of the findings.

Among the general population we would expect that being female, older, having more education, and being in poor health would have a positive effect on the volume of medications purchased. The effect of household size on consumption measured at the individual-level is likely to be negative as disposable income must be divided between more members. The influence of income, however, might go either way in an empirical study. While we would expect the effect of income to be positive according to traditional economic theory, there is also the consideration that the physician is making the primary decisions regarding which medications are necessary. Given the positive relationship between income and health (Macinko et al., 2003), if health is not fully controlled for in the regression, income may pick up some of its effects, and thus income may exhibit a negative effect on volume.

Table 3.12. Prescription drugs: the effect other covariates on volume, the general population

Variable	Volume	Studies
Female	+	**Foxman et al.** (1987) [US, ES, CD, R]; **Cameron et al. (1988)** [AU, OS, CD, R]; **Caussat and Glaude** (1993) [FR, OS, CD, R]; **Motheral and Henderson** (1999) [US, NS, CD, R]
Age	+	**Cameron et al. (1988)** [AU, OS, CD, R]; **Smith and Watson** (1990) [UK, OS, CD, R]; **Caussat and Glaude** (1993) [FR, OS, CD, R]; **Lundberg et al.** (1988) [SW, OS, CD, R]; **Motheral and Henderson** (1999) [US, NS, CD, R]
Income	+	**Caussat and Glaude** (1993) [FR, OS, CD, R]; **Van Vliet et al.** (1999) [NE, OS, CD, R]
Income	-	**Foxman et al.** (1987) [US, ES, CD, R]; **Smith and Watson** (1990) [UK, OS, CD, R]; **Van Vliet et al.** (1999) [NE, OS, CD, R]
Education	+	**Lundberg et al.** (1998) [SW, OS, CD, R]
Household size	-	**Van Vliet** (2001) [NE, OS, CD, R]
Poor health	+	**Foxman et al.** (1987) [US, ES, CD, R]; **Cameron et al. (1988)** [AU, OS, CD, R]; **Smith and Watson** (1990) [UK, OS, CD, R]; **Van Vliet et al.** (1999) [NE, OS, CD, R]; **Van Vliet** (2001) [NE, OS, CD, R]
Physical health problems	+	**Cameron et al. (1988)** [AU, OS, CD, R]; **Caussat and Glaude** (1993) [FR, OS, CD, R]; **Van Vliet** (2001) [NE, OS, CD, R]
Chronic illness	+	**Cameron et al. (1988)** [AU, OS, CD, R]; **Motheral and Henderson** (1999) [US, NS, CD, R]; **Van Vliet et al.** (1999) [NE, OS, CD, R]; **Van Vliet** (2001) [NE, OS, CD, R]

Country: AU = Australia; FR = France; NE = the Netherlands; SW = Sweden; UK = United Kingdom; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques

In line with the explanation above regarding the effects of various covariates on volume, the findings from the literature are relatively consistent with the expected results. As mentioned above, the effect of income could be positive or negative, and interestingly, there were mixed results in the literature regarding this variable. Van Vliet et al. (1999), for instance, found that income increased volume up to a certain

point, beyond which there was a negative association between the two variables. The other varying income results were likely due to institutional factors in the populations studied. Specifically, the Caussat and Glaude (1993) paper considered demand for prescription drugs in France, where the low-income population was generally less protected from user fees than their higher-income counterparts at the given time. As the high-income group generally purchased supplementary prescription drug insurance, this may have explained the positive association between income and volume, particularly if the insurance variable did not fully control for this effect of insurance in Caussat and Glaude's regression. Notably, in the other studies that found a positive effect of income, the low-income population had greater subsidies for prescription drugs than the higher-income population.

Other determinants of demand for prescription drugs: the elderly and chronically ill

Among the elderly and chronically ill, certain determinants of demand, for instance age and morbidity, may play a different role than in the general population. To account for these possibilities, we provide the findings from the literature that examined these subgroups in Table 3.13.

Table 3.13. Prescription drugs: the effect other covariates on volume, the elderly and chronically ill

Variable	Volume	Studies
Female	+	**Shih** (1999) [US, OS, CD, R]; **Klick and Stratmann** (2005) [US, OS, CD, R]
Age	+	**Grootendorst et al.** (1997) [CA, OS, CD, R]
Age	-	**Coulson and Stuart** (1995) [US, OS, CD, R]; **Coulson et al.** (1995) [US, OS, CD, R]; **Shih** (1999) [US, OS, CD, R]; **Klick and Stratmann** (2005) [US, OS, CD, R]
White (vs. other race)	+	**Fillenbaum et al.** (1993) [US, OS, CD, R]; **Shih** (1999) [US, OS, CD, R]
Income	-	**Coulson and Stuart** (1995) [US, OS, CD, R]; **Grootendorst et al.** (1997) [CA, OS, CD, R]
Education	+	**Shih** (1999) [US, OS, CD, R]
Household size	+	**Grootendorst et al. (1997)** [CA, OS, CD, R]
Poor health	+	**Coulson and Stuart** (1995) [US, OS, CD, R]; **Grootendorst et al.** (1997) [CA, OS, CD, R]; **Klick and Stratmann** (2005) [US, OS, CD, R]
Physical health problems	+	**Coulson and Stuart** (1995) [US, OS, CD, R]
Number of limitations to activities of daily living	+	**Klick and Stratmann** (2005) [US, OS, CD, R]
Chronic illness	+	**Coulson and Stuart** (1995) [US, OS, CD, R]; **Klick and Stratmann** (2005) [US, OS, CD, R]
Prior hospitalization	+	**Fillenbaum et al.** (1993) [US, OS, CD, R]; **Coulson and Stuart** (1995) [US, OS, CD, R]; **Klick and Stratmann** (2005) [US, OS, CD, R]
Number of doctor/outpatient visits	+	**Fillenbaum et al.** (1993) [US, OS, CD, R]; **Klick and Stratmann** (2005) [US, OS, CD, R]

Country: CA = Canada; US = United States
Type of study: OS = observational study
Type of data analyzed: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques

The factors that we would expect to have a positive influence on consumption are: education, poor health, and greater past consumption of medical care. In the elderly population, age could have a mixed effect. Specifically, a number of chronic conditions tend to afflict individuals when they are near-elderly or young-elderly, causing a sharp rise in expenditures (Zweifel et al., 1999). Advances in medicines have allowed these individuals to live longer in a healthier state. Evidence from other research on aging and expenditures (Kildemoes et al., 2005) indicates that prescription drug consumption rises with age but seems to peak between 60 and 70 years of age and either levels off or decline afterwards. Also, among the oldest of the elderly, the use of numerous medications increases the risk of adverse events (Gurwitz and Avorn, 1991) such that physicians may prescribe fewer medications for this group.

In countries like the United States where the public health insurance system for the elderly only recently began offering any help for most outpatient prescription medications, the elderly face more difficulty obtaining prescription drug insurance and face higher premiums, higher cost sharing requirements, and exclusions for pre-existing conditions and certain medications under any insurance they can acquire. These circumstances may exacerbate the effects of aging on health consumption, causing a sharper decline in consumption as the elderly age.

The effect of income could be either positive or negative for the reasons explained above. Furthermore, the effect of household size could also be positive or negative. While larger households may have to spread disposable income among more members, larger households with elderly or chronically ill members may actually have a positive effect on consumption for these individuals if other family members are involved in their prescription purchase decisions.

In terms of the empirical results, there were mixed results for age, although these variations are likely due to the country-specific contexts. For reasons listed above, older populations in the United States may experience sharper declines in prescription drug consumption as they age. The same may not be true in Canada if the effect of generous insurance outweighs other factors that may lead to a negative relationship between aging and drug consumption. Interestingly, all of the studies that found a negative relationship between aging and volume were from America, while the one study that found a positive relationship was from Canada (Grootendorst et al., 1997).

The income findings were also interesting. The two studies that found an effect of this variable determined that the effect was negative (Coulson and Stuart, 1995; Grootendorst et al., 1997), perhaps because the poorest of the elderly in these samples were heavily subsidized for prescription drugs.

Other determinants of demand for prescription drugs: the low-income groups

There were no papers that reported the effect of individual-specific covariates, such as income, age, and health, on the volume of prescription drugs obtained among the low-income population.

3.4.3. Prescription drugs: the price elasticity of demand

As discussed earlier in Section 3.4.2, the price elasticity of demand provides a clearer picture for policymakers and researchers as it offers a unitless measure that quantifies the effect of cost sharing on use. Because the elasticity can differ vastly between different subpopulations, we again break the discussion into three main groups: (i) the general population, (ii) the elderly and chronically ill, and (iii) the low-income population. While we would expect the elderly and chronically ill to be the least sensitive to price changes, it is not clear whether the general population or the low-income group are more sensitive to user fees. While low-income groups have less disposable income to spend on prescription drugs, they may also be more protected from user fees than the general population. Thus, empirical studies of the low-income group may measure the effect of cost sharing at a lower point on the demand curve.

In some cases the authors of a paper may have reported an elasticity other than the arc or point elasticity. Where possible we have recalculated their estimates to reflect the standard definitions of elasticity. Whether we used an arc, point, or constant elasticity calculation depended on the type of statistical analysis used and the information reported by the authors. The elasticity values that have been recalculated are marked in the table.

Price elasticity of demand for prescription drugs: the general population

Examining the price elasticity of demand for prescription drugs at the level of the general population is useful for two main reasons: (i) it provides an average estimate for policymakers who are interested in determining the effect of cost sharing changes at the population level, and (ii) it provides a baseline against which we can assess the price elasticity of demand among other more vulnerable populations. Table 3.14 provides the existing price elasticity estimates for the general population.

At the aggregate level the price elasticity values range from -0.80 to -0.09, while at the individual-level the elasticity values ranged from -0.58 to -0.02. While the range of estimates is rather large for both types of datasets, macroeconomic estimates appear to be higher than the microeconomic estimates, a result that is not surprising given the greater noise in aggregate datasets. The wide range of estimates at the individual level is likely to due study-specific factors such as the extent of prescription drug subsidies in the population, the magnitude of the cost sharing increase, unmeasured general attitudes toward prescription drugs, and other factors.

The range of elasticity values for brand-name drugs is even larger (-1.60 to -0.03). This result can be expected, though, given that the demand for brand-name drugs should be very inelastic when there are few therapeutic and no molecular substitutes and much higher when there are generic drugs available. The price elasticity for generics also varied widely, likely due to the availability of other generic and therapeutic substitutes.

Table 3.14. Prescription drugs: the price elasticity of demand, the general population

Study	Type of cost sharing	Price elasticity	Price elasticity (brand)	Price elasticity (generic)
Carrin and Van Dael (1991) [BE, OS, TD, R]	Mixed system	-0.35		
Gibson et al. (2005) [US, NS, PD, R]	Multi-tier formulary (vs. 1- or 2-tiers)	-0.04	-0.27 to -0.03	
Grootendorst and Levine (2001) [CA, OS, CD, R]	Mixed system	-0.04		
Harris et al. (1990) [US, NS, TD, NR]	Co-payment	-0.17[a] to -0.06[a]		
Hughes and McGuire (1995) [US, NS, TD, R]	Co-payment	-0.37 to -0.32		
Lavers (1989) [UK, NS, TD, R]	Co-payment	-0.22		
Liebowitz et al. (1985) [US, ES, CD, R]	Coinsurance	-0.10[b]		
McManus et al. (1996) [AU, NS, TD, R]	Co-payment	-0.80[a] to -0.50[a]		
Mortimer (1997) [US, OS, CD, R]	Mixed system		-1.60 to -0.07	-0.56 to -0.03
Motheral and Henderson (1999) [US, NS, CD, R]	Multi-tier formulary (vs. 1- or 2-tiers)		-0.32[a]	
O'Brien (1989) [US, NS, TD, R]	Co-payment	-0.64 to -0.23		
Puig-Junoy (1988) [SP, OS, TD, R]	Coinsurance	-0.13		
Ryan and Birch (1991) [UK, NS, TD, R]	Co-payment	-0.11 to -0.09		
Smith (1993) [US, OS, CD, R]	Mixed system	-0.10		
Smith and Watson (1990) [UK, OS, CD, R]	Co-payment	-0.58[b]		
Van Doorslaer (1984) [BE, NS, TD, R]	Change from co-payment to coinsurance	-0.60		
Van Vliet et al. (1999) [NE, OS, CD, R]	Deductible	-0.02		

[a]calculated by this author using the arc elasticity formula:
$e_d = ((Q_2 - Q_1)/(Q_2 + Q_1))((P_2 + P_1)/(P_2 - P_1))$.

[b]calculated by this author using a log-linear calculation: $e_d = B_j \bar{x}$, where B_j represents the coefficient on the price variable and $\bar{x}$ is the mean price.

[c]calculated by this author using the point elasticity formula: $e_d = ((Q_2 - Q_1)/(Q_1))((P_1)/(P_2 - P_1))$

Country: AU = Australia; BE = Belgium; CA = Canada; FR = France; IT = Italy; NE = the Netherlands; SP = Spain; UK = United Kingdom; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model

Price elasticity of demand for prescription drugs: the elderly and chronically ill

In general, we would expect the elderly and chronically ill groups to be less sensitive to increases in user fees. To determine if this is indeed the case, Table 3.15 lists the price elasticity values from the literature for the elderly and chronically ill populations.

Among the elderly and chronically ill, the price elasticity values range from -0.40 to -0.09 at the aggregate level and from -0.56 to 0.14 at the micro-level. Interestingly, the range of values is larger at the micro-level, which is likely due to the specific context of each study. The positive estimate of 0.14 (Grootendorst and Levine, 2001) indicated that among older Canadians, demand for prescription drugs actually increased as price increased (albeit by a small proportion). This may have been due to unobservable variables; in particular, when out-of-pocket costs rise and patients face flat fees, physicians may increase prescription sizes to ease the financial burden. Alternatively, when patients face out-of-pocket costs proportional to actual drug costs, doctors may prescribe cheaper drugs (Grootendorst and Levine, 2001). At the other extreme Klick and Stratmann (2005) found an estimate of -0.58, although the authors excluded those with Medicaid and employer-sponsored insurance, and the remaining sample was likely to be the most sensitive to price changes.

Table 3.15. Prescription drugs: the price elasticity of demand, the elderly and chronically ill

Study	Type of cost sharing	Price elasticity
Anessi Pessina (1997) [IT, OS, TD, R]	Co-payment	-0.75 to -0.07
Carrin and Van Dael (1991)[b] [BE, OS, TD, R]	Mixed system	-0.09
Coulson and Stuart (1995)[b] [US, OS, CD, R]	Primary insurance (vs. none)	-0.18[a]
Gardner et al. (1997) [US, NS, TD, R]	Co-payment	-0.38 to -0.23
Grootendorst and Levine (2001) [CA, OS, CD, R]	Mixed system	-0.40 to 0.14
Grootendorst et al. (1997) [CA, OS, CD, R]	Supplementary insurance (vs. none)	-0.13[a] to -0.09[a]
Klick and Stratmann (2005) [US, OS, CD, R]	Mixed system	-0.56
Li et al. (2006) [CA, NS, PD, R]	Mixed system	-0.20[b] to -0.11
Soumerai et al. (1987)[b] [US, NS, TD, R]	Co-payment	-0.05[a]
Van Doorslaer (1984) [BE, NS, TD, R]	Change from co-payment to coinsurance	-0.40 to -0.06

[a]calculated by this author using the arc elasticity formula: $e_d = ((Q_2 - Q_1)/(Q_2 + Q_1))((P_2 + P_1)/(P_2 - P_1))$.

[b]subgroup also includes low-income individuals

Country: AU = Australia; BE = Belgium; CA = Canada; FR = France; IT = Italy; NE = the Netherlands; SP = Spain; UK = United Kingdom; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model

Although economic theory leads to a prediction that demand would be relatively inelastic among the elderly and the chronically ill, this is not what has been found in the literature. Overall, it is unclear what the true range of price elasticities for this group should be.

Price elasticity of demand for prescription drugs: the low-income group

As discussed earlier the sensitivity to prescription charges among the poor could either be significantly lower or higher than among the general population. A few papers from the literature have considered the elasticity among this subpopulation, and the results from these studies are provided in Table 3.16.

Table 3.16. Prescription drugs: the price elasticity of demand, the low-income population[a]

Study	Type of cost sharing	Price elasticity	Price elasticity (brand)	Price elasticity (generic)
Carrin and Van Dael (1991)[b] [BE, OS, TD, R]	Mixed system	-0.09		
Coulson and Stuart (1995)[b] [US, OS, CD, R]	Primary insurance (vs. none)	-0.18[a]		
Grootendorst and Levine (2001) [CA, OS, CD, R]	Mixed system	-0.10		
Li et al. (2006)[b] [CA, NS, PD, R]	Mixed system	-0.20[b]		
Mortimer (1997) [US, OS, CD, R]	Mixed system		-1.91 to -1.66	-0.65 to -0.35
Nelson et al. (1984) [US, OS, TD, R]	Co-payment	-0.06[a]		
Soumerai et al. (1987)[b] [US, NS, TD, R]	Co-payment	-0.05[a]		
Van Doorslaer (1984)[a] [BE, NS, TD, R]	Change from co-payment to coinsurance	-0.40		

[a]calculated by this author using the arc elasticity formula:

$$e_d = ((Q_2 - Q_1)/(Q_2 + Q_1))((P_2 + P_1)/(P_2 - P_1)).$$

[b]subgroup also includes the elderly

Country: AU = Australia; BE = Belgium; CA = Canada; FR = France; IT = Italy; NE = the Netherlands; SP = Spain; UK = United Kingdom; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model

At the aggregate level there were two studies from Belgium (Carrin and Van Dael, 1991; Van Doorslaer, 1984) and two studies from the United States (Nelson et al., 1984; Soumerai et al., 1987). The range of price elasticities was from -0.40 to -0.05. The wide range of elasticity estimates may have occurred because the Belgian studies had relatively few observations.

At the micro-level Grootendorst and Levine (2001) obtained an estimate of -0.10, while Li et al. (2006) also reported an estimate of –0.20. Both of these estimates were from British Columbia, Canada. In the United States we calculated a price elasticity of -0.18 from Coulson and Stuart (1995). It is not clear whether we should expect lower elasticity estimates from Canada, though. On the one hand, Canadians can substitute free inpatient, outpatient, and physician care for prescription drugs. On the other hand, low-income individuals in Canada are relatively well protected from user fees. In the case of the estimate from Grootendorst and Levine (2001), it seems that the effect of

measuring prescription charges along the low-end of the demand curve outweighed the ability of Canadians to substitute free core health care services. However, Li et al. (2006) found a higher elasticity estimate among the poor, and their sample consisted of individuals with rheumatoid arthritis who we would expect to be less sensitive to price.

The wide range of estimates for generic and brand-name drugs from Mortimer (1997) is expected given that elasticities can vary significantly based on the number of therapeutic and generic substitutes available. The author considered all of these possibilities, from drugs with monopoly status to drugs with a significant number of competitors.

In sum, the price elasticity for the low-income population appears to depend on the country-specific context (particularly whether the low-income population is well protected from user fees), whether the measure is for a specific groups of drugs, the availability of substitutes, and whether the elasticity is measured at the aggregate or individual level. More research is clearly needed to shed light on the topic.

3.4.4. Prescription drugs: conclusions related to the literature review

Section 3.4 has covered the two main outcome variables from the literature on cost sharing for prescription drugs: the volume of prescription drugs purchased and the price elasticity of demand. Across the general population, the elderly and chronically ill group, and the low-income population, user fees lowered the demand for prescription drugs, regardless of the form of cost sharing employed. Meanwhile, insurance coverage increased the volume of drugs demanded, whether it was primary or supplementary insurance coverage.

In addition to the cost sharing variable, the main determinants of demand appear to be gender, age, income, and health, although other variables such as education and race have sometimes been found to be important. The effect of these variables, however, seems to depend on the sample characteristics. Age, for instance, exhibits a negative effect beyond a certain point in samples of elderly Americans. Yet, the opposite effect is generally picked up in estimations on the general population, the low-income group, or elderly individuals in other countries like Canada. Another interesting observation is that only a few of the estimations accounted for individual-specific factors that may be not be measurable, such as consumer preferences for medical care and wealth, even though the failure to account for these may bias the results.

In terms of the price elasticity of demand, Table 3.17 lists the main micro-level elasticity ranges found for each of the three subpopulations that we considered.

The large range of prescription drug price elasticity values for the general population offers little insight into an average value for this group. There were not many studies that considered the low-income population, but interestingly, elasticity estimates from the existing studies were relatively low (in absolute value).

Table 3.17. Prescription drugs: the price elasticity of demand

Population group	Price elasticity
General population	-0.58 to -0.02
Elderly and chronically ill	-0.56 to 0.14
Low-income population	-0.20 to -0.05

Although it is clear that the general population and the low-income population are relatively insensitive to changes in out-of-pocket prices, it is possible that the elderly could be relatively insensitive or unaffected by out-of-pocket price changes. While we would expect some variation in elasticity estimates, the ranges of estimates for the elderly and chronically ill are rather large, and it is difficult to determine if the midpoint is even close to a "true" estimate for this group. The implication of these estimate ranges is that more research is needed in the area.

3.5. Limitations of cost sharing studies

While a number of conclusions have been drawn from this literature review, it is important to keep in mind that several limitations can occur in the design and use of datasets. There are always limitations to the datasets employed, and the assumptions and statistical techniques employed by various authors are not always robust. This section discusses a few of the main limitations that typically occur in statistical studies of cost sharing. More detailed information regarding the specific limitations of each study is available in Appendix B, Table B.14.

Problems may arise when datasets are limited to certain subpopulations such as individuals with employer-sponsored insurance or persons attending a certain health care clinic. These studies inform the reader about how cost sharing influences the demand for prescription drugs among specific populations, however, the findings may not be extendable to other populations. For example, individuals in employer-sponsored plans may be healthier and may have more income than an average person in the population.

Of the studies that do analyze a larger population of individuals, many only use cross-sectional data. There are a number of disadvantages to using cross-sectional datasets, including omitted variable bias and an inability to account for the dynamics of change, but these issues are discussed in Appendix B.1.

Another limitation may surface because all or some of the variables in a dataset are self-reported. Individuals sometimes have an incentive to hide or skew information, often fearing that the data will not be kept confidential. Particularly with self-reported health status, individuals with the same condition and the same level of severity may have different perspectives of their health status based on their own perceptions of pain and suffering, their cultural background, their reaction to prescribed drugs, and

other factors. These unmeasured differences in individual responses may bias the results.

The statistical method used in the analysis also affects the quality of the results. Endogeneity can occur through different pathways. As discussed in Chapter 2, the existence of adverse selection in a private insurance market may cause endogeneity problems. Specifically, the insurance contracts available on the market are affected by high-risk consumers who do not reveal their risk characteristics, and these unobserved risk characteristics of each consumer influence both the preferred insurance contract and the number of prescription drugs consumed. Another source of endogeneity may occur because individuals that are more likely to purchase insurance are also more likely to increase their consumption of prescription drugs once they have insurance. Although it may be impossible to determine the source of endogeneity, a failure to account for endogeneity from any source may mean that the estimates will be biased and inconsistent and that the statistical tests will be invalid (Dougherty, 2002). A third source of endogeneity may occur if the co-payment variable is computed from a non-linear price schedule (for instance, there is a mix of deductibles, co-payments, coinsurance, and/or out-of-pocket limits); in this case the average co-payment depends on the level of consumption.

A significant number of studies, particularly from the United States where a large proportion of insurance is purchased in the private market, did not account for endogeneity issues when there was potential for these to exist, indicating that coefficients on the cost sharing variables may have been biased. Another problem that may occur is sample selection; in this situation the dependent variable is only observed for a restricted, non-random sample. For example, consumption of prescription drugs is only observed for individuals that purchase any prescription drugs. Some individuals may have no need for any prescriptions in a given year, but we would like to know how cost sharing would influence their demand for prescriptions if they did fall ill. Because there is a concentration of zeros for individuals that purchased no prescription drugs in a given year, regression estimates that do not account for sample selection will be biased.

Although insurance typically increases the number of prescriptions that an individual demands, there is uncertainty as to whether the marginal benefits of these prescriptions outweigh the marginal cost. Based on the data, the researcher is often unable to determine whether additional prescriptions are inappropriate or suboptimal for the patient. This measurement problem is confounded by the fact that doctors may unknowingly prescribe nonessential treatments. Determining whether the prescriptions obtained are appropriate would be useful in estimating whether cost sharing has a negative influence on the future health of individuals.

3.6. Gaps in the literature on cost sharing for prescription drugs

While there have been a number of different outcome variables considered in the literature as highlighted in this chapter and Appendix B, important questions still remain, particularly given some of the limitations of studies highlighted in the

previous section. Many of these issues are related to the relationship between equity, the inappropriate use of medications, the true value of the welfare loss of prescription drug insurance, and the use of new technologies, but the consideration of these issues is beyond the scope of this thesis.

Thus, this section focuses on the gaps in the literature related to the price elasticity of demand. The relationship between user fees and the volume of prescription drugs obtained has been well-answered in the literature. Whether or not the analysis was robust, virtually all papers have found that cost sharing reduces the number of drugs demanded. Nonetheless, because the relationship between user fees and the volume of prescription drugs naturally falls out of the calculation of the price elasticity of demand, we provided an overview of the literature on this particular dependent variable.

A more interesting area is the analysis of the price elasticity of demand because it quantifies the relationship between user fees and volume in a unitless measure, allowing us to compare sensitivities across different countries and population groups. Importantly, there are a number of questions remaining regarding the price elasticity of demand. As highlighted in Section 3.5.4, the estimates from the literature vary widely across different settings and even within specific population groups, implying the need for more research. One specific implication is that a statistical analysis which the compares the various estimates, taking into account the type of dataset, the quality of the study, the institutional setting, and other factors, would offer a better idea of the "true" elasticity and how this elasticity might vary according to specific characteristics.

Although numerous papers have investigated vulnerable subpopulations such as the elderly and low-income individuals, no papers have provided comparisons of the prescription drug elasticities of demand for the vulnerable populations and the general population. This is despite a number of papers in the literature discussing the potential adverse effects of cost sharing on the poor and chronically ill (Evans and Barer, 1995; Kutzin, 1998; Robinson, 2002). While it is possible to compare elasticity estimates from different investigations, differences between the methods of data collection, the culture of the population considered, the institutional setting, the time period of the analysis, and other factors mean that the comparison of elasticities based on one dataset may offer a clearer picture. Within each country a comparison of this type would better highlight the heterogeneity in responses to cost sharing across subpopulations and allow decision-makers to tailor cost sharing requirements. For example, if the elderly are not particularly responsive to changes in prices of prescription drugs while the poor are very responsive, third-party payers might consider minimal user fees for the poor and higher user fees for the wealthier, older groups. Thus, an analysis that compares elasticity estimates among these different subpopulations using a dataset drawn from the same overall population could shed more light on these questions for policymakers.

Given the discussion of limitations in the previous section, the methodology of many investigations in the area is one aspect that could use improvement. The Duan et al.

(1983) study sparked a debate over whether the Heckman two-step or the two-part model proposed by Duan et al. (1983) was more appropriate in the context of the censored dependent variables (Jones, 2000). The advantage of this debate was that it highlighted the need for non-linear regression techniques in the analysis of cost sharing for medical services, and a number of papers since then have explicitly taken this into account. Yet, few of these studies have simultaneously accounted for unobserved heterogeneity and sample selection even though panel data can overcome some of the shortcomings of cross-sectional data[3]. An even further problem with studies that include privately insured individuals in the sample is the potential endogeneity of the cost sharing variable, a limitation that was discussed in the previous section. However, only a few papers have tested for this problem, and even fewer have employed corrections.

3.7. Conclusion

This chapter has provided a brief overview of the literature covering the relationship between cost sharing for various medical services and the demand for medical care. Section 3.1 provided the intuition for performing the literature review, while Section 3.2 discussed the search strategy that was employed. Because prescription drugs are one portion of the overall health care that a patient receives, we provided a brief overview of the literature related to user fees for medical care in general, inpatient care, and physician and outpatient services in Section 3.3. While there was little disagreement that user fees reduced the number of services obtained, within each outcome variable, there were ranges of estimated price elasticity values. Interestingly, the ranges of elasticities for inpatient and physician care were relatively close, while the range of elasticities for medical care was rather small at -0.20 to -0.10. Nonetheless, the price elasticity of demand for medical care, inpatient care, and physician services appeared to be relatively inelastic, which led us to expect the same result for prescription drugs.

Section 3.4 offered a more comprehensive overview of the relationship between prescription charges and the volume of drugs demanded and the price elasticity of demand. The literature was split into three categories: studies that examined the general population, studies that examined the elderly or chronically ill, and papers that considered the low-income population. Across all three of these groups and the various forms of cost sharing employed, user fees consistently reduced the volume of services demanded. Section 3.4 also considered the other covariates that were employed in the literature, and the main determinants of demand appeared to be gender, age, income, and health. The importance and effect of these variables, however, seemed to be related to the subpopulation being considered. In terms of the price elasticity of demand, estimates varied widely across the general and elderly populations, and there was little indication of whether the average estimates for these populations were different. There were only a few price elasticity estimates for the low-income group. The price elasticity results for prescription drugs imply a need for

[3] Hsu et al. (2006) and Anis et al. (2005) both considered a two-part model that accounted for unobserved heterogeneity, but no other studies simultaneously employed these corrections.

more research in the area to shed light on the "true" or "corrected" elasticity estimate and the differences in estimates between population groups.

Section 3.5 then highlighted the main limitations of papers from the literature, many of these being methodological in nature. Issues such as sample selection, endogeneity, and unmeasured heterogeneity are common, and yet few studies have explicitly accounted for these specific pitfalls. Based on these limitations of studies in the area and the wide range of calculated price elasticity values, Section 3.6 highlighted the need for more research in the area of user fees for prescription drugs. In particular, the focus of this section was on the need for a "corrected" elasticity estimate and an analysis that compared price elasticity values across different subpopulations drawn from the same overall population.

Chapter 4: Meta-regression of the price elasticity of demand for prescription drugs

4.1. Introduction

The previous chapter highlighted the considerable variation in prescription drug price elasticity estimates between studies. The estimates differ significantly by the institutional setting, the extent of public financing, the aggregation of the data, the methods employed, and other factors. As an extension to the literature review, an interesting exercise is to obtain an "adjusted" or "composite" price elasticity value, holding these study-specific factors constant. Meta-regression analysis (MRA) is a technique that extends the literature review into a simple regression to output the adjusted elasticity value. Not only is a composite price elasticity estimate useful as a baseline value for policymakers, but a composite estimate is also valuable for this dissertation. MRA provides an average estimate across the developed world, which offers a useful comparator for the subsequent elasticity estimates that we obtain for the United States and British Columbia.

A continuous problem with published elasticity estimates is that journals tend to select estimates which confirm existing hypotheses regarding the elasticity (Stanley and Jarrell, 2005). While literature reviews of the existing studies offer some information regarding the range of estimates, it is argued that even when weights are employed, there is considerable subjectivity in specifying the range of an elasticity estimate (Stanley and Jarrell, 2005). An increasingly popular methodological alternative to such a review in the medical, science, and psychological literature is meta-regression analysis. This technique involves integrating and evaluating the empirical results from different studies to obtain a hypothetically unbiased estimate which depends on the current state of the empirical literature (Stanley, 2001). MRA reduces the subjectivity implicit in empirical research and allows the researcher to test the sensitivity of the estimated parameters to changes in study characteristics.

The aim of this chapter is to use MRA to obtain an adjusted estimate of the price elasticity of demand for prescription drugs that accounts for the existing heterogeneity in three main factors: the institutional setting, the study characteristics, and the publication determinants. This estimate can then be judged against the primary estimates for the United States and British Columbia (obtained in Chapters 6 and 7) to consider why the elasticity values might vary between settings. The organization of the chapter is as follows: Section 4.2 is devoted to a brief review of the literature that has covered cost sharing and the price elasticity of demand for prescription drugs. Section 4.3 describes the methodology employed, specifically meta-regression analysis. Section 4.4 goes over the results of the regression, while Section 4.5 offers a discussion. Finally, Section 4.6 concludes the chapter and discusses the limitations of this study.

4.2. Brief review of the literature on the price elasticity of demand

This chapter complements the earlier work in Chapter 3 by providing a meta-analytic overview of the price elasticity of demand based on the existing literature. To motivate the need for meta-regression analysis, we highlight the significant variation that exists in the existing price elasticity estimates. Many of the papers are quite recent because (i) data on drug prices and drug utilization has been made public relatively recently in a number of cases, and (ii) the quality of the data has improved over time. In any case, the intent is not to give a systematic overview of the literature but to highlight major differences across studies that may account for differences in calculated estimates of price elasticities.

The earliest investigations used aggregate data to obtain an elasticity value. Two Belgian studies (Carrin and Van Dael, 1991; Van Doorslaer, 1984) considered both the working population and a subsample of widows, invalids, orphans, and retired persons with incomes below a certain level. These investigations reported larger estimates (-0.60 to -0.35) for the employed population, but the estimate for the non-employed group (unemployed, retired, etc.) was not significantly different from zero in the Carrin and Van Dael (1991) study. However, both of these investigations were hampered by relatively small sample sizes. A number of papers (Hughes and McGuire, 1995; Lavers, 1989; O'Brien, 1989; Ryan and Birch, 1991) also used aggregate data to examine changes in co-payments over time for the United Kingdom, and these results ranged from -0.64 to -0.09, with most estimates falling in the middle of this range.

Using aggregate data a similar study from Spain (Puig-Junoy, 1988) determined that the price elasticity of demand for prescription drugs was -0.13, although this analysis also suffered from a small sample size. An Australian investigation (McManus et al., 1996) distinguished between the use of essential and discretionary medicines among the non-elderly population and found inelastic but comparatively large values for both classes of medicines, potentially indicating that consumers were unable to distinguish between unnecessary and necessary medications. Interestingly, a Dutch study (Van Vliet et al., 1999) used individual-level data aggregated to the policy level and determined that the elasticity of demand for prescription drugs was -0.021 in the Netherlands.

Other researchers have used non-aggregate data to calculate the price elasticity of demand. Smith (1993) looked at individuals from employer-groups covered by a national managed care company and calculated an elasticity of -0.098. Meanwhile, Motheral and Henderson (1999) considered a similar population and reported an estimate of -0.32. Coulson and Stuart (1995) and Klick and Stratmann (2005) have examined a more vulnerable population: the elderly. Their elasticity estimate of -0.56 indicated that although demand is relatively inelastic among this group, there is still some sensitivity to price. A fifth American paper (Mortimer, 1997) considered individuals receiving antidepressants and beta blockers and found wide ranges of elasticity values, depending on the type of medication, whether the drug was a brand or generic, and the number of competitors.

Outside of the United States, there was one study from Canada (Grootendorst and Levine, 2001) that reported elasticities for the elderly, individuals receiving social assistance, and the rest of the population. There were a wide range of calculated values, depending on the subpopulation and the class of drugs considered, although most estimates were inelastic. Another Canadian study (Li et al., 2006) examined a group of seniors with rheumatoid arthritis and found price elasticities of -0.20 and -0.11 for the low-income and non low-income elderly, respectively. Additionally, Anessi Pessina (1997) investigated the elasticity of demand for particular classes of medications in Italy, and his findings ranged from -0.75 to -0.07. This wide range of estimates was likely due to the degree of substitutability between the investigated classes and other forms of care, the perceived necessity of the specific medications, and other factors.

Overall, most of the literature has obtained inelastic estimates for demand, although Grootendorst and Levine (2001) found positive elasticities for some subgroups. There appears to be significant heterogeneity as the type of data has differed by study, the subpopulations considered have varied, and other factors have differed between investigations. Beyond this basic inference about the elasticity, it is unclear how these estimates are influenced by country effects, other characteristics of individual studies, or even the mediums where the estimates are published.

4.3. Methods for the meta-regression analysis

The main thrust of this chapter is to examine the extent to which the predicted meta-regression elasticity differs from zero ($\beta_i \neq 0$) or unity ($\beta_i \neq 1$) and to determine the adjusted magnitude of the elasticity estimate. A general problem with the first consideration, the testing of the hypothesis that the price elasticity differs from a certain value, is that of publication bias which can occur because (Card and Krueger, 1995):

(i) referees and editors may be more likely to accept articles that are consistent with their personal views,
(ii) researchers may be predisposed towards models that confirm conventional results (e.g. models that confirm a significant negative effect for the price elasticity), and
(iii) researchers, reviewers, and editors may be more likely to treat statistically significant results favorably.

Publication bias is a problem in empirical economics as it can cause empirical effects to appear larger than actuality, and thus methods that neutralize this problem need to be considered (Stanley, 2001), particularly since a number of other papers employing MRA have encountered this bias (Ashenfelter et al., 1999; Card and Krueger, 1995; Rose and Stanley, 2005). To account for this difficulty, we expanded our literature search to include papers published outside of journals and included the standard error of the elasticity estimate as a variable in the model. The following sections describe the data and methodology used to investigate these elasticity issues.

4.3.1. Meta-regression analysis

While the literature review has revealed that the price elasticity of demand for prescription drugs appears to be inelastic, there is a wide range of estimates and considerable uncertainty as to the correct magnitude of this estimate. Thus, the elasticity may not be significantly different from zero or even unity. The purpose of MRA is to resolve these questions while controlling for differences in study characteristics.

Meta-regression analysis is a quantitative technique which allows the researcher to combine and evaluate empirical estimates from the literature in a systematic manner and identify the determinants that influence the precision of specific estimates (Stanley and Jarrell, 2005). The analysis treats each elasticity estimate from the literature as an individual observation drawn from a general overall statistical population, and the conditions associated with each value are recorded as covariates. This compiled dataset permits testing of the hypotheses that the price elasticity of demand is different from zero or unity. The dataset can also be used to determine if various features of the analyzed studies influence the elasticity estimate.

Numerous meta-regression analyses have been carried out, and the studies have encompassed topics such as the effect of common currencies on international trade (Rose and Stanley, 2005), the effect of immigration on wages (Longhi et al., 2005), the gender wage gap (Stanley and Jarrell, 1998; Weichselbaumer and Winter-Ebmer, 2005), and the income elasticity of money demand (Knell and Stix, 2005). Typically, meta-regression studies have contained between 20 and 100 observations, although this number has differed by the study purpose and area of study. For instance, Geleijnse et al. (2002) employed 36 observations, Greenwood et al. (1999) employed 51 observations, Sexton (2005) used 31 observations, while Rose and Stanley (2005) utilized 34 observations.

The intuition behind performing MRA is that literature reviews are generally a subjective exercise. The researcher determines which studies to include in the review, how to interpret the results, and what reasons contribute to the differences across studies. While a systematic review overcomes some of these pitfalls, there is still considerable subjectivity in the interpretation of the results and the attribution of various factors to differences in results. Moreover, a systematic review still does not produce a consensus on estimates from the literature. Thus, the ultimate objective of the methodology is to obtain an "estimate of estimates" with some acceptable precision (Stanley and Jarrell, 2005).

MRA therefore begins with a collection of N estimates of the statistic of interest, in this case the price elasticity arising from out-of-pocket expenditures on prescription drugs. The collection of N estimates should consist of the entire empirical literature on the variable of interest. Defining this as β_i, we have $i=1,\ldots,N$ individual estimates upon which the MRA can be estimated. We identify the k characteristics of the diverse studies in the literature and integrate the findings as follows:

$$\beta_i = \beta + \sum_{k=1}^{K} \alpha_k Z_{ik} + \mu_i \qquad (4.1).$$

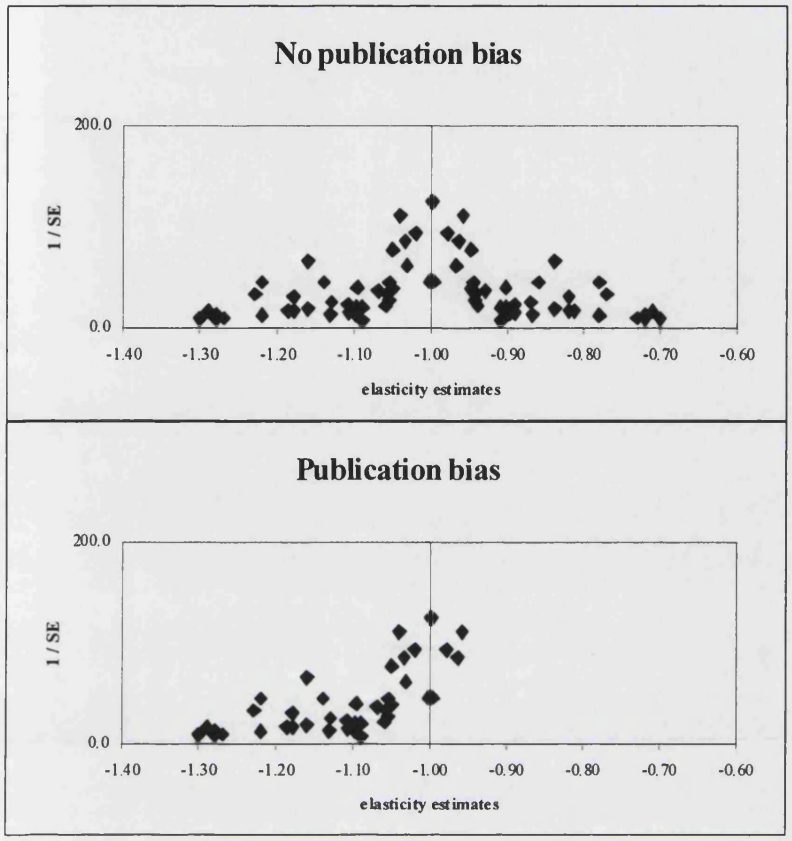
This allows us to calculate a composite estimate of the price elasticity, controlling for a number of study characteristics. The reported elasticity estimate of each study (β_i) is the dependent variable and equals the adjusted elasticity estimate (β) adjusted for the k characteristics (Z_{ik}) of each published study. Finally, each parameter (α_k) represents the magnitude of how specific characteristics may lead to different elasticity estimates (Stanley and Jarrell, 2005). In other words each α_k can be considered the average bias introduced by misspecifications in the original studies (Stanley and Jarrell, 2005). The Z_{ik} are variables measuring the characteristics of the study, e.g. the impact factor of the journal, dummy variables related to data characteristics like outlier observations, as well as numerical continuous variables accounting for other data characteristics like the study size. A dummy variable for the institutional setting is included to permit comparability of different health care settings.

Given that estimates are obtained by varying degrees of precision, we control for publication bias by including the standard error of each elasticity observation. The intuition behind the inclusion of this variable is that studies with smaller sample sizes are liable to produce statistically insignificant results and will need to search more for models that produce significant effects (Stanley, 2001). The resulting effects from small sample sizes are thus likely to be larger than effects found with larger sample sizes. Under the assumption that journals are more likely to publish significant estimates, the averages of effect magnitudes will be biased upwards across this literature. Thus, a significant coefficient on the standard error would imply that precision or publication bias exists.

In specifying a model that is based on estimates from previous models, it is important to examine the distributional properties of the data. MRA coefficients are expected to be unbiased and consistent (Stanley and Jarrell, 2005), but given the heterogeneity of the revised studies, differing sample sizes, and various controls and methods, meta-regression errors may be heteroskedastic. A common method of visually identifying irregular behavior of observations in MRA is to use a funnel graph (Stanley, 2001), which depicts publication selection by comparing precision versus the non-standardized effect.

The precision can be measured in a number of ways (Stanley, 2001), although we use the inverse of the standard error, and the non-standardized effect is the elasticity estimates. In the absence of publication selection, the graph will resemble an inverted funnel, where small sample studies will comprise the mouth of the funnel and larger sample studies make up the stem. Figure 4.1 provides examples of two funnel graphs: one funnel graph is for regression errors that are not heteroskedastic, and the second funnel graph is for regression errors that are heteroskedastic. Note that Figure 4.1 is drawn for a hypothetical distribution that centers around

Figure 4.1. Example funnel graphs of elasticity estimates



Thus, the funnel graph is a useful visual tool for determining if publication bias is a likely problem with the dataset. Not surprisingly, it is common practice in MRA to test for heteroskestadicity and apply weighted least squared (WLS) estimates by dividing (4.1) by the standard error of β_i (S_β) if heteroskedasticity is confirmed. Accordingly, the dependent variable becomes the t-statistic:

$$t_i = \frac{\beta_i}{S_\beta} = \frac{\beta}{S_\beta} + \sum_{k=1}^{K} \frac{\alpha_k Z_{ik}}{S_\beta} + \frac{\mu_i}{S_\beta} \qquad (4.2).$$

Assuming no further misspecification, this model controls for specific meta-effects. One way to determine the sensitivity of a model to misspecifications is to measure the effect of varying independent variables. These independent variables (Z_{ik}) identify the processes which explain the production of empirical results (Stanley and Jarrell, 2005).

Another important consideration is homogeneity, in particular, the existence of a common mean. This can be tested using the $Q = \sum(\beta_i - \overline{\beta}_{var(\beta)})^2 / var(\beta_i)$ statistic, where β_i is each elasticity estimate, $\overline{\beta}_{var(\beta)}$ is a weighted average of each elasticity

estimate corrected by the variance of the estimate, and var(β_i) is the variance of each estimate. The null hypothesis is homogeneity, and Q is distributed as χ^2_{N-1} where N is the number of studies. As an alternative to the Q-statistic, the I^2-statistic assesses the proportion of inconsistency in individual studies that is not explainable by chance (Higgins et al., 2003). Values of the I^2-statistic that are close to 100 percent indicate a significant degree of heterogeneity. Overall, the existence of heterogeneity implies the need for regression analysis.

4.3.2. Data selection

In terms of the information that we selected from each study, there are a number of study-specific variables that may have an impact on the elasticity value. Based on previous meta-regressions from the economic literature (Stanley and Jarrell, 1998), the independent variables can be classified as:

(i) study-specific characteristics (e.g. number of observations),
(ii) institutional setting (e.g. health system),
(iii) method or data specific controls (e.g. presence of outliers), and
(iv) publication or dissemination effects (e.g. type of journal).

Ideally, each of these effects would capture specific biases that influence the dependent variable. An example of a dissemination effect is that economic journals might be biased towards publishing studies with negative elasticity estimates, which confirm the expected predictions from standard consumer theory and suggest a negatively sloped demand for drugs. Study characteristics such as the number of observations and whether the study relies on aggregate or individual-level data might be important for determining the precision of the specific estimates. The institutional setting is key to health-related studies given that the extent of health insurance coverage and specific health system characteristics are likely to influence the response to different cost sharing structures. A number of these characteristics might also be thought of as quality controls; for example, papers with more observations or papers published in journals with larger impact factors may be of higher quality.

Details on the literature search that was performed to identify relevant papers are available in Chapter 3. From the literature review we selected the papers which investigated the link between prescription charges and the volume of drugs obtained. An important point is that MRA is intended to reduce the existing subjectivity in the selection of empirical elasticity estimates. Accordingly, all papers that reported an elasticity estimate were retained, and all papers where we could calculate both an elasticity value (Coulson and Stuart, 1995; Grootendorst et al., 1997; Liebowitz et al., 1985; Motheral and Henderson, 1999; Smith and Watson, 1990) and the associated standard error (Anessi Pessina, 1997; Coulson and Stuart, 1995; Grootendorst and Levine, 2001; Grootendorst et al., 1997; Hughes and McGuire, 1995; Lavers, 1989; Liebowitz et al., 1985; McManus et al., 1996; Motheral and Henderson, 1999; O'Brien, 1989; Ryan and Birch, 1991; Smith, 1993; Smith and Watson, 1990; Van Doorslaer, 1984; Van Vliet et al., 1999) from the data were also retained.
The pre-screening of the relevant studies and then the selection and classification of each investigation allowed us to create a database of estimates and potential

explanatory variables. We employed four main elasticity formulas, which are listed in Table 4.1.

Table 4.1. Elasticity estimation methods

Regression specification	Statistical model	Elasticity formula
Linear	$y = \gamma_0 + \gamma_1 x + e$	$\gamma_1 (\bar{x}/\bar{y})$
Log-log	$\ln(y) = \gamma_0 + \gamma_1 \ln(x) + e$	γ_1
Linear-log	$y = \gamma_0 + \gamma_1 \ln(x) + e$	$\gamma_1 (1/\bar{y})$
Log-linear	$\ln(y) = \gamma_0 + \gamma_1 x + e$	$\gamma_1 \bar{x}$

Note that when we had specific data points from the demand curve, we used the arc elasticity formula following Phelps and Newhouse (1972), as the point elasticity formula is sensitive to values chosen for the initial price and quantity[1]. When an investigation used a count data model, either the log-log or log-linear elasticity formula was used to calculate the elasticity estimate, depending on whether the price variable was also in logarithms. Although a number of papers have examined the relationship between cost sharing and health service utilization based on the RAND experiment, only one paper from the RAND study (Liebowitz et al., 1985) reported enough information for us to calculate an elasticity estimate for prescription drugs. Table 4.2 lists the studies that reported price elasticities and the papers that detailed enough information for us to calculate elasticities with their estimated standard errors[2].

Obtaining the standard errors was more difficult in some cases. When the study reported a standard error for the price variable, we simply used the same formula for calculating the elasticity, except that we substituted the standard error of the price variable for γ_1 (the coefficient on the price variable). However, a number of papers reported the t-value associated with γ_1 rather than the standard error, and in this instance, we first had to calculate the standard error of γ_1. This was accomplished by using the formula for the t-value:

$$t - value = \frac{\gamma_1 - 0}{s.e.(\gamma_1)} \qquad (4.3),$$

[1] For studies that focused on the introduction of user charges, we also used the arc elasticity formula, as it is impossible to divide by zero in the point formula and as point estimates are sensitive to chosen values that are close to zero.

[2] It is important to note that Table 4.2 does not include all studies mentioned in the literature review as some studies did not report elasticity estimates or sufficient information for us to calculate elasticities or standard errors.

substituting in the known values of γ_1 and the t-value, and solving for $s.e.(\gamma_1)$. Further difficulties occurred where the authors only reported whether the study was significant at the 1 percent, 5 percent, or 10 percent level. In this instance we used the t-value associated with the reported significance level and calculated the maximum standard error that could be associated with γ_1 using formula (4.3).

Table 4.2. Range of elasticity estimates used in the meta-regression

Study	Range of elasticities
Anessi Pessina (1997)	-0.75 to -0.07
Carrin and Van Dael (1991)	-0.35 to -0.09
Coulson and Stuart (1995)	-0.18[a]
Gibson et al. (2005)	-0.05 to –0.04
Grootendorst and Levine (2001)	-0.16 to 0.09
Grootendorst et al. (1997)	-0.13[a] to -0.09[a]
Hughes and McGuire (1995)	-0.37
Klick and Stratmann (2005)	-0.56
Lavers (1989)	-0.22 to -0.18
Li et al. (2006)	-0.20 to –0.11
Liebowitz et al. (1985)	-0.10[a]
McManus et al. (1996)	-0.80 to -0.50
Motheral and Henderson (1999)	-0.32[b]
Nelson et al. (1984)	-0.06[a]
O'Brien (1989)	-0.64 to -0.23
Puig-Junoy (1988)	-0.13
Ryan and Birch (1991)	-0.11 to -0.09
Smith (1993)	-0.10
Smith and Watson (1990)	-0.58[c]
Soumerai et al. (1987)	-0.05[a]
Van Doorslaer (1984)	-0.60 to -0.06
Van Vliet et al. (1999)	-0.02

[a] calculated by authors of this paper using the arc elasticity formula:
$e_d = ((Q_2 - Q_1)/(Q_2 + Q_1))((P_2 + P_1)/(P_2 - P_1))$.

[b] calculated by the authors of this paper using the point elasticity formula:
$$e_d = ((Q_2 - Q_1)/(Q_1))((P_1)/(P_2 - P_1))$$

[c] calculated by the authors of this paper using a log-linear calculation: $e_d = B_j \bar{x}$, where B_j represents the coefficient on the price variable and $\bar{x}$ is the mean price.

4.4. Results

This section covers the results of the estimations. We first discuss the descriptive results and offer some basic insight into the publication bias that appears to exist in

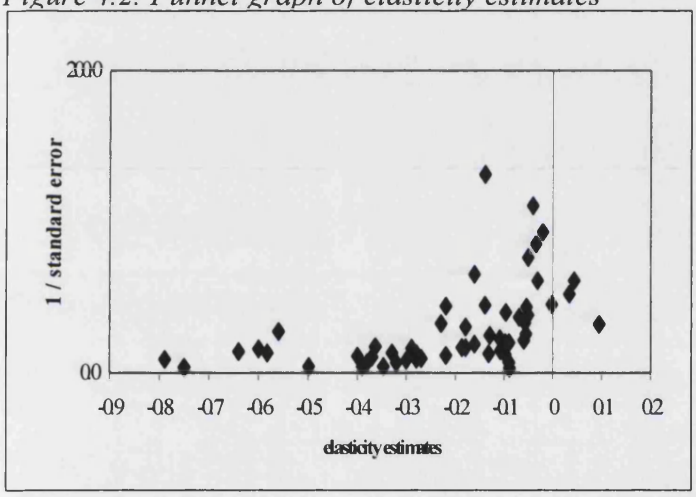
our sample. We then present the regression results and provide estimated price elasticity values based on the regression results.

The final dataset consisted of 58 observations from a total of 23 studies (some papers reported more than one elasticity estimate). The analysis of the dataset was carried out in STATA 9.2, and all of the regressions used the [*regress*] command.

4.4.1. Descriptive statistics

Before proceeding with the econometric estimation, it is useful to explore some of the characteristics of the data. As discussed in Section 4.3.1, we can visually inspect the funnel graph to determine if publication bias is a consideration for the sample. Based on Figure 4.2, it appears that publication selection is a problem as the scatter plot resembles only half of a funnel.

Figure 4.2. Funnel graph of elasticity estimates



Given the exploratory nature of the study, it is also useful to examine the summary statistics, and Table 4.3 lists these statistics along with definitions of the variables.

The summary statistics indicate that the mean elasticity is around –0.211, and the corresponding mean standard error of these estimates is around 0.027. Approximately 16 percent of the studies were published in economic journals, and the average journal impact factor is 0.86. The average number of observations for each elasticity estimate is roughly 9240, although there is significant variability around this estimate. Over 50 percent of the observations in our dataset are derived from aggregate datasets, and the mean age of a study from which an observation is obtained is 11.3 years. Around 14 percent of the observations are for health care systems which imposed coinsurance rates on patients, while around 35 percent of the observations are from systems that employed various combinations of cost sharing arrangements. Approximately 67

percent of the sample is derived from tax-based insurance systems, and 16 percent of the sample is derived from social health insurance systems.

Table 4.3. Definitions of the variables and summary statistics

Variable	Definition	Mean[a]	Median	10th percentile	90th percentile
absolute value of the elasticity	absolute value of the elasticity	0.211 (0.027)	0.140	0.019	0.561
standard error	standard error of the elasticity	0.072 (0.009)	0.056	0.011	0.156
study published in economic journal	indicates whether the estimate was published in an economic journal	0.155 (0.048)	0.000	0.000	1.000
impact factor of journal	the impact factor of the medium where the estimate was published	0.856 (0.154)	0.100	0.000	2.907
number of observations	the number of observations in the study sample	9240 (2822)	1080	17.90	19251
study used aggregate data	whether the data was at the aggregate level	0.534 (0.066)	1.000	0.000	1.000
age of the study	indicates the number of years since the study was published	11.29 (0.871)	9.000	4.600	22.00
coinsurance regime	indicates whether the insurer charged a coinsurance rate for drugs	0.138 (0.046)	0.000	0.000	1.000
mixed cost sharing regime	indicates whether the insurer charged mix of cost sharing types for drugs	0.345 (0.063)	0.000	0.000	1.000
tax-based health system	indicates whether the health care system of interest was tax based	0.672 (0.062)	1.000	0.000	1.000
social health insurance system	indicates whether the health care system of interest was social health insurance based	0.155 (0.048)	0.000	0.000	1.000

[a]standard deviations in parentheses

Additionally, we investigated homogeneity in the sample by calculating the Q-statistic. The calculated value of the Q-statistic was high at 50,540 (p=0.000). With a value of 100 percent, the I^2-statistic further confirmed the result of the Q-statistic. Both of these measures indicated that there was significant heterogeneity in the sample, suggesting that regression analysis was merited.

4.4.2. Regression results: what are the estimation biases?

To obtain an adjusted price elasticity estimate, we followed two separate empirical specifications. First, we defined the elasticity estimate as the dependent variable, which is the common practice in MRA (Stanley and Jarrell, 2005). Second, we used the t-value as the dependent variable in an attempt to correct for heteroskedasticity.

The first set of models (Models 1 – 5) used the individual study estimates of the elasticity as the dependent variable, and these results are reported in Table 4. The models differ in terms of the included independent variables and corrections for various statistical issues. All of the models were corrected for potential

heteroskedasticity and clustered observations[3]. Model 1 included only the standard error as the independent variable, while Models 2 through 5 each included subsequent variables that were considered potential predictors. We initially included a number of other variables, particularly whether the elasticity estimate was for the elderly population, for the low-income population, or for the population with a chronic condition. We also considered whether the estimate was from the United States, Canada, or another country, however, none of these variables were significant in the regression, and they were subsequently removed. We also considered a number of possible interaction terms, for example, an interaction between the number of observations and whether the data was aggregate, but only the interaction term between the standard error of the estimate and the number of observations was significant.

There were a few issues that required further examination, in particular, potential heteroskedasticity and the possibility of omitted variables. A residual plot of the standard errors appeared to exhibit heteroskedasticity, and this was confirmed with a Breusch-Pagan test for heteroskedasticity. Adding additional controls to the model did not correct for this problem, so we used the White (1980) estimator to make the standard errors of the corrected regressions (Models 1 – 5) robust.

From Table 4.4 we see that with the exception of Model 5, the coefficient on the standard error variable remained significant, even as more covariates were added to the model. The coefficient was typically between 0.91 and 1.55, indicating that as the standard error of the elasticity increased by one unit, the elasticity estimate also increased by a little more than one unit. However, the insignificance of the standard error variable in Model 5 was interesting because this appears to be caused by the addition of the interaction term between the standard error and the number of observations.

The adjusted elasticity value ranges from a significant -0.11 in Model 1 to an insignificant -0.16 in Model 5. In terms of the quality variables, the indicator for whether the elasticity estimate was published in an economic journal was significant in all of the models, although in Model 3, it was only significant at the 10 percent level. The coefficient ranged from 0.14 to about 0.18, signifying that elasticity estimates which were published in economic journals were larger than estimates that were published in non-economic journals, working papers, or books. The coefficient on the other quality indicator, the impact factor of the journal, was never significant in any of the models.

Most of the variables representing the characteristics of each specific study were not significant. The variable representing the number of observations was positive but only significant in Model 4. It appears that elasticity values derived from aggregate datasets are larger than those obtained from non-aggregate datasets, a result that is not surprising given the greater amount of noise in aggregate datasets. The coefficient on the variable indicating that the observation was obtained from a tax-based health care

[3] There were certain studies that yielded more than one elasticity value, and we accounted for these clustered observations in the corrected regressions.

system was also significant at the 10 percent level in Models 4 and 5 and signified that individuals in these systems were less sensitive to prices than individuals in private insurance or mixed systems. In addition, the variable representing the interaction between the standard error of the estimate and the number of observations in the study was significant and positive in Model 5.

Table 4.4. OLS regressions with the elasticity as the dependent variable[a]

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Publication biases					
standard error	1.460§ (0.545)	1.546§ (0.541)	1.339§ (0.602)	1.229* (0.631)	0.913 (0.621)
study published in economic journal		0.159§ (0.060)	0.140* (0.068)	0.180§ (0.067)	0.155§ (0.062)
impact factor of journal		-0.004 (0.023)	-0.002 (0.019)	0.004 (0.018)	0.003 (0.016)
Study characteristics					
number of observations			0.000 (0.000)	0.000§ (0.000)	0.000 (0.000)
study used aggregate data			0.116* (0.057)	0.140§ (0.056)	0.222§ (0.056)
age of the study			-0.002 (0.005)	-0.004 (0.007)	-0.008 (0.006)
Institutional setting					
tax-based health system				-0.134* (0.077)	-0.156* (0.084)
social health insurance system				-0.073 (0.130)	-0.051 (0.115)
Interaction terms, constant					
standard error * number of observations					0.000§ (0.000)
constant	0.106§ (0.046)	0.078 (0.047)	0.051 (0.069)	0.156 (0.111)	0.156 (0.113)
N	58	58	58	58	58
Number of clusters	23	23	23	23	23
R^2	0.245	0.324	0.368	0.423	0.483

[a] standard errors in parentheses
§significant at the 5% level, *significant at the 10% level

In addition to the models with the elasticity as the left-hand side variable, we conducted a weighted least squares regression by dividing the dependent and independent variables by the standard error of the elasticity. Thus, the dependent variable of this model was the conventional t-value (Stanley and Jarrell, 2005). Table 4.5 reports the results of the regression with the t-value as the dependent variable.

Table 4.5. OLS regression with t-value as left-hand side variable[a]

Variable	Model 6
Publication biases	
standard error / standard error	1.591 (1.176)
study published in economic journal / standard error	0.213* (0.111)
impact factor of journal / standard error	0.007 (0.028)
Study characteristics	
number of observations / standard error	0.000§ (0.000)
study used aggregate data / standard error	0.372§ (0.101)
age of the study / standard error	-0.026§ (0.010)
Institutional setting	
tax-based health system / standard error	0.078 (0.060)
social health insurance system / standard error	0.417* (0.197)
Interaction terms, constant	
standard error * number of observations / standard error	0.001§ (0.000)
constant / standard error	-0.091* (0.038)
N	58
Number of clusters	23
R^2	0.213

[a] standard errors in parentheses
§significant at the 5% level, *significant at the 10% level

Model 6 did not perform as well as Model 5, but we still discuss the results briefly here. The results of Model 6 indicate that the adjusted elasticity of demand is -0.159 (p=0.109), which is not significantly different from zero. The indicator of whether the study was published in an economic journal (divided by the standard error) was significant and positive at the 10 percent level. Meanwhile, all of the study characteristics (divided by the standard error) were significant. While the number of observations (divided by the standard error) and the indicator of whether the study used aggregate data (divided by the standard error) were positive, the age of the study (divided by the standard error) was negative. The indicator of whether the observations were drawn from a social health insurance system (divided by the standard error) was significant and positive, but only at the 10 percent level. Finally,

the interaction between the standard error and the number of observations (divided by the standard error) was significant and positive at the 5 percent level.

4.5. Discussion

The predicted elasticity value indicates that the demand for prescription drugs is relatively inelastic at –0.16 (p=0.181). These estimates imply that across the developed world, consumers are not virtually unresponsive to changes in out-of-pocket prices for prescription drugs. This may be due to a perceived necessity of prescription medications and a lack of suitable substitutes. However, there may be an existing bias as most of these papers have calculated elasticities at the lower end of the demand curve, and these values may be considerably higher for greater levels of cost sharing. It is important to keep this possibility in mind when evaluating the "adjusted" price elasticity value.

The fact that many of the covariates were not significant predictors of the elasticity indicates that only a few variables exert an influence on the elasticity estimates for prescription drugs. As expected, publication and precision bias have some influence on this estimate, as the standard error of the elasticity was an important explanatory variable across some of the specifications. The significance of the economic journal indicator may reflect other underlying factors, for example, a preference for significant and relatively higher elasticity values among economic journal editors.

The indicator for whether the study employed aggregate or non-aggregate data was significant. The finding is not surprising as there is considerably more noise in aggregate datasets, suggesting that not only do the specific characteristics of the study matter, but the precision of the estimate is higher when individual-level data are employed. Another interesting result was that consumers in tax-based health insurance systems seem to be less sensitive to changes in out-of-pocket prices than consumers in other types of systems. Compared with those in private insurance systems, those who are under tax-based health care generally face lower cost sharing requirements for prescription drugs and less uncertainty as to whether their out-of-pocket burden will increase significantly in the future.

There were a few studies that published elasticity estimates or enough information for us to calculate the elasticity, but these papers did not offer enough information for us to calculate standard errors. The results from our meta-regression are generally lower than findings from other studies. An early study from Canada (Greenlick and Darsky, 1968) reported enough information for us to calculate an unadjusted arc elasticity value of -0.38. A second study (Harris et al., 1990), this time from the US, also allowed us to calculate elasticities, and we determined that when the co-payment increased from $0 to $1.50, the unadjusted arc elasticity was -0.17, while the adjusted arc elasticity was -0.06. Meanwhile, we were able to calculate arc elasticities from a later American investigation (Johnson et al., 1997); the results were that when the co-payment increased from $1 to $3, the elasticity of demand for prescription drugs was -0.02 and when the co-payment increased again from $3 to $5, the elasticity of demand was -0.24. The low elasticity values of -0.02, -0.06, and -0.17 may have been due to

the relatively small co-payment values that beneficiaries in these studies faced. Finally, Mortimer (1997) used American data to calculate elasticities for antidepressants and beta-blockers and to compare generic and brand-name drugs. In general, the elasticity results from Mortimer (1997) were higher than our predicted values, although this was probably due to the analysis of the two specific product markets where a number of products in the market are interchangeable.

4.6. Conclusion

The purpose of this chapter has been to amalgamate the existing elasticity estimates of demand for prescription drugs into a dataset and use MRA to obtain a composite and presumably unbiased estimate of this elasticity. This involved identifying the effects which significantly influence individual study elasticity estimates and calculating how this elasticity estimate differed across individual studies due to the quality of the published papers, the institutional setting, and the characteristics of the study that might have affected estimation biases.

The chapter began with a brief overview of the literature on the price elasticity of demand, which highlighted the variation in estimates between studies. We then developed the meta-regression analysis methodology and discussed the collection of data and the calculation of price elasticity estimates and standard errors. The results of the MRA indicated that an "adjusted" price elasticity of demand across the developed world is around -0.16, although this value is not significantly different from zero. Not surprisingly, across various health care systems patients are relatively insensitive to price changes of prescription drugs. The important predictors of the price elasticity estimate were the indicator for whether the paper was published in an economic journal, the indicator for aggregate data, and the indicator for consumers living in tax-based health systems. When we do not include an interaction effect for the number of observations and publication bias, there appears to be an important effect of publication bias on the results.

The use of MRA has some caveats, for instance, this method is unavoidably subject to the limitations of the studies included in the analysis. For example, the publication of empirical evidence might be the result of a non-random process (Stanley and Jarrell, 2005). Some specific time patterns might be in place, for instance, certain topics are more in fashion during certain periods perhaps because of political factors, and this phenomenon might lead to meta-errors, however, including a time pattern can alleviate this. Another shortcoming of this approach is that MRA aggregates all of the data used in the elasticity calculations such that we lose information on specific subpopulations. We can somewhat control for this issue through dummy variables, although we are still limited by the sample size, which explains why the dummy variables are frequently insignificant. Policymakers should bear in mind the broad interpretation of the meta-elasticity result when considering the applicability of the elasticity estimate to policy. Finally, it is important to note that although MRA reduces some of the subjectivity related to classifying and weighting the existing empirical evidence, selection effects might still exist. However, MRA allows for replication, and the specific influence of any selection effect can easily be tested.

Similarly, as with meta-analysis, we explicitly state the rules of inclusion and selection of estimates for the sample, so we can potentially capture systematic variation within the sample.

Chapter 5: Description of the health and pharmaceutical systems in the United States and British Columbia

5.1. Introduction

As a precursor to the empirical analysis of demand-side cost sharing for prescription drugs in the United States and British Columbia, Canada, this chapter provides an overview of the health care and pharmaceutical systems in the US and Canada. The description of pharmaceutical policies in Canada focuses on British Columbia, though, because prescription drug coverage is defined at the provincial level in Canada. The purpose of this chapter is twofold. First, by describing the health care system in each country, we can flag any specific issues that may affect the empirical specification chosen for that country. Second, the health care description sets the scene for later interpretation of the empirical results (Chapters 6 and 7) and for policy conclusions specific to each health care system (Chapter 8).

As pointed out by Evans et al. (1991), Americans and Canadians share a multitude of similarities. The two countries share a common language, their economies and the media are closely linked, their cultural and historical experiences are related, and the geographic setting means that cross-border transfers are common. These underlying similarities have not played out in the health care sector as both countries have gone down divergent paths in funding and regulating health care since the late 1960s (Evans et al., 1991). The combination of these underlying similarities and the widely divergent health care systems has led a number of researchers to compare aspects such as the health of residents, the income distribution and health, the quality of care, and the costs of care versus the amount of care provided in each country (Evans and Roos, 1999). By considering the pharmaceutical market from the demand side, an aspect of Canadian and American health care that has not been considered in the context of a comparison, we contribute to this existing literature on health care comparisons between the two countries.

The organization of this chapter is as follows: the next section provides an overview of the US health care system and includes a description of pharmaceutical coverage in the country. Section 5.3 then covers the health care system in Canada, as the provision of core medical services are defined at the national level. Since the pharmaceutical system is defined at the provincial level, Section 5.3 also provides an overview of pharmaceutical coverage in British Columbia. Section 5.4 then discusses the differences between the US and Canadian health systems and the implications for price elasticity estimates, while Section 5.5 concludes the chapter.

5.2. The US health care and pharmaceutical system

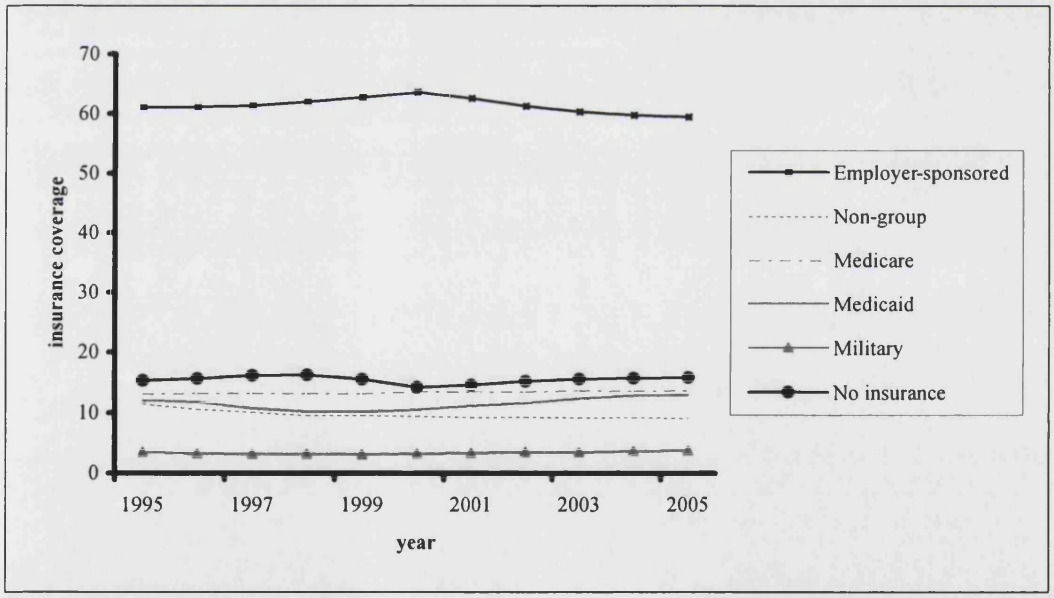
This section first provides a brief overview of the health insurance market in the US and then provides more detailed descriptions of the multiple sources of coverage, including trends in health insurance over time.

5.2.1. General overview

Health insurance coverage in the United States is fragmented with individuals receiving coverage from various private and public third-party payers and a significant proportion of the population having no insurance coverage. With the exception of some public insurance programs, third-party payers heavily rely on demand-side cost sharing to limit moral hazard and constrain health care expenditures, particularly pharmaceutical expenditures. Although pharmaceutical expenditures comprised about 10 percent of total national health spending in 2004, prescription drugs contributed 14.7 percent of total health care spending growth from 1994-2004 (KFF, 2006g).

Around 46.6 million Americans had no health insurance in 2005 (US Census Bureau, 2006) up from approximately 41.6 million in 2001 (US Census Bureau, 2005). Public insurance is available to those who are above the age of 64, low-income individuals as defined at the state level, certain public employees, and military veterans. The main public insurance programs include Medicare, Medicaid, US Department of Veterans Affairs (USVA) health insurance, and TRICARE. The rest of the insured population, ineligible for public insurance, typically receives coverage from employer-sponsored health insurance, non-group health insurance, and medical savings accounts.

Figure 5.1. Sources of health insurance coverage in the US (percentage of the total population)[a,b]



Source: US Census Bureau (2006)

[a] individuals receiving coverage from multiple sources are counted more than once such that the percents add up to more than 100, [b]Military insurance coverage includes CHAMPUS (Comprehensive Health and Medical Plan for Uniformed Services)/Tricare, Veterans Administration, and military health care

Figure 5.1 indicates that employer-sponsored private coverage increased between 1995 and 2000 and began to decline after 2000, while there has been a general decline in non-group coverage since 1995. The proportion of the population with Medicare and/or Medicaid has grown slightly since 1995, while the proportion of the population with military coverage has remained relatively steady.

There has been a slight increase in the uninsured population since 2000, and most of this change is related to fewer workers with employer-sponsored coverage (KFF, 2005a). There are fewer families with two-full time workers, more families with only one full-time worker, and more families with no full-time workers. The decrease in employer-sponsored coverage is also due to a shift in employment from large companies to self-employment and firms with fewer than 25 employees (KFF, 2005a), which are less likely to offer employer-sponsored coverage because of smaller risk pools. It appears that a decrease in household incomes and an increase in the number of individuals in poverty (KFF, 2005a) contributed to fewer individuals picking up alternate forms of insurance. Although Medicaid and SCHIP (State Children's Health Insurance Program) coverage increased significantly for children and Medicaid coverage increased slightly for adults (KFF, 2005a), these increases were not sufficient to offset declines in other types of health insurance.

Other facts related to the decline in insurance coverage point to certain demographic groups experiencing more difficulties. Among adults that became uninsured between 2000 and 2004, 46 percent were poor and 22 percent were near-poor (KFF, 2005a). Not surprisingly, while young adults (ages 19-34) make up approximately one-third of the non-elderly population, this segment of the population comprised almost half of the growth in the uninsured population (KFF, 2005a). Young adults are arguably more likely to change jobs, more likely to be self-employed, and may view health insurance as less of a necessity as they tend to be healthier. Interestingly, minorities and non-citizens did not account for most of the growth in the uninsured population even though these groups are more likely to be uninsured overall (KFF, 2005a).

While Medicaid, USVA insurance, and TRICARE typically offer prescription drug coverage, not all private insurance contracts include this type of coverage, although nearly all individuals with employer-sponsored insurance had a prescription drug benefit in 2005 (KFF/HRET, 2005). As a result, fewer individuals have prescription drug coverage than health insurance coverage, with 24 percent of adults between the ages of 19 and 64 having no prescription drug insurance and 40 percent of persons over 65 having no identifiable prescription drug coverage (KFF, 2006f). In comparison, 23 percent of non-elderly adults had no prescription drug coverage and 36 percent of Medicare beneficiaries had no prescription drug insurance in 1996 (KFF, 2003).

The following sections offer more detail regarding each of the main insurance programs in the United States, with an emphasis on cost sharing requirements and trends over time.

5.2.2. Medicare

Medicare is a national public insurance program for individuals over the age of 64, some non-elderly persons with specific disabilities, and persons of all ages with End Stage Renal Disease (CMS, 2006b). The program is funded through taxation, premiums, user fees, and other sources. All employed persons in the US pay a 1.45 percent tax that is earmarked for Medicare and Medicaid, and employers match this amount. More information about Medicare premiums and user fees is provided below.

Under traditional fee-for-service (FFS) Medicare, the program consists of three main parts: A, B, and D. Medicare Part A applies to all Medicare beneficiaries and comprises hospital stays, skilled nursing facilities, limited home health care, and hospice care for terminally ill persons. Although most beneficiaries do not face a premium for Part A, there is cost sharing that depends on the specific service consumed (Table 5.1).

Table 5.1. Various forms of cost sharing under Medicare Part A

Deductibles	Co-payments	Coverage maximums
Inpatient hospital care	Inpatient hospital care	Inpatient hospital care
	Skilled nursing facility care	Skilled nursing facility care
	Hospice care	Home health agency

Source: CMS (2007a)

Table 5.2 lists some of the current and historical premiums and out-of-pocket requirements for Medicare Part A. For comparability over time, the values in Table 5.2 are in 2005 dollars[1].

The percents in parentheses represent the inflation-adjusted annual growth rates, where the value for the previous year is used as a basis for calculating the growth rate. There are a few trends that we can highlight based on the information in Table 5.2. The inflation-adjusted inpatient deductible and co-payments declined between 1998 and 2000 but began to rise somewhat faster than the rate of inflation after 2000. Meanwhile, median household income among elderly households generally increased faster than inflation up through 2000 and afterwards declined or remained relatively flat.

[1] For this particular table and all subsequent tables in this section where the values are adjusted by inflation, the American Consumer Price Index (US-CPI) for all major expenditure classes (Council of Economic Advisors, 2007) was used to deflate the nominal amounts. The deflation factors are available in Appendix C.1.

Table 5.2. Selected information on out-of-pocket costs for Medicare Part A and median household income[a,b]

Year	Annual deductible	Co-payment (61st – 90th day in hospital)	Co-payment for lifetime reserve days[c]	Median income[d]
1990	$885 (0.30%)	$221 (0.30%)	$442 (0.30%)	$44,743 (-1.72%)
1995	$1,027 (0.04%)	$257 (0.04%)	$513 (0.04%)	$48,862 (2.71%)
1996	$1,025 (-0.21%)	$256 (-0.21%)	$512 (-0.21%)	$49,405 (1.11%)
1997	$1,027 (0.26%)	$257 (0.26%)	$514 (0.26%)	$50,014 (1.23%)
1998	$1,007 (-1.98%)	$252 (-1.98%)	$503 (-1.98%)	$51,243 (2.46%)
1999	$984 (-2.25%)	$246 (-2.25%)	$492 (-2.25%)	$52,152 (1.77%)
2000	$966 (-1.86%)	$241 (-1.86%)	$483 (-1.86%)	$52,267 (0.22%)
2001	$964 (-0.23%)	$241 (-0.23%)	$482 (-0.23%)	$51,384 (-1.69%)
2002	$973 (0.95%)	$243 (0.95%)	$486 (0.95%)	$50,813 (-1.11%)
2003	$985 (1.21%)	$246 (1.21%)	$492 (1.21%)	$50,780 (-0.06%)
2004	$994 (0.89%)	$248 (0.89%)	$497 (0.89%)	$50,281 (-0.98%)
2005	$1,006 (1.23%)	$251 (1.23%)	$503 (1.23%)	$51,087 (1.60%)
2006	$1,033 (2.76%)	$258 (2.76%)	$517 (2.76%)	NA

Sources: CMS (2006), Council of Economic Advisors (2007), US Census Bureau (2007a)
[a]all values in 2005 dollars, [b]percentage increase from previous year in inflation-adjusted dollars in parentheses, [c]lifetime reserve days are 60 days of inpatient hospital coverage that Medicare offers to cover inpatient costs after a 90-day stay in the hospital, [d]where the head of the household is over 64 years of age

In addition to Medicare Part A, Medicare Part B is a voluntary insurance program that covers outpatient and physician services for a monthly premium. Part B covers some medical services not covered under Medicare Part A such as some services offered by physical and occupational therapists and certain home health care services. In terms of prescription drugs, Medicare Part B reimburses beneficiaries for medicines that are injectable and infusible, not usually self-administered, and administered by a physician (Sharon et al., 2005). There is an annual deductible and coinsurance depending on the type of services received, although these are usually 20 percent of the maximum allowable charges (CMS, 2007a). There are also maximum-approved amounts for Medicare-approved physical, speech, or occupational therapy services performed in non-hospital settings. Many common medical services are not covered under Medicare Part B, including long-term care, routine eye care, dental services, and prescription drugs and biologics that can be self-administered. Most beneficiaries pay a monthly premium, but some beneficiaries with low incomes or assets are eligible for subsidies under the Medicare Savings Program (KFF, 2007c). Table 5.3

lists historical premiums and annual deductibles for Medicare Part B in 2005 dollars. The table does not include information for 2007 as the premium structure changed in that year. An important note is that the percentage increase from previous year in inflation-adjusted dollars is in parentheses, and the parentheses listed for 1995 represent the percentage increase in inflation-adjusted dollars from 1994 to 1995.

Even though the inflation-adjusted increases in Medicare Part A deductibles and premiums were relatively small, it appears that costs have been rising significantly for Medicare Part B, particularly since 2000. One note is that the significant decrease in the Medicare Part B premium in 1990 was an anomaly due to the Medicare Catastrophic Coverage Act of 1988, most of the provisions of which were repealed in 1989 (CMS, 2006). Until 2001 premiums generally fell in real terms, but after this point in time, premiums rose from 6 percent to 13 percent per year in real terms. However, it wasn't until 2005 that the deductible for Medicare Part B was increased (previously it was $100 in nominal terms), and the increases in the 2005 and 2006 deductibles were both greater than the inflation rate.

Table 5.3. Information on premiums and deductibles for Medicare Part B and median household income[a,b]

Year	Annual premium	Annual deductible	Median income[c]
1990	$513 (-14.94%)	$112 (-5.13%)	$44,743 (-1.72%)
1995	$709 (9.07%)	$128 (-2.76%)	$43,668 (2.71%)
1996	$635 (-10.45%)	$124 (-2.87%)	$44,178 (1.17%)
1997	$640 (0.75%)	$122 (-2.24%)	$45,029 (1.92%)
1998	$630 (-1.53%)	$120 (-1.53%)	$46,590 (3.47%)
1999	$640 (1.64%)	$117 (-2.16%)	$47,707 (2.40%)
2000	$619 (-3.25%)	$113 (-3.25%)	$47,623 (-0.18%)
2001	$662 (6.85%)	$110 (-2.77%)	$46,568 (-2.22%)
2002	$703 (6.32%)	$109 (-1.56%)	$46,039 (-1.13%)
2003	$748 (6.28%)	$106 (-2.23%)	$45,978 (-0.13%)
2004	$826 (10.52%)	$103 (-2.59%)	$45,836 (-0.31%)
2005	$938 (13.57%)	$110 (6.40%)	$46,326 (1.07%)
2006	$1,029 (9.63%)	$120 (9.20%)	NA

Sources: CMS (2006), Council of Economic Advisors (2007), US Census Bureau (2007a)
[a]all values in 2005 dollars, [b]percentage increase from previous year in inflation-adjusted dollars in parentheses, [c]for households where the head of household is older than 64

Until 2000 median incomes generally rose, and thus Part B beneficiaries were better off as premiums and deductibles were declining in real terms while median incomes were rising. The situation reversed after 2000, and the trend has likely continued as recent increases in Part B premiums and deductibles have been substantial. If we view the premium information from another perspective, we see that annual premiums as a percentage of median income were 1.15 percent of income in 1990 and 2.03 percent of income in 2005.

In January 2007 the premiums for Medicare Part B changed significantly. While the standard monthly premium increased to a nominal value of $93.50 per month in 2007 (up from a nominal value of $88.50 per month in 2006) (SSA, 2006), higher-income beneficiaries now pay larger premiums based on income. Table 5.4 lists the main premium amounts for Medicare beneficiaries with higher incomes who file joint tax returns[2].

Table 5.4. Medicare premiums for higher income beneficiaries, 2007

Beneficiaries who file an individual tax return with income:	Beneficiaries who file a joint tax return with income:	Annual premium per beneficiary
less than or equal to $80,000	less than or equal to $160,000	$1,122
$80,000 to $100,000	$160,001 to $200,000	$1,272
$100,001 to $150,000	$200,001 to $300,000	$1,496
$150,001 to $200,000	$300,001 to $400,000	$1,721
greater than $200,000	greater than $400,000	$1,945

Source: SSA (2006)

Because data from the CPI for 2007 were not yet available at the time of writing, we only discuss premium increases in nominal terms. For the lowest-income beneficiaries listed in Table 5.4, premiums increased 5.7 percent in nominal terms between 2006 and 2007. Meanwhile, nominal premiums for the highest-income beneficiaries in Table 5.4 increased 62.0 percent in nominal terms.

Medicare Part D, which was implemented in January 2006, offers supplementary prescription drug coverage where the monthly premium varies by the plan in which the beneficiary enrolls. Low-income beneficiaries may be partially or fully subsidized for premiums (CMS, 2007a). Although Medicare oversees the prescription drug program, other entities (such as private companies or public groups) actually provide the coverage. Beneficiaries can choose to receive coverage from any private companies offering Medicare Part D in their region, and the specific prescriptions, premiums, and cost sharing amounts available differ between companies. However,

[2] Beneficiaries who are married but file a separate tax return from their spouse and lived with their spouse sometime during the taxable year pay slightly different amounts than those who file an individual tax return.

all companies must provide at least a minimum level of coverage, defined by Medicare as the "basic coverage" plan. The average premium in 2007 was $27.35 (not weighted by enrollment), although premiums varied by plan and region: the lowest available premium was $9.50 for a standard benefit plan, and the highest premium was $135.70 for an enhanced benefit plan (KFF, 2007c).

The recommended prescription drug coinsurance rates for non-Medicaid beneficiaries for 2006 and 2007 are listed in Table 5.5, although these varied by insurance plan. As Part D was implemented in 2006, only two years of data are available.

Table 5.5. Recommended coinsurance rates for Medicare Part D, 2006-2007

Total prescription drug spending, 2006	Total prescription drug spending, 2007	Coinsurance rate
$0 - $250	$0 - $265	100%
$250.01 - $2,250	$265.01 - $2,400	25%
$2,250.01 - $5,100	$2,400.01 - $5,451.25	100%
$5,100.01 and above	$5,451.26 and above	5%

Source: KFF(2005b), KFF (2007c)

The new benefit recommended that insurance plans charge a $265 deductible with 25 percent cost sharing up to total drug spending of $2,400 in 2007. Between total spending of $2400 and $5451.25, there was 100 percent coinsurance, what analysts have deemed the "donut hole". Above $5,451.25 there was catastrophic coverage where beneficiaries only paid 5 percent of the cost.

Data from June 2006 indicate that the new Medicare prescription drug benefit had enrolled approximately 22.5 million beneficiaries at that point (CMS, 2007b). Of this total, 10.4 million beneficiaries had purchased stand-alone drug coverage through Medicare Part D, 6 million had purchased prescription drug coverage as part of a Medicare Advantage plan, and 6.1 million were automatically enrolled as dual eligibles (more information on dual eligibles is given in the section on Medicaid).

Outside of the traditional fee-for-service Medicare program, Medicare contracts with certain organizations to provide care for beneficiaries that choose Medicare Advantage (Medicare Part C). Medicare has divided the US into regions, and plans willing to participate in the program must serve an entire region. At a minimum these organizations are required to provide the current Medicare benefit package. Additional services can also be covered, and private plans are required to offer additional coverage if plan costs are lower than the Medicare payments received by the plan. Each of these Medicare Part C plans has its own cost sharing requirements, which are typically lower than the out-of-pocket requirements under traditional FFS Medicare.

At a glance, average out-of-pocket spending across all health services for Medicare beneficiaries reveals a trend of increasing out-of-pocket payments. Per capita out-of-pocket spending for the elderly increased from $613 in 2000 to $1,005 in 2004 and $1,139 in 2005 (KFF, 2005c). This was increase of almost 86 percent over the period at an average rate of 17.2 percent per year. As a percentage of the median household income among the elderly, average out-of-pocket spending rose from 2.66 percent of income in 2000 to 4.1 percent of income in 2004.

5.2.3. Medicaid

Medicaid is another public insurance program that is overseen by the Federal government and administered by each of the 50 states (CMS, 2005b). The program is intended to cover low-income individuals and families, although each state establishes its own eligibility requirements. Each state also determines the type, duration, and scope of payments and sets the rate of payment for services. The program insured more than 55 million people in 2003 (KFF, 2007b). In terms of funding, the Federal government pays a share of each state's Medicaid medical expenditures, which is known as the Federal Medical Assistance Percentage (FAMP). The FAMP is determined annually by comparing the state's average per capita income level with the national income average and must be between 50 percent and 83 percent (CMS, 2005b). States with a higher per capita income levels are reimbursed a smaller share of their costs.

States have considerable freedom to determine eligibility for coverage, although there are certain groups that states must cover in order to receive Federal funds (CMS, 2005b). Examples of groups that states are required to cover include: persons that meet the requirements for the Aid to Families with Dependent Children (AFDC) program, children under the age of six whose family income is at or below 133 percent of the Federal Poverty Level[3], and pregnant women whose family income is below 133 percent of the FPL. States also have considerable discretion in determining what services to cover, although as with eligibility, the Federal government requires that certain medical services be covered if the state receives Federal funds. Some of these services comprise: inpatient hospital services, outpatient hospital services, prenatal care, vaccines for children, physician services, and laboratory and x-ray services. States can establish the duration and scope of services, again subject to Federal restrictions generally stating that coverage limits must result in a sufficient level of services to reasonably achieve the purpose of the benefits. Limits on benefits may be different between beneficiaries based on medical diagnosis or condition. More detailed information on Medicaid enrollment, payments per enrollee, and physician and inpatient co-payments is available in Appendix C.2.

Prior to 2006 states were not permitted to impose premiums on Medicaid beneficiaries, however, this changed when the president signed the Deficit Reduction Act (DRA) of 2005 into law in February 2006 (KFF, 2006c). The DRA allows states to charge unlimited premiums for beneficiaries with incomes at or above 150 percent of the

[3] In 2007 the Federal Poverty Level was $10,488 for a single individual under 65 years of age and $9,669 for a single elderly individual (US Census Bureau, 2007b).

Federal Poverty Level (FPL) (KFF, 2006c), although states are prohibited from charging premiums for protected groups that include certain children and pregnant women who are covered by Medicaid.

In terms of user fees, prior to 2006 states could only charge nominal cost sharing amounts (no more than $3) for certain services, and some low-income groups such as pregnant women and children could not be charged user fees. Beneficiaries generally could not be charged for services such as emergency room visits, family planning services, and hospice care (KFF, 2006c). Since the introduction of the DRA, states may also impose coinsurance rates up to 20 percent of the cost of medical care services for higher-income beneficiaries (incomes at or above 150 percent of the FPL). For families with incomes between 100 percent and 150 percent of the FPL, states can set coinsurance rates as high as 10 percent (KFF, 2006c). However, state Medicaid programs may not impose user fees on protected Medicaid recipients that include certain children and pregnant women. Specific medical services such as preventative services for children, pregnancy-related services, and emergency services are exempt from cost sharing requirements. An important note is that the sum of all cost sharing amounts may not exceed five percent of a family's income over a one month or a quarterly time period (DPC, 2006). Kentucky and West Virginia have taken advantage of the cost sharing changes permitted by the DRA.

There are a number of Medicaid beneficiaries who are "dual eligibles": individuals who are eligible for both Medicare and Medicaid (KFF, 2006d). There are approximately 7.5 million dual eligibles, and these beneficiaries receive premium and cost sharing assistance along with additional services not covered by Medicare Part B such as long-term care and prescription drugs. States spend around 40 percent of total Medicaid spending on dual eligibles, as this is generally an unhealthier population that often faces illnesses such as diabetes, heart disease, dementia, or severe mental illness (Jensen, 2005).

Medicaid eligibility varies significantly between states. In 2006 the median eligibility for working parents was 65 percent of the Federal Poverty Level (Cohen Ross et al., 2007). In 14 states eligibility was less than 50 percent of the FPL, in 21 states eligibility was 50-99 percent of the FPL, and in 16 states eligibility was 100 percent or more of the FPL (Cohen Ross et al., 2007). Eligibility thresholds for children are generally higher with 17 states requiring children from a family of three to have income below 200 percent of the FPL, 24 states providing coverage at 200 percent of the FPL, and 10 states providing coverage above 200 percent of the FPL (Cohen Ross et al., 2007).

Coverage restrictions and cost sharing requirements differ by state for prescription drugs, and Table 5.6 offers a snapshot of prescription drug coverage in each state. Information on coverage is only available for 2003 and 2004.

Table 5.6. State-specific information related to prescription drug coverage for Medicaid enrollees, 2003-2004

State	Pharmaceutical co-payments 2003	Pharmaceutical co-payments 2004	Medicaid drug spending per enrollee[a,b]	Median state income
Alabama	$.50-$3/Rx depending on drug cost	$.50-$3/Rx depending on drug cost	$591.77	$34,135
Alaska	$2/Rx	$2/Rx	$751.54	$51,571
Arizona	None	None	$4.33	$40,558
Arkansas	$.50-$3/Rx depending on drug cost	$.50-$3/Rx depending on drug cost	$482.67	$32,182
California	$1/Rx	$1/Rx	$365.82	$47,493
Colorado	$0.75/generic or multi-source Rx, $3/brand or single source Rx	$1/generic or multi-source Rx, $3/brand or single source Rx	$475.02	$47,203
Connecticut	None	None	$745.22	$53,935
Delaware	None	None	$548.57	$47,381
District of Columbia	$1/Rx	$1/Rx	$350.40	$40,127
Florida	None	None	$649.05	$38,819
Georgia	$.50/preferred drug or generic Rx, $.50-$3/non-preferred or brand Rx depending on drug cost	$.50/preferred drug or generic Rx, $.50-$3/non-preferred or brand Rx depending on drug cost	$457.82	$42,433
Hawaii	None	None	$407.57	$49,820
Idaho	None	None	$690.09	$37,572
Illinois	$1/generic Rx, $3/brand Rx	$3/brand Rx	$706.31	$46,590
Indiana	$.50-$3/brand or single source Rx, $.50/generic Rx	$3/Rx	$749.21	$41,567
Iowa	$1/Rx	$1/generic Rx, $.50-$3/brand Rx depending on drug cost	$787.22	$39,469
Kansas	$3/Rx	$3/Rx	$763.09	$40,624
Kentucky	$1/Rx	$1/Rx	$818.27	$33,672
Louisiana	$.50-$3/Rx depending on drug cost	$.50-$3/Rx depending on drug cost	$757.10	$32,566
Maine	$2/generic or single source brand Rx, $3/multi-source brand Rx	$2.50/Rx, up to $25/month, $0 for mail order Rxs	$907.46	$37,240
Maryland	$2/Rx	$1/Rx for generic or preferred brand, $2/Rx for non-preferred brand	$665.38	$52,868
Massachusetts	$2/Rx	$1/generic Rx or OTC product, $3/brand Rx	$893.55	$50,502
Michigan	$1/Rx	$1/Rx	$465.48	$44,667
Minnesota	N/A	$1-$3/generic Rx, $3/brand Rx, up to $20/month	$474.98	$47,111
Mississippi	$1/generic Rx, $3/brand Rx	$1/generic Rx, $2/preferred brand Rx, $3/other brand Rx	$797.38	$31,330
Missouri	$.50-$2/Rx depending on drug cost	$.50-$2/Rx depending on drug cost	$771.99	$37,934
Montana	$1-$5/Rx depending on drug cost, up to $25 max per month	$1-$5/Rx depending on drug cost, up to $25 max per month	$750.84	$33,024
Nebraska	$2/Rx	$2/Rx	$768.27	$39,250
Nevada	None	$1/generic Rx, $2/brand Rx	$445.36	$44,581
New Hampshire	$.50/generic or single source brand Rx, $1/multi-source brand or compound Rx	$1/generic Rx, $2/brand or compound Rx	$948.74	$49,467
New Jersey	None	None	$718.60	$55,146
New Mexico	$2/Rx with annual maximum across all services based on income	$5/Rx with annual maximum across all services based on income	$87.90	$34,133
New York	$.50/generic Rx and over the counter product, $2/brand Rx	$.50/generic Rx and over the counter product, $2/brand Rx	$870.61	$43,393

State	Pharmaceutical co-payments 2003	Pharmaceutical co-payments 2004	Medicaid drug spending per enrollee[a,b]	Median state income
North Carolina	$1/generic Rx and covered OTC products, $3/brand Rx	$1/generic Rx and covered OTC products, $3/brand Rx	$788.85	$39,184
North Dakota	$3/brand Rx	$3/brand Rx	$737.18	$34,604
Ohio	None	$3/Rx if not on Preferred Drug List	$803.44	$40,956
Oklahoma	$1/generic Rx, $2/brand Rx	$1-$2/Rx, depending on drug cost	$422.80	$33,400
Oregon	$2/generic Rx, $3/brand Rx	$2/generic Rx, $3/brand Rx	$434.30	$40,916
Pennsylvania	$1/Rx	$1/Rx	$441.97	$40,106
Rhode Island	None	None	$634.63	$42,090
South Carolina	$3/Rx	$3/Rx	$562.08	$37,082
South Dakota	$2/Rx	$2/Rx	$541.52	$35,282
Tennessee	$5-$10/Rx	$5-$10/Rx	$167.34	$36,360
Texas	None	None	$539.12	$39,927
Utah	depends on beneficiary group	depends on beneficiary group	$511.45	$45,726
Vermont	depends on beneficiary group	$1-$3 depending on drug cost	$751.96	$40,856
Virginia	$1/Rx	$1/generic Rx, $3/brand Rx	$682.05	$46,677
Washington	None	None	$528.55	$45,776
West Virginia	$.50-$2/Rx depending on drug cost	$.50-$3/Rx depending on drug cost	$758.50	$29,696
Wisconsin	$1/Rx up to $5/month and $.50/over the counter drug	$1/generic Rx and $3/brand Rx up to $5/month	$636.19	$43,791
Wyoming	$2/Rx	$1/generic Rx, $2/preferred brand Rx, $3/non-preferred brand Rx	$643.29	$37,892

Sources: Statistical Abstract of the United States, KFF (2006a), KFF (2006e), US Census Bureau (2007a)
[a]for the year 2002 (the latest available year), [b]rough calculation of enrollment obtained by dividing state Medicaid pharmaceutical expenditures by the state Medicaid enrollment

Before 2006 states could not charge more than $3 per prescription, and pharmacists were required to fill Medicaid prescriptions even if the beneficiary was unable to pay the co-payment. According to the table, there were 38 states that had cost sharing requirements for prescription drugs in 2003, and this number had increased to 41 states by 2004 (KFF, 2004). The states which made changes to their prescription charges in 2004 were: Colorado, Indiana, Iowa, Maine, Maryland, Massachusetts, Mississippi, Nevada, New Hampshire, New Mexico, Oklahoma, Vermont, West Virginia, Wisconsin, and Wyoming.

Although this is not listed in the table, in 2003 there were 32 states[4] and the District of Columbia that required prior authorization for certain prescription drugs, and this number had increased to 33 states in 2004 (KFF, 2004). The state that added a prior

[4] Alaska, Arkansas, Colorado, Connecticut, Florida, Hawaii, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Minnesota, Mississippi, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New York, North Carolina, Ohio, Oregon, Rhode Island, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming

authorization program in 2004 was Georgia. There were also 30 states[5] in 2003 that had some sort of coverage restrictions for prescription drugs (KFF, 2004); for example, limits on the number of prescriptions per month or limits on the number of days supply that a beneficiary could receive. All of these 30 states continued to have coverage restrictions in 2004, and Texas also began imposing coverage restrictions in that year.

According to Table 5.6, there does not appear to be a correlation between median state spending on prescription drugs and median income. While 13 of the states with incomes below the median level spent more than the median level of prescription drug spending, 12 of the states with incomes above the median level spent more than the median level of prescription drug spending. It is important to bear in mind the effect of the FAMP when examining the relationship between median income and spending; those states with lower per capita incomes will receive a higher percentage of matching funds for Medicaid from the Federal government. This would lead to a tendency for a negative correlation between median income and prescription drug spending.

Table 5.7. Low-income individuals and Medicare Part D, 2007

			Coinsurance/ co-payments	
Category or income/asset limit	**Premium assistance**	**Deductible**	**Below out-of-pocket threshold**	**Above out-of-pocket threshold**
Full subsidy groups				
Full-benefit Medicaid or Medicare Savings Program beneficiary with income at or below 100% of FPL	100%	$0	$1 generic or preferred, $3.10 other	$0
Full-benefit Medicaid or Medicare Savings Program beneficiary with income above 100% of FPL	100%	$0	$2.15 generic or preferred, $5.35 other	$0
Other beneficiary with income below 135% of FPL assets at or below $6,000 (individual), $9,000 (couple)	100%	$0	$2.15 generic or preferred, $5.35 other	$0
Partial subsidy groups				
Income below 135% of FPL, assets $6,001-11,710 (individual), $9,001-$23,410 (couple)	100%	$0	15%	$2.15 generic or preferred, $5.35 other
Income 135%-150% of FPL, assets at or below $11,710 (individual), $23,410 (couple)	Sliding scale, 100%-0%$	$50	15%	$2.15 generic or preferred, $5.35 other

Source: Merlis (2007)

[5] Alabama, Arkansas, California, Colorado, Connecticut, Delaware, Florida, Georgia, Kansas, Louisiana, Maine, Maryland, Minnesota, Nebraska, Nevada, New Hampshire, New Mexico, New York, North Carolina, North Dakota, Oklahoma, Oregon, Pennsylvania, South Carolina, South Dakota, Utah, Vermont, Virginia, West Virginia, Wisconsin

An important note is that since January 2006 all dual eligibles and certain other low-income individuals receive prescription drug coverage through Medicare Part D, although a clawback system is in operation to retrieve some of this cost from the states. This clawback is a monthly payment by states that is intended to approximate the amount the state would have paid if the Medicaid beneficiary was still covered under the state Medicaid program instead of Medicare Part D (Schneider, 2004). In 2006 the sum of the state clawback payments was projected to be $6 billion (Schneider, 2004). Although prescription drug benefits for non-elderly beneficiaries vary by state, the premiums and out-of-pocket costs for the low-income elderly are set at the Federal level (see Table 5.7).

One difference for dual eligible beneficiaries is that some prescriptions may be more expensive. Specifically, co-payments for Medicaid beneficiaries were capped at $3 prior to Medicare Part D (unless the state received a waver from CMS allowing it to charge higher amounts), and now beneficiaries can pay up to $5 per prescription for brand-name drugs.

Another important note is that in 2006 when the Deficit Reduction Act was implemented, Federal rules changed to allow states to charge coinsurance rates of up to 20 percent for prescription drugs (KFF, 2006c). There are certain qualifications, though. For instance, prescription drug coinsurance rates may not exceed 10 percent for beneficiaries with incomes between 100 percent and 150 percent of the FPL. There are no provisions in the DRA for beneficiaries with incomes below 100 percent of the FPL (KFF, 2006c), but the Department of Health and Human Services (DHHS) Secretary has indicated that no state plans which allow prescription drug co-payments for this group to exceed nominal co-payments[6] will be approved (DPC, 2006).

The DRA also allows states to impose differing user fees according to preferred and non-preferred drug status, but the maximum out-of-pocket costs for prescription drugs still apply to non-preferred drugs. States are permitted to charge the preferred co-payment amount for the non-preferred drug if a physician concludes that a preferred medication is not effective or causes adverse health effects (DPC, 2006).

An additional aspect of the Deficit Reduction Act is the enforceability provision. Previously, pharmacists were not permitted to deny medications for any Medicaid beneficiaries that could not pay the co-payment. According to the DRA, states can not allow pharmacists to deny medications for recipients who cannot pay (DPC, 2006).

5.2.4. Other public health insurance programs

As for other public programs, the US Department of Veterans Affairs (USVA) provides health care coverage for qualified veterans of the US military (USVA, 2006)[7]. The USVA health care program is funded on a discretionary basis determined

[6] Co-payments are capped at $3, although if the DHHS Secretary chooses, this can be increased with inflation according to the medical care component of the consumer price index.

[7] TRICARE is another public program that provides coverage for members of the military, Public Health Service employees, the National Oceanic Administration employees, and the dependents of

by Congress each fiscal year, and most medical services are covered. One unique aspect is that beneficiaries typically must obtain care from Veterans Administration centers. Some veterans, such as those who have received a Purple Heart Medal, former Prisoners of War, individuals with certain military service-connected disabilities, and low-income persons, are exempt from out-of-pocket payments (USVA, 2007). Otherwise, co-payments depend on the beneficiary's income and the type of service received. A typical co-payment in 2007 was $15 for a physician visit (USVA, 2007). The annual co-payment for the first 90 days of care in an inpatient facility was $992 in 2007, and the co-payment for each additional 90 days of care was $496. Certain low-income veterans that live in high-cost areas can receive up to an 80 percent reduction in these inpatient charges (USVA, 2007). There was also a $10 per-diem charge for inpatient care in 2007.

As for prescription drugs, the VA uses a national formulary and a competitive bidding process to select one or a limited number of contractors to supply drugs within specified therapeutic classes. One or two drugs within each category are admitted to the formulary based on negotiations with the manufacturers. There was no cost sharing for inpatient prescriptions in 2007, and non-exempt beneficiaries faced a co-payment of $8 per outpatient prescription for a 30-day supply. Some veterans had an annual out-of-pocket limit of $960 (USVA, 2007).

5.2.5. Employer-sponsored private insurance

For Americans that are not eligible for public health coverage, a number of private companies offer health insurance. The main types of health insurance providers are commercial health insurers (indemnity plans), health maintenance organizations (HMOs), preferred provider organizations (PPOs), and point of service plans (POSs). Appendix C.3 provides a brief summary of these four types of health insurance providers.

Most residents obtain employer-sponsored insurance as opposed to non-group insurance because there are tax incentives for employers that offer health insurance. Employers typically bear a larger share of the premium, although this translates into lower wages for employees, a form of "in-kind" payment. Premiums vary by employer and the type of insurance coverage chosen. All employer-sponsored health plans have some form of cost sharing with 82 percent of individuals with employer-sponsored coverage facing co-payments only, 11 percent facing coinsurance only, and one percent facing a combination of co-payments and coinsurance for doctor visits in 2006 (KFF/HRET, 2006). Among the workers facing coinsurance rates for physician visits, coinsurance rates generally ranged from 20 to 25 percent for in-network providers (KFF/HRET, 2006). Table 5.8 contains inflation-adjusted premium and deductible information for employer-sponsored health insurance. Premium and deductible information is only available from 1999, and deductible information is not available for 2006.

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these beneficiaries. This program will not be discussed as it is relatively small compared to other forms of coverage. Public information on the number of TRICARE enrollees is not available.

In general, monthly premiums for both single and family coverage policies grew faster than inflation and median incomes from 2000 to 2006. Average deductibles also increased significantly for single coverage during the entire period and for family coverage after 2001, perhaps indicating a greater willingness on the part of insurers to pass more out-of-pocket costs on to consumers. After 2002 the growth rate of deductibles for both types of coverage was significantly greater than inflation and the growth rate of median incomes.

Table 5.8. Average annual premiums and deductibles for employer-sponsored coverage[a]

Year	Annual premium (single coverage)[b]	Annual premium (family coverage)[b]	Average deductible (single coverage)[c]	Average deductible (family coverage)[c]	Median income (single person)	Median income (family)[d]
1999	$380 (NA)	$1,815 (NA)	$292 (NA)	$710 (NA)	$24,584 (1.81%)	$69,816 (4.26%)
2000	$381 (0.33%)	$1,837 (1.25%)	$271 (-7.14%)	$618 (-12.99%)	$24,338 (-1.00%)	$70,713 (1.29%)
2001	$397 (4.18%)	$1,972 (7.32%)	$264 (-2.77%)	$659 (6.69%)	$23,997 (-1.40%)	$69,028 (-2.38%)
2002	$508 (27.98%)	$2,319 (17.60%)	$293 (11.21%)	$722 (9.47%)	$23,365 (-2.63%)	$67,814 (-1.76%)
2003	$535 (5.29%)	$2,560 (10.41%)	$408 (39.05%)	$833 (15.41%)	$23,277 (-0.38%)	$68,327 (0.76%)
2004	$583 (9.00%)	$2,754 (7.58%)	$428 (5.02%)	$890 (6.84%)	$23,325 (0.21%	$68,015 (-0.46%)
2005	$612 (4.95%)	$2,712 (-1.53%)	$602 (40.65%)	$1,192 (33.91%)	$23,736 (1.76%)	$69,605 (2.34%)
2006	$605 (-1.23%)	$2,883 (6.31%)	NA	NA	NA	NA

Sources: KFF/HRET (2000), KFF/HRET (2002), KFF/HRET (2005), KFF/HRET (2006), US Census Bureau (2007a), Council of Economic Advisors (2007)
[a]all values in 2005 dollars, [b]worker's portion, [c]for conventional health insurance plan, [d]for a household of four people

Approximately 98 percent of covered workers in an employer-sponsored plan received prescription drug coverage in 2006 (KFF/HRET, 2006). However, insurance companies generally pass on part of the prescription costs and often employ various tools to guide usage. Formularies, where insurers steer consumers towards lower-cost therapeutic and generic alternatives, are common. Approximately 90 percent of covered workers face tiered co-payment systems, where the lowest co-payments are for generic drugs, preferred medications require higher co-payments, and the highest co-payments are for non-preferred medications (KFF/HRET, 2006). Table 5.9 lists historical co-payments for prescription drugs in 2005 dollars[8].

[8] This data was only available from 2000.

Table 5.9. Average prescription drug co-payments for individuals in employer-sponsored plans that face prescription drug co-payments[a,b]

Year	Generic drugs	Preferred drugs	Non-preferred drugs	Fourth-tier drugs	Median income[c]
2000	$7.94 (NA)	$14.74 (NA)	$19.28 (NA)	NA	$70,713 (1.29%)
2001	$8.82 (11.12%)	$16.54 (12.19%)	$22.06 (14.39%)	NA	$69,028 (-2.38%)
2002	$9.77 (10.75%)	$18.46 (11.57%)	$27.14 (23.05%)	NA	$67,814 (-1.76%)
2003	$9.55 (-2.23%)	$20.17 (9.27%)	$30.78 (13.42%)	NA	$68,327 (0.76%)
2004	$10.34 (8.23%)	$21.71 (7.66%)	$34.12 (10.84%)	$49.63 (NA)	$68,015 (-0.46%)
2005	$10.00 (-3.28%)	$22.00 (1.33%)	$35.00 (2.58%)	$74.00 (49.11%)	$69,605 (2.34%)
2006	$10.66 (6.56%)	$23.25 (5.68%)	$36.81 (5.18%)	$61.03 (-17.53%)	NA

Sources: KFF/HRET (2006), US Census Bureau (2007a), Council of Economic Advisors (2007)
[a]all values in 2005 dollars, [b]percentage increase from previous year in parentheses, [c]for a household of four people

Unfortunately, because the nominal co-payment values that we obtained did not include any decimal points, the inflation-adjusted growth rates of out-of-pocket prices are rough estimates. Nonetheless, it appears that all three co-payment tiers grew faster than the inflation rate and the rate of increase in median income. However, the average growth rates between the three classes of medications differed markedly. While the out-of-pocket price of generic drugs grew at an average of 5.70 percent annually (in inflation-adjusted terms) between 2000 and 2005, the corresponding average annual growth rates for preferred and non-preferred drug prices were 9.62 percent and 15.16 percent, respectively. From 2004 to 2006 (the only years where data are available), the co-payments for fourth-tier drugs grew at an annual rate of 11.49 percent (in real terms). Thus, it appears that insurers were attempting to steer beneficiaries towards generic drugs and preferred medications over time.

5.2.6. Direct purchase (non-group or individual) private health insurance

For individuals that are unable to obtain health insurance coverage through an employer, there is the option of purchasing non-group coverage. Individuals who obtain this type of insurance are more likely to be working part-time, self-employed, or working for a business with less than 25 employees. Most beneficiaries are white non-Hispanic and married (Ziller et al., 2004). Unlike premiums in employer-sponsored health insurance, premiums for non-group insurance usually vary by the age of the purchaser or the ages of the family members for family coverage, the geographic area of insurance purchase, and the type of coverage chosen. In 2003 single person premiums averaged $148.80 per month, while family premiums averaged $277.62 per month (KFF and eHealthInsurance, 2004). Cost sharing amounts vary widely between non-group plans, with 25 percent of plans having

deductibles between $2,000 and $3,000 in 2003 (KFF and eHealthInsurance, 2004). Although there are no national trend data available on average premiums for individual health insurance policies, data from California indicate that premiums rose 45 percent (in constant dollars) between 1996 and 2003 (Buntin et al., 2004).

Private non-group health insurance may not cover prescription drugs, although there is a lack of research examining prescription drug benefits among this group of individuals. Lav and Friedman (2001) examined the types of insurance policies a family could obtain in the low price range ($2,000 - $2,500 premiums per year), and most of the policies available did not offer prescription drug coverage. Only 80 percent of enrollees with non-group health insurance had prescription drug coverage in 2000 (Gabel et al., 2002). In contrast, 98 percent of enrollees with employer-sponsored insurance had prescription drug coverage in 2006 (KFF/HRET, 2006).

5.2.7. Health Savings Accounts

Another substitute for health coverage in the private market is a Health Savings Account (HSA), although uptake of these plans has been limited in the US. An HSA is a tax-sheltered account earmarked for medical expenses. In contrast to traditional insurance plans, HSAs spread the costs of medical care over time[9] rather than over a pool of insured beneficiaries. The costs of prescription drugs along with all other non-catastrophic expenses are paid for out of the Health Savings Account. Because this type of coverage is not extensively used in America and because HSAs are different from traditional insurance, this type of coverage will not be discussed any further.

5.2.8. Recent development

A recent policy initiative in Massachusetts is intended to have the opposite effect on insurance coverage. In April 2006 the Massachusetts legislature passed a bill requiring all citizens of that state to purchase health insurance (KFF, 2007a), and the plan (called MassHealth) became operational on 1 July 2007. Under the policy some low-income residents are offered free or heavily subsidized health insurance, while higher-income individuals that refuse to obtain insurance face both financial incentives and tax penalties. For instance, residents who do not purchase insurance may face tax penalties of up to 50 percent of a health insurance premium (KFF, 2007a). Businesses that fail to offer health insurance to their employees may be forced to pay a Free Rider surcharge. The reform also requires firms with more than 10 employees to provide a fair and reasonable contribution to each employee's health insurance premium; otherwise, the firm will be required to contribute up to $295 per employee to a common fund each year (KFF, 2007a).

[9] When an individual does not use all of the funds in his HSA during a given year, the funds are carried over for subsequent years. Thus, it is expected that individuals will have lower risks of health problems when they are young and higher risks of health problems when they are old, such that they will spend less than the annual contribution at younger ages and use these reserves to cover health costs as they age.

The centerpiece of MassHealth is the Commonwealth Health Insurance Connector, which is intended to offer affordable, quality insurance products to residents (KFF, 2007a). The Connector is meant for small business and individuals that can not obtain coverage through their employer. MassHealth also provides subsidies for low-income individuals on a sliding-scale basis (KFF, 2007a). Residents with incomes up to 300 percent of the FPL can be partially subsidized for premiums[10], while residents with incomes below 150 percent of the FPL pay no premiums. Affordability standards have also been approved for individuals with incomes above 300 percent of the FPL (KFF, 2007a).

Managed care programs that participate in Massachusetts Medicaid offer plans through the Commonwealth Care (KFF, 2007a). Although the Commonwealth Health Insurance Connector Board approved minimum creditable coverage in June 2007, concerns that some employers and beneficiaries would need to switch plans to comply with these standards have caused enforcement of the provisions to be delayed until January 2009 (KFF, 2007a).

Because the implementation of the plan is so recent, it is difficult to gauge the success of MassHealth. Researchers such as Holahan and Blumberg (2006) have raised concerns about the affordability provisions of the plan. There are also questions related to whether fines of $295 per employee for firms that do not offer coverage are sufficient to change firm behavior. Nonetheless, other states are closely watching the MassHealth plan, and the success of the program will likely have an impact on health insurance policies in other parts of the country (KFF, 2007a).

5.2.9. Summary of the US health care market

This description of the US health care market has highlighted the fragmented nature of insurance in the country. The main sources of coverage are public health insurance (Medicare, Medicaid, and other Federal programs), private employer-sponsored coverage, and private non-group health insurance. A significant proportion of the population does not have any coverage. Premiums vary between the programs, with Medicaid and USVA beneficiaries paying no premiums. Non-poor Medicare beneficiaries paid from $93.50 to $162.10 per month in premiums in 2007 for Medicare Part B and from $9.50 to $135.70 with an average of $27.35 (not weighted by enrollment) for Medicare Part D (KFF, 2007c). Medicaid subsidizes premiums for selected Medicare beneficiaries. In comparison, individuals with single-coverage employer-sponsored insurance paid approximately $52 per month in premiums in 2006, while those with family-coverage employer-sponsored insurance[11] paid approximately $248 per month (KFF/HRET, 2006). In contrast, those with non-group single-coverage paid $148.80 per month in 2003, and those with non-group family-coverage paid $277.62 per month (KFF and eHealthInsurance, 2004). A comparison of these premiums indicates that Medicare subsidizes its beneficiaries, although coverage is not complete, and many beneficiaries obtain additional coverage from

[10] For example, individuals with incomes between 151 and 200 percent of the FPL pay monthly premiums ranging from $35 to $40 per month.
[11] Premium cost for a family of four

other sources such as employer-sponsored insurance or Medigap. As employer-sponsored insurance premiums are lower than non-group insurance premiums, employers seem to pick up a significant portion of the insurance premium cost.

Cost sharing amounts also vary significantly insurance plans. In 2007 Medicare beneficiaries faced an annual deductible of $992 for inpatient services and $131 for covered Medicare Part B services (KFF, 2007c). On top of this, non-poor elderly individuals generally faced 20 percent co-payments for Part B services. Typically, there were lower out-of-pocket requirements for Medicaid beneficiaries (KFF, 2007b). Meanwhile, workers with employer-sponsored coverage faced even higher deductibles: among single-covered workers who faced deductibles, the average deductibles were $352 for health maintenance organization (HMO) plans, $473 for preferred provider organization (PPO) plans, $553 for point of service (POS) plans, and $1,715 for high-deductible health plans (HDHP) (KFF/HRET, 2006). Among family-covered workers who faced deductibles, the average deductibles were $751 for HMO plans, $1,034 for PPO plans, $1,127 for POS plans, and $3,511 for HDHP (KFF/HRET, 2006). Virtually all of these enrollees faced some sort of cost sharing for medical services. Those with non-group health insurance fared even worse, with a significant proportion of these individuals facing deductibles between $2,000 and $3,000 in 2003.

Thus, it appears that Medicare passes a large proportion of the medical costs on to beneficiaries, and this burden has been increasing significantly over time. While the out-of-pocket burden that Medicaid beneficiaries face differs between states, most states do not impose a significant burden. Similar to the trends that we observe with Medicare, those with employer-sponsored coverage are increasingly facing greater out-of-pocket burdens, and the burden becomes even more severe for those with non-group insurance.

In terms of pharmaceutical cost sharing, there are thousands of different cost sharing regimes that individuals face. Within Medicare many of the elderly did not have prescription drug coverage until 2006, as Medicare did not offer outpatient prescription drug benefits before that year. All Medicaid programs cover prescription drugs, and many states employ a number of tools to limit prescription drug expenditures. Prior to 2006 co-payments could not exceed $3 for prescription drugs without a waver from CMS, but since the implementation of the DRA states can impose user fees of up to 20 percent (KFF, 2006c). Meanwhile, prescription drug benefits are becoming less generous with employer-sponsored insurance. While data are lacking on this subject for those with non-group insurance, some researchers have indicated that prescription drug benefits are often non-existent or less extensive among this group of individuals.

This description has highlighted the significant changes that have been occurring for prescription drug benefits and indicates that an analysis of the impact of these changes on consumption behavior may reveal some interesting findings. The description has also emphasized the disparity in coverage between various groups of the population and even within different forms of insurance coverage, indicating that comparisons

across individuals might be useful. In addition, cost sharing requirements have risen substantially over from 1996 to 2003, allowing us to formulate elasticity estimates from out-of-pocket prices that are not always at the low end of the demand curve.

5.3. The Canadian health care system and prescription drug insurance in British Columbia

5.3.1. General overview of health insurance in Canada

This portion of the chapter offers a brief description of the Canadian health care system and more in-depth coverage of prescription drug coverage in British Columbia. The Canadian health care system is a mix of core public coverage and supplementary private coverage for certain goods and services. The public sector accounts for approximately 70 percent of total health care expenditures (Marchildon, 2005). The public portion, commonly known as Medicare, is publicly funded and administered on a provincial or territorial basis within guidelines set by the federal government. The federal government, however, directly finances and administers health care for certain groups, including services for First Nation individuals living on reserves, Inuit, members of the military and the Royal Canadian Mounted Police, veterans, and individuals in federal prisons (Marchildon, 2005). One unique aspect of the Canadian system is that a group of socialized health insurance plans provides universal coverage for most health care services.

In terms of the health care system, there is universal coverage for most procedures. The primary sources of funding are federal and provincial taxes, although British Columbia and Alberta mandate that residents pay premiums (Irvine et al., 2005). Nonetheless, these premiums account for a relatively small proportion of health care funding in both provinces (Marchildon, 2005). The health care system is governed by the 1984 Canada Health Act, which describes the conditions and criteria that provincial governments must abide by in order to receive full funding from the national government. The Canada Health Act also mandates that 100 percent of the population in each province have health insurance coverage. For example, provincial governments must ensure that health care administration is managed by a non-profit public authority. Other conditions of this Act relate to the health services covered, portability of coverage, accessibility, reporting of health service information, extra billing, and cost sharing. Residents are able to choose their own medical practitioners and hospitals, and most care is free at the point of delivery. Thus, although there is regulation at the national level, provincial governments have some discretion over what services are covered, how contracts with providers are negotiated, how to make up shortfalls in funding, and other aspects of funding and provision.

Medicare covers what the Canadian government deems essential services, but interestingly, outpatient pharmaceuticals are not part of the core Medicare package[12]. In fact, while all provinces and territories provide coverage for vulnerable population groups, many individuals who do not fall into these classifications purchase drug coverage on the private market. The likely reason that pharmaceuticals were not

[12] Prescription drugs administered in an inpatient setting are covered by Medicare.

included in the core medical package is because spending on physician services outstripped spending on pharmaceuticals (Lewis et al., 2001) when the Health Canada Act was implemented. As a result of the growing out-of-pocket and private burden for prescription drugs in Canada, the Ministers of Health in each province and territory put together a document that, among other things, indicated the need for a National Pharmaceuticals Strategy (NPS) (Health Canada, 2004). The Ministers then put together a task force to develop and implement a National Pharmaceuticals Strategy, and the task force reported on its progress in June 2006 (Health Canada, 2006).

The National Pharmaceutical Strategy has nine elements to ensure equitable access to safe, effective, and appropriately prescribed prescription medications (Health Canada, 2006). Because only one of these elements is relevant to the discussion, we will not discuss the other eight components. One of the short-term goals of the NPS is to develop, assess, and cost alternatives for catastrophic prescription drug coverage. The task force recommended that income-based catastrophic coverage be considered as an option. Under income-based catastrophic coverage, the amount that the individual would be expected to pay before receiving catastrophic coverage would increase with income. The next phase of the program is for provincial and territorial governments to research the financial and policy aspects of catastrophic drug coverage to gain a better understanding of different options. The report did not list a timeline for this next phase of the program.

5.3.2. Public health insurance in British Columbia

The previous section has highlighted the general principles of health coverage in Canada, but the discussion in this section focuses on British Columbia because the empirical analysis in Chapter 7 is limited to British Columbia. In BC insurance coverage for medically necessary procedures is provided through the Medical Services Plan (MSP), which covered around 4.2 million people in 2005-2006 (MSP, 2007). All residents of BC are required to enroll with the MSP[13]. The dependents of MSP beneficiaries are also eligible for MSP coverage provided that they reside in British Columbia (MSP, 2007).

A number of medical services are publicly covered, including medically required services provided by a physician enrolled with the MSP, maternity services, medically required eye exams, diagnostic services, and medically required dental and oral surgery. Beneficiaries receive all of these covered services free of charge. Other services like prescription drugs, preventative services, and screening tests where there is little evidence of clinical effectiveness are not always covered by MSP, and many residents must buy supplementary coverage for these services. One interesting aspect of health insurance coverage in many Canadian provinces, including British Columbia, is that individuals are prohibited from entering into contracts that cover publicly insured services (Flood and Archibald, 2001). In addition, British Columbia explicitly

[13] A resident must be a citizen of Canada or lawfully admitted to Canada for permanent residence, must claim British Columbia as a home, and must be physically present in the province at least six months during a calendar year.

invalidates any part of an insurance contract that covers any goods or services already covered by the MSP (Flood and Archibald, 2001).

For individuals who do not receive premium assistance, premiums for the Medical Services Plan depend on family size. Table 5.10 lists historical premium information for primary insurance coverage in British Columbia. In order to compare inflation-adjusted growth rates, the values in Table 5.10 are in 2005 dollars[14].

Table 5.10. Annual premiums for the Medical Services Plan in British Columbia[a, b]

Year	Premium: single person	Premium: two-person family	Premium: family of three or more	British Columbia: median income	Canada: median income
1992	$540 (-2.60%)	$957 (-2.60%)	$1,081 (-2.60%)	$44,900 (-0.44)	$45,800 (1.33)
1993	$526 (-3.38%)	$932 (-3.38%)	$1,053 (-3.38%)	$43,700 (-2.67)	$44,900 (-1.97)
1994	$508 (0.91%)	$901 (0.91%)	$1,017 (0.91%)	$44,400 (1.60)	$44,900 (0.00)
1995	$513 (-2.22%)	$912 (-2.22%)	$1,026 (-2.22%)	$44,000 (-0.90)	$45,300 (0.89)
1996	$502 (-0.92%)	$892 (-0.92%)	$1,003 (-0.92%)	$43,500 (-1.14)	$44,200 (-2.43)
1997	$497 (-0.73%)	$884 (-0.73%)	$994 (-0.73%)	$43,300 (-0.46)	$43,800 (-0.90)
1998	$493 (-0.27%)	$877 (-0.27%)	$987 (-0.27%)	$44,800 (3.46)	$44,400 (1.37)
1999	$492 (-1.08%)	$875 (-1.08%)	$984 (-1.08%)	$46,100 (2.90)	$44,600 (0.45)
2000	$487 (-1.85%)	$865 (-1.85%)	$974 (-1.85%)	$46,700 (1.30)	$44,100 (-1.12)
2001	$478 (-1.65%)	$849 (-1.65%)	$956 (-1.65%)	$47,800 (2.36)	$44,500 (0.91)
2002	$470 (46.56%)	$835 (46.56%)	$940 (46.56%)	$47,600 (-0.42)	$45,000 (1.12)
2003	$689 (-2.08%)	$1,224 (-2.08%)	$1,377 (-2.08%)	$47,500 (-0.21)	$44,300 (-1.56)
2004	$674 (-1.95%)	$1,199 (-1.95%)	$1,349 (-1.95%)	$48,100 (1.26)	$46,400 (4.74)
2005	$661 (-2.00%)	$1,175 (-2.00%)	$1,322 (-2.00%)	$48,800 (1.46)	$47,200 (1.72)
2006	$648 (-1.73%)	$1,152 (-1.73%)	$1,296 (-1.73%)	N/A	N/A

[a]all premium values in nominal 2005 Canadian dollars, [b]percentage increase from previous year in real dollars in parentheses (BC-CPI used for the adjustment)
Sources: Warburton (2003), Statistics Canada (2006b), personal correspondence with the British Columbia Medical Services Plan

[14] For this particular table and all subsequent tables where the values are adjusted by inflation, the Canadian Consumer Price Index (CA-CPI) and the British Columbia Consumer Price Index (BC-CPI) for all major expenditure classes (Statistics Canada, 2007) were used to deflate the nominal amounts to 2005 dollars. The deflation factors are available in Appendix C.1.

In Table 5.10 the numbers in parentheses are the inflation-adjusted growth rates based on the Consumer Price Index from British Columbia (BC-CPI) where we use 2005 as the base year[15]. As the MSP only raises premiums every few years, premiums appear to fall in real terms over most of the examined period, with the exception of 1994 and 2002 when the MSP raised premiums. Over the entire examined period, the MSP increased premiums 21 percent in real terms (on average around 1.5 percent annually), meaning that residents faced higher average premiums in real terms in 2006 than they did in 1996. Of course, this picture is slightly misleading given that premiums only increase every few years and our snapshot is only for 1992 to 2006.

Real median income in Canada grew slower than inflation from 1992 to 1993, from 1995 to 1997, and from 2002 to 2003. The growth rates for median income in British Columbia were slightly different. From 1992 to 2005 median income in Canada grew 8.69 percent in inflation-adjusted terms, while median income in British Columbia grew 3.06 percent in real terms. In comparison with the MSP premiums, real income in both Canada and British Columbia grew at much slower rates than premiums.

We can also examine the premium trends from another perspective by considering premiums as a percentage of the median income. In 1992 the (annual) premium for a single individual was around 1.17 percent of BC median income, the premium for a two-person family was around 2.08 percent of BC median income, and the premium for a family of three or more was around 2.34 percent of BC median income. These percentages continued to decrease somewhat until 2002, where there was an increase in premiums across the board. From 2002 onwards the premium for a single individual was around 1.5 percent of median income, the premium for a two-person family was around 2.6 percent of median income, and the premium for a family of three or more was around 2.8 percent of median income.

The provincial government provides premium assistance for low-income individuals who have been resident in British Columbia for at least 12 months (Warburton, 2005), and there were approximately 1.2 million people who received premium assistance in 2005-2006 (MSP, 2007). There are two forms of assistance: temporary premium assistance and regular premium assistance. Temporary premium assistance is for residents who are unable to pay premiums because of temporary financial hardship. Regular premium assistance provides subsidies according to family-adjusted net income, although the threshold income levels are $3,000 lower for each person aged 65 and older, disabled, or under the age of 19 (Warburton, 2005). Table 5.11 contains the nominal family income thresholds for subsidy eligibility in the province.

An interesting observation is that the inflation-adjusted growth of subsidy thresholds has varied by the subsidy level. The inflation-adjusted growth rate of the subsidy threshold has been the largest for those receiving 100 percent premium subsidies; for these families the subsidy threshold has increased 42.6 percent from 1992 to 2006 (an average of 3.1 percent per year in real terms). As the subsidy has decreased, the growth rate of the subsidy threshold has consistently decreased. The subsidy threshold

[15] We use 2005 as the base year to compare the premium growth rates with the median income growth rates, as the median income data are only available in 2005 Canadian dollars.

for those receiving 20 percent premium subsidies has only increased 15.6 percent from 1992 to 2006 in real terms (an average of 1.1 percent annually in real terms). Thus, it appears that British Columbia has been targeting more subsidies at the lowest-income groups over time.

Table 5.11. Premium subsidy family income thresholds for the MSP in British Columbia

Year	100% subsidy threshold	80% subsidy	60% subsidy	40% subsidy	20% subsidy
1992 - 1998	$0 - $11,000	$11,001 - $13,000	$13,001 - $15,000	$15,001 - $17,000	$17,001 - $19,000
1999 - 2001	$0 - $12,000	$12,001 - $14,000	$14,001 - $16,000	$16,001 - $18,000	$18,001 - $20,000
2002 - 2005	$0 - $16,000	$16,001 - $18,000	$18,001 - $20,000	$20,001 - $22,000	$22,001 - $24,000
2006 - present	$0 - $20,000	$20,001 - $22,000	$22,001 - $24,000	$24,001 - $26,000	$26,001 - $28,000

Sources: Warburton (2005)

In 2003 the BC health care system underwent restructuring, mainly through the reduction of covered services and increased privatization (Fuller et al., 2003). One of the major changes was the elimination of reimbursement for supplementary therapies such as chiropractic services, physiotherapy, massage therapy, and routine eye services. The province also closed a number of hospitals and long-term care facilities while reducing the number of services and beds in other institutions. Another change was the reduction in subsidies for prescription drugs for seniors, although this is discussed in more detail below. The reform paved the way for increased participation of the private sector through the opening of a private surgery center, the contracting out of certain services, and other initiatives.

Although most medically necessary health services are covered under the Medical Services Plan, public prescription drug insurance is part of a different program called PharmaCare. In general, residents who are ineligible for PharmaCare either have no prescription drug coverage or receive coverage from their employer as there are tax incentives for purchasing insurance through specific organizations.

PharmaCare is only available to certain population groups, mainly the elderly and low-income populations. To obtain assistance an individual must be a BC resident for at least three months, be registered with the MSP, and have filed the most recent tax return (PharmaCare, 2003). Currently, PharmaCare splits the eligible population into specific groups and assigns each group to a plan. Table 5.12 lists the specific PharmaCare plans for 2007.

Table 5.12. PharmaCare plans in 2007

PharmaCare plan	Information
Plan I (Fair PharmaCare)	Offers financial assistance for prescription drug costs for eligible low-income families and elderly individuals (above the age of 64). Cost sharing is based on income.
Plan B	Residents of designated long-term care (LTC) facilities have no out-of-pocket requirements for PharmaCare. Pharmacies collect a monthly capitation rate from each LTC facility based on the number of occupied beds.
Plan C	Individuals receiving income assistance from the Ministry of Human Resources receive full funding for PharmaCare benefits
Plan D (Cystic Fibrosis)	Individuals with cystic fibrosis who are registered with a provincial cystic fibrosis clinic receive digestive enzymes free of charge when prescribed by a physician at the clinic, although the enzymes are dispensed through community pharmacies.
Plan F (At-home children program)	Children under the age of 19 who are eligible for benefits under the At Home Program of the Ministry of Children and Family Development receive certain prescription drugs free of charge.
Plan G (no charge psychiatric medicine)	Clients of mental health service centers who qualify for MSP premium assistance receive designated psychiatric medicines free of charge.
The BC Centre for Excellence in HIV/AIDS	HIV-positive individuals receive antiretroviral drugs free of charge when enroled in this program, which operates out of St. Paul's hospital in Vancouver.

Sources: Working Group on Drug Prices (2000), PharmaCare (2004)

Table 5.12 indicates that low-income individuals who receive premium assistance from the MSP or who receive income assistance from the federal government are eligible for PharmaCare. Residents aged 65 and above also receive coverage through PharmaCare under Plan I. As Table 5.12 also indicates, other vulnerable groups, such as those in LTC facilities are eligible for PharmaCare.

Up until 2003 the elderly received generous prescription drug coverage from PharmaCare. Lower-income groups also received coverage from PharmaCare, but their coverage was less generous than that of the elderly. The cost sharing requirements for all recipients changed significantly in 2003 with the implementation of Fair PharmaCare, and more information regarding the new cost sharing requirements is available below. Table 5.13 lists cost sharing requirements for PharmaCare recipients until 2002, the year before Fair PharmaCare was implemented.

The cost sharing values in Table 5.13 are inflation-adjusted Canadian dollars based on the BC-CPI, and the values in parentheses are real growth rates. As PharmaCare tends only to raise deductibles and maximum contributions every few years, in most years the growth of cost sharing appears to be negative. Also because of this, the increases in deductibles for low-income and social assistance recipients in 1993 and 1994 appear to be rather large, although the table does indicate that these deductibles stabilized (in nominal terms) for a few years.

One important note is that although Table 5.13 does not list this, all non-senior social assistance recipients in BC received full prescription drug coverage. Coverage for other non-senior residents did not differ between low- and higher-income households until 1994 when PharmaCare reduced coinsurance rates for low-income groups to 0 percent and increased coinsurance rates for higher-income groups to 30 percent. A beneficiary was considered low-income when he received MSP premium assistance (see Table 5.11 for MSP premium assistance income thresholds). Deductibles

remained constant in nominal dollars for non-senior low-income households until 2002 when these households experienced a CDN $200 increase in their deductibles. Non-senior higher-income households saw their deductibles rise faster with a CDN $200 increase in 1998 and another CDN $200 increase in 2002. Over the entire period, deductibles increased 402 percent in real terms (real annual growth of 33 percent on average) for non-senior low-income households and 527 percent in real terms (real annual growth of 44 percent on average) for non-senior higher-income households. However, for all non-senior households there was an annual maximum contribution by family of CDN $2,000 per year, and this maximum contribution was constant between 1990 and 2002. As a result, the annual out-of-pocket maximum decreased 22 percent in real terms over the entire period (an annual decrease of 1.8 percent on average). The overall indication regarding user fees for prescription drugs is that the BC government shifted a significant amount of costs to both low-income and higher-income non-senior beneficiaries over the examined period.

Table 5.13. Cost sharing amounts for PharmaCare recipients[a,b]

	Seniors		Non-seniors, low-income			Non-seniors, higher-income		
Year	co-payment	maximum contribution	deductible	coinsurance	maximum contribution[c]	deductible	coinsurance	maximum contribution[c]
1990	75% of disp. fee	$170 (-5.09%)	$170 (-5.09%)	20%	$2,712 (-5.09%)	$170 (-5.09%)	20%	$2,712 (-5.09%)
1991	75% of disp. fee	$161 (-5.13%)	$161 (-5.13%)	20%	$2,573 (-5.13%)	$161 (-5.13%)	20%	$2,573 (-5.13%)
1992	75% of disp. fee	$157 (-2.60%)	$501 (211.68%)	20%	$2,506 (-2.60%)	$501 (211.68%)	20%	$2,506 (-2.60%)
1993	75% of disp. fee	$151 (-3.38%)	$605 (20.77%)	20%	$2,421 (-3.38%)	$605 (20.77%)	20%	$2,421 (-3.38%)
1994	100% of disp. fee	$238 (56.97%)	$713 (17.73%)	0%	$2,375 (-1.90%)	$713 (17.73%)	30%	$2,375 (-1.90%)
1995	100% of disp. fee	$232 (-2.22%)	$697 (-2.22%)	0%	$2,323 (-2.22%)	$697 (-2.22%)	30%	$2,323 (-2.22%)
1996	100% of disp. fee	$230 (-0.92%)	$690 (-0.92%)	0%	$2,301 (-0.92%)	$690 (-0.92%)	30%	$2,301 (-0.92%)
1997	100% of disp. fee	$228 (-0.73%)	$685 (-0.73%)	0%	$2,284 (-0.73%)	$685 (-0.73%)	30%	$2,284 (-0.73%)
1998	100% of disp. fee	$228 (-0.27%)	$683 (-0.27%)	0%	$2,278 (-0.27%)	$911 (32.97%)	30%	$2,278 (-0.27%)
1999	100% of disp. fee	$225 (-1.08%)	$676 (-1.08%)	0%	$2,254 (-1.08%)	$901 (-1.08%)	30%	$2,254 (-1.08%)
2000	100% of disp. fee	$221 (-1.85%)	$664 (-1.85%)	0%	$2,212 (-1.85%)	$885 (-1.85%)	30%	$2,212 (-1.85%)
2001	100% of disp. fee	$218 (-1.65%)	$653 (-1.65%)	0%	$2,175 (-1.65%)	$870 (-1.65%)	30%	$2,175 (-1.65%)
2002	$25 / $10 (N/A)	$292 / $213 (34.35% / -2.29%)	$850 (30.28%)	0%	$2,126 (-2.29%)	$1,063 (22.14%)	30%	$2,126 (-2.29%)

[a]all figures are in nominal 2005 Canadian dollars, [b]percentage increase from previous year in real dollars in parentheses (BC-CPI used for the adjustment), [c]per family
Source: Grootendorst (2002), Grootendorst and Racine (2005), PharmaCare (2003)

Meanwhile, coverage did not differ between low- and high-income seniors from 1992 to 2002. Until 1994 seniors paid 75 percent of the pharmacist's dispensing fee for each prescription up to a maximum yearly out-of-pocket contribution of CDN $125. For example, the average dispensing fee that pharmacists charged was CDN $5.74 in 1992 (Working Group on Drug Prices, 2000), while the maximum dispensing fee was CDN $7.84 in 2002 (PharmaCare, 2003). The annual out-of-pocket maximum increased to CDN $200 in 1994, and another change was that seniors were then expected to pay 100 percent of the pharmacist's dispensing fee.

In 2002 the program split seniors into two groups: those receiving MSP premium assistance and the rest of the elderly. The elderly receiving premium assistance faced maximum co-payments of $10 per prescription (including the dispensing fee) and an annual limit on out-of-pocket contributions of $200 (PharmaCare, 2003). Higher-income seniors faced maximum co-payments of $25 per prescription (including the dispensing fee) with an annual limit of $275 on out-of-pocket spending. Because the policy change in 2002 created two separate annual out-of-pocket maximums according to family income, the inflation-adjusted growth rate that low-income and higher-income beneficiaries faced over the period differed.

According to Table 5.13, from 1990 to 2002 the maximum out-of-pocket contribution increased around 72 percent in real terms (real annual growth of 6 percent on average) for higher-income elderly beneficiaries. For lower-income beneficiaries, the maximum contribution increased around 60 percent in real terms (an average real annual growth rate of 5 percent). The implication of this discussion is that from 1992 to 2002, many seniors saw an increase in their out-of-pocket costs for prescription drugs.

As part of the BC health care reform, the PharmaCare program went through a major restructuring in 2003, effectively ending universal prescription drug coverage for seniors. The new program is deemed "Fair PharmaCare" and is intended to target most subsidies at low-income individuals (Fuller, 2003). To phase in the new program, beneficiaries born before 1939 face lower deductibles and coinsurance rates than the rest of the population. The deductible for this group is progressive, depending on family income. Once the deductible is reached, the recipient is responsible for 25 percent of the prescription drug cost up to an annual family out-of-pocket maximum that increases with family income. For individuals who turn 65 after 2005, the deductibles are higher although still related to income. Once the deductible is reached, there is a 30 percent coinsurance rate up to an annual family out-of-pocket maximum. These maximum family amounts are higher than the corresponding amounts for those born before 1939. Table 5.14 provides a comparison of the previous out-of-pocket costs for individuals under PharmaCare and the new costs under Fair PharmaCare.

For non-seniors and those born after 1938, Fair PharmaCare has lowered the out-of-pocket requirements for the poorest families as those with family incomes below $20,000 now pay no deductible and face a significantly lower annual out-of-pocket maximum. For seniors born before 1939, the lowest income groups still do not face a deductible, and the income level at which the deductible applies is higher than for

non-seniors and those born after 1938. Additionally, the annual out-of-pocket maximum decreased for the lowest-income seniors born before 1939. For both groups in the higher income brackets, the deductibles and annual out-of-pocket maximums have increased, although these are comparatively lower for seniors born before 1939 than for non-seniors and those born in 1939 and thereafter.

Table 5.14. Comparison of previous PharmaCare program and Fair PharmaCare

Family income	Old deductible[a]	New deductible	Old maximum	New family maximum
Non-seniors and those born in 1939 and thereafter				
$10,000	$600	$0	$2,000	$200
$15,000	$600	$0	$2,000	$300
$20,000	$600	$400	$2,000	$600
$25,000	$800	$500	$2,000	$750
$30,000	$800	$600	$2,000	$900
$35,000	$800	$1,050	$2,000	$1,400
$40,000	$800	$1,200	$2,000	$1,600
$45,000	$800	$1,350	$2,000	$1,800
$50,000	$800	$1,500	$2,000	$2,000
$55,000	$800	$1,650	$2,000	$2,200
$60,000	$800	$1,800	$2,000	$2,400
$65,000	$800	$1,950	$2,000	$2,600
$70,000	$800	$2,100	$2,000	$2,800
Seniors born before 1939				
$10,000	$0	$0	$200	$125
$15,000	$0	$0	$200	$188
$20,000	$0	$0	$200	$250
$25,000	$0	$0	$200	$313
$30,000	$0	$0	$200	$375
$35,000	$0	$350	$200	$700
$40,000	$0	$300	$200	$800
$45,000	$0	$450	$200	$900
$50,000	$0	$500	$200	$1,000
$55,000	$0	$1,100	$200	$1,650
$60,000	$0	$1,200	$200	$1,800
$65,000	$0	$1,300	$200	$1,950
$70,000	$0	$1,400	$200	$2,100

Source: Fuller (2003)

[a]under the old PharmaCare system, the income levels for the deductible were based on the individual qualifying for MSP premium assistance. This table uses the figures for a single individual, but families would have a higher income threshold for the same deductible

In British Columbia pharmacists can only dispense medications that have been prescribed by a licensed Canadian practitioner, which includes physicians, dentists, midwives, and podiatrists (PharmaCare, 2003). PharmaCare does not reimburse the costs of all drugs on the market (British Columbia Ministry of Health, 2006). Specifically, a drug must first be approved for marketing in Canada by Health Canada (Anis, 2000). Then the medication undergoes an examination by the Common Drug Review, which is an independent, national review that provides recommendations to all provincial health programs regarding whether a drug should be included in the provincial formulary. British Columbia also requires that a medication undergo a review by the Therapeutics Initiative, another independent body at the University of British Columbia. The decision to include a drug in the BC formulary is based on safety, clinical effectiveness and health outcomes, value for money as compared to existing treatments, and impact on the budget. Based on these reviews PharmaCare determines whether the drug should be reimbursed as a regular benefit, whether the patient must meet clinical criteria to qualify for coverage, whether the drug will be partially reimbursed because an equivalent drug is available at a lower cost, or whether the drug will not be reimbursed at all (Anis, 2000).

For certain drugs there is a reference pricing (RP) system in place (Graham, 2002). These drugs include nitrates, ACE inhibitors, some calcium channel blockers, histamine-2 receptor antagonists (H2RAs), and non-steroidal anti-inflammatory drugs (NSAIDs). In a RP system, certain drugs are clustered by therapeutic class and a maximum reimbursement price is established for each therapeutic cluster (Kanavos and Reinhardt, 2003). How this maximum reimbursement price is set is unique to every system, although the reference price for each therapeutic class is based on the cheapest drugs in the class in British Columbia (Graham, 2002). When a medication is priced above the reference price, the patient is responsible for the difference between that price and the reference price. This out-of-pocket cost is in addition to any user charges that the patient already faces. However, if a physician determines that an individual must have a specific medication because of medical need, PharmaCare may agree to reimburse the medication as if it was under the regular reimbursement system. There are also automatic individual exemptions, for example, asthmatics and diabetics are automatically exempted from restrictions on calcium channel blockers and ACE inhibitors. Another feature of BC's reference pricing system is that on-patent drugs are included in each therapeutic class. There are a number of arguments for and against reference pricing; however, it is beyond the scope of this thesis to discuss these issues.

PharmaCare also employs a "Low Cost Alternative Program" (PharmaCare, 2003). When there is a generic version of a prescription drug, PharmaCare fully reimburses the cost of the lower-priced medications and partially reimburses the cost of the higher-priced medications. PharmaCare also defines some medications needing Special Authority approval because these medications are not typically considered first-line therapies for treatment due to the cost (PharmaCare, 2003). For these defined medications the program has established criteria under which the medication may be eligible for full reimbursement. The criteria are related to the patient's illness, intolerance for alternative treatment, and other factors (PharmaCare, 2003). To

receive coverage for one of these medications, the patient's medical practitioner needs to apply for reimbursement through the Special Authority process and obtain approval.

The Canadian Institute for Health Information (CIHI) (2006) estimated drug expenditures of CDN $2,771 in 2005 or 15.1 percent of total health expenditures. PharmaCare was estimated to pay 42.1 percent of total drug expenditures in the province in 2005, a percentage that has steadily been declining since a high of approximately 60 percent in 1986.

5.3.3. Private health insurance in British Columbia

In addition to the public insurance system, there is a private insurance system where some residents purchase coverage for goods and services not covered by Medicare. BC residents are prohibited from purchasing private coverage that offers a private alternative or faster access to medically necessary inpatient and physician care (Marchildon, 2005). In general, employers, unions, professional organizations, and similar organizations sponsor group insurance as British Columbia residents receiving benefits through these plans are exempt from taxation on these benefits (Stabile, 2002). In fact, around 95 percent of the market for health insurance has traditionally been provided by employers and unions (Deber et al., 1999).

5.3.4. Pharmaceutical expenditures in British Columbia

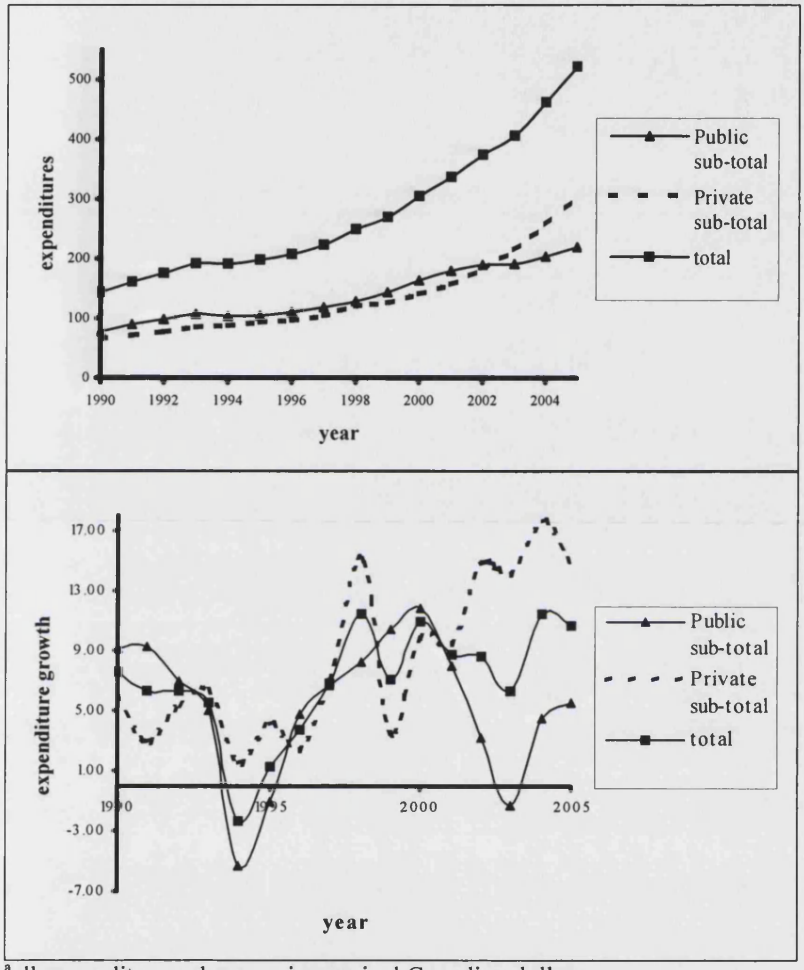
As a partial justification for the policy change that resulted in the Fair PharmaCare program, policymakers argued that the increase in public pharmaceutical expenditures was unsustainable (Morgan et al., 2006). To shed light on this argument, Figure 5.2 lists information on pharmaceutical expenditures from different sources in the province. The top graph in Figure 5.2 shows the nominal values for public, private, and total pharmaceutical expenditures and suggests an upward trend in expenditures over time. The lower graph in Figure 5.2 plots the inflation-adjusted expenditure growth for each of these pharmaceutical expenditure categories.

Not surprisingly, given the arguments for the implementation of Fair PharmaCare, provincial expenditures for publicly-covered drugs have grown well in excess of inflation over the past decade. There was a brief period in 1994 and 1995 when public expenditures fell in real terms, although this change was likely due to one-off savings from the reference pricing system that was first implemented in 1994. Interestingly, private expenditures on prescription drugs have generally grown at a faster rate than public expenditures. From 1990 to 2005, public expenditures increased by 106 percent in real terms, while private expenditures increased by 236 percent, implying either that the government has been exercising greater control than private insurance over costs (e.g. through the reference pricing system) and/or that the government has been shifting costs to individuals (e.g. through higher user fees).

Another interesting observation is that public expenditures decreased in 2003, the same year that Fair PharmaCare came into play, while private expenditures began to grow more rapidly beginning in 2002. This increase in private expenditures may have

been due to the higher co-payments that PharmaCare imposed in 2002 and the purchase of private insurance by PharmaCare recipients in 2003 who no longer received such generous public coverage.

Figure 5.2. Pharmaceutical expenditures per capita and expenditure growth by public, private, and total pharmaceutical expenditures in British Columbia, 1990-2005[a]



[a]all expenditure values are in nominal Canadian dollars
Source: CIHI (2006)

5.3.5. Recent developments

In September of 2006, the BC government launched a "Conversation on Health", a program intended to elicit public opinion on health care in the province (BC, 2007). The government hopes to obtain public input on methods of reducing and prioritizing spending in the health care system. Organizations such as the Canadian Centre for Policy Alternatives (CCPA), however, have suggested that the motives of the BC government are misguided (CCPA, 2007). The argument is that the BC government is promoting this discourse as a means of making private insurance more attractive. That

is, the CCPA claims that the BC government's projections of health expenditures are biased upwards (CCPA, 2007), which causes the prospect of continuing to publicly fund health care appear unsustainable.

Moreover, the government of British Columbia indicated in 2006 that it was committed to a comprehensive review of the delivery of health services in the province (Skolrood, 2006). This public announcement came on the heels of the "Chaoulli Decision" in Quebec where the Supreme Court ruled that residents had the right to purchase private insurance to cover surgical procedures as there were excessive waiting times for surgery in Quebec (CCPA, 2007). One of the main issues related to the improvement of health care in BC is whether increasing private sector involvement will lead to better health outcomes or whether it will cause greater inequities and damage to the public system (Skolrood, 2006). The British Columbia Health Coalition (BCHC) claims that the BC government favors a health funding system similar to that in the United Kingdom (BCHC, 2006). Specifically, hospitals in BC would compete with each other and with for-profit medical clinics and US-owned hospital chains for publicly funded inpatient services.

As the consultation on health care is ongoing, it is unclear at this point whether the province will move forward in its desire to introduce more private competition into health care. Nonetheless, because BC residents can already purchase private prescription drug insurance, these potential changes should have little effect on the pharmaceutical market.

5.3.6. Summary of health care in Canada and BC

This description of the Canadian health care system and the BC PharmaCare program indicates that universal health insurance coverage exists in the country. The core medical services publicly covered are medically required services provided by a physician, maternity services, medically required eye exams, diagnostic services, and medically required dental and oral surgery. Notably, prescription drugs are not included in the core medical services benefit package. There is no cost sharing for the core medical services, but for services outside of the defined benefits package, residents sometimes buy supplementary insurance coverage. Private insurance coverage for benefits such as prescription drugs is often sponsored by employers, unions, professional organizations, and other similar organizations.

In terms of the cost of medical care, most provinces fund the core medical services through taxation, but British Columbia also requires residents to pay monthly premiums for the Medical Services Plan. These premiums varied from CDN $54 per month for a single person to CDN $108 per month for a family of three or more in 2007. Depending on family income, premiums are subsidized at the 100 percent, 80 percent, 60 percent, 40 percent, 20 percent, and 0 percent levels. The maximum family income level for the 100 percent subsidy was CDN $20,000 in 2007.

The pharmaceutical system consists of public and private insurance coverage. PharmaCare is the public insurance program for the elderly, certain low-income

individuals, and other select groups. Cost sharing differs between these groups, with insurance coverage traditionally having been the most generous for the elderly. There are also other cost containment mechanisms in place, such as a reference pricing system and a Low Cost Alternative Program. The BC pharmaceutical reimbursement system has recently changed, and new cost sharing requirements were implemented in May 2003. Pharmaceutical subsidies are now tiered according to income, with higher-income groups facing greater levels of cost sharing.

Since the early 1990s the pharmaceutical system in British Columbia has gone through a few major changes. In addition to increases in co-payments and deductibles every few years, the province also implemented programs such as the reference pricing system and the Low Cost Alternative Program. Fair PharmaCare was a significant departure from the traditional model, as the program is meant to favor lower-income recipients. In general, coverage has been relatively predictable for the elderly, at least before 2002, and this may play a role in the price elasticity estimates. The relatively small out-of-pocket burden that elderly beneficiaries face also provides an interesting case for comparison with the US where the price elasticity estimates are measured on a higher portion of the demand curve.

5.4. Discussion

This section offers a broad comparison of the US and Canadian health care systems and the pharmaceutical system in the US and British Columbia. The purpose of this section is to highlight the main differences between the areas and to discuss the importance of these differences for price elasticity estimates.

While health care in the United States is fragmented between various third-party payers, all coverage for what the Canadian government defines as core medical services are publicly funded. Core medical services are also free at the point of use in Canada, while most Americans face significant user fees even for physician and inpatient visits. This disparity in the structure and out-of-pocket costs of health care has an important implication for pharmaceutical consumption. Alternative forms of care are likely to be more attractive in Canada than in the US because of the zero price for some services in Canada, which may increase the price elasticity of demand for pharmaceuticals in BC. Of course, waiting lists for care would dampen this effect. There is evidence of significant waiting lists for a number of procedures in Canada (Sanmartin et al., 2000). It is not clear which of these effects (free care or long waiting lists) is dominant, although evidence from British Columbia indicates the effect of free care may be greater. In an older sample of individuals, Li et al. (2006) determined that significant and positive cross-price elasticities between prescription drugs and physician services exist.

In terms of cost sharing for prescription drugs, we do not have data on average cost sharing amounts for residents of British Columbia ineligible for PharmaCare. For older people, though, individuals in the United States generally face much higher user fees for prescription drugs than their counterparts in British Columbia. Prior to 2006 Medicare did not even have an outpatient prescription drug benefit, and many of the

privately insured beneficiaries faced significant out-of-pocket requirements. In contrast, prior to 2002 elderly residents of British Columbia only faced dispensing fees and other potential out-of-pocket costs[16] with maximum annual outlays. Even after the introduction of Fair PharmaCare, pharmaceutical coverage for older beneficiaries in the province was still more generous on average than pharmaceutical coverage in the United States. The implication is that an empirical analysis of prescription drug consumption among the elderly in the United States is likely to measure consumption at a higher point on the demand curve than an empirical analysis from British Columbia. According to this argument, we would thus expect American seniors to be more responsive to out-of-pocket price changes than seniors in British Columbia.

As for low-income beneficiaries, a comparison between this population in the United States and British Columbia is less straightforward than a comparison of the elderly in both countries. The reason is because health care and pharmaceutical coverage varies by state in the US, and there are large disparities in the generosity of Medicaid coverage between states. Prior to 2003 many low-income beneficiaries in British Columbia faced deductibles, and it is possible that some of them paid more out-of-pocket than some of their counterparts (for instance, in terms of income and health status) in the United States. Since the introduction of Fair PharmaCare, this is less likely to be the case. Now, the lowest-income beneficiaries face no or very low deductibles, and they also have annual out-of-pocket maximums, a feature that is not prevalent in the Medicaid program. Because of the difficulty in comparing the generosity of coverage among low-income beneficiaries before 2003, it is unclear whether price elasticity values would differ between low-income groups in the United States and British Columbia. After 2003 it is likely that low-income beneficiaries in British Columbia would be measured at a lower point on the demand curve than their American counterparts, potentially leading to a lower estimate for BC seniors.

The differences in the funding of pharmaceutical coverage in the United States and British Columbia leads to implications for each empirical model. Because private insurance makes up a large proportion of pharmaceutical coverage in the United States, there may be a potential endogeneity problem with the analysis. If we are unable to observe past consumption or expectations of consumption, this important predictor of the co-payment level may bias the estimates. Techniques such as instrumental variables regression may need to be used to correct for this bias. Endogeneity may also be a problem in British Columbia if we analyze consumption among the non-elderly portion of the population, as a number of these individuals are likely to hold private insurance for prescription drugs. Among the elderly there is unlikely to be an endogeneity problem related to adverse selection or consumption expectations because user fees are partially set at the provincial level and partially set by pharmacies within small price bands. That is, the level of the co-payment that the elderly individual faces is based on factors such as his income, which are unrelated to unobservable variables such as past consumption. However, as we discuss in Chapter

[16] For instance, PharmaCare beneficiaries that chose medications priced above the reference price paid the difference between the total price of the drug and the reference price.

7, there may be endogeneity issues related to the non-linearity of the BC price variable.

5.5. Conclusion

This chapter has provided a background description of the health care and pharmaceutical systems in the United States and British Columbia. The intent has been to highlight the main aspects of each system, which bring up important considerations for the empirical specifications of the models. Another reason for providing the background description is to set the scene for the policy analysis of each health care system in Chapter 8.

The description of the American health care system highlighted the fragmented nature of coverage in the country. While around 70 percent of the population had private coverage, 25 percent were publicly insured, and around 15 percent were uninsured in 2005. The population that was insured, however, still faced significant cost sharing for all types of medical care, including prescription drugs. Even public programs like Medicare passed a large proportion of the costs to beneficiaries. Furthermore, out-of-pocket costs have been rising faster than inflation, and the burden of co-payments has been increasing steadily as a percentage of median income.

In contrast, beneficiary costs have been rising at a much slower rate for residents of British Columbia. Premiums and co-payment levels have generally remained fixed for a few years at a time, although these less frequent increases can be quite substantial. The overall trend in cost sharing and premium increases throughout time has been lower in British Columbia than in the United States. This is likely due to the centralized nature of health care in Canada, as the central government keeps a tighter control on costs and typically has lower overheads than private insurance (Evans et al., 1991).

The discussion pointed out that these differences in health care between the US and Canada will likely lead to different price elasticity results. On the one hand, the existence of free care for core medical services in British Columbia may lead to higher elasticity estimates, although the effect of longer waiting times is likely to have a dampening effect. On the other hand, the fact that an analysis of elderly individuals in the United States would measure these individuals at a higher point on the demand curve than their counterparts in British Columbia may lead to higher elasticity estimates in the United States. A comparison of low-income individuals in each country could lead to differing effects because of the difficulty in determining whether user fees for this group are higher in the United States or Canada.

Chapter 6: Analysis of prescription drug cost sharing in the United States

6.1. Introduction

This chapter is a natural extension of Chapters 2, 3, and 5. Specifically, Chapter 2 provided the theoretical foundation behind insurance and cost sharing and offered insight into other important predictors of demand. We use this theoretical foundation along with the previous results from the literature to motivate the empirical specification and choice of variables for the United States. Chapter 5 offered an overview of the US health care system - a description that provides some indication of what results we can expect from an empirical model.

As a number of questions regarding the impact of cost sharing on the demand for prescription drugs remain for the United States, this chapter aims to fill some of those gaps in the literature (discussed in Chapter 3). In particular, there are no existing estimates of the price elasticity of demand for prescription drugs among the elderly American population or among the low-income population. Estimates for these populations are pertinent as a new Medicare prescription drug benefit with significant cost sharing requirements has recently been implemented for the elderly. Additionally, the Deficit Reduction Act of 2005 will allow states to charge Medicaid (low-income) beneficiaries higher co-payments (KFF, 2006c), a change that could have a profound impact on prescription drug consumption in this population. Given that public insurance coverage is related to income and age, we would expect a distinct response to price after a certain age or in the event of low income. It is because of these characteristics of coverage for low-income groups and the elderly that we run separate estimations for these two groups.

While a number of studies using non-aggregate data have calculated the price elasticity of demand for prescription drugs (see Chapter 3), it is unclear whether this elasticity has changed over time as many of the previous estimates are outdated, relating to periods of substantially lower pharmaceutical prices, lower individual income, and different levels of insurance coverage. The seminal RAND study overcame many methodological problems that other studies addressing this issue often face, but it has been 25 years since this experiment was implemented (Manning et al., 1987). Recent US studies focused on specific subgroups rather than the general population or on specific therapeutic or disease categories. Recent elasticity estimates also exist for Canada and the Netherlands, but it is by no means certain that these results are transferable to the US health care system.

As important as the dated evidence, the methodologies adopted by the older studies were not always appropriate; in particular, no study of price elasticity in this area has simultaneously accounted for unobserved heterogeneity, sample selection, and an endogenous co-payment variable (where appropriate). Unobserved heterogeneity is important given that information is always lacking, and only three studies (Balkrishnan et al., 1997; Gibson et al., 2005; Grootendorst et al., 1997) have used panel data. The non-linearity of drug consumption means that linear regression techniques may not be appropriate. Finally, while panel data allows improved

specification of a consumption pattern that is prone to longitudinal aspects, for example with a high obvious positive correlation with an individual's state of chronic health, endogeneity must be considered. A failure to account for these factors in non-experimental settings may have led to biased estimates which subsequently misinform policy responses. Only recently have specific estimators which control for such elements within a single specification been developed for panel data.

The purpose of this chapter is to offer an updated estimate of the price elasticity of demand for prescription drugs using the 1996-2004 Medical Expenditure Panel Survey (MEPS). Novel panel data techniques are employed to account for the problems of heterogeneity, sample selection, and endogeneity. The organization is as follows: Section 6.2 puts forward the research questions that will be addressed for the United States, while Section 6.3 then describes the dataset employed (MEPS) and provides a description of the variables that might be important predictors of the demand for prescription drugs. Section 6.4 goes over statistical considerations relevant to the unique design of the dataset that may need to be addressed and then presents the chosen econometric model that accounts for these statistical considerations. Section 6.5 presents the results of the empirical analysis, and Section 6.6 discusses the results. Finally, Section 6.7 wraps up the chapter.

6.2. Research questions for the United States

The research questions for the US are based on the economic theory of moral hazard, the gaps in the literature highlighted in Chapter 3, and the description of insurance coverage in the US from Chapter 5. Specifically, the economic theory implies that price elasticity values differ between various population groups, and yet there is little literature that explicitly takes this into account. Chapter 5 further highlighted that insurance coverage differs between the elderly and low-income groups, additionally implying that price elasticities vary between the two groups. We are also interested in estimates for the general population as a basis for comparison. Because of our interest in the general population for a broad estimate and the elderly and low-income groups for separate estimates, we split the regression into three groups along these lines. Based on these considerations, the particular questions that this chapter addresses are:

Q1. What is the effect of cost sharing for prescription drugs on demand for the average individual in the population? What is the price elasticity of demand for this group?

Q2. What is the effect of cost sharing for prescription drugs on demand among the elderly? What is the price elasticity of demand for this group?

Q3. What is the effect of cost sharing for prescription drugs on demand among low-income individuals? What is the price elasticity of demand for this group?

Q4. How does the price elasticity of demand compare across the general population, the elderly, and the low-income population?

Questions 1, 2, and 3 are covered in Section 6.5, while Question 4 is addressed in the discussion (Section 6.6).

6.3. The dataset and explanation of potential covariates

This section first gives an explanation of the dataset that is used to empirically answer the questions posed in Section 6.2. This section also provides information on the advantages and drawbacks of using this particular dataset and information on variables that are relevant to the analysis. We first discuss the co-payment variable and then cover other potential covariates, mainly demographic characteristics, socioeconomic characteristics, and health status.

6.3.1. The Medical Expenditure Panel Survey

To answer the research questions put forward in the previous section, statistical analyses are employed using the 1996-2004 Medical Expenditure Panel Survey (MEPS)[1], a study co-sponsored by the Agency for Healthcare Research and Quality (AHRQ) and the National Center for Health Statistics (NCHS) (AHRQ, 2004). One of the main reasons we chose this time period is pragmatic: 1996 to 2004 are all of the years available in the MEPS database. Furthermore, around the middle of this chosen period in 2000, a US recession started and appears to have lasted until 2002 (Davis, 2005). In relation to this recession, employer-sponsored coverage began to decline after 2000 (Gould, 2004). Meanwhile, because of the economic slowdown, Medicaid enrollment and spending growth declined between 2002 and 2003 (KFF, 2005b) after a period of significant enrollment and spending growth in the 1990s (KFF, 2001). Additionally, the discussion of the US health care system in Chapter 5 highlighted the changes that have occurred in out-of-pocket costs since 2000. Thus, 1996-2004 appears to be a dynamic period where a number of changes in Medicaid and private insurance were occurring, allowing for a richer analysis.

In comparison to other national surveys that contain health care information such as the Panel Study of Income Dynamics (PSID), the National Ambulatory Medical Care Survey (NAMCS), and the Medicare Current Beneficiary Survey (MCBS), there are a number of advantages to employing the MEPS database. While both the PSID and the NAMCS lack information on prescription drug utilization, the MCBS only includes information on individuals covered under the Medicare program, mainly those over 65 and some of the disabled. As public policy can be informed by elasticity estimates

[1] An advantage of this dataset, as evidenced by the literature review, is that no other studies have used MEPS to examine the impact of cost sharing on prescription drug utilization

for individuals of all ages, we were interested in including the non-elderly in our sample.

Unfortunately, because the MEPS dataset is only available through 2004, we were unable to examine an important policy change: the introduction of Medicare Part D, which was implemented in January 2006. However, we can use the results of our analysis to discuss the price elasticity of demand for prescription drugs among the elderly for 1996-2004 and use these results to make inferences related Medicare Part D (See Chapter 8 for this discussion).

The MEPS is a nationally representative sample of the US civilian, non-institutionalized population with over sampling of Hispanics and blacks. The MEPS is an overlapping panel in which five in-person interviews are collected over a two-year calendar period using computer-assisted personal interviewing (CAPI) technology. The survey collects data from a new sample of households each subsequent year, allowing for overlapping panels of survey data and longitudinal analysis. The raw data comprises N=272,277 individual-level observations.

The component of the MEPS most relevant to this thesis is the Household Component (HC). This portion of the survey contains information about demographic and socioeconomic characteristics, health status and conditions, utilization of medical care services, charges and payments for medical care, access to care, and health insurance coverage. The Medical Provider Component (MPC) of the MEPS is also appropriate as this portion of the survey contains information collected from medical providers and pharmacies identified by HC respondents. The MPC comprises information on the medical and financial characteristics of reported medical and pharmacy events. The prescription drug portion of the MPC can be used to determine the number of prescription drugs obtained by an individual and the amount paid by the recipient for the drug.

6.3.2. Explanation of the dependent variable and potential covariates

Certain variables may be important predictors of the demand for prescription drugs, and the following section describes the dependent variable along with the explanatory variables that may be valuable in the model, such as price, income, and other controls. The choice of potential controls is based on findings from the literature on cost sharing for prescription drugs and the theoretical background on insurance. The description begins with an explanation of the dependent variable and then discusses the co-payment variable other potential covariates, including demand-side variables, particularly demographic and socioeconomic characteristics and health status. When special consideration regarding the calculation of a particular variable was needed, the method used to compute the variable is described.

The dependent variable is the number of prescription drugs purchased (including initial prescriptions and refills). And important point regarding the dependent variable is that it is made up of both brand and generic drugs. As we were unable to distinguish

between brand and generic drugs in the MEPS dataset, we assumed perfect substitutability between brand and generic drugs.

As the impact of co-payments on the demand for prescription drugs is the central theme of this thesis, an explanation of why this variable may be an important predictor is necessary. The co-payment is a proxy for the generosity of insurance coverage as it provides an indication of an individual's risk sharing arrangements with the insurance company. That is, individuals with 100% coinsurance either have no insurance or have insurance that does not cover prescription drugs. Individuals with low co-payments or coinsurance tend to have generous insurance. According to the neo-classical economic theory of insurance put forward in Chapter 2, the market will separate high- and low-risk consumers. High-risk consumers will obtain the most generous insurance at the appropriate price, while low-risk consumers will obtain the least generous insurance coverage (normally with co-payments) or may forego insurance altogether. However, in practice, there are a number of reasons why this outcome may not occur. One reason is that private insurance is typically offered through employers in the United States, and because unhealthy individuals may be unable to work, this type of insurance tends to cover a healthier population. Employment insurance does not always extend into retirement either. Also, high-risk persons are less likely to have private insurance because they are typically priced out of the market as insurers can partially identify their risk profiles. This situation has led the Federal government to establish some public coverage for the high-risk members of society: low-income persons and the elderly. In fact, research from the Kaiser Family Foundation indicates that in the absence of public insurance coverage, only about 9 percent of these enrollees would have access to some other source of insurance coverage (Long and Graves, 2006). There is also an ex-post moral hazard element of insurance as lower coinsurance rates lead to higher consumption of prescription drugs. Thus, health status, income, and other factors are likely to influence the level of the co-payment, and in turn, the level of the co-payment has an impact on the demand for prescription drugs.

The MEPS dataset does not contain an explicit variable for the co-payment, however, there is information regarding the individual's total pharmaceutical consumption and out-of-pocket pharmaceutical expenditures. As a result, it is possible to compute an average co-payment at the individual level by weighting the individual's annual out-of-pocket drug expenditures by the total number of prescriptions consumed (including initial purchases and refills). We recognize that this is a summary variable that proxies prescription drug cost sharing as some individuals may face additional deductibles, coverage limits, or out-of-pocket maximums. The computed co-payment variable is nonetheless an indicator of the average out-of-pocket burden that an individual faces and maps the generosity of his prescription drug coverage as it correlates with actual co-payment levels. Moreover, while the amount the individual pays out-of-pocket differs by the type of health insurance he possesses; the prices in the region where he obtains his medication; the amount that the pharmacy charges if he is uninsured; and the size of the pack, the dosage, and the number of units that he obtains may be important; the MEPS does not contain enough information to control for these differences. However, it is not clear whether better information would change the

outcome of our analysis, particularly as we further control for unobserved heterogeneity (as detailed in Section 6.4).

Importantly, the co-payment is potentially endogenous as the number of prescriptions an individual consumes in the past and the number of prescriptions he expects to consume in a given year will affect the type of insurance contract that he chooses, and we are unable to measure consumption expectations. The potential for adverse selection in a private insurance market is also an important reason to test for endogeneity as the existence of different risk types may cause insurance companies to design benefit packages that induce different risk types to choose different insurance contracts. A third potential source of endogeneity is the non-linearity of the co-payment variables. That is, because the co-payment is constructed as an average, and patients may face deductibles, co-payments, coinsurance, and/or out-of-pocket limits simultaneously, the size of the constructed co-payment variable depends on consumption. Therefore, we are unable to assume independence between the covariates and the error term. An explanation of how we test for endogeneity and correct for the problem is covered in the econometric model description and the Appendix.

There are a number of variables in addition to the co-payment that may be important predictors of the demand for prescription drugs. Our predictions regarding the effects of these variables on prescription drug consumption are listed in Table 6.1.

Table 6.1. Predicted signs of possible variables measuring of the demand for prescription drugs

Variable	Number of drugs (Adult sample)	Number of drugs (Elderly sample)	Number of drugs (Low-income sample)
Drug co-payment	-	-	-
Age	-	+	-
Age squared	+	-	+
Male	-	-	-
Female	+	+	+
White	+	+	+
Black	-	-	-
Hispanic	-	-	-
Other race/ethnicity	-	-	-
Income	+	+	+
Married	+/-	+/-	+/-
Not married	+/-	+/-	+/-
Good health	-	-	-
Poor health	+	+	+
Diagnosed with a major disease	+	+	+
Not diagnosed with a major disease	-	-	-

For each of the samples, we hypothesized that a negative relationship would exist between the co-payment and the demand for prescription drugs because of the downward sloping law of demand. In general, we predicted that consumption of prescription drugs would fall with age as individuals become more focused on work and their children's health than on their own health, but we hypothesized that after a certain age, demand would begin to rise again. This is because around middle age adults begin to face more chronic problems such as diabetes and heart disease. However, as individuals consume more medicines, the likelihood of contraindications and adverse reactions increases, and doctors may actually prescribe fewer medications for the oldest of the elderly.

Sex is typically another significant predictor of demand intensity; men may have different preferences for medications than women, and evidence suggests that health care use differs between the sexes (Bertakis et al., 2000). Additionally, men and women often suffer from somewhat different diseases; for instance, men are more likely to have cardiovascular problems, while women are more likely to have osteoporosis. There is also evidence that women are more risk averse than men, which would imply greater use of prescription drugs among women (Zinkhan and Karande, 1991).

Race/ethnicity is another characteristic that may be an important determinant of demand for prescription drugs; for instance, race may be an indicator of cultural differences. Hispanic or Asian persons may have different preferences for medical care, particularly prescription drugs, than white individuals. Race/ethnicity may also be an indicator of socioeconomic status, as white individuals frequently live in wealthier areas even if they have lower income themselves, and these areas might exhibit better quality of medical care than non-white areas. Race/ethnicity may also be related to health status as blacks are more likely to suffer from diabetes (American Diabetes Association, 2006) and coronary heart disease (National Heart, Lung, and Blood Institute, 1994).

Other factors such as income, household size, and marital status are also important in prescription drug consumption decisions. Higher-income persons are less likely to face tradeoffs between necessities such as food and shelter and other goods and services where consumption can sometimes be delayed such as doctor visits and prescription drugs. Thus, it is expected that the demand for prescription drugs will increase with income. Meanwhile, larger families are forced to spread the income over more family members and may forego pharmaceuticals to achieve savings[2]. The same may be true with married individuals, although spouses may also be more likely to push for medical treatment.

Health status, which is an indicator of need for medications, may be one of the most important predictors of prescription drug consumption. Not only are individuals in

[2] An alternative to including both income and household size in the analysis is to divide total family income by household size (family income per person). The effect of this variable should be similar to that of income in a regression that also controls for family size.

poorer health more likely to visit the physician, but they are also more likely to receive a prescription from the physician once they have visited the doctor.

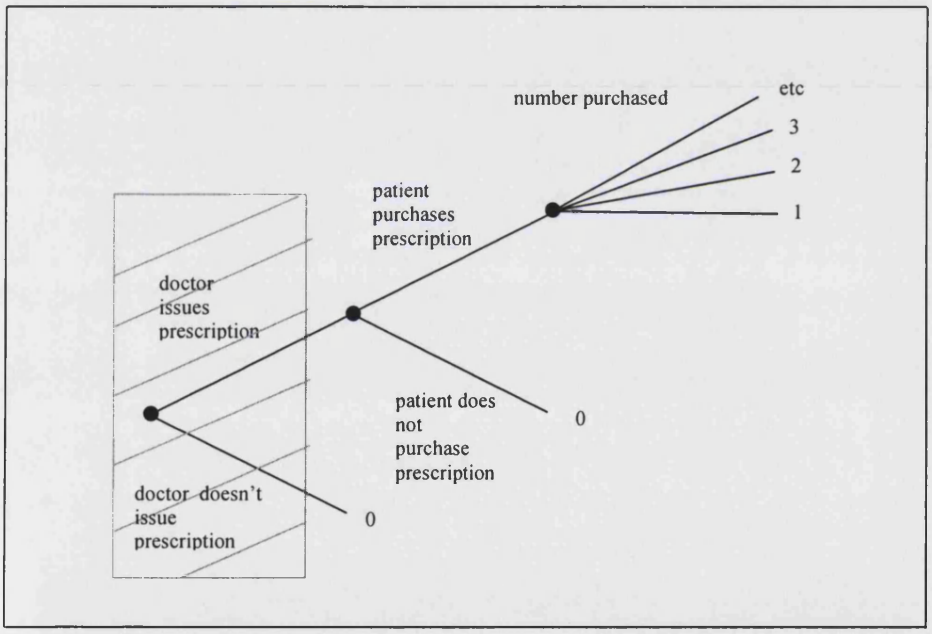
6.4. Development of an econometric model specification

This section outlines the process of obtaining a prescription drug in the United States and the potential empirical issues that accompany this process. Based on this discussion, we then develop the preferred econometric specification for the analysis.

6.4.1. Basic framework of the model

There are a number of important aspects of the model that merit attention. The main variable of interest is the total number of prescriptions that the individual obtains in a given year including initial purchases and refills. The process of obtaining a prescription could be made quite complex, and Figure 6.1 depicts various stages in the process.

Figure 6.1. Process of obtaining prescriptions in the United States



There can be quite a few stages in the process leading up to the patient obtaining a prescription, and this diagram has simplified the process significantly[3]. Given that the object of interest is not the decision-making process and given the lack of

[3] For example, the process could begin with the patient falling ill and deciding whether or not to visit the physician or the hospital. The pharmacist could also enter at a later stage of the process, perhaps by advising the patient to purchase an OTC medication instead of a prescription medication.

observational variables in the MEPS for each stage of the decision process, it would be statistically infeasible and undesirable to model the entire process. For example, it is not possible to determine whether the doctor issued a prescription to the patient during a particular visit. Nonetheless, the important considerations for this dissertation are the cost/benefit comparisons regarding prescription drugs made by both patients and physicians. Specifically, once the patient has chosen to visit the doctor, the physician makes a marginal cost/marginal benefit comparison to determine whether or not to issue a prescription. The physician's marginal cost may be affected by a capitated budget, the likelihood of credibility loss if the prescription does not work or causes severe side effects, or the time it takes to explain to the patient the need for a particular prescription. After the physician issues a prescription, the patient makes his own marginal cost/marginal benefit comparison and decides whether to purchase the medication. The patient's marginal benefit evaluation may be based on his cultural views of medication, his faith in the doctor's recommendation, his view of the severity of illness, and other factors. While we cannot observe the outcome of the physician's cost/benefit comparison, we are able to establish whether a patient determined that his own net benefit outweighed the marginal cost; that is, the patient purchased medication.

One issue that we are unable to address is compliance. That is, we cannot ascertain whether the patient received a prescription from the physician but chose not to fill the prescription for economic, personal, or other reasons. We are also unable to ascertain whether the patient complied with the prescription instructions once he obtained the medication; for instance, we do not know whether the patient took half of the required dosage or skipped dosages because of economic reasons.

6.4.2. Econometric specification of the model

Based on the need to model the process that determines the consumption of prescription drugs and the nature of the dataset, there are a number of important considerations for developing an econometric specification.

Sample selection

The implication of this sequence of events is that we are unable to determine whether zero prescription drug consumption represents a true choice of zero consumption. For example, we cannot distinguish between the whether the physician issued a prescription and the patient chose not to fill the prescription (a true zero) and whether the physician never issued a prescription but the patient would have filled the prescription had he received one (not a true zero). An OLS regression on the selected sample would be inconsistent.

Alternative statistical techniques have been developed to account for the preponderance of zeros, and some of these methods include the two-part model, the double hurdle model, and the Heckman correction procedure. After consideration of different estimation techniques, the method that we employ in this dissertation is a Heckman (1979) sample selection model, and the description of this model is given in

Appendix D.1. The reasons for choosing the sample selection model over the alternatives are also discussed in Appendix D.1. In brief, the model occurs over two stages where the individual chooses to consume any medications in the first stage, and in the second stage we model the number of drugs he consumes contingent upon consumption in the first stage.

Endogeneity

In addition to sample selection, there is also a potential endogeneity problem related to the co-payment variable. While we posit that the co-payment has an impact on the number of prescriptions consumed, the number of prescriptions consumed may also influence the insurance contract chosen by the individual and thus the co-payment. Because consumers do not always reveal these expectations regarding future drug consumption to insurers, issues of adverse selection influence the types of insurance contracts available on the market. Likely, individuals who perceive a greater need for prescriptions will purchase more generous insurance with a lower co-payment. A final potential source of endogeneity is the non-linearity of the co-payment variable. The problem is that we are unable to measure these insurance contracts, expectations regarding drug consumption, or specifics regarding the non-linearity, meaning that the error term in the regression is not independent of the co-payment variable. This can lead to biased estimates. Instrumental variable methods, which involve estimating the endogenous variable with at least one instrument that is not correlated with the dependent variable of interest and using this estimate for the endogenous variable in the main equation, have been developed for this purpose. Appendix D.3 provides an overview of the instrumental variables model.

Panel data techniques

While sample selection and endogeneity are problems that need to be addressed, having a panel dataset is an improvement over cross-sectional data as it allows us to account for unobserved heterogeneity. Econometric techniques have been developed to address panel data. The two main models for panel data are fixed effects and random effects, although there are a number of variations based on these two models. The fixed effects model introduces dummy variables to account for the impact of omitted variables that are specific to individual cross-sectional units but constant over time. This model can allow for the impact of time-specific omitted variables that are constant across individual cross-sectional units. Meanwhile, the random effects model assumes that there are a large number of factors which influence the dependent variable but have not been included in the model as explanatory variables (random disturbances). For our particular dataset and given question, a fixed effects approach is more appropriate as there are individual-specific factors that influence the choice of prescription drug consumption[4]. A more detailed explanation of the fixed effects model is given in Appendix D.4.

[4] We test the assumption that fixed effects is more appropriate than random effects in the simple linear case. Appendix D.6 lists the results of this test in a footnote.

Combining sample selection, endogeneity, and panel data techniques

The previous sections detailed various considerations that arise in empirical work, however, both the sample selection and endogeneity corrections were only described for cross-sectional cases. The purpose of this section is to bring together both the sample selection and endogeneity techniques into one model that simultaneously corrects for unobserved heterogeneity. An appropriate model to apply to this consumption decision was developed by Semykina and Wooldridge (2006) and consists of three main equations. Using s_{it} as a selection indicator, these equations are:

$$y_{it} = x_{it}\beta + g_i + u_{it} \qquad \text{for } t = 1,...,T. \qquad (6.1)$$

$$s_{it} = 1[z_{it}\gamma + \eta_i + \varepsilon_{it} > 0] \qquad \text{for } t = 1,...,T. \qquad (6.2).$$

The variables from equation (6.1) represent the following: y_{it} is the total number of prescriptions that the individual obtains in a given year including initial purchases and refills, which is censored according to s_{it}. The x_{it} are the explanatory variables that determine y_{it} (some of which can be endogenous; in our case we consider the potentially endogenous co-payment variable, demographic and socioeconomic variables, health variables, and time variables) and β is the coefficient on x_{it}. In addition, g_i is the individual-specific term, and u_{it} is the error term. In equation (6.2) s_{it} is the indicator variable, z_{it} are the instruments associated with the endogenous variable, γ are the coefficients for z_{it}, η_i is the individual-specific term, and ε_{it} is the error term. We assume that $\varepsilon_{it}|z_i, \eta_i \sim \text{Normal}(0,1)$, allowing s_{it} to be estimated through an unobserved effects probit model.

The Semykina and Wooldridge (2006) estimator further allows for correlation between the individual-specific effect (η_i) and the instrumental variables (z_i). The chosen method is based on Mundlak (1978) and Chamberlain (1980) and models the unobserved effects from (6.1) and (6.2) as:

$$\eta_i = \bar{z}_i\xi + \tau + a_i. \qquad (6.3)$$

$$g_i = \bar{z}_i\xi_1 + \tau_1 + a_{i1}. \qquad (6.4).$$

This assumes that the correlation between the unobserved effect and the z_i occurs only through the time means of z_i, while a_i is independent of z_i (Mundlak, 1978; Semykina and Wooldridge, 2006). Incorporating (6.3) and (6.4) into equations (6.1) and (6.2) allows us to rewrite the main and selection equations as:

$$y_{it} = x_{it}\beta + \bar{z}_i\xi_1 + \tau_1 + \psi_{it} \qquad \text{for } t = 1,...,T. \qquad (6.5)$$

$$s_{it} = 1[z_{it}\gamma + \tau + \bar{z}_i\xi + v_{it} > 0] \qquad \text{for } t = 1,...,T. \qquad (6.6).$$

While a_{i1} additively combines with u_{it} in equation (6.1) to form ψ_{it}, a_i combines additively with the ε_{it} in the indicator function to form v_{it}, where $v_{it}|z_i \sim \text{Normal}(0,1)$[5]. To obtain an estimatable form of the model, two further assumptions are needed:

$$E(a_{i1}|z_i, v_{it}) = E(a_{i1}|v_{it}) = \phi_{t1} v_{it} \quad (6.7)$$

$$E(u_{it}|z_i, v_{it}) = E(u_{it}|v_{it}) = \rho_t v_{it} \quad (6.8).$$

Given that $\psi_{it} = a_{i1} + u_{it}$:

$$E(\psi_{it}|z_i, v_{it}) = E(a_{i1}|z_i, v_{it}) + E(u_{it}|z_i, v_{it}) = \phi_t v_{it} + \rho_t v_{it} = \kappa_t v_{it} \quad (6.9),$$

and substituting (6.9) into (6.1) results in:

$$y_{it} = x_{it}\beta + \bar{z}_i\xi_1 + r + \kappa_t E(v_{it}|z_i, s_{it})_1 + e_{it} \quad (6.10),$$

where $E(v_{it}|z_i, s_{it}) = 0$.

The model is made robust to heteroskedasticity by using the White (1980) estimates of variance. When endogenous variables are included in the estimator, the model is labeled the "SS FE-2SLS" (fixed effects two stage least squares correcting for sample selection) model.

The procedure to obtain the estimates for y_{it} is as follows: we first estimate a probit equation of z_{it} and z_i on s_i by estimating a separate probit equation for each year. Using these estimates, we construct the inverse Mills ratio. We then run a two-stage least squares regression with y_{it} as the main variable of interest and the co-payment variable as the endogenous variable for the sample where $s_{it} = 1$, including z_i in both stages to account for the fixed effects.

To determine whether this procedure is merited for the given sample, Semykina and Wooldridge (2006) developed a test, which involves first estimating a probit model of this equation for each time period:

$$P(s_{it} = 1|z_i) = \Phi(z_{it}\gamma + \bar{z}_i\xi_2 + r_2) \quad (6.11).$$

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[5] The assumption regarding $v_{it}|z_i \sim \text{Normal}(0,1)$ does not hold strictly. But following $v_{it}|z_i \sim \text{Normal}(0, 1 + \tau_2^2)$, we simplify the true variation to specify a less restrictive form without weakening the argument; this simplification is based on Semykina and Wooldridge (2006). This allows the coefficients in the individual-year selection equations to be entirely unrestricted. Full details of this assumption can be found in Section 4 of Semykina and Wooldridge (2006), pg. 15-16.

Then, the results of each probit are used to calculate the inverse Mills ratios, λ_{it}. For the sample where $s_{it} = 1$, a fixed effects two-stage least squares approach is used to estimate the equation:

$$y_{it} = x_{it}\beta + \rho\lambda_{it} + g_i + u_{it} \qquad (6.12).$$

If the coefficient for λ_{it} is significant, the null hypothesis of no selection bias is rejected. Note that by interacting the inverse Mills ratio with the time dummies and using a robust variance matrix, a test of the joint significant of all of those terms can be undertaken with a Wald test.

In the analysis that follows in Section 6.5, the dependent variable (y_{it}) is the number of prescription drugs obtained per person per year, whereas the sample selection indicator (s_{it}) equals one if the individual obtained any prescriptions in a given year and zero otherwise. As mentioned previously, we hypothesize that the co-payment is an endogenous variable (c_{it}).

6.5. Results

This section discusses the results of the descriptive statistics and the econometric estimation. The creation of the dataset and subsequent analyses were carried out in STATA 9.2. For some of the panel data analyses, the STATA [*xt*] commands, which account for unbalanced panels, were employed. We also used the [*regress*] command along with time averages for each explanatory variable for the SS FE-2SLS estimator; the variances for this model were also adjusted to account for sample selection and endogeneity according to Semykina and Wooldridge (2006). The STATA code for the estimator along with the variance correction code is available in Appendix D.5.

The raw data consisted of 272,277 observations, and after removing individuals under the age of 18 (83,123 observations) and excluding observations with missing data (2,554 observations), the final sample consisted of 186,600 observations[6]. The analysis extended to three different samples: an adult, an elderly, and a low-income sample[7]. We chose the adult sample to represent the general population, and we excluded individuals under the age of 18 because in the US, the child's guardian typically has discretion over the child's type of insurance coverage and consumption of medical care. The elderly sample consisted of individuals aged 65 and above as 65 is the age at which Americans become eligible for Medicare and a typical retirement age. Inclusion in the low-income sample was based on family size, and we defined low-income individuals as those who belonged to a family with an income below 200% of the Federal poverty level. The amount for a single filer is similar to the

[6] All of these totals include both observations for individuals that appeared twice in MEPS.

[7] We conducted a Chow test for the equality of coefficients between the three samples. Specifically, we rejected the null hypothesis of no structural difference between the general population and the elderly group, and we rejected the null hypothesis of no structural difference between the general population and the low-income group.

amount that has been suggested as the lower threshold for the middle class (Kacapyr et al., 1996).

6.5.1. Descriptive results of the sample

Table 6.2 lists the explanatory variables that we considered for the model along with their means and standard deviations, although not all of these variables were included in the final model for reasons discussed below.

Table 6.2. Percent of sample exhibiting specific characteristics, 1996-2004

Variable	Adult sample (N = 186,600)	Elderly sample (N = 29,244)	Low-income sample (N = 51,112)
Drug co-payment, <=$6.84	51.12	26.25	55.91
Drug co-payment, $6.85 – $12.81	16.35	16.91	12.12
Drug co-payment, $12.82 – $24.57	16.26	22.92	13.69
Drug co-payment, >$24.57	16.26	33.92	18.29
Age <=30	25.1	N/A	26.17
Age, 31 - 45	31.15	N/A	29.94
Age, 45 - 65	28.08	N/A	21.47
Age, 65 – 74	8.58	54.76	10.49
Age >74	7.09	45.24	11.93
Male	46.14	40.96	40.01
Female	53.86	59.04	59.99
White	60.25	73.15	42.57
Black	13.65	12.17	20.00
Hispanic	21.62	11.76	33.56
Other race/ethnicity	4.48	2.92	3.87
Income, <=$7,955	25.57	26.43	85.62
Income, $7,966 – $15,910	26.87	31.36	14.38
Income, $15,911 – $23,865	17.38	17.33	N/A
Income, $23,866 – $31,820	10.5	9.57	N/A
Income, >$31,820	19.69	15.31	N/A
Married	56.53	52.28	46.06
Not married	43.47	47.72	53.94
Good health	85.35	72.7	75.13
Poor health	14.65	27.3	24.87
Diagnosed with a major disease	17.51	39.04	21.37
Not diagnosed with a major disease	82.49	60.96	78.63
Has a limitation to activities of daily living	2.16	8.28	3.99
Does not have a limitation to activities of daily living	97.84	91.72	96.01

Various trends appear when we examine the summary statistics, which were calculated using all 186,600 observations. The co-payment bands were chosen by

taking the co-payment at the 25th, 50th, and 75th percentiles for individuals with positive prescriptions, as the co-payment is not observed for those who do not consume any prescriptions in a given year. The descriptive statistics reveal that approximately half of the sample has a co-payment of less than $6.84, although this percent is relatively large because it includes the sample that did not consume any drugs. Note that we are unable to observe the actual co-payment for individuals that did not consume any prescriptions in a given year, and this calculation likely overestimates the proportion of the sample with a low co-payment. The percent of the sample was split relatively evenly between the other co-payment bands; thus, the number of people purchasing prescriptions with high out-of-pocket costs was comparatively large. The proportion of respondents in the various co-payment bands was relatively similar for the low-income group, although an alarming result was that over 18 percent of the low-income sample faced a co-payment greater than $24.57 per prescription. The distribution of elderly individuals between the co-payment bands was different though, with a smaller proportion facing a low co-payment (less than $6.84) and a much larger proportion facing higher co-payment (above $24.57).

The summary statistics for age reveal that most of the adult sample is between the ages of 18 and 65, while a slightly greater proportion of the elderly sample is between 65 and 74. Compared with the adult sample, the low-income group had a greater proportion of respondents under the age of 30 and a slightly larger proportion over the age of 64. Meanwhile, the gender variables indicate that females make up a slightly larger proportion of the adult sample. This difference becomes even more pronounced in the elderly and low-income samples, likely because women have higher life expectancies than men. Slightly more than half of the sample is white, while blacks and Hispanics make up almost 40% of the sample. Because of the study design where blacks and Hispanics were over-sampled, this proportion is higher than the national average.

The income variable was created by dividing total family income by the number of persons in the household[8]. To calculate the income bands in Table 6.2, we used the Federal Poverty Level, where each band represents an increase in income to n percent of the FPL (where n = 100 percent, 200 percent, 300 percent, and 400 percent). The income variable indicates that a disproportionate part of the adult sample has very low income, and the elderly appear to have less income on average than the adult population. A little over half of the adult, elderly, and low-income samples were married.

In terms of the health status variables, most of the adult sample reported being in good health, although this proportion was lower for the elderly and low-income samples. Only about 18 percent of the adult sample had been diagnosed with one of the leading causes of death (asthma, coronary heart disease, stroke, chronic obstructive pulmonary disease, malignant cancer, and diabetes (CDC, 2006)). This proportion was higher for the low-income group and more than twice as large for the elderly. Finally, only about 2 percent of the adult sample faced at least one limitation to an

[8] This allowed us to implicitly account for family size, a variable that may not change significantly from one year to the next, in the fixed effects framework.

activity of daily living, although this proportion was about 4 percent for the low-income group and four times as large for the elderly.

As described previously, we are primarily interested in the effect of co-payments on the number of prescription drugs consumed. As pointed out in the literature review, the decision to consume at least one prescription may be different than the choice of how much to consume. Because of this distinction, we examined descriptive statistics for the probability of consuming a prescription drug and the number of drugs purchased conditional upon positive consumption (Table 6.3).

In terms of the probability of obtaining a prescription drug, this likelihood increases with age in all of the samples. Females are more likely to obtain a prescription drug in all three samples, while the probability of an individual who is white obtaining a prescription drug is higher than for someone who is black, Hispanic, or of another race or ethnicity. As for income there doesn't appear to be much of a difference between this likelihood among the different income bands, except for those at or below 100% of the FPL in the adult and low-income sample, as the poorest group was less likely to obtain a prescription. In all of the samples, the probability of a married respondent receiving a drug was about the same as for an unmarried respondent. In general, the likelihood of positive consumption was much higher for individuals who reported being in poor health than for their healthier counterparts. The trend was the same for those who had been diagnosed with at least one of the leading causes of death and those reporting at least one limitation to an activity of daily living.

There were interesting trends for total prescription drugs consumed, conditional upon the respondent having at least one prescription. As the co-payment increased the number of prescriptions obtained actually increased. This positive association may have been due to the other factors such as need, expected drug consumption, and the availability of insurance contracts on the market. This descriptive result implies the need to further investigate the relationship between the co-payment and consumption, for instance, by considering the possibility that the co-payment is endogenous to consumption.

Not surprisingly, there was a positive relationship between age and total drugs consumed, likely because health stock declines with age. Females also tended to have more prescriptions than men, except for in the low-income sample where men and women consumed similar amounts of prescriptions. The trends for the different racial and ethnic groups were somewhat different than with the probability of obtaining a prescription. Among the adult and low-income populations, whites and blacks consumed about the same number of drugs, while Hispanics and individuals of other races and ethnicities consumed fewer prescriptions. For the elderly population, consumption was similar across all racial and ethnic groups, with blacks consuming the most prescription drugs.

Table 6.3. Statistical information about the possible predictors of demand for prescription drugs, 1996-2004

Variable	Adult sample (N = 186,600)		Elderly sample (N=29,244)		Low-income sample (N =51,112)	
	Prob. of at least one prescription	Number of drugs[a]	Prob. of at least one prescription	Number of drugs[a]	Prob. of at least one prescription	Prob. of at least one prescription
Drug co-payment, <=$6.84	N/A	13.18	N/A	26.00	N/A	19.74
Drug co-payment, $6.85 – $12.81	N/A	14.51	N/A	26.21	N/A	18.79
Drug co-payment, $12.82 – $24.57	N/A	17.83	N/A	27.99	N/A	22.10
Drug co-payment, >$24.57	N/A	17.83	N/A	26.88	N/A	21.67
Age, <=30	0.488	5.87	N/A	N/A	0.451	6.08
Age, 31 - 45	0.580	9.91	N/A	N/A	0.529	12.27
Age, 45 - 65	0.738	19.43	N/A	N/A	0.736	27.58
Age, 65 – 74	0.878	25.60	0.878	25.60	0.882	29.62
Age, >74	0.914	28.38	0.914	28.38	0.917	30.70
Male	0.551	14.32	0.872	24.26	0.520	19.37
Female	0.736	16.82	0.910	28.63	0.714	21.23
White	0.720	16.72	0.905	26.76	0.755	23.67
Black	0.616	17.00	0.884	29.01	0.638	21.47
Hispanic	0.500	11.98	0.856	25.89	0.489	14.13
Other race/ethnicity	0.553	13.32	0.820	25.00	0.592	19.64
Income, <=$7,955	0.598	18.53	0.892	30.24	0.608	19.16
Income, $7,966 – $15,910	0.641	16.53	0.897	27.86	0.802	27.22
Income, $15,911 – $23,865	0.668	15.09	0.892	26.42	N/A	N/A
Income, $23,866 – $31,820	0.688	14.39	0.893	23.37	N/A	N/A
Income, >$31,820	0.695	13.38	0.896	21.83	N/A	N/A
Married	0.674	14.71	0.895	24.34	0.614	17.46
Not married	0.620	17.44	0.893	29.68	0.655	23.15
Good health	0.613	12.06	0.870	22.20	0.561	14.05
Poor health	0.871	31.32	0.959	38.20	0.864	33.50
Diagnosed with major disease	0.944	29.29	0.976	36.05	0.950	35.31
Not diagnosed with major disease	0.588	11.26	0.842	20.08	0.551	13.73
Limitation to activities of daily living	0.947	43.38	0.957	44.40	0.952	45.68
No limitation to activities of daily living	0.644	14.95	0.889	25.18	0.623	19.03

[a]for an individual with at least one prescription, the mean number of prescriptions consumed

As income increased among the adult and elderly samples, the number of prescription drugs declined, possibly indicating that lower-income populations have greater need for prescription drug treatments. The results from the marital status variable indicated

that although married respondents had a higher probability of consuming at least one prescription, unmarried respondents actually consumed more prescription drugs once we account for the probability of positive consumption. Not surprisingly, individuals who were in poor health, who had been diagnosed with at least one of the leading causes of death, or who faced at least one limitation to daily activities purchased significantly more prescriptions.

6.5.2. Results of the econometric analysis

The following section discusses the variables included in the models and the results of the models. We first go over general information about the model, including the transformations of some variables and information regarding which variables were included in the equations. Then, the section offers the regression results for the total number of prescription drugs obtained.

We transformed the dependent variable (total prescription drugs obtained) and two of the major explanatory variables (the prescription drug co-payment and income per person in each family) into logarithms as these variables were highly skewed to the right. Given the use of the fixed effects estimator, time-invariant variables, including gender and race/ethnicity, did not return coefficients. A number of variables that were hypothesized to significantly predict the demand for prescription drugs (such as education) had little effect in the fixed effects framework possibly because omitted variables, such as preferences for prescription drugs and access to pharmacies, were capturing much of the impact on the demand for prescription drugs. Interaction effects, for instance age and income, age and morbidity, and morbidity and self-reported health status were also defined, but none of these were significant.

The instrumental variables chosen for the adult sample were the main regressors, whether the individual had non-Medicare public insurance coverage[9], and whether the individual reported being self-employed[10]. The public insurance variable was intended to control for the effect of different prescription drug prices as public insurance agencies tend to obtain the highest discounts for prescription drugs and can use these savings to keep the out-of-pocket burden for public insurance beneficiaries low[11]. As for the self-employed variable, we hypothesized that individuals who were self-employed would be less risk averse (Brown et al., 2006) and thus more likely to forego insurance coverage, particularly because evidence suggests that self-employment lowers income and failure rates are high (De Meza and Southey, 1996).

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[9] We did not include Medicare coverage as Medicare did not offer an outpatient prescription drug benefit during the study period.

[10] We also tried the variable indicating whether the individual had changed insurance plans during the year; this variable was a suitable instrument, and the results were almost identical to the results using the self-employment variable as an instrument.

[11] Co-payments for non-Medicare public programs are relatively low, and major coverage benefits arise through the negotiation of lower drug prices and Federal and state policies that mandate certain ceilings and rebates on drugs for government purchasers above those given to private purchasers (GAO, 2007). These policies help public insurers provide more generous coverage (for instance, coverage that does not have prescription limits) and keep co-payments lower, effectively reducing the out-of-pocket burden for beneficiaries.

The validity of this instrument has been confirmed elsewhere for the MEPS dataset (Meer and Rosen, 2003).

Because the elderly and low-income populations are less likely to be self-employed, we chose different instruments for these samples; specifically, the instruments were the main regressors along with whether the individual had non-Medicare public insurance coverage and whether the individual switched insurance coverage at least once during the year[12]. We hypothesized that individuals who switch insurance plans are likely to experience a change in their out-of-pocket requirements as a result.

Another important point is related to identification of the annual probits that were used to predict the Mills lambda. While identification can theoretically be achieved through the functional form of the Mills lambda, it is preferable to have instruments that predict the probability of prescription drug consumption but do not predict the number of drugs consumed. We tried a variety of potential instruments, but none of these were feasible.

There are separate tables of the coefficient estimates for each of the population groups. We only report the results from the main variables of interest in this section; tables that include all time variables, λ coefficients, and time averages from the main equation along with the results from the sample selection and endogenous variable equations are available in Appendix Sections D.7, D.8, and D.9. Furthermore, the results of the specification tests for the appropriateness of the SS FE-2SLS model and the chosen variable are available in Appendix D.6.

Number of prescription drugs obtained, adult sample

In order to obtain a general price elasticity value for the broad population, we estimated the effect of a change in the co-payment on the annual number of prescription drugs obtained for the adult sample. We ran five different models on the restricted sample of individuals that consumed at least one prescription and appeared in the sample twice: a simple OLS model with an exogenous co-payment variable that did not account for the panel nature of the data[13] (Pooled OLS), a 2SLS model that also did not account for the panel nature of the data (Pooled 2SLS), a fixed effects model with an exogenous co-payment variable (Fixed Effects), a fixed effects 2SLS (Fixed Effects 2SLS or FE-2SLS) model, and a fixed effects 2SLS model that accounted for sample selection (SS FE-2SLS). The intuition behind running these different specifications was to provide some indication of how the coefficients, particularly the elasticity values, change across specifications. Because the preferred specification is the SS FE-2SLS model, the discussion of Table 6.4 covers the results of the other specifications but focuses on the FE-2SLS model.

[12] This variable indicated whether the individual changed between any of these insurance types at least once in a given year: Medicare, Medicaid, TRICARE, other state insurance programs, other public insurance programs, employer union insurance, other group insurance, self-employment insurance, non-group insurance, or private insurance (source unknown).

[13] In the pooled OLS and pooled 2SLS estimations, we controlled for repeated observations through clustering.

The additional variables that we considered such as marital status, urban area, and potential interaction effects were not significant. We conducted an F-test on the set of instruments, as discussed in Staiger and Stock (1997), to examine the null hypothesis that the instrumental variables were not significantly correlated with the endogenous variable. A rule of thumb is that the F-test on all the instruments needs to exceed 10, and our F-value of 57.48 was sufficient to determine that we did not have weak instruments. We also performed a Sargan test for over-identifying restrictions to determine whether the instruments were independent of the error term in the main equation. A statistically significant test statistic indicates that the instrument set is not independent of the error term, but as the value of our statistic from this test was 0.032 (p=0.859), we failed to reject the null hypothesis at $\chi^2(1)$. Furthermore, neither of the instruments was a significant predictor of the total number of prescription drugs consumed.

Table 6.4. Estimates for the log of total number of prescription drugs obtained equation (adult sample)[a,b,c]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.058§ (0.004)	-0.284§ (0.014)	0.036§ (0.004)	-0.262§ (0.041)	-0.250§ (0.039)
age between 30 and 39	0.207§ (0.012)	0.226§ (0.013)	-0.030 (0.033)	-0.039 (0.034)	-0.052 (0.036)
age between 40 and 49	0.461§ (0.012)	0.503§ (0.013)	-0.010 (0.042)	0.007 (0.042)	-0.030 (0.046)
age between 50 and 64	0.749§ (0.012)	0.812§ (0.013)	0.079 (0.049)	0.102* (0.049)	0.039 (0.053)
age between 65 and 74	0.878§ (0.014)	1.009§ (0.016)	0.113* (0.056)	0.146* (0.058)	0.051 (0.061)
age above 74	0.948§ (0.015)	1.094§ (0.016)	0.075 (0.064)	0.099 (0.072)	-0.029 (0.069)
(log) income per person in family	0.023§ (0.001)	0.028§ (0.001)	0.003 (0.002)	0.003 (0.003)	0.002 (0.003)
individual reports poor health	0.558§ (0.009)	0.534§ (0.010)	0.060§ (0.009)	0.061§ (0.010)	0.060§ (0.010)
individual diagnosed with at least one of leading causes of death	0.520§ (0.009)	0.534§ (0.009)	0.204§ (0.012)	0.218§ (0.014)	0.194§ (0.017)
constant	1.242§ (0.016)	1.982§ (0.034)	2.243§ (0.041)	2.919§ (0.102)	1.814§ (0.000)
N	90,088	90,088	90,088	90,088	90,088
R^2	0.298	0.207	0.229	0.027	0.117

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death
§significant at the 5% level, *significant at the 10% level

The coefficients on all of the variables were generally larger in the pooled cross-sectional models, implying that the included variables in the cross-sectional models

were capturing individual-specific effects that were not included in the regression. The coefficient on the prescription drug co-payment variable was positive for the regressions where the endogeneity of the co-payment was not considered and negative in the models where we corrected for endogeneity. The positive coefficient on the co-payment in some of the regressions could be explained by the existence of omitted variables (Angrist and Krueger, 2001). As a result, the residuals on the co-payment variable, which have essentially been removed in the endogeneity correction, were likely biasing the coefficient on the co-payment variable upwards. Interestingly, the coefficient on the co-payment variable was relatively stable between the FE-2SLS model and the FE-2SLS model accounting for sample selection, implying that the primary effect of the co-payment on the demand for prescription drugs was through the volume of drugs consumed and not the probability of consumption. In the fixed effects model that accounted for endogeneity and sample selection, the price elasticity of demand was –0.250 (p=0.000).

In general, the coefficients on the age variables were positive for higher ages, indicating that prescription drug consumption increases with age. The age coefficients were significant in the pooled regression setting and sometimes significant in the panel data models, potentially because the age variables were capturing unobserved effects in the pooled models. In fact, age appears to work partially through the initial decision to consume at least one prescription and partially through the determination of the co-payment, at least for higher age levels.

While the income variable was significant in the pooled models and never significant in the panel data models, the coefficient on this variable was positive across all specifications. Both of the included health variables were significant and positive, indicating that deteriorating health has an important effect on prescription drug consumption. Specifically, an individual that reports being in poor health consumes 6.18 percent more prescriptions on average than an individual who reports being in good health. Also, an individual who has been diagnosed with at least one of the leading causes of death consumes 21.41 percent more prescriptions on average than an individual who has not been diagnosed with one of these conditions.

Number of prescription drugs obtained, elderly sample

While the price elasticity estimates for the general population are useful, policymakers are also interested in the elasticity of demand for the elderly as they are generally considered a more vulnerable group. There may be different factors that influence consumption among seniors, but for comparability we provide the results of the model using the regressors from the regression on the general population (see Table 6.5). We then provide the results of the estimation for a set of regressors that is specific to the elderly (see Table 6.6).

When we used the same variables for the regressions on elderly sample, the trends in the explanatory variables across the pooled and fixed effects settings were similar to the trends we observed in the adult sample. We included this table and report the price elasticity results for these specifications, though, in order to provide a consistent

comparison with the results from the adult and low-income samples. The coefficient on prescription drug price elasticity variable was –0.096 (p=0.235) in the fixed effects two-stage least squares model, which was not significant.

Table 6.5. Estimates for the log of total number of prescription drugs obtained equation (elderly sample)[a,b]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.031[§] (0.008)	-0.186[§] (0.023)	0.022[§] (0.008)	-0.129* (0.079)	-0.096 (0.080)
individual is above the age of 74	0.080[§] (0.015)	0.090[§] (0.016)	-0.064[§] (0.029)	-0.068* (0.035)	-0.098[§] (0.030)
(log) income per person in family	0.021[§] (0.003)	0.023[§] (0.003)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)
individual reports poor health	0.418[§] (0.015)	0.389[§] (0.016)	0.044[§] (0.015)	0.047[§] (0.017)	0.039[§] (0.015)
individual diagnosed with at least one of leading causes of death	0.495[§] (0.015)	0.497[§] (0.016)	0.135[§] (0.022)	0.139[§] (0.023)	0.105[§] (0.027)
constant	2.210[§] (0.035)	2.773[§] (0.066)	2.798[§] (0.046)	3.188[§] (0.213)	2.567[§] (0.231)
N	21,780	21,780	21,780	21,780	21,780
R^2	0.148	0.103	0.094	0.023	0.084

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 75, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death
[§]significant at the 5% level, *significant at the 10% level

As mentioned earlier, there may be different factors that influence elderly consumption of prescription drugs. In particular, among the elderly there may not be much difference in drug consumption until the individual becomes very old; at that point, the elderly may actually take fewer medications as the risk of adverse events increases (Avorn et al., 2001). Also, the magnitude of illness may be a more important predictor of consumption for this group of the population because most individuals are already consuming some medications. Whether or not the individual is retired may also be another key variable as this is a proxy for the amount of free time the individual has. By including these variables in the model, we obtain the results in Table 6.6.

The inclusion of other variables in the model did not create a multicollinearity problem as we obtained a variance inflation factor of 3.82 and a condition index of 13.3. To test for the performance of the instruments, we again used an F-test and obtained an acceptable value of 15.61. The Sargan test for the independence of the instruments from the main error terms had a value of 0.010 (p=0.922). In addition, neither of the instruments was a significant predictor of the total number of prescription drugs consumed among this sample.

Table 6.6. Revised estimates for the log of total number of prescription drugs obtained equation (elderly sample)[a,b]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.029§ (0.008)	-0.150§ (0.022)	0.021§ (0.008)	-0.133* (0.079)	-0.108 (0.079)
individual is above the age of 79	0.017 (0.017)	0.033* (0.018)	-0.038 (0.032)	-0.038 (0.036)	-0.066§ (0.032)
(log) income per person in family	0.023§ (0.003)	0.024§ (0.003)	0.005 (0.005)	0.005 (0.004)	0.005 (0.005)
individual is retired	-0.006 (0.015)	0.003 (0.015)	-0.027 (0.018)	-0.030* (0.016)	-0.034* (0.018)
individual reports poor health	0.407§ (0.016)	0.386§ (0.016)	0.041§ (0.015)	0.044§ (0.016)	0.037§ (0.015)
individual faces at least one limitation to an activity of daily living	0.342§ (0.027)	0.321§ (0.027)	0.082§ (0.029)	0.098§ (0.034)	0.089§ (0.030)
individual has at least one pre-defined high-cost and/or high-prevalence diseases[14]	0.584§ (0.017)	0.592§ (0.017)	0.191§ (0.026)	0.198§ (0.026)	0.139§ (0.041)
constant	2.035§ (0.037)	2.490§ (0.066)	2.731§ (0.050)	3.127§ (0.203)	2.416§ (0.231)
N	21,780	21,780	21,780	21,780	21,780
R^2	0.171	0.140	0.135	0.048	0.120

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 79, individual is not retired, individual reports being in good health, individual does not have at least one limitation at activities of daily living, individual has not been diagnosed with at least one of the pre-defined diseases
§significant at the 5% level, *significant at the 10% level

The co-payment variable was only significant in the pooled cross-sectional regressions and the fixed effects OLS regression that did not account for sample selection or endogeneity. The co-payment was negative across all specifications that accounted for endogeneity. In the fixed effects 2SLS model accounting for sample selection, the calculated price elasticity was –0.108 (p=0.172). The age variable was significant in the pooled cross-sectional models and the SS FE-2SLS model, and according to the preferred model, older geriatrics consume less than their younger counterparts. In line with the result from the adult sample, income was only significant in the pooled models and appears to have a slightly positive impact on drug consumption. While the variable indicating whether the individual was perceived as being in poor health was significant in the pooled cross-sectional models, it was not significant at the conventional level in the fixed effects models. However, the coefficient on the variable indicating whether the individual faced an ADL suggested that having this health problem caused the individual to consume 9.31 percent more prescriptions. Similarly, individuals diagnosed with at least one high-cost, high-

[14] The high-cost and/or high-prevalence diseases were defined as hypertension, diabetes, cancer, chronic obstructive pulmonary disease, acute myocardial infarction, coronary heart disease, and stroke according to Joyce et al. (2005).

prevalence disease consume 14.91 percent more prescriptions on average that individuals who are not diagnosed with one of these diseases.

Number of prescription drugs obtained, low-income sample

Another group that is generally considered to be more vulnerable is those who are poor. They tend to have less disposable income to spend on prescriptions, and there is a positive association between poor health and low income (Macinko et al., 2003). Yet, the literature review of cost sharing for prescription drugs in Chapter 3 pointed out the lack of studies comparing price elasticity estimates for low-income and general population groups. To remedy this gap in the literature, the results of this analysis are available in Table 6.7.

Table 6.7. Estimates for the log of total number of prescription drugs obtained equation (low-income sample)[a,b,c]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.002 (0.007)	-0.261[§] (0.016)	-0.261[§] (0.012)	-0.239[§] (0.054)	-0.199[§] (0.046)
age between 30 and 39	0.256[§] (0.031)	0.304[§] (0.033)	0.304[§] (0.026)	-0.148* (0.081)	-0.151* (0.082)
age between 40 and 49	0.600[§] (0.034)	0.690[§] (0.036)	0.690[§] (0.027)	-0.168 (0.118)	-0.188* (0.112)
age between 50 and 64	0.903[§] (0.032)	1.016[§] (0.034)	1.016[§] (0.026)	-0.034 (0.136)	-0.087 (0.127)
age between 65 and 74	0.934[§] (0.034)	1.085[§] (0.037)	1.085[§] (0.028)	0.002 (0.146)	-0.078 (0.142)
age above 74	0.951[§] (0.033)	1.134[§] (0.036)	1.134[§] (0.028)	-0.073 (0.142)	-0.194 (0.157)
(log) income per person in family	0.047[§] (0.004)	0.046[§] (0.004)	0.046[§] (0.003)	0.003 (0.004)	0.003 (0.005)
individual reports poor health	0.525[§] (0.018)	0.494[§] (0.019)	0.494[§] (0.015)	0.070[§] (0.018)	0.069[§] (0.018)
individual diagnosed with at least one of leading causes of death	0.532[§] (0.019)	0.541[§] (0.020)	0.541[§] (0.015)	0.199[§] (0.027)	0.138[§] (0.035)
constant	1.296[§] (0.034)	1.786[§] (0.046)	1.786[§] (0.039)	3.200[§] (0.163)	1.691[§] (0.125)
N	16,786	16,786	16,786	16,786	16,786
R^2	0.355	0.112	0.173	0.040	0.099

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death
[§]significant at the 5% level, *significant at the 10% level

The F-test on the set of instruments at 22.43 was high enough to merit the use of our chosen instruments. However, we experimented with numerous other potential instruments and combinations of potential instruments, and the instruments chosen for

this analysis performed better than any other possibilities. As for the Sargan test to determine the relationship between the instruments and the error term in the main equation, our resulting value was 1.61 (p=0.205), and we failed to reject the null hypothesis of independence. Another finding was that both instruments were not significant predictors of the total number of prescription drugs consumed among the low-income group.

Similar to the analyses for the other samples, the coefficients on the explanatory variables were smaller in the fixed effects models, implying that there were unobserved variables that we could not account for in the pooled cross-sectional regression analysis. The co-payment variable exhibited the same pattern as observed in the previous regressions; it was positive for the models that did not account for endogeneity and negative for the models that did correct for this bias. The price elasticity of demand decreased as more biases were controlled for, and the final price elasticity value was –0.199 (p=0.000). The only other variables that were significant in the fixed effects framework were the health status variables, which indicated that an individual who reports being in poor health consumes 7.14 percent more prescriptions on average than an individual who reports being in good health. Also, a respondent who is diagnosed with one of the leading causes of death obtains 14.80 percent more prescriptions on average than one who is not diagnosed with one of these conditions.

6.6. Discussion

This section of the chapter brings together the results from the various analyses that were conducted and discusses why we might have observed the specific outcomes. This chapter does not offer policy implications based on our analysis; instead, the policy relevance of our work is discussed in Chapter 8. One interesting phenomenon was the observed positive association between the out-of-pocket cost and the demand for prescription drugs in the raw data. As this is the opposite of what we would expect, we hypothesized that other factors which determine the co-payment, particularly the existence of both public and private insurance in the United States and the non-linearity of the co-payment variable, were influencing this result. Based on this hypothesis, we empirically examined whether the co-payment was endogenous and confirmed that we needed to correct for this bias.

Across all of the samples and dependent variables that we examined, the fixed effects framework was more efficient than pooled cross-sectional OLS. This implies that a number of individual-specific factors, such as preferences for prescription drugs, unobserved wealth, and access to health care, are important predictors of the demand for prescription drugs. As the coefficients on all of the explanatory variables decreased when the fixed effects framework was used, this implies that at least some coefficient estimates from the literature may be larger than if the authors had accounted for unobserved individual-specific effects.

Based on the results of the preferred specification (SS FE-2SLS), Table 6.8 lists the price elasticity values that we obtained from each specific population group.

Table 6.8. Comparison of elasticity results for different samples[a]

Population group	Price elasticity
Adults	-0.250 (p=0.000)
Elderly	-0.108 (p=0.172)
Low-income	-0.199 (p=0.000)

[a]standard errors in parentheses

The price elasticities are significantly different from zero in the adult and low-income samples but not significantly different from zero in the elderly sample. One feature of our calculations is that the price elasticity value in the low-income sample is lower than the elasticity in the adult sample, but we would expect the opposite result as the low-income population has less disposable income. The income variable in the low-income regression may account for some of the greater sensitivity that we would expect. Another possibility is that we are unable to observe wealth, and some individuals classified as poor, such as elderly individuals, may be incorrectly classified as such because they are not working and can afford to live off of their wealth. Also, some of the poor are covered by Medicaid, which generally requires little or no cost sharing for prescription drugs, and as these individuals are clustered near the low-end of the demand curve, they may be less responsive to changes in the out-of-pocket price.

The lower price elasticity value (in absolute value) for the elderly was not surprising, although the value of the elasticity was interesting. As the marginal efficiency of investments in health is lower for the elderly, they must spend a greater amount on medical care to maintain their health. They may also perceive fewer substitutes for prescription drugs. For example, changes in diet and exercise may be insufficient to improve their health, and alternatives such as surgery are more dangerous for the elderly and thus less appealing. The result is that seniors are likely to be less sensitive to changes in the out-of-pocket prices of prescription drugs, and we observe this expected trend with the given analysis.

In comparison with the elasticity values from the literature, our calculated price elasticity estimate of -0.250 for the adult population is higher than the value of -0.156 that we obtained in the meta-regression analysis in Chapter 4. Nonetheless, the estimate of -0.250 from the American sample is significantly different from -0.156 (p=0.007). Our elasticity may be somewhat different because we only examined the adult American population in this chapter, while the meta-regression analysis considered the general population across a number of developed countries.

In terms of our estimates for the elderly, there were only a few papers that that calculated the price elasticity of demand among the elderly at the non-aggregate level (or offered enough information for us to calculate the price elasticity of demand) (Coulson and Stuart, 1995; Gardner et al., 1997; Grootendorst and Levine, 2001;

Grootendorst et al., 1997; Klick and Stratmann, 2005; Li et al., 2006). The price elasticity values from these papers ranged from –0.56 to 0.04. With the exception of the Grootendorst and Levine (2001) Canadian calculation[15], our price elasticity estimate of –0.108 for the elderly is smaller in absolute value than estimates from the literature.

A few papers have also examined low-income groups at the non-aggregate level (Coulson and Stuart, 1995; Grootendorst and Levine, 2001; Li et al., 2006), and our American estimate for the low-income group of -0.199 is at the high end of this range. Nonetheless, all estimates for the low-income group are relatively inelastic.

In general, there are a number of reasons why our estimates might differ from those found in the literature. Differences in estimation techniques is likely an important reason for the variation in estimates, and the differences in samples selected for the analyses may also be an important contributor to variation. Furthermore, authors that used datasets from outside the United States may have obtained different results as other developed countries have universal health insurance systems, and individuals in these countries may face less uncertainty related to changes in their out-of-pocket costs.

In terms of the other variables that we used to predict the demand for prescription drugs, age was always significant in the pooled cross-sectional models and sometimes significant in the fixed effects framework. Specifically, the variable representing whether the respondent was between the ages of 65 and 74 had a positive coefficient in the regression for total drugs consumed among the general population. The variable also tended to be positive as age increased and decreasing at very high ages, although this wasn't necessarily true in the low-income population when we used the fixed effects two-stage least squares framework. This may have been because the endogenous co-payment variable was capturing most of the age effects. Interestingly, the negative result of age among the elderly is consistent with the findings from the literature review (see Chapter 3, Section 3.4). We pointed out that beginning at certain ages in the American elderly population, age is likely has a negative effect, but the same effect may not hold for other elderly populations in countries like Canada, where there is generous insurance coverage.

As for the income variable, this was never significant in the fixed effects models, likely because wealth is a better predictor of drug consumption. It may be that wealth is a better predictor of drug consumption, and the fixed effects may be capturing these wealth effects. Other variables such as health status may be picking up the income effects as there is generally a positive correlation between income and health (Macinko *et al.*, 2003). Alternatively, the primary effect of income may be through the determination of the co-payment variable.

[15] While the Canadian elderly are shielded from most out-of-pocket prescription drug costs, they also face no out-of-pocket costs for essential medical services (as defined by the Canadian government). In the Grootendorst and Levine (2001) estimation, it appears that the effect of lower prescription drug cost sharing may have led to a lower price elasticity estimate as they were measuring elasticities at a lower point on the demand curve.

Across all samples and dependent variables considered, the health status variables were significant and positive. It is not surprising that individuals who are perceived to be in poorer health and who suffer from the specific diseases that are the leading causes of death in the United States would be more likely to seek pharmaceutical treatment. These findings regarding health status are in line with the findings from the literature on cost sharing for medical services and prescription drugs.

6.7. Conclusion

This chapter has outlined the US health care system, highlighting the fragmented nature of funding in the country, and estimated the individual determinants of the demand for prescription drugs consumed in the United States. The analysis began with a description of the MEPS and the potential regressors and then developed a preferred econometric specification. The results of the econometric analysis indicated that the price elasticity of demand for prescription drugs was relatively low across all of the samples that were considered. Moreover, in the fixed effects framework, age and income appeared to have little effect on the demand for prescription drugs, although health status was always a significant explanatory variable.

There are a number of limitations that should be kept in mind when considering the results of this analysis. Although the dependent variable representing the number of prescriptions obtained by the individual was a count variable, we were unable to use count variable techniques for this analysis because truncated panel data models are not yet available. Our analysis instead assumed that the individual could theoretically consume an infinite number of prescriptions. Future research could incorporate these techniques into the analysis to determine if the outcomes differ by population group.

A second issue is our inability to measure whether respondents complied with their therapies. For example, although the doctor may have written a prescription for two weeks of painkillers, the patient may not have filled his prescription, may have only filled one week of medicine, or may have cut his pills in half or skipped pills. In these situations we are unable to measure whether user fees changed the individual's behavior.

Another question that remains after this analysis is whether cost sharing led to a decrease in the use of inappropriate medications, appropriate medications, or both in the studied population. If higher levels of cost sharing cause patients to decrease their consumption of inappropriate medications, then this is an improvement in the medication-related quality of care. However, if cost sharing leads to a decrease in both appropriate and inappropriate medications, the net effect on quality is unclear. An analysis of the relationship between cost sharing and inappropriate medication use could be useful for policymakers and insurance companies if they were interested in charging higher prescription user fees for potentially inappropriate medications.

A fourth limitation is our inability to measure adverse selection because the MEPS does not contain information on premium payments. Economic theory indicates that

adverse selection will occur in a private insurance market, and testing for the existence of this phenomenon would offer insights into arguments regarding universal insurance coverage and a national insurance program in the United States.

Furthermore, there is a possibility that past prescription drug consumption influences current drug consumption, perhaps through a learning effect. That is, an individual that uses a medication and sees improvement in his health or few side effects is more likely to continue consuming that medication in the future, particularly if he has a chronic condition. Because our data only measures two years maximum of consumption for each individual in the sample, we cannot account for the effect of past prescription drug consumption on current consumption.

Chapter 7: Analysis of prescription drug cost sharing in British Columbia, Canada

7.1. Introduction

Although demand-side cost sharing for prescription drugs in developed countries outside of the United States is generally less burdensome for patients, debate still rages in countries like Canada about the suitability of user charges, the impact of co-payments on the most vulnerable populations, and other aspects of cost sharing (Evans and Barer, 1995). Because PharmaCare, the provincial prescription drug program in British Columbia, covers the population subgroups that the government of BC considers to be the most vulnerable, policymakers are interested in how these residents fare under cost sharing. Balanced against this interest in protecting vulnerable groups is the persistent rise in pharmaceutical expenditures and consumption within the province, and an interesting question is whether the historically low levels of cost sharing for public beneficiaries have contributed to growth in the use of publicly funded medications.

Yet, as discussed in Chapter 3, there are still gaps in the literature related to the price elasticity of demand for prescription drugs in Canada. For example, there are only two published estimates of the price elasticity of demand for older people in Canada (Grootendorst and Levine, 2001; Li et al., 2006). While one estimate is for a specific population with rheumatoid arthritis, a group that may be less sensitive to price than the general elderly population, the other elasticity estimate is positive (Grootendorst and Levine, 2001)[1]. Given the usual negative relationship between price and quantity demanded, it is not clear whether this result is a true indicator of the price elasticity of demand among this population. The other existing price elasticity estimates are from the United States, but these results are unlikely to be applicable to Canada as the estimates were derived from specific groups within the American population, in particular, elderly individuals from Pennsylvania not enrolled in an HMO (Coulson and Stuart, 1995), publicly-employed seniors with state-funded insurance coverage (Gardner et al., 1997), and elderly individuals without Medicaid or employer-sponsored insurance (Klick and Stratmann, 2005). As important as the applicability of the evidence to Canada are the methodologies employed by the existing studies; specifically, few of these studies simultaneously accounted for non-negative values of the dependent variable and unobserved heterogeneity. An advantage of this research is that we are able to account for unobserved heterogeneity and a nonlinear dependent variable within a single specification.

The purpose of this chapter is to offer an updated estimate of the price elasticity of demand for prescription drugs, and the 1992-2002 British Columbia Linked Health Database (BCLHD) is used to achieve this purpose. Due to the nature of the data, which is discussed in detail below, we restrict the empirical analysis to the elderly.

[1] It is also possible to calculate price elasticity values from the Grootendorst et al. (1997) study, but the elasticity is based on a change from an unknown prescription drug insurance status to full prescription drug coverage and thus does not account for specific price changes.

The organization of the chapter is as follows: Section 7.2 addresses the relevant research questions for British Columbia. Section 7.3 gives an overview of the dataset and some unique aspects of the dataset that merit special consideration, and Section 7.3 also offers a description of potential covariates that are considered for the analysis. Section 7.4 then explains the econometric techniques that are utilized, while Section 7.5 offers the main results of the analysis. We then provide a discussion of the econometric results in Section 7.6 and conclude the chapter in Section 7.7.

7.2. Research questions for British Columbia

The development of research questions is based on the economic theory of insurance, gaps in the literature highlighted by the literature review, and the description of the health care and pharmaceutical system in British Columbia. However, due to data constraints that are detailed in the next paragraph, the research questions are focused on the elderly population.

The selection of the sample for the estimation requires further explanation. As there is both private and public drug coverage in British Columbia, residents who are under the age of 65 may hold either type of drug coverage. Although we were able to obtain data on patients between the ages of 18 and 64 that received subsidized prescription drugs from PharmaCare, we were unable to determine if these individuals simultaneously held private drug coverage. However, seniors (those aged 65 and above) received comprehensive drug coverage from PharmaCare until 2003, and thus we assume that they were unlikely to hold private drug coverage before 2003[2]. As drug coverage for seniors became less comprehensive when Fair PharmaCare was implemented in 2003, we could no longer assume that seniors did not hold private drug coverage after 2002. As a result, we restrict the sample to beneficiaries aged 65 and above, and the time period studied ends in 2002.

The specific research questions that we address in this chapter are:

Q1: In terms of volume, what is the impact of cost sharing on the average elderly individual?

Q2: What is the price elasticity of demand for prescription drugs among elderly individuals?

Both of these questions are addressed empirically in Section 7.5.

[2] Although there are no data on private prescription drug coverage among the elderly in BC, the high likelihood that BC seniors do not have private coverage was confirmed via personal communication with Dr. Steve Morgan, an expert in Canadian pharmaceutical policy from the University of British Columbia Centre for Health Services and Policy Research.

7.3. The dataset and explanation of potential covariates

This section is meant to provide an explanation of the dataset that is used to address the research questions. Another aim is to offer information on relevant variables for the analysis, with a focus on the co-payment variable. We also discuss other potential covariates, mainly demographic and socioeconomic characteristics and health status.

7.3.1. The British Columbia Linked Health Database

To explore the given research questions, the British Columbia Linked Health Database (BCLHD) is employed for the empirical analysis. The BCLHD is a longitudinal database of linkable files covering all beneficiaries of the Medical Service Plan in British Columbia (over four million residents). The database is developed and housed at the University of British Columbia's Centre for Health Services and Policy Research. Most of the BCLHD files are available from 1985 to 2004, and the files contain individual-level information regarding demographic characteristics and health care use.

Although data were available beginning in 1985, our sample period begins in 1992 and ends in 2002. There were a couple of reasons for starting in 1992. One reason was that Canada came out of a recession around 1992 (Statistics Canada, 2006a), and thus it seemed interesting to examine the effect of cost sharing during a period of rising incomes. Another reason for starting in 1992 is that changes to user fees occurred in 1994, allowing us to examine the time trend effects of major PharmaCare changes. Although data were available through 2004, the sample period ended in 2002 as Fair PharmaCare (a less generous prescription drug program than PharmaCare) began in 2003, and some of the elderly may have purchased private drug coverage when this began. As mentioned in Section 7.2, we are unable to observe their consumption of privately funded drugs, and thus we exclude this segment of the sample.

Although there are a number of linkable files in the BCLHD, not all of these files are relevant to this investigation. The most useful files are the Registry, Medical Services Plan, and the PharmaCare files. The Registry file consists of demographic and socioeconomic information for beneficiaries, including sex, income decile, date of birth, post code, and number of days registered in the MSP. The Medical Services Plan component contains information regarding health care utilization linked to the Medical Services Plan. This component also contains some individual-specific information, such as area of residence and age. The other useful component is the PharmaCare file, which consists of data on drugs purchased through the provincial drug program.

Although the BCLHD allows researchers to track individuals over a number of years, there are still a few major limitations. One problem is that the database only contains limited information on demographic and socioeconomic characteristics. For example, the database does not list specific income levels; instead, it only provides information on the income decile into which the individual falls based on his postcode. There is also information on whether the resident qualifies for MSP premium assistance because of low income. Other relevant information that would be useful to the

analysis is education level and the employment status, but these variables are also missing from the dataset.

7.3.2. Explanation of the dependent variable and potential covariates

The likely determinants of the demand for prescription drugs were discussed in both Chapters 2 and 3. Specifically, Chapter 2 discussed the traditional economic intuition behind the effect of higher prices and other potential covariates on consumption, while Chapter 3 covered the main determinants that have been considered in the empirical literature. This section describes both the dependent variable and these variables that are potentially important predictors for the model, such as the out-of-pocket price, the socioeconomic decile, and age. We first offer a discussion of the dependent variable and then cover the formation of the co-payment variable and the intuition behind the other explanatory variables.

The dependent variable is the number of prescription drugs purchased (including initial prescriptions and refills). And important point regarding the dependent variable is that it is made up of both brand and generic drugs. As we were unable to distinguish between brand and generic drugs in the BCLHD dataset, we assumed perfect substitutability between brand and generic drugs.

The main explanatory variable of interest in this thesis is the co-payment, as we are primarily concerned with estimating the price elasticity of demand for prescription drugs. Because of the unique cost sharing arrangements within the BC PharmaCare program and because of the way that cost information for prescription drugs is presented in the BCLHD, a description of how we created the co-payment variable is necessary. As highlighted previously in Chapter 5, PharmaCare subsidizes prescription drugs for eligible low-income and elderly residents. While most prescription drugs are covered under the program, there are certain measures in place, such as reference pricing and prior authorization, which sometimes require beneficiaries to pay an amount above any other cost-sharing requirements. The BCLHD reports the amount that the pharmacist received for the drug and the amount that PharmaCare paid for the drug. Thus, any difference between these two amounts was paid out-of-pocket by the individual. In addition, there is often a dispensing fee that the pharmacist collects from the beneficiary, and this also represents an out-of-pocket cost.

To obtain the average co-payment per prescription drug received, we first summed the difference between the amount the pharmacist received for a prescription drug (not including the dispensing fee) and the amount that PharmaCare reimbursed the pharmacist for the drug for each observation of pharmaceutical consumption. We then summed the dispensing fee that the patient paid for each prescription over all prescriptions that he obtained. The sum of these two totals represented the total annual out-of-pocket burden that each beneficiary faced, and we divided this annual burden by the annual number of prescriptions obtained to calculate the average co-payment.

As with the calculation of the co-payment variable in the MEPS database, this variable is a proxy for prescription drug user fees because cost sharing requirements differ over individuals in PharmaCare. Nonetheless, the computed co-payment variable is an indicator of the average out-of-pocket burden that an individual faces and thus the generosity of his PharmaCare coverage. This variable is still a reflection of the marginal cost/marginal benefit comparisons of prescription drugs that each patient makes, and as put forward by the basic theoretical background, there should still be a negative relationship between the out-of-pocket price and consumption of prescription drugs.

In addition to the co-payment variable, there are other variables available in the BCLHD that may determine the demand for prescription drugs. Table 7.1 lists the expected effect of these predictors on the number of drugs consumed and prescription drug expenditures for the elderly sample.

Table 7.1. Predicted signs of possible variables measuring of the demand for prescription drugs

Variable	Elderly sample
	Number of drugs
Drug co-payment	-
Age	+
Age squared	+
Male	-
Female	+
Socioeconomic level	+
Diagnosed with a major disease	+
Not diagnosed with a major disease	-

Because we expect the demand curve for prescription drugs to be downward sloping, there is likely to be a negative relationship between the prescription drug co-payment and the number of drugs consumed. In terms of age, there is likely to be a positive relationship between age and consumption. While the demand for prescription drugs might actually decline after a certain age in places like the United States where there is less generous insurance coverage and exclusions, we do not expect this to be the case in British Columbia. The reason is that prescription drug coverage in BC is public, there are no coverage restrictions based on illness, and there are out-of-pocket limits that protect heavy users.

As with females in the American samples, we expected that females in British Columbia would consume more prescription drugs than males. While evidence suggests that women use more health care services than men (Bertakis et al., 2000) both in the United States and Canada (Kandrack et al., 1991), men and women may also suffer from different diseases in Canada. Women typically face problems like

osteoporosis and are more likely to die of cardiovascular disease in Canada than men (Heart and Stroke Foundation of Canada, 1997). Moreover, the onset of disease may occur at different periods of the life cycle for women and men; for instance, in Canada the onset of stroke and heart disease generally occur a decade later for women (Heart and Stroke Foundation of Canada, 1997). Furthermore, evidence suggests that women are more risk averse than men (Zinkhan and Karande, 1991), implying that women may be more likely to seek care for medical problems and fill prescription drugs.

Income is likely to have a positive effect on the consumption of prescription drugs as higher-income individuals may be less likely to face tradeoffs between necessities such as food and shelter and other goods and services whose consumption can sometimes be delayed such as doctor visits and prescription drugs. Health status is another variable that is expected to positively affect the demand for prescription drugs. As a proxy for need, those who are in worse health are generally prescribed more medications and may be more likely to fill prescriptions due to personal perceptions of need.

7.4. Development of an econometric model specification

This section provides an overview of the considerations for the econometric specification and details the specific model chosen for the analysis.

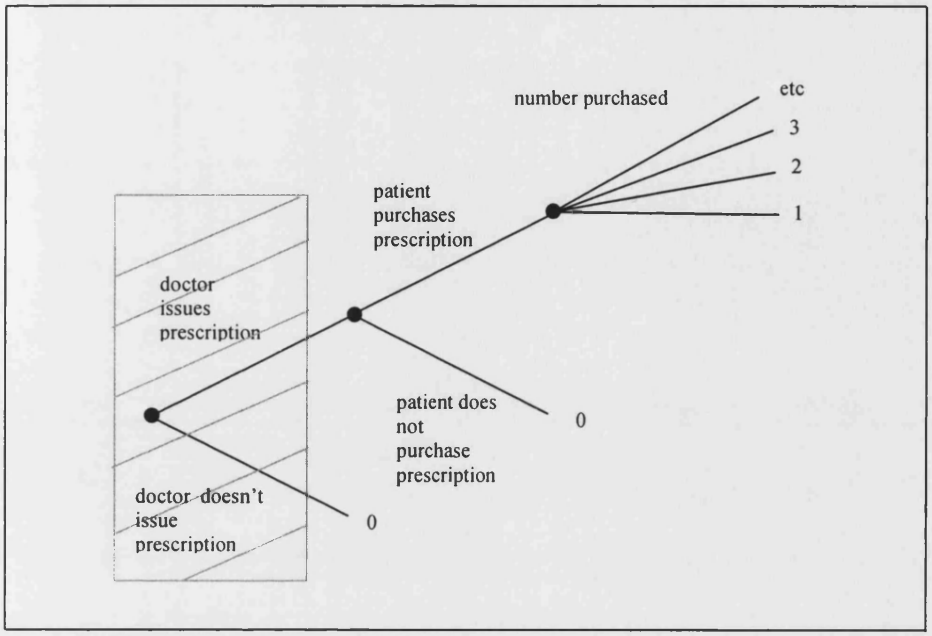
7.4.1. Basic framework of the model

To model the demand for prescription drugs in British Columbia, there are various institutional and data characteristics that need to be considered. As with the United States, the main variable of interest in the analysis is the number of prescription drugs purchased including initial purchases and refills. A basic model of the process of obtaining prescription drugs is given in Figure 7.1, and further information regarding the conceptual and mathematical development of the model is provided below.

As with the American analysis, we do not have information from British Columbia on the number of prescriptions issued by physicians. However, it is not desirable to model this process as we are primarily interested in the effect of cost sharing at the patient level. We can only observe the point at which the patient actually fills a prescription and the number of prescriptions that he obtains in a given year. Yet, the inferences that we are interested in making are related to patient-level marginal benefit/marginal cost comparisons that occur for prescription drug consumption decisions.

Similar to the American analysis, we are unable to make inferences about compliance with prescribed medication regimes. The main issue is that it is impossible to determine if the physician wrote a prescription but the patient chose not to fill the prescription for economic, personal, or other reasons. We also cannot ascertain anything about compliance once the patient fills his prescription, for instance, whether he actually takes the pills or skips dosages.

Figure 7.1. Process of obtaining prescriptions in British Columbia, Canada



7.4.2. Econometric specification of the model

In order to model the prescription process outlined above, there are a few important factors that should be considered for the econometric specification. Each of these factors is briefly discussed in this section, but more information is available in the appendix to Chapter 6 (Appendix D) and the appendix to this chapter[3] (Appendix E).

Sample selection

One prominent aspect of the sequence of events that leads to prescription drug consumption is that whether the decision to consume represents a true choice by the patient. For instance, it is impossible to distinguish between whether the doctor wrote a prescription and the patient did not fill it (a true zero) and whether the physician did not issue a prescription but the patient would have filled a prescription had he received one (not a true zero). Thus, an OLS regression on the selected sample would be inconsistent. To reduce the bias from the nonnegative values, we employ a Heckman sample selection correction. As Section 6.4.1 in Chapter 6 and Appendix D.1 provided a detailed explanation of the Heckman correction for sample selection, we do not provide any further information on the basic procedure here.

[3] Because some of the econometric considerations were already detailed in the appendix to Chapter 6 (Appendix D), we refer the reader to these details rather than repeating them in the appendix to this Chapter (Appendix E).

Endogeneity

In the American context the co-payment variable is endogenous to the model as individuals choose among various insurance contracts and the expected consumption of prescription drugs affects the level of co-payment chosen. The BCLHD only contains information on public consumption of prescription drugs, but it is likely that elderly respondents do not have supplementary private insurance coverage due to the generosity of PharmaCare. As a result, the estimation only includes consumption of publicly covered prescription drugs among the elderly. Given that eligibility for PharmaCare is automatic when the individual turns 65, there are no unobserved factors related to risk selection or consumption expectations that determine the level of the co-payment. However, it is possible that the co-payment is endogenous due to its construction. Specifically, because out-of-pocket prices are non-linear (based on co-payments and out-of-pocket limits) in BC, the constructed co-payment variable may depend on the number of prescription drugs consumed. To consider this possibility, we tested for the number of individuals that exceeded the out-of-pocket maximum during the year and determined that it was less than 5 percent of the sample. As a result, we assume that endogeneity is not a significant issue with the sample.

Panel data techniques

While one aspect of the data is the non-observability of consumption for some individuals, another aspect is the repetition of observations for most respondents. That is, we can observe more than one year of data for all elderly individuals in dataset who enter PharmaCare before 2002 and who do not die within one year of becoming eligible for PharmaCare. The panel is unbalanced as individuals only enter the dataset once they turn 65 and as some of the elderly die during the given time period. More detail on panel data techniques is also given in Appendix D.4.

We hypothesize that an approach which accounts for individual-specific unobserved heterogeneity is more appropriate for the analysis[4]. The reasoning is that we are unable to observe a number of individual-specific factors that affect the demand for prescription drugs; for example, preferences for drugs over different types of medical care, access to pharmacies, and wealth.

Combining sample selection and panel data techniques

Given that the dependent variable is nonlinear and given the longitudinal nature of the dataset, the purpose of this section is to bring together both the sample selection and panel data techniques into one model[5]. In line with the American analysis, an appropriate model to apply to the consumption decision was developed by Semykina and Wooldridge (2006). The model detailed in this section is a slight variation of their specification given that the co-payment variable is not endogenous. Using s_{it} as a selection indicator, these equations are:

[4] We formally test and accept this assumption and present the results in Appendix E.2 in a footnote.
[5] We also considered a dynamic fixed effects sample selection model, however, there was persistent autocorrelation that was possibly related to the dynamic aspect of the model. Nonetheless, we provide the results of this regression in Appendix E.5.

$$y_{it} = x_{it}\beta + g_i + u_{it} \qquad \text{for } t = 1,...,T. \qquad (7.1)$$

$$s_{it} = 1[z_{it}\gamma + \eta_i + \varepsilon_{it} > 0] \qquad \text{for } t = 1,...,T. \qquad (7.2).$$

The variables from equation (7.1) represent the following: y_{it} is the total number of prescriptions that the individual obtains in a given year including initial purchases and refills, which is censored according to s_{it}. The x_{it} are the explanatory variables that determine y_{it} (some of which can be endogenous; in our case we do not have any endogenous variables) and β is the coefficient on x_{it}. In addition, g_i is the individual-specific term, and u_{it} is the error term. In equation (7.2) s_{it} is the indicator variable, z_{it} are the instruments associated with the endogenous variable, γ are the coefficients for z_{it}, η_i is the individual-specific term, and ε_{it} is the error term. We assume that $\varepsilon_{it}|z_i, \eta_i \sim \text{Normal}(0,1)$, allowing s_{it} to be estimated through an unobserved effects probit model.

The Semykina and Wooldridge (2006) estimator further allows for correlation between the individual-specific effect (η_i) and the instrumental variables (z_i). The chosen method is based on Mundlak (1978) and Chamberlain (1980) and models the unobserved effects from (7.1) and (7.2) as:

$$\eta_i = \bar{z}_i\xi + \tau + a_i. \qquad (7.3)$$

$$g_i = \bar{z}_i\xi_1 + \tau_1 + a_{i1}. \qquad (7.4).$$

This assumes that the correlation between the unobserved effect and the z_i occurs only through the time means of z_i, while a_i is independent of z_i (Mundlak, 1978; Semykina and Wooldridge, 2006). Incorporating (7.3) and (7.4) into equations (7.1) and (7.2) allows us to rewrite the main and selection equations as:

$$y_{it} = x_{it}\beta + \bar{z}_i\xi_1 + \tau_1 + \psi_{it} \qquad \text{for } t = 1,...,T. \qquad (7.5)$$

$$s_{it} = 1[z_{it}\gamma + \tau + \bar{z}_i\xi + v_{it} > 0] \qquad \text{for } t = 1,...,T. \qquad (7.6).$$

While a_{i1} additively combines with u_{it} in equation (7.1) to form ψ_{it}, a_i combines additively with the ε_{it} in the indicator function to form v_{it}, where $v_{it}|z_i \sim \text{Normal}(0,1)$[6]. To obtain an estimatable form of the model, two further assumptions are needed:

[6] The assumption regarding $v_{it}|z_i \sim \text{Normal}(0,1)$ does not hold strictly. But following $v_{it}|z_i \sim \text{Normal}(0,1+\tau_2^2)$, we simplify the true variation to specify a less restrictive form without weakening the argument; this simplification is based on Semykina and Wooldridge (2006). This allows

$$E(a_{i1}|z_i, v_{it}) = E(a_{i1}|v_{it}) = \phi_{t1} v_{it} \quad (7.7)$$

$$E(u_{it}|z_i, v_{it}) = E(u_{it}|v_{it}) = \rho_t v_{it} \quad (7.8).$$

Given that $\psi_{it} = a_{i1} + u_{it}$:

$$E(\psi_{it}|z_i, v_{it}) = E(a_{i1}|z_i, v_{it}) + E(u_{it}|z_i, v_{it}) = \phi_t v_{it} + \rho_t v_{it} = \kappa_t v_{it} \quad (7.9),$$

and substituting (7.9) into (7.1) results in:

$$y_{it} = x_{it}\beta + \overline{z}_i \xi_1 + r + \kappa_t E(v_{it}|z_i, s_{it})_1 + e_{it} \quad (7.10),$$

where $E(v_{it}|z_i, s_{it}) = 0$.

The model is made robust to heteroskedasticity by using the White (1980) estimates of variance. When there are no endogenous variables included in the estimator, the model is labeled the "SS FE" (fixed effects correcting for sample selection) model.

The procedure to obtain the estimates for y_{it} is as follows: we first estimate a probit equation of z_{it} and z_i on s_i by estimating a separate probit equation for each year. Using these estimates, we construct the inverse Mills ratio. We then run an ordinary least squares (OLS) regression with y_{it} as the main variable of interest and the co-payment variable as the endogenous variable for the sample where $s_{it} = 1$, including z_i in both stages to account for the fixed effects.

To determine whether this procedure is merited for the given sample, Semykina and Wooldridge (2006) developed a test, which involves first estimating a probit model of this equation for each time period:

$$P(s_{it} = 1|z_i) = \Phi(z_{it}\gamma + \overline{z}_i \xi_2 + r_2) \quad (7.11).$$

Then, the results of each probit are used to calculate the inverse Mills ratios, λ_{it}. For the sample where $s_{it} = 1$, a fixed effects OLS approach is used to estimate the equation:

$$y_{it} = x_{it}\beta + \rho\lambda_{it} + g_i + u_{it} \quad (7.12).$$

If the coefficient for λ_{it} is significant, the null hypothesis of no selection bias is rejected. Note that by interacting the inverse Mills ratio with the time dummies and

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the coefficients in the individual-year selection equations to be entirely unrestricted. Full details of this assumption can be found in Section 4 of Semykina and Wooldridge (2006), pg. 15-16.

using a robust variance matrix, a test of the joint significant of all of those terms can be undertaken with a Wald test.

In the analysis that follows in Section 7.5, the dependent variable (y_{it}) is the number of prescription drugs including initial prescription and refills obtained per person per year. Meanwhile, the sample selection indicator (s_{it}) equals one if the individual purchased any prescriptions in the observed year and zero otherwise.

7.5. Results

In this section of the chapter, we present the results of the descriptive statistics and the econometric estimation. As the dataset was extremely large, we cleaned the dataset using 64-bit STATA version 9.2, and the subsequent analysis was also carried out using 64-bit STATA version 9.2. Again, we used the STATA [*xt*] commands, which account for unbalanced panels, for some of the panel data analysis. For the SS FE analysis we used the [*regress*] command along with time averages for each explanatory variable. The specific STATA code for this model along with the variance correction code is given in Appendix E.1.

There were 5,785,201[7] observations of those aged 65 and above in the raw BCLHD file, although we removed 118,693 individuals who had not died in the given year and who had been registered for the MSP less than 365 days[8]. Additionally, we removed 294,987 individuals whose socioeconomic decile was not reported. According to Statistics Canada, some residents could not be assigned a socioeconomic classification because of missing postcodes or because there were postal codes that straddled more than one geographic region (Statistics Canada, 2006c)[9]. We also dropped individuals that were 65 years of age as we did not have a full year of data for these residents (301,571 observations). The resulting sample consisted of 5,069,950 individuals.

7.5.1. Descriptive results of the sample

Table 7.2 lists the main variables that are likely to be important predictors of the demand for prescription drugs.

There are a number of trends that we observe based on the descriptive statistics. To be consistent with the MEPS analysis, the average co-payment bands were chosen by taking the co-payment at the 25th, 50th, and 75th percentiles for individuals with positive prescriptions, since the co-payment is not observed for those who do not

[7] All of these totals include all observations for beneficiaries that appeared more than once in the BCLHD.

[8] The reasons for this may have been that the beneficiary moved into or out of BC during the given year or the beneficiary may not have resided in the province for at least six months, perhaps due to business in another country or province.

[9] For each postcode, Statistics Canada assigns a socioeconomic decile based on the average income in the postcode. Thus, the BCLHD does not report income but instead reports this socioeconomic decile information.

consume any prescriptions in a given year. While around 38% of the entire sample faced a co-payment of less than CDN $4.48, the sample was evenly divided between the higher co-payment bands.

Table 7.2. Percent of sample exhibiting specific characteristics, 1992-2002

Variable	Elderly (N = 5,069,950)
RX co-payment <= $4.48	38.06
RX co-payment, $4.48 - $6.60	21.01
RX co-payment, $6.60 - $8.00	20.66
RX co-payment > $8.00	20.28
Age, 65 – 74	51.31
Age, 75 – 84	36.36
Age > 84	12.33
Male	43.37
Female	56.63
Socioeconomic decile = 1	24.09
Socioeconomic decile = 2	20.66
Socioeconomic decile = 3	18.67
Socioeconomic decile = 4	17.96
Socioeconomic decile = 5	18.62
Diagnosed with a major disease	48.55
Not diagnosed with a major disease	51.45

In terms of the age variables, slightly more than half of the sample is comprised of individuals less than the age of 75, while 36% are between 75 and 84, and a little more than 12% is older than 84. Not surprisingly, given that females have greater life expectancies, more than half of the sample is made up of women. The socioeconomic variables indicate that around a quarter of elderly PharmaCare recipients fall in the lowest socioeconomic quintile, and about a fifth of the sample falls in the second lowest socioeconomic quintile. The sample is divided relatively evenly between the higher socioeconomic quintiles.

An interesting finding is that 49% of the sample has been diagnosed with a major disease (hypertension, diabetes malignant cancer, chronic obstructive pulmonary disease, acute myocardial infarction, coronary heart disease, and stroke[10]). Thus, a relatively large proportion of the sample appears to suffer from a chronic condition, although this may be a reflection of the greater age of the sample.

[10] These prevalent, high cost diseases are identical to the ones used in the revised regression for the American elderly in Chapter 6.

In addition to examining the distribution of individuals with specific characteristics, we can also examine the relationship between the main variables of interest and the number of prescription drugs consumed. Since the decision to consume at least one prescription may be somewhat different than the choice of how much to consume, one important dependent variable to examine is the probability of obtaining a prescription. Conditional upon the individual having at least one prescription, we also looked at the number of drugs consumed. Table 7.3 provides descriptive information related to drug consumption.

The probability of obtaining a prescription drug increases somewhat when the individual is between the ages of 75 and 84 as opposed to being between the ages of 65 and 74. However, beyond the age of 84 the probability of obtaining a prescription actually decreases. Females exhibit a higher probability of obtaining at least one prescription drug. Interestingly, the likelihood of obtaining at least one prescription is relatively constant across socioeconomic groups. Another result that was not surprising was that individuals who have been diagnosed with at least one major disease have a much higher probability of acquiring a prescription medication than their healthier counterparts.

Table 7.3. Statistical information about the possible predictors of demand for prescription drugs, 1992-2002

Variable	Elderly sample (N = 5,069,950)	
	Prob. of at least one prescription	Number of drugs[a]
RX co-payment <= $4.48	N/A	20.84
RX co-payment, $4.48 - $6.60	N/A	14.56
RX co-payment, $6.60 - $8.00	N/A	15.43
RX co-payment > $8.00	N/A	17.97
Age, 65 – 74	82.10	14.21
Age, 75 – 84	82.76	18.58
Age > 84	77.82	25.18
Male	78.49	15.22
Female	84.36	18.45
Socioeconomic decile = 1	81.28	18.85
Socioeconomic decile = 2	81.84	17.05
Socioeconomic decile = 3	81.80	16.91
Socioeconomic decile = 4	81.86	16.30
Socioeconomic decile = 5	82.45	15.91
Diagnosed with a major disease	92.52	19.80
Not diagnosed with a major disease	71.71	13.83

[a]for an individual with at least one prescription and the defined characteristic, the mean number of prescriptions consumed

In terms of the descriptive results related to the number of prescription drugs purchased, a finding that was not surprising was that individuals with co-payments that were in the lowest 25th percentile had the highest consumption of medications. Another noteworthy finding was that individuals with the highest co-payments (above CDN $8.00) consumed more prescription drugs than individuals with co-payments between CDN $4.48 and $8.00.

As age increased the number of prescriptions obtained simultaneously increased even though the probability of obtaining a prescription decreased beyond the age of 84. In terms of gender, men consumed fewer prescriptions than women. Consumption of drugs decreased with socioeconomic quintile. Finally, those who were diagnosed with a major disease consumed more prescription medications than their healthier counterparts.

7.5.2. Results of the econometric analysis

This section includes information regarding the variables that were included in the models and the results of the estimation. Two of the variables were transformed into logarithms because they were highly skewed to the right: total prescription drugs obtained and the prescription drug co-payment. Because the fixed effects estimator performed better than pooled OLS, we did not include variables that were time invariant in the estimation, and subsequently the coefficient on gender is not reported. We also examined a number of interaction effects, for instance age and socioeconomic level and age and morbidity. As many of these interaction effects were significant, we provide an additional table in this section detailing changes to the elasticity value when interaction effects are added to the preferred specification.

A mentioned in Chapter 6, it is preferable to have instruments that predict the probability of prescription drug consumption but do not predict the number of drugs consumed for identification purposes. Given the restricted number of variables available in the BCHLD dataset, we were unable to find a suitable instrument for the first stage probits.

The results table includes the coefficient estimates from the main econometric specification as well as other potential model specifications. Only the results from the main variables of interest are reported in the table, and information related to the time variables, λ coefficients, and time averages from the main equation along with the results from the sample selection (first stage) equations is provided in Appendix Sections E.3 to E.4. Additionally, we provide information on the appropriateness of the model and the chosen variables in Appendix E.2.

To calculate the price elasticity of demand for the elderly population, we estimated the effect of a change in the co-payment on the number of prescription drugs obtained annually, holding all other factors constant. Table 7.4 lists the results of the fixed effects model that corrected for sample selection (SS FE or SS Fixed Effects), although we also ran a simple OLS model that did not account for the panel nature of

the data or sample selection[11] (Pooled OLS) and a fixed effects model that did not account for sample selection (FE or Fixed Effects).

Table 7.4. Estimates for the log of total number of prescription drugs obtained equation (elderly sample)[a,b,c]

Explanatory variable	Pooled OLS	Fixed Effects	SS Fixed Effects
(log) drug co-payment	-0.306[§] (0.002)	-0.167[§] (0.001)	-0.295[§] (0.002)
age between 65 and 74	0.188[§] (0.002)	-0.017[§] (0.001)	0.074[§] (0.002)
age between 75 and 84	0.358[§] (0.003)	0.010[§] (0.002)	0.141[§] (0.003)
second socioeconomic quintile	-0.041[§] (0.002)	0.002 (0.001)	-0.002 (0.002)
third socioeconomic quintile	-0.041[§] (0.002)	0.003[§] (0.001)	-0.002 (0.002)
fourth socioeconomic quintile	-0.053[§] (0.002)	0.001 (0.001)	-0.010[§] (0.002)
fifth socioeconomic quintile	-0.065[§] (0.003)	0.005[§] (0.002)	-0.007[§] (0.002)
individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease	0.458[§] (0.001)	0.165[§] (0.001)	0.188[§] (0.003)
individual died this year	-0.079[§] (0.003)	-0.418[§] (0.002)	-0.429[§] (0.003)
constant	2.696[§] (0.004)	2.427[§] (0.002)	2.095[§] (0.010)
N	4,071,186	4,071,186	4,071,186
R^2	0.122	0.043	0.060

[a]standard errors in parentheses; [b]excluded dummy variables are age greater than 84, individual lives in a postcode that is in the lowest socioeconomic quintile in British Columbia, individual has not been diagnosed with at least one of the pre-defined high-cost and/or high-prevalence diseases
[§]significant at the 5% level, *significant at the 10% level

In the cross-sectional model the coefficients on most of the variables, with the exception of the variable indicating that the individual died in the given year, were larger than in the panel data models. This suggests that the independent variables in the cross-sectional model were capturing individual-specific effects that were not included in the regression. An interesting result with regards to the co-payment variable was that the coefficient in the fixed effects model accounting for sample selection was similar to the coefficient in the cross-sectional model, while the coefficient in the fixed effects model that did not correct for sample selection was smaller in absolute value. In the preferred model (SS FE) the elasticity of demand for prescription drugs was –0.295 (p=0.000).

[11] In the cross-sectional model we controlled for repeated observations through clustering.

In terms of the other covariates in the model, in all of the specifications the age variables were negative and significant. The proxy for income, socioeconomic deprivation, was significant in the pooled OLS model and significant some of the time in the two fixed effects models. In the SS FE model, the effect of socioeconomic quintile was negative and significant for the highest two socioeconomic quintiles. Across all of the specifications, the variable indicating whether the patient had been diagnosed with one of the leading causes of death was positive and significant. In the preferred specification, the coefficient on this variable indicated that an ill individual consumes 20.68 percent more prescriptions on average than an individual who has not been diagnosed with one of these conditions. Finally, the variable indicating whether the individual had died in the studied year was negative across all of the specifications, indicating that the effect of an individual dying in the early months of the year and thus consuming less on an annual basis outweighed any increases in consumption observed immediately before death.

Although the time trends are not shown in the table (see Appendix Section E.4), there are some interesting findings related to time. Specifically, drug consumption decreased in 1994 and 1995 but increased in 1993 and in every year after 1995. All of the coefficients on the time variables were significant.

We also ran the preferred specification (SS FE) with a number of interaction effects as covariates. Table 7.5 provides the price elasticity results when different interaction effects are included.

Table 7.5. Price elasticity values when different interaction effects are added to the model

Interaction effect	Price elasticity
co-payment and morbidity	-0.298 (p=0.000)
socioeconomic deprivation and morbidity	-0.295 (p=0.000)
age and morbidity	-0.286 (p=0.000)

Table 7.5 indicates that with the exception of the interaction effect between age and morbidity, the interaction effects have a minimal impact on the price elasticity of demand. Even the age and morbidity interaction only decreases the price elasticity by about 3%.

7.6. Discussion

This final portion of chapter goes over the results from the empirical analysis. The purpose of this section is not to offer the policy implications of the analysis as these are discussed in Chapter 8. Instead, this section discusses the meaning of the results.

While there appeared to be a positive association between the co-payment and consumption in the raw American data, we observed the opposite relationship in the raw data from British Columbia. The likely reason is that prescription drug insurance among the elderly in the province is not endogenous as all individuals receive relatively generous public coverage when they turn 65.

An exploration of different possible models for the demand for prescription drugs indicated that the fixed effects model correcting for sample selection (SS FE) was the most appropriate. As a panel data specification was utilized, this implies that other unobserved individual-specific factors such as the wealth and preferences for care are important predictors of the demand for prescription drugs. In comparison with the cross-sectional model, nearly all of the coefficients on the independent variables decreased in the fixed effects models.

We determined that the elasticity of demand among the elderly is –0.295 (p=0.000). Thus, the price elasticity of demand for prescription drugs is relatively low for older people in BC, indicating that older persons in the province are not particularly sensitive to changes in the out-of-pocket prices of their medications. This is likely related to the fact that we measured consumption along the low end of the demand curve as total out-of-pocket payments were relatively low during the study period.

Nonetheless, the elasticity is somewhat higher than what we might expect for the elderly population. The marginal efficiency of investments in health is lower for the elderly than for younger population groups, which means that they must spend more on medical care to maintain their health. As discussed in Section 5.8 of the previous chapter, older people may also perceive fewer substitutes for prescription drugs. As a result, older people are likely to be less sensitive to changes in the out-of-pocket prices of prescription drugs than the general population.

There are only a few studies that calculated price elasticity values for the elderly at the microeconomic level (or included enough information for us to calculate elasticities), and all of these studies were confined to the US (Coulson and Stuart, 1995; Gardner et al., 1997; Klick and Stratmann, 2005) and Canada (Grootendorst and Levine, 2001; Grootendorst et al., 1997; Li et al., 2006). The price elasticity values ranged from -0.56 to 0.04, and our price elasticity value is in the range of those found in the literature, with the exception of the value of 0.04 calculated by Grootendorst and Levine (2001). The result from Grootendorst and Levine (2001) may have differed from ours because they could only examine the number of prescription drugs taken within the past two days. Thus, their sample of consumed medications may have been skewed towards those for chronic conditions, which might have biased the elasticity value.

In terms of the other variables that we used to predict the demand for prescription drugs, age, socioeconomic deprivation, and morbidity were important predictors of demand. The increasing effect of age on demand is interesting because it is in line with the results from the literature review in Chapter 3, Section 3.4. In that chapter we indicated that although age is likely to have a negative effect on consumption among

the elderly in the US, in other countries like Canada, the effect is likely to be in the opposite direction. In the United States, where unmeasured conditions in the insurance market (like pre-existing condition exclusions and limited lists) make insurance coverage less generous for seniors, the age variable may pick up these effects. In British Columbia, where before 2003 coverage was generous for all of the elderly regardless of income or health, there are unlikely to be unmeasured factors such as those in the United States that dampen the demand for prescription drugs.

The result for the socioeconomic deprivation variable was also interesting. In comparison to those living in postcodes in the lowest income quintile, those living postcodes with higher incomes consumed fewer prescription drugs, although this was only significant for those living in the top two quintiles. It is important to keep in mind that socioeconomic deprivation is an aggregate variable, and thus it may also be picking up regional effects that we cannot account for with the fixed effects regression. For example, individuals that live in the wealthiest postcodes may be less ill on average, and thus, there may be fewer pharmacies in the wealthiest areas.

Not surprisingly, there was a positive relationship between morbidity and the number of prescription drugs consumed, with ill individuals consuming about 20 percent more prescriptions than their healthier counterparts. Morbidity is a proxy for need, and thus we would expect that those who are sicker would have to consume more prescription drugs to maintain their health.

7.7. Conclusion

This chapter has presented an analysis of the demand for prescription drugs among older people in British Columbia. After covering the research questions for the analysis, we provided a description of the BCLHD and the variables that might be important predictors of prescription drug demand. We then developed an econometric specification to model the effect of the co-payment on the number of prescription drugs consumed.

The results of the SS FE model indicated that the co-payment variable was negative and significant at -0.295 ($p=0.000$). Elderly individuals are relatively insensitive to out-of-pocket prices for prescription drugs in the province. Another significant predictor of demand was age, which was positive, suggesting that individuals must consume more medical care as they age to maintain their health. Meanwhile, the socioeconomic decile variable was negative and significant, perhaps because of unmeasured variables related to less deprived socioeconomic areas. Morbidity, as a proxy for need, was also an important positive predictor of the demand for prescription drugs.

As with any analysis, there are limitations that need to be kept in mind. One limitation that also existed with the MEPS analysis was our inability to use count variable techniques for the number of prescription drugs obtained. We instead assumed that the individual could theoretically consume an infinite number of prescriptions. To

determine if the outcome differs, future research could employ count variable techniques for the dependent variable when these become available.

Another limitation that we also faced in the MEPS analysis is that we could not determine whether PharmaCare recipients complied with their drug therapies. Non-adherence to medication regimes can have significant consequences for the health of the elderly and measurement of this problem is important for policymakers. However, measuring adherence can be difficult and costly, and as a result, the major datasets that include prescription drug consumption do not include information on adherence.

There is also a question of whether cost sharing decreased the use of inappropriate medications, appropriate medications, or both among older people. There can be an improvement in the medication-related quality of care if higher cost sharing decreases consumption of inappropriate medications. If cost sharing has the opposite effect, though, there may be a decrease in quality. Information regarding the relationship between cost sharing and inappropriate medication use could be useful for policymakers if they wanted to tailor prescription charges according to the appropriateness of pharmaceutical treatments.

Chapter 8: Comparison of results and policy implications

8.1. Introduction

Beyond the research results it is important to discuss the implications of these results in a policy context. The results from the meta regression and the American and Canadian analyses are particularly interesting in light of the literature review, which highlighted the significant range of price elasticity values that exists there, because our results are within a smaller range. Our work implies a relatively inelastic demand for prescription drugs, which has a number of policy implications for health systems in general in addition to the specific implications for the United States and British Columbia.

As pointed out in Chapter 1 of this dissertation, the price elasticity of demand has traditionally been evaluated from a neo-classical economic perspective that assumes that consumption greater than the equilibrium quantity in a free market is over-consumption. This perspective is useful for quantifying the relationship between price and quantity demanded while controlling for other covariates. It is also valuable if we assume that health care has the same value to society as other consumer goods and services. But health policymakers generally employ a different definition of efficiency (what we deem as "health care efficiency" or "health policy efficiency"[1]) than neo-classical economists (who often use Pareto efficiency[2] to mean efficiency). Moreover, the two definitions are not always compatible. Thus, it is important to provide a distinction between both types of efficiency and to discuss the implications of both within the economic and policy realms.

The primary purpose of this chapter is to bring together the results from each of the estimations and to offer a cohesive policy analysis of the results. In Section 8.2 we discuss why the results differ across specifications. Then we consider the findings in terms of the insurance and moral hazard literature in Section 8.3. As highlighted in the previous paragraph, there is a disconnection between the economic and health care definitions of efficiency, and this distinction is discussed in Section 8.4. As equity is also an important policy goal (Le Grand, 1991; Lindbladh et al., 1998), we provide a comparison of Pareto and health care efficiency and equity in Section 8.4. In Section 8.5 this general discussion of the issues surrounding equity and efficiency allows us to then cover the policy implications of our price elasticity estimates, not only in broad terms but also with specific reference to the United States and British Columbia. Finally, Section 8.6 wraps up the economic and policy discussions.

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[1] Although a detailed definition of "health care efficiency" / "health policy efficiency" is given in Section 8.4, briefly, it is an allocation of resources that maximizes health gain (Williams, 1997).

[2] As defined earlier in Chapter 2, Pareto efficiency is an allocation of resources that cannot be changed to make one individual better off without simultaneously making another feel worse off (Reinhardt, 1992). Some argue that the Kaldor-Hicks compensation principle is a more useful principle of efficiency as Pareto efficiency can be difficult to achieve in practice. However, within the moral hazard literature, efficiency has explicitly or implicitly been defined as Pareto efficiency (see for instance, Pauly, 1974). Thus, we employ Pareto efficiency as the working definition for this thesis as this concept has influenced cost sharing policies in the medical care sector, particularly in the United States.

8.2. Comparison of results from the meta-regression, the United States, and British Columbia

While it is difficult to directly compare the results from the meta-regression analysis and the American and Canadian analyses because the context of each sample (e.g. policy environment) is disparate, it is still interesting to offer a general discussion related to the various findings. Table 8.1 lists the price elasticity values that we obtained from each model. For comparison purposes we provide the meta-regression elasticity estimate based on non-aggregate data as both the American and Canadian estimations were run on non-aggregate datasets.

Table 8.1. Price elasticity values obtained from Chapters 4, 6, and 7[a]

Country/Region	Population	Elasticity value
Australia, Belgium, Canada, Italy, the Netherlands, Spain, United Kingdom, United States	different population groups are represented in different samples from each country	-0.156 (p=0.181)
United States	all individuals above the age of 17	-0.250 (p=0.000)
United States	all individuals 65 and older	-0.108 (p=0.172)
United States	all individuals with income below 200% of the Federal Poverty level	-0.199 (p=0.000)
British Columbia, Canada	all individuals 65 and older	-0.295 (p=0.000)

[a]p-values in parentheses

To shed further light on the differences between elasticity values in Table 8.1, Table 8.2 provides the results from pairwise comparisons of the differences in elasticities (based on the student's t-test).

Table 8.2. T-test comparisons of price elasticity values obtained from Chapters 4, 6, and 7[a]

	MRA	US – general population	US – elderly	BC - elderly
US – general population	-3.96 (p=0.079)	-	-	-
US – elderly	2.02 (p=0.146)	-257.8 (p=0.001)	-	-
US – low-income	-1.81 (p=0.161)	134.9 (p=0.002)	-141.7 (p=0.002)	-
BC - elderly	-5.85 (p=0.0544)	-346.3 (p=0.001)	-349.3 (p=0.001)	-270.4 (p=0.001)

[a]The t-values are listed in the table along with the associated p-values in parentheses

The white cells in Table 8.2 each represent the result of a student's t-test for the comparison of two price elasticity values. For instance, the cell that is the intersection of the second row and second column of the table indicates the t-value from comparing the price elasticity value from the meta-regression analysis and the price elasticity value from the US analysis on the general population. Interestingly, Table 8.2 indicates that most of the estimated price elasticity values are different from each other with the exception of the meta-regression elasticity value and the US elderly and low-income estimates.

The differences between the elasticity values for the three main sub-populations in the United States were already discussed in Chapter 6, so the nuances of the US findings will not be discussed again here.

8.2.1. Comparison of meta-regression and US results

The price elasticity value for the US general population is twice as high as and significantly different from the meta-regression estimate. In comparison with populations in other developed countries, adults in the United States generally face higher cost sharing for prescription drugs, and thus elasticity values among the American population are probably measured at higher points on the demand curve.

The fact that the US estimate is higher is interesting, not the least because Americans face substantially higher cost sharing for prescription drugs than individuals in most other developed countries. Thus, we might have expected an even higher elasticity value for the American general population. Other cultural and institutional factors in the United States may contribute to a lower estimate. For example, since a substantial portion of health care financing in the country is private, Americans may take more of a role in health care decision-making because inappropriate decisions are more financially costly. That is, most Americans face substantial cost sharing for physician and inpatient visits in addition to prescription drugs. As a result, Americans may actually be less sensitive to price than we would expect given their high out-of-pocket burden; they may place a higher value on the medications they have already chosen to consume in comparison with patients in other countries where the self-care movement is less developed.

As part of consumer-driven health care, direct-to-consumer advertising (DTCA) might also be an important influence because DTCA may help patients feel that they have more of a stake in their prescription decisions, may positively influence perceptions of advertised medications, and may increase the population that seeks treatment for advertised conditions. The movement towards tiered formularies also could be an important contributor to this low elasticity estimate. Although the evidence has indicated that tiered formularies do still lower overall drug consumption, patients appear to switch to generic and preferred drugs within the formularies (Gleason et al., 2005), implying that volume reductions may be less severe than under other cost sharing designs.

A final reason for the US general population estimate that seems to be lower than we might expect is the changes in the structure of health care management and delivery in the United States. That is, the rise of managed care as a major force in the American health care system may have had a dampening effect on the demand for prescription drugs. This is because managed care controls the supply of medicines more tightly now through pharmacy benefit managers and formularies.

The price elasticity estimate for elderly Americans is slightly lower than the meta-regression price elasticity, although this difference is not significant. This is an expected result given that older patients have less time in which to implement lifestyle changes to improve their health. Other options, such as surgery, may be less appealing because of the costs and the associated risks. Indeed, with the exception of one value of -0.559 (Klick and Stratmann, 2005), all of the price elasticity values used in the meta-regression sample were less than -0.20. The Klick and Stratmann (2005) value was likely higher than the true value for the elderly population because they restricted their sample to Medicare recipients without employer-sponsored insurance or Medicaid, and the resulting sample was likely more price-sensitive because they faced the highest co-payments. Additionally, Klick and Stratmann (2005) did not control for unobserved heterogeneity, and omitted variable bias may have influenced the magnitude of their elasticity estimate.

Meanwhile, the price elasticity value for low-income Americans was higher than the meta-regression result, but it was not significantly different from the MRA value. Interestingly, all of the values for low-income populations from the meta-regression were less than -0.20, with the exception of one elasticity estimate (-0.40) from Van Doorslaer (1984). We might expect the low-income population to be more sensitive to changes in out-of-pocket prices for medications than the general population because low-income groups have less disposable income available for medical and pharmaceutical treatment. However, in most developed countries, including the United States, there are substantial subsidies and even exemptions related to prescription drugs for low-income groups. This measurement of cost sharing at the low end of the demand curve is a likely reason for the lower elasticity estimates among the poor, both in the meta-regression sample and the US sample. Yet, the US price elasticity estimate for the low-income group is still slightly higher than almost all of the estimates from the meta-regression sample. Our elasticity estimate is also higher than the two American estimates from the meta-regression, which were -0.05 (Soumerai, 1987) and -0.14 (Martin and McMillan, 1996)[3]. The likely reasons for our larger US estimate are that (i) Medicaid coverage varies widely between states as highlighted in Chapter 5 such that coverage may be insubstantial or non-existent for a number of low-income individuals, (ii) the calculated estimates from Soumerai (1987) and Martin and McMillan (1996) were for chronically ill patients or high users of prescription drugs who are likely more insensitive to out-of-pocket prices out of necessity, and (iii) the Soumerai (1987) estimate was for the low-income elderly who we expect to be more price insensitive for reasons previously discussed.

[3] Both of these elasticity values were calculated by the author of this dissertation because the original authors did not provide elasticity estimates.

8.2.2. Comparison of meta-regression and BC results

The difference between the meta-regression result and the price elasticity value for the older population in British Columbia is also worth discussion. The BC estimate is higher than the MRA result, and the difference is significant at the 10 percent level, which is somewhat surprising given that we expect the elderly to be more insensitive to price. Furthermore, out-of-pocket prices for the elderly in BC were low during the period studied (1992-2002), and the populations from which the MRA results were drawn generally faced higher cost sharing than elderly British Columbians. However, another aspect of the Canadian health care system may be having an important influence on the elasticity estimate. In particular, as discussed in Chapter 5, all core medical services in British Columbia are free of charge for MSP beneficiaries, although there are significant waiting times for some services. Given the higher price elasticity value, it is likely that the effect of free care outweighs the effect of waiting times. Thus, it could be that elderly British Columbia residents are substituting physician and inpatient care for prescription drugs when faced with higher cost sharing amounts. In fact, Li et al. (2006) found positive cross-price elasticities between prescription drugs and physician visits in British Columbia during the 2002 policy change which increased patient co-payments for prescription drugs.

8.2.3. Comparison of US and BC results

If we also compare the price elasticity values from the elderly populations in the US and BC, there are interesting inferences. An important point to make is that the American and British Columbian samples may have consisted of different types of respondents. Specifically, the US sample excluded institutionalized elderly individuals, while the British Columbia sample did not exclude any residents. However, institutionalized individuals in the British Columbia sample would likely have purchased medications from their institution rather than a pharmacy, and thus these medications would not be included in the PharmaCare database (as the PharmaCare database covers prescriptions dispensed from pharmacies in BC).

The price elasticity value from British Columbia is larger than the American (elderly) estimate, and statistically there is a significant difference between the two values. This is surprising because we would expect the US estimate to be higher than the BC estimate as Medicare did not offer an outpatient prescription drug benefit during the study time period of the American analysis (1996-2004). This means that older Americans sometimes faced substantial out-of-pocket costs for their medications. However, there may be other cultural factors at play, including greater patient involvement in health care decision-making in the United States and DTCA. The influence of these two factors has been discussed in Sections 8.2.1 and 8.2.2 and will not be repeated here. In addition, the ability of elderly residents in British Columbia to substitute free inpatient, outpatient, and physician care for prescription drugs may also have been an important factor in the higher BC estimate.

8.2.4. Comparison of US results, BC results, and results from the literature review

Another interesting exercise is to put the results of the analyses from this dissertation into the context of the literature. Table 8.3 lists the elasticity values from this dissertation and the ranges of elasticity values that we obtained in the literature review.

Table 8.3. Non-aggregate price elasticity values from the literature review and this dissertation

Source	Population	Outcome variable	Price elasticity
Literature review	All groups	Medical care	-0.20 to -0.10
	All groups	Inpatient care (admissions)	-0.85 to -0.04
	All groups	Physician and outpatient care	-0.51 to -0.01
	General population	Prescription drugs	-0.58 to -0.02
	Elderly and chronically ill	Prescription drugs	-0.56 to 0.14
	Low-income population	Prescription drugs	-0.20 to -0.05
This dissertation	General population	Prescription drugs	-0.25 to -0.16
	Elderly	Prescription drugs	-0.30 to -0.11
	Low-income population	Prescription drugs	-0.20

In comparison with the elasticity values found for medical care, inpatient services (note that we only include elasticity values for inpatient admissions), and physician and outpatient services, the price elasticity values that we obtained seem to fall at the lower end of these ranges. Our estimates are also close to those obtained from the RAND experiment, which ranged from -0.20 to -0.10 (Manning et al., 1987). Thus, it may be that patients are not any more sensitive to changes in the prices of prescription drugs than to changes in the prices of other types of core medical services. This is in contrast to Pauly (1968) as he hypothesized that elasticity values should differ between various forms of medical care. The contrasting results may be due to advances in medicine that have occurred over the last 30 years: prescription drugs can now improve health for patients suffering from a number of different chronic conditions, such as hypertension, migraines, and osteoporosis, among others. Previously, inpatient and physician care may have been more important than prescription drugs.

Our estimates also fall within the ranges from the literature for the general population and the elderly, although given the wide range of estimates from the literature, this is not unlikely. There were only a few estimates at the microeconomic level for the low-income population from the literature. Our price elasticity estimate was in range of these estimates, although it was at the high end of this range.

8.3. Neoclassical economic theory and the results

Given the insurance-related problem of moral hazard and its relationship to the elasticity of demand, it is important to place all of the price elasticity results in an economic context. As discussed in more detail in Chapter 2, neo-classical economists see moral hazard as a Pareto efficiency problem; that is, because patients with insurance coverage obtain prescription drugs that have a negative net marginal benefit, there is a welfare loss. Yet, the other extreme where there is no insurance is also not Pareto efficient given that consumer welfare can be improved by purchasing health insurance. Although there is no first-best outcome in this situation, economists have posited that an outcome somewhere in between these two extremes is ideal (Cutler and Zeckhauser, 2000).

Thus, two questions arise from this discussion: (i) do consumers reduce their consumption when faced with higher user fees, and (ii) if so, to what extent do they reduce their consumption?

8.3.1. The relationship between cost sharing for prescription drugs and consumption

The relationship between prescription charges and the volume of medications purchased has been extensively addressed in the literature on cost sharing for prescription drugs, and there is clear evidence of a downward-sloping demand curve for prescription medications. Furthermore, with the exception of the finding for elderly Americans, the results from Chapters 4, 6, and 7 also confirm what has been found in the literature: individuals reduce their consumption of prescription medications when faced with higher user fees. The finding of no relationship between cost sharing for prescription drugs and volume among older Americans has already been discussed in Chapter 6 and Section 8.2 of this chapter.

8.3.2. The extent to which prescription charges reduce consumption

A number of authors have attempted to address the second question, but the findings have varied widely. One reason for the variance in the literature, though, is that the extent to which consumers reduce their consumption is crucially dependent on the context. For example, the sensitivity of older individuals to price changes is different than the sensitivity of younger individuals to price changes. The price elasticity of demand is also likely to differ substantially between different types of medications, depending on consumer perceptions of medication necessity, the availability of other substitutes, side effects, and other related aspects. Another reason for this variance may be the robustness of estimates; that is, few studies accounted for important factors such as unobserved heterogeneity, sample selection, and endogeneity (where appropriate). Because of this variance in price elasticity estimates and because many of the robust estimates (for instance, from the RAND study) are outdated or for specific populations, there was a need for more recent and robust estimates for the general population that could elucidate the moral hazard problem. There were also few comparisons of estimates between different age and income groups within a country and across countries.

The resulting estimates from this analysis were between -0.25 and -0.20 for the general population, between -0.30 and -0.11 for the older population (although as the estimate of -0.11 was not significant, the upper range of elderly estimates was essentially 0), and -0.20 for the low-income population. The reasons for these varying estimates have already been covered in Section 8.2 of this chapter, but the fact that all of the values were less than -0.31 is interesting from an economic standpoint. The average person from each of these samples is not particularly sensitive to changes in out-of-pocket prices, implying that the perceived marginal benefits of most of the medications that these patients were taking outweighed the marginal costs (from the perspective of the individual). This result is relatively consistent across the different population groups.

In terms of Pareto efficiency, all of these results, with the exception of the American estimate for the elderly, indicate that moral hazard does exist, although it is not very extensive for prescription drugs. Our findings therefore imply that there is a relatively small welfare loss (by neo-classical economic standards) for prescription drug coverage. Therefore, moral hazard is unlikely to be a driving force behind pharmaceutical expenditure increases in developed countries. Because we do not have corresponding information on premiums for these populations, it is not possible to determine the optimal premium and coinsurance rates according to the neoclassical economic theory, but this would be an interesting exercise for the future.

As pointed out in Chapter 2, there are alternative theories of moral hazard within the health care arena. Rice (1992) argues that the demand curve does not accurately reflect willingness to pay, but for reasons discussed in Chapter 2, we believe that the demand curve can still be used as a tool to measure preferences. Nyman (1999), however, presents an alternative framework for measuring the welfare effect of moral hazard. His main point is that the traditional economic theory may overestimate the welfare loss of insurance because it does not consider the income transfer that insured individuals receive when ill. In particular, because we are unable to fully account for this income transfer, our analysis likely overstates the true elasticity value. The degree of this bias, however, depends on the income elasticity of demand and the percentage of the individual's budget that out-of-pocket health care spending comprises and thus will differ across subgroups within a population. Nonetheless, Nyman's (1999) framework does not change our interpretation that all of the groups that we considered in this dissertation were relatively insensitive to price.

A more interesting implication of Nyman's (1999) framework is that the welfare loss of prescription drug insurance is likely relatively small (or even positive) given our price elasticity estimates. This is because Nyman accounts for improvements in access to prescription drugs and other goods brought about by insurance. Moreover, Nyman does not consider the effect that insurance companies have on prescription drug prices. That is, insurance companies have substantial negotiating power such that they pay

significantly lower prices for medications than uninsured patients (Frank, 2001)[4]. This likely offsets some of the moral hazard effect of insurance. Although it is impossible for us to calculate the net welfare effect of insurance under Nyman's framework, it does appear that the welfare loss of insurance would be relatively small. There may even be a welfare gain for the elderly population in the United States given the insignificant elasticity estimate for this group.

8.4. Health care efficiency, equity, and the results

The economic perspective is useful for quantifying the relationship between cost sharing for prescription drugs and demand, and it also provides insight into the covariates that determine this relationship. The problem is that some policymakers have different objectives for the health system that may actually contradict the goals of economic theory, where health systems are primarily concerned with issues such as improving the overall health of the population, containing costs, and improving equity (Le Grand et al., 1998; Lindbladh et al., 1998)[5]. As these differing objectives determine the interpretation and relevance of the elasticity values for health systems, it is important to provide definitions and a discussion of efficiency and equity. In this section we also discuss the elasticity results from this dissertation in light of efficiency and equity.

8.4.1. Background on efficiency and equity

A useful exercise is to provide a discussion of how efficiency and equity are defined in this dissertation and the meaning of efficiency within neo-classical economics and policy evaluation. Specifically, we are interested in examining the conflict between neo-classical economists' perceptions of efficiency and health policymakers' perceptions of efficiency. This highlights the importance of providing clear definitions for a cohesive policy discussion.

Although there are different types of efficiency (for instance technical and productive), the definition often implied by economists for efficiency and the one most useful to our discussion is one of Pareto efficiency. Pareto efficiency was defined in Chapter 2 and discussed in Section 8.3 of this chapter. As a corollary to Pareto efficiency, economists sometimes assume that increasing the production of one commodity while holding the production of another commodity constant or even increasing production of both commodities will be a welfare improvement for society (Reinhardt, 1992). Yet, this definition of welfare depends on resources being allocated to those who are willing and able to pay, a concept that may be unrelated to health. The implication is that the neo-classical concept of efficiency may be unrelated to social welfare from an ethical standpoint and of limited use to policymakers who want to enhance population health given a fixed budget. Because we want to consider our price elasticity results from a policy stance, we employ the use of "health care efficiency", a concept that is

[4] For instance, pharmacy benefit managers (PBMs) can steer patients towards specific brands through the use of formularies, giving the manufacturer an incentive to be included in the formulary. This gives the PBM more power to negotiate a lower price.

[5] Improving quality and expanding choice are additional objectives that policymakers may consider.

different from efficiency in a neo-classical sense. We define health care efficiency as an allocation of resources that maximizes health gain, where health gain is measured in a standardized manner (for instance, through years of life lost or quality-adjusted life years) (Williams, 1997).

Another important objective in some health systems is equity as many policymakers view health differences as unfair or unjust (Macinko and Starfield, 2002). Three common principles of equity are (Oliver and Mossialos, 2004):

- Equal access to health care for those in equal need of health care,
- Equal utilization of health care for those in equal need of health care, and
- Equitable health outcomes (for example, measured by quality adjusted life years, morbidity, or mortality), also known as equity in health.

Equal access to health care for those in need of medical care requires circumstances in which individuals with equal needs have equal opportunities to access health care (horizontal equity), and as a corollary, individuals with unequal needs have appropriately unequal opportunities to access health care (vertical equity) (Oliver and Mossialos, 2004). This is not to imply that given an equal playing field, all individuals will make equal use of health care resources; there are acceptable reasons such as preferences for care or risk aversion for not making use of available resources.

Equal utilization of health care for those in equal need requires circumstances in which those who are in equal need of health care actually make equal use of health care (Oliver and Mossialos, 2004). This principle requires policymakers to take an even stronger stance than the first definition of equity because policymakers would need to override the potentially acceptable reasons for not making use of health care.

The third definition of equity, equal health outcomes, requires the most proactive efforts from policymakers as they would have to provide conditions for all patients to achieve the same health outcomes (Oliver and Mossialos, 2004)[6]. In fact, the third definition of equity is undesirable in that policymakers would have to severely restrict the ways in which people choose to live.

Given that the equal access for equal need definition is the least restrictive to individual choice, this would at first blush seem to be the most useful definition to adopt in this dissertation. The problem is that measuring access is not straightforward as it encompasses the opportunities open to people to obtain care. Yet, the literature and policymakers have often taken equal access for equal need as the working definition of equity, the implication being that utilization is a proxy for access (Wagstaff and Van Doorslaer, 2000). While access to treatment and receipt of treatment are argued to be different (Wagstaff and Van Doorslaer, 2000), for policy analysis it makes sense to use a definition of equity that is generally more accepted by

[6] A similar but less restrictive definition of equity is equitable health outcomes, which would allow for some inequity, for instance because of free choice.

policymakers. Thus, we employ "equal access for equal need" as the definition of equity in this dissertation[7].

Within the characterization of equity, there is also a need to define the terms "access" and "need". At a general level access to care can be defined as involving the capacity to acquire a specified set of health care goods and services at a defined level of quality that is conditional on a specified maximum out-of-pocket cost and personal inconvenience and a specified level of information (Goddard and Smith, 2001). The word "specified" in the definition allows policymakers to tailor access to their own country- or region-specific circumstances as the feasibility of access levels may differ between areas. The importance of this definition is that it elucidates some of the important factors that need to be considered for the improvement of access, for instance, the necessary minimum level of information inconvenience, disutility, time and financial costs of obtaining services, and the appropriate range and quality of health care services available (Oliver and Mossialos, 2004).

Meanwhile, there is less agreement on the definition of need, although two components of need stand out as being important: (i) the state of the patient's pre-treatment health where poorer health implies greater need (generally the clinical definition), and (ii) the patient's capacity to benefit from treatment where the amount of health care resources needed to exhaust the individual's capacity to benefit governs the extent of their need (generally the health economics definition) (Oliver and Mossialos, 2004). Unfortunately, these two aspects of need may be conflicting in that treatments for patients who have the most debilitating illnesses are not always available, and there is a need for a more cohesive definition of need. For the purposes of this dissertation where we are taking an aggregate view of the sample when running regressions, the first component of need is more relevant.

On both the supply and demand sides of the health care market, there are important factors that influence equal access for equal need. On the supply side, the availability of health care resources within a given area determines the ease with which patients can access necessary health care. More relevant to this dissertation is the demand side, particularly the patient's ability to pay for health care. Other important demand-side factors are cultural beliefs, knowledge, information, and preferences, some of which we could control through covariates and some of which we could control through a fixed effects approach.

As highlighted by others such as Williams (1997) and Le Grand (1990), researchers often speak of a trade-off between efficiency (whether it is Pareto efficiency, health care efficiency, or an alternative definition of efficiency) and equity[8]. Specifically, the

[7] Our intent is not to argue or imply that equal access for equal need is the most appropriate definition of equity. Others such as Le Grand (1991) and Wagstaff and Van Doorslaer (2000) have offered detailed discussions of equity and related concepts, and we refer the reader to these publications.

[8] Le Grand (1990) argues that there are two types of equity and efficiency trade-offs. One trade-off concerns values and the other concerns production. We refer the reader to Le Grand (1990) for a distinction between the two, but in this dissertation we are concerned with discussing the equity and efficiency trade-off as it relates to production. That is, we are more interested in the feasibility of different policy alternatives in terms of equity and efficiency.

achievement of Pareto or health care efficiency may exacerbate inequities[9], mainly depending on how the gains from efficiency are distributed. That is, economists may deem an insurance policy with coinsurance for medical services as more efficient (Cutler and Zeckhauser, 2000)[10], but this policy may not enhance social welfare from a policymaker's standpoint. The reason is that the chronically ill and the poor may be unable to pay for their medications under a coinsurance regime, although their medications may be necessary from a medical standpoint. This could potentially create social tensions between the rich and the poor and the healthy and the unhealthy. In a similar vein, allowing individuals to purchase private supplementary insurance may be efficient from a health care efficiency standpoint, but this policy will exacerbate existing inequities as private insurance coverage is related to health and wealth. Acknowledging the trade-offs between these three definitions is important because if we only assess the effect of prescription charges from one of these angles, the applicability of the analysis to policy will be limited.

8.4.2. Relevance of price elasticity estimates for efficiency and equity

The neo-classical economic implications of our price elasticity estimates have already been discussed in Section 8.3, but the implications of the estimates in terms of health care efficiency and equity are considered in this section. For the relationship between prescription charges and health care efficiency, we inevitably need to determine whether implementing or raising user fees has any effect on population health. We can measure the effect of user fees for prescription drugs on health through different routes. The direct method is to simply measure the relationship between prescription charges and defined measurements of health, such as mortality, morbidity, or other specific outcomes like blood pressure levels. A second indirect method to proxy health is to investigate whether patients stop purchasing medications that are unnecessary for their well-being, and a third method is to analyze whether patients reduce their consumption of inappropriate medications. However, the aggregate effect of these two possibilities depends on whether there is a simultaneous reduction in appropriate medications that is of equal or greater magnitude. A fourth option is to measure the relationship between prescription charges and adherence. Empirically investigating all of these possibilities is beyond the scope of this dissertation, and some of these considerations have already been addressed in the literature (see Appendix B).

In addition, there is another indirect method for measuring the effect of cost sharing on health care efficiency. Specifically, we can consider whether cost sharing has a differential impact on consumption for various population groups and hypothesize

[9] There is debate in the literature regarding the existence of an equity-efficiency trade-off, but the arguments often hinge upon the specific definition of efficiency employed. For instance, it would be more difficult to make the case for an equity and efficiency trade-off if our working definition of efficiency was the Kaldor-Hicks compensation principle, which posits that a reallocation of resources is a social improvement if the gainers from the move can compensate the losers from the move and still remain gainers (Kaldor, 1939). For more discussion of these matters, see Le Grand (1990; 1991).

[10] Economists such as Cutler and Zeckhauser (2000) argue that an insurance contract with cost sharing is second-best as there is a trade-off between the welfare loss of insurance (due to moral hazard) and the benefits of greater risk sharing across beneficiaries.

whether reductions in prescription consumption would be more detrimental among certain groups. Our finding related to the low-income subgroup does shed some light on the health care efficiency issue. We found that the price elasticity of demand among the low-income population was actually less than the price elasticity of demand for the general population. Given that the low-income population tends to be unhealthier than the general population and thus may be more in need of pharmaceutical treatment, it is somewhat alarming that these individuals are still sensitive to changes in out-of-pocket prices, even if some of them are partially protected from user fees by Medicaid. The implication is that imposing prescription charges on this subgroup may lead to a decline in their overall health, a hypothesis that was partially confirmed by the RAND experiment for general medical services (Rice and Morrison, 1994).

At the other extreme, the price elasticity of demand for the older population was not significantly different from zero in the US analysis but around -0.30 in the British Columbia analysis. Older people may be at least as medically needy as the poor, and at least in BC they appear to be sensitive to changes in prescription drug prices. Given that pharmaceutical treatment increases in importance with age, there may be negative health care efficiency implications related to user fees, at least in British Columbia[11]. In contrast, the insignificant estimate in the United States implies that demand-side cost sharing may have little effect on health among US seniors.

The relationship between user fees and equity is also something that we can partially discuss in the context of our results. The finding that the price elasticity of demand is relatively small implies that a cost sharing policy shifts expenditures from the third-party payer to the patient, as the decline in consumption is less than proportionate (in absolute value) to the increase in price. Indeed, evidence regarding the relationship between cost sharing for prescription drugs and out-of-pocket expenditures confirms that user fees increase individual expenditures (Alan et al., 2005). The fact that the price elasticity of demand among low-income Americans was even lower than among the general population implies that, at least to some degree, prescription charges among this group reflect expenditure shifting from the government and private insurers to patients. Although it is true that the poorest Americans generally receive prescription medications at little cost from Medicaid, the magnitude of this elasticity value implies that Medicaid cost sharing is not significantly reducing what policymakers deem "unnecessary consumption"; instead it is shifting the burden of payment to beneficiaries.

This raises important equity issues if the cost sharing policy does not protect the poor and heavy users of prescription drugs as they will bear the largest burden of this revenue transfer. Although there are no empirical studies of inequities in access to prescription drugs, there is research on inequities in access to medical care (Van Doorslaer et al., 2006; Van Doorslaer et al., 2000). Van Doorslaer et al. (2006) found

[11] Of course, if cost sharing led patients to decrease their use of inappropriate medications, there could potentially be an improvement in health care efficiency. Evidence suggests otherwise, though, as patients are generally unable to distinguish between necessary and unnecessary treatments and reduce consumption of both when faced with user fees (Foxman et al., 1987; McManus et al., 1996).

that the highest pro-rich inequities for GP visits are typically in the United States and Mexico, the only two countries without universal health insurance that they surveyed. There also appears to be a significant pro-rich bias for specialist services, but the evidence regarding inpatient care is mixed (Van Doorslaer et al., 2000). Based on this evidence regarding other medical services, it is likely that significant inequities in access to prescription drugs exist as cost sharing for prescription drugs is generally more prevalent than for other medical services. Nonetheless, there is a clear need for more research to quantify the inequities.

8.5. Policy implications

The previous two sections discussed cost sharing for prescription drugs in terms of economic efficiency, health care efficiency, and equity without offering guidance for policymakers. The perspective that policymakers take, whether it is one focused on economic efficiency, health care efficiency, and/or equity, determines the intrinsic value of the price elasticity estimate for that specific health system. Based on these different perspectives, we raise a number of policy issues related to our findings from the literature review and from the empirical analysis. We begin with an overall developed health systems perspective and then take a narrower view and discuss the policy issues relevant to the United States and British Columbia.

8.5.1. General policy implications

Since the original premise of cost sharing for medical services is based on economics, one place to start with the analysis is the policy implications from an economic perspective. While it is likely that the welfare loss of prescription drug insurance is relatively low due to the relatively small price elasticity values (see Section 8.3), other aspects of insurance such as the reduction in uncertainty regarding future income and the ability of insurers to negotiate deep discounts for prescription drugs are welfare gains to consumers. The extent to which the welfare loss of increased consumption is reduced by the gain from guaranteed future income and lower drug prices is unclear and a question that is beyond the scope of this dissertation. However, if we assume that there is a welfare loss of insurance based on estimates of the price elasticity, the implication is that at least among the general and low-income populations, third-party payers need to impose some form of cost sharing to reduce the negative effects of this welfare loss.

As discussed in Chapter 2 and Section 8.3 of this chapter, if we instead take Nyman's (1999) point of view, there may be little or no welfare loss associated with insurance, particularly if we add in the gain from lower drug prices to his model. Hence, other demand- and supply-side measures to contain expenditures may be preferable to cost sharing. Nyman (1999) also points out that the traditional economic theory predicts that patients will reduce their consumption of both effective and ineffective prescription drugs when out-of-pocket prices rise. This implies that even according to the economic theory, cost sharing is a blunt instrument. Thus, from this perspective third-party payers may consider offering full insurance coverage for prescription

drugs and using other mechanisms to influence potentially inappropriate or unnecessary consumption.

Shifting away from the traditional economic perspective, perhaps the most important question to consider when evaluating user fees from a policy perspective is whether patients are the appropriate target for reductions in demand. Given that patients delegate prescription decisions to medical practitioners, there is little reason to believe that the patient is more knowledgeable than the physician regarding the appropriateness of prescriptions. The fact that inappropriate medications are still prescribed even after multiple articles in the literature have highlighted these problems (see for instance, Beers et al., 1991 and Zhan et al., 2001) is alarming and indicates that more should be done to target inappropriate prescribing by physicians. Perhaps the smartest strategy would be to target those who research, manufacture, prescribe, and dispense drugs. Clinical guidelines from third-party payers or other professional organizations, whether mandatory or recommended, are an important start. Other mechanisms such as drug utilization reviews and electronic prescribing systems to alert pharmacists to potentially inappropriate medications are additional possibilities.

In addition, it is important to ask whether physician and pharmacist incentives are appropriately aligned. For instance, pharmacists may have an incentive to dispense more expensive medications if their revenue is based on a percentage of the prescription cost. The political economy of health systems does not make these suggestions attractive options for policymakers, but in the light of our analysis, it appears that these other measures should at least be considered in lieu of demand-side cost sharing. It is important that these possibilities are openly debated within the health care system.

Furthermore, improvements in medical technologies (including drugs) leading to wider use are generally acknowledged to be the main drivers of health expenditures (Newhouse, 1992). New prescription drugs can increase expenditures by expanding the population that can receive treatment (for instance, when drugs for previously untreatable conditions become available) and allowing treatment for secondary diseases within a disease (for instance, erythropoietin can treat anaemia in dialysis patients) (Rettig, 1994). The recent increase in the use of cost-effectiveness analysis for pricing and reimbursement decisions in Europe indicates that policymakers are beginning to consider the value of new technologies to the health care system. The valuation of these technologies is a first step in determining whether the use of these new medications should be promoted or hindered. For new medications that are deemed cost-effective, there are significant equity considerations, as groups that are privately insured or wealthier are more likely to receive these technologies (Goldman and Smith, 2005). Cost sharing is likely to exacerbate these inequities, although there is a need for more research on the relationship between cost sharing for prescription drugs and the diffusion of new technologies as little has been done on this area. The point is that it is important to question the value of new medications, to determine whether the health system is willing to bear the cost of these new technologies given their value, and to assess the distributional effects of their use.

Another important consideration is the disparity between cost sharing for prescription drugs and cost sharing for other medical services. As mentioned earlier, this disparity may exist because of previous beliefs regarding the necessity and usefulness of prescription drugs when user fees were first implemented. Advances in medical technology mean that prescription drugs are now a vital aspect of medical care, and the similar ranges of elasticity values for the various types of medical care indicate that for consumers, there is little distinction between the necessity of prescription drugs and other forms of medical care. Trends in prescription charges in some countries perhaps reflect a growing awareness of this fact. In the United States, for example, health maintenance organizations offer lower user fees for prescription drugs than other insurance types such as fee-for-service, and the implementation of the Medicare prescription drug benefit has lowered out-of-pocket costs for a number of beneficiaries. In France the government increased subsidies for prescription drug consumption among low-income groups.

However, given that prescription charges are already built into most health systems, third-party payers may be reluctant to lose this valuable source of revenue. Taking this political reality into account, we consider other recommendations for prescription charges that are meant to protect the most vulnerable groups of the population. Policymakers have two main options to contain pharmaceutical budgets, minimize negative effects on equity, and/or maximize health care efficiency: first, to introduce mechanisms that protect poorer people and heavy users of prescription drugs (for example, older people and those with chronic conditions) and second, to differentiate prescription charges based on generic vs. brand-name status or cost-effectiveness. Although research in these areas is limited, we suggest that smarter cost-sharing systems would be carefully designed to ensure that any protection mechanisms available reflect need, are consistently applied, and do not conflict with other health policy goals. Correlations between income, age, and health (Macinko et al., 2003) combined with evidence from our analysis and the literature showing that low-income groups are sensitive to price, suggest that policymakers should focus on protecting poorer groups and heavy users of prescription drugs from the financial burden of cost sharing. In some countries protection mechanisms in the form of exemptions or reduced rates cover groups not considered to be particularly vulnerable, such as high-income older people. This may be motivated by dislike of the administrative costs and stigma associated with means testing, forcing policymakers to balance concerns for equity with concerns for administrative efficiency and political fall-out. In other countries voluntary insurance may be the predominant protection mechanism, but as it only protects those who are able to pay for it, its impact may be limited, and it may even exacerbate inequalities in access. Ideally, policymakers would target prescription drug subsidies at the most needy in the population: low-income groups and heavy users of medications, but at minimum, decisions about cost sharing should reflect an open debate about values and goals.

8.5.2. Policy implications for the United States

Sections 8.5.2 and 8.5.3 provide specific policy implications for the two main regions considered in this dissertation: the United States and British Columbia. The policy implications for the United States can be broken down into four main groups: individuals with Medicaid, Medicare beneficiaries, privately insured individuals, and the uninsured.

As discussed in Chapter 5, the Deficit Reduction Act of 2005 permits states to charge premiums and higher co-payments to selected Medicaid beneficiaries, although few states have taken advantage of this option. Given our relatively low elasticity estimate for low-income groups and the discussion regarding economic and health care efficiency, higher user fees for Medicaid beneficiaries do not appear to be the most efficient and equitable policy option. Even if we take an economic perspective, the welfare loss from Medicaid appears to be relatively low. From a health care efficiency standpoint, Medicaid recipients are a vulnerable group because of the correlation between income and health (Macinko et al., 2003), and co-payment increases may adversely affect the health of this population. In a setting where significant inequities in access to prescription drugs likely exist, policy changes that increase the out-of-pocket burden for the poor will only exacerbate these inequities. However, at the national level equity does not appear to be a prominent policy objective within the United States given that Medicaid is state-run, which automatically leads to horizontal inequities.

In light of these comments, the DRA conflicts with the policy objective of maximizing health care efficiency within a given budget. We recommend that Medicaid policymakers instead maintain low cost sharing amounts for Medicaid recipients and focus on other tools such as medical guidelines, drug utilization reviews, and formularies to maximize the appropriateness of prescriptions and contain costs.

We can also draw parallels to the new outpatient Medicare prescription drug benefit. The details of Medicare Part D were previously provided in Chapter 5, but the benefit basically entails significant out-of-pocket requirements, particularly for beneficiaries that fall into the "donut hole" (total drug spending between $2400 and $5451.25)[12]. Before analyzing the efficiency and equity implications of this benefit, though, it is useful to point out that Medicare Part D is a significant improvement in coverage for a number of elderly beneficiaries, particularly those that were previously uninsured. However, some dual-eligible beneficiaries face higher co-payments for brand-name prescription drugs and more restrictive formularies depending on the previous Medicaid coverage in their state of residence. In addition, the generosity of coverage is likely to decline over time as the market matures (KFF, 2006d). With these considerations in mind, it is important for the Federal government to carefully monitor the experience of low-income beneficiaries and institute more protections for dual-eligibles if the generosity of their coverage begins to decline.

[12] It is worth noting that not all Part D prescription drug plans include the donut hole as part of the contract. Instead, around one-third of plans offer generic drug coverage for spending that falls within the donut hole, however, these plans simultaneously charge higher premiums (KFF, 2006b).

As Avorn (2006) points out, the construction of the Part D benefit was based on a moral hazard assumption, so that by including such extensive out-of-pocket sharing for beneficiaries, prescription drug plans could limit over-consumption. Yet, the evidence from the analysis in this dissertation points to the opposite conclusion, that moral hazard is very low for the average Medicare beneficiary. This implies that in general insurers may be able to shift expenditures to patients, allowing the insurance industry to retain higher revenues. Although competition does seem to be driving down out-of-pocket costs below those recommended by Medicare in some regions, which limits revenue shifting, beneficiary cost sharing is still substantial (Merlis, 2007). Among beneficiaries that are low-income but not eligible for additional subsidies from Medicare, the effects of cost sharing can be detrimental; this was not picked up by the price elasticity estimate among the elderly because it was an average estimate. The fact that these beneficiaries still face a substantial out-of-pocket burden creates significant inequities. Further horizontal inequities are created by the fact that the generosity of prescription drug coverage differs between Medicaid beneficiaries in the same state depending on whether they are under or over 65 years of age. A more equitable policy option (but a politically less feasible policy option) would be to target the Part D benefits at the lowest income beneficiaries, as higher-income beneficiaries are already likely to have prescription drug coverage through private sources (Safran et al., 2002).

For those who are privately insured, we can obtain a rough approximation of the elasticity value[13]. The relatively inelastic value of -0.26 indicates that insurers are able to shift expenditures to beneficiaries. In fact, recent evidence suggests that the insurance industry has consolidated, increasing the market power of individual firms (Davis et al., 2007). Subsequently, despite persistent increases in cost sharing among privately insured beneficiaries, insurance profit margins have risen over the past few years (Davis et al., 2007). The implication is that until consumers become more price sensitive (which might happen as co-payments continue to rise) or until the insurance market becomes more competitive, insurers are likely to continue passing these costs along to patients. There is no question that private insurance is highly inequitable, but whether the current state of private insurance in the US contributes to greater health care efficiency is not clear. Since privately insured patients do not significantly reduce their consumption of prescription drugs when faced with higher co-payments, there may be little effect on health. However, it might be that patients are switching to less effective or less appropriate medications with lower co-payments to lower their out-of-pocket burden, and this could adversely influence health.

[13] We obtained elasticity estimates for those who had private insurance, public insurance, and no insurance using the same method. Using the formula $e_d = (\Delta Q/\Delta P)(P/Q)$, we calculated $(\Delta Q/\Delta P)$ using the elasticity estimate (e_d) from the regression on the general population and the means of the co-payment and consumption variables (P/Q). Then we made the assumption that $(\Delta Q/\Delta P)$ was constant across different populations and used the mean co-payment and consumption values for those with private insurance, public insurance, and no insurance to calculate elasticity values for each of these groups.

There is also interesting research regarding the offer and uptake of employer-sponsored insurance. Although employer-sponsored coverage has been steadily declining since 2000, evidence suggests that the decline has mainly been due to take-up rates by employees rather than offer rates by employers (Cutler, 2002a; Reschovsky et al., 2006). That is, employers are still offering insurance at roughly the same rate, but employees are choosing not to purchase the insurance. This decline in insurance coverage is consistent with increases in price caused by increases in both premiums and user fees (Reschovsky et al., 2006). The implication is that not only are higher user fees for medical services (including prescription drugs) reducing the demand for care, but they are also contributing to a decline in employer-sponsored coverage. This is alarming given that most of these individuals are unlikely to be eligible for Medicare and Medicaid, indicating that they are either purchasing non-group insurance or going without insurance. Both of these possibilities are disturbing if a catastrophic event occurs; even if the individual has non-group insurance during a catastrophic event, he may be unable to renew his insurance coverage at an affordable price afterwards and may even face difficulty in obtaining coverage. Thus, it is crucial that more discussion regarding the adverse effects of costly illnesses for the insured be held at the Federal and state level in the US.

As there are around 46.6 million uninsured Americans, it is also important to discuss the implications of the price elasticity estimate for the uninsured population. Our rough approximation of the price elasticity value for uninsured Americans was -0.64, which, not surprisingly, is larger than the price elasticity values for the general population and for individuals with private health insurance. Not only do the uninsured face the full price of prescription drugs, but pharmacies often charge uninsured consumers higher prices than institutional payers because consumers have the least negotiating power. Foregoing insurance is likely to have significant health care efficiency implications as there is evidence of a positive relationship between insurance coverage and overall health (Baker et al., 2001) and a negative relationship between insurance coverage and mortality (McDavid et al., 2003; McWilliams et al., 2004; Roetzheim et al., 2000). Moreover, the uninsured population faces substantial barriers in access to prescription drugs, not only because of the higher prescription prices but also because of higher physician prices, leading to large inequities in the US population. From a health care efficiency and equity standpoint, extending insurance coverage to this population, whether through greater regulation of private insurance or extended public insurance coverage, could improve equity and the health of this currently uninsured group.

8.5.3. Policy implications for British Columbia, Canada

As we were only able to estimate the price elasticity of demand for older people in British Columbia, our policy implications are more relevant to PharmaCare recipients over the age of 64. The new Fair PharmaCare program that tiers deductibles and out-of-pocket maximums according to family income has led to lower out-of-pocket costs for the poorest beneficiaries, especially seniors with family incomes below CDN $15,000 per year. Beneficiaries with family incomes around CDN $20,000-$30,000 per year may face slightly higher out-of-pocket maximums, and beneficiaries with

family incomes above CDN $35,000 begin to face significantly higher out-of-pocket drug costs. The price elasticity estimate of -0.30 indicates that elderly British Columbians are to some degree sensitive to price. An interesting exercise would be to look at price elasticity values among different income groups within the elderly PharmaCare population, but due to data limitations, we were unable to do so in this dissertation.

Along these lines, Fair PharmaCare may only cause a small increase in consumption among the lowest income group of beneficiaries (who now receive more generous coverage under the program). In fact, Caetano et al. (2006) found that Fair PharmaCare had no effect on access to prescription treatments for the poorest of PharmaCare beneficiaries after its implementation. The elasticity estimate also indicates that Fair PharmaCare may have a small dampening effect on consumption for beneficiaries that now face higher deductibles and out-of-pocket maximums under the program. However, given that these beneficiaries have higher incomes, they may purchase supplementary insurance to cover some of the out-of-pocket costs that PharmaCare no longer covers. Thus, the effect of PharmaCare prior to 2003 may have simply been to crowd out private insurance purchase among this group. Whether the crowd-out of private insurance contributes to or hinders the goals of health policymakers in British Columbia is a question that is beyond the scope of this dissertation. Nonetheless, more research on this question is clearly needed.

Given the relatively inelastic price elasticity value, it is unclear whether there will be any adverse effects on the health of the average elderly beneficiary in BC. Essentially, Fair PharmaCare shifts expenditures from the government to beneficiaries, creating savings for the government. Yet, if there are negative effects on health, the policy is inefficient. Moreover, the problem with Fair PharmaCare is that it does not address the root of expenditure growth. As technology is a more important driver of health expenditures (Newhouse, 1992), pharmaceutical expenditures are likely to continue growing at the same rate as in the past. In fact, Morgan et al. (2006) indicate that after the implementation of Fair PharmaCare, there was a 17% decrease in public drug expenditures and an 18% increase in private drug expenditures compared with the situation that would have resulted in the absence of the new policy. Thus, according to their analysis, Fair PharmaCare actually had no influence on expenditure growth.

Overall, while the reduction in the out-of-pocket burden for low-income beneficiaries under Fair PharmaCare is an improvement in equity, there is potential for improvement in health care efficiency. One suggestion is for the PharmaCare program to implement additional mechanisms to promote generic drug use such as lower dispensing fees for generic drugs, generic substitution laws, and pharmacist payments that encourage generic dispensing. The government could also consider using tiered co-payments to steer patients toward lower-priced or more cost-effective medications. This would also allow the government to negotiate with pharmaceutical manufacturers for inclusion in the formularies. These additional measures are more likely to reduce pharmaceutical expenditures and could allow the province to provide more generous drug coverage for middle-income elderly beneficiaries.

8.6. Conclusion

This chapter has summarized and discussed the results and placed our findings in the context of economic and policy analysis. This section provides a brief summary of the main points.

Section 8.2 compared the price elasticity values that we obtained in Chapters 4, 6, and 7. The estimate from the US general population was slightly higher than the MRA estimate, likely because the American elasticity values were measured higher on the demand curve. The estimate for the low-income group in the US was almost identical to that from the MRA, although we might expect the elasticity among the poor to be higher. The reason for this discrepancy may be due to cultural factors in the United States and the fact that low-income beneficiaries generally face low user fees for prescription drugs under Medicaid. The price elasticity estimate for seniors from the US was more in line with our predictions. A more interesting result was that US seniors were less sensitive to prices than BC seniors, although this may have been due to cultural factors and the existence of generous insurance for core medical services in BC.

Section 8.3 then discussed the elasticity results in the context of the neo-classical and extended economic theories. We found that moral hazard exists in the prescription drug insurance market, although it does not appear to be a driving force of greater consumption due to its low value. We also considered Nyman's (1999) extended theory of moral hazard and postulated that based on our elasticity values, the net welfare loss of insurance under Nyman's framework was probably small. Under Nyman's (1999) framework, there may have been a welfare gain for the elderly population in the US.

Section 8.4 brought in the policy interpretation of the elasticity estimate, paying particular attention to the conceptual differences between economic efficiency, health care efficiency, and equity. We then considered the relevance of the elasticity value from the perspective of health care efficiency and equity. Overall, it appears that user fees for prescription drugs may be detrimental to the health of certain population groups, particularly those who are low-income and unhealthy. In terms of equity, unless designed properly user fees have adverse effects on equity given that low-income individuals tend to be in poorer health, although more research is needed on this area.

The fifth section then provided the implications of the results for health care policymakers in developed countries, the United States, and British Columbia. From a neo-classical economic point of view, it appears that there is a welfare loss from prescription drug insurance, and the effect of moral hazard may be to discourage some individuals from purchasing insurance. The implication is that third-party payers need to impose some form of cost sharing to discourage excess consumption. Meanwhile, Nyman's (1999) analysis leads us to the opposite conclusion; we determined that third-party payers should focus on other mechanisms of reducing demand. Shifting away from the traditional economic perspective, we point out that it is important for

policymakers to openly debate the value of imposing cost sharing on consumers when physicians are making the primary decisions regarding prescriptions.

Section 8.5 also offered a policy discussion for the United States. While public health care policy seems to be moving in different directions depending on the form of coverage (e.g. Medicare or Medicaid), we indicated that other options for curbing expenditures that are less detrimental to equity and efficiency should be considered by public insurers. In the private insurance market US health care policy is significantly lacking, and more needs to be done to protect this group of the population. The same could be said for the uninsured group where more regulation of private insurance or an extension of public coverage could significantly improve equity and health outcomes among this group.

In British Columbia the new Fair PharmaCare policy appears to have maintained access to prescription drugs for all income groups within the elderly population. The overall effect is that the government transferred a proportion of expenditures to private payers. However, Fair PharmaCare is unlikely to constrain pharmaceutical expenditures in the long run, and the BC government should consider other measures to address pharmaceutical growth such as generic drug policies and tiered co-payments.

Chapter 9: Concluding remarks

9.1. Introduction

The main research question addressed in this thesis was the extent to which prescription user fees influence the number of prescription drugs consumed. As the initial motivation for exploring this question was based on the neo-classical economic perspective, we empirically estimated the price elasticity using three main datasets: the first was a collection of price elasticity estimates from the literature, the second was a sample of individuals from the United States, and the third was a sample of older people from British Columbia, Canada. These different specifications allowed us to compare and contrast the results and to hypothesize why the findings might differ between the three datasets. Based on the empirical results, we further explored the relationship between user charges for prescription drugs and demand by considering the policy implications from economic efficiency, health care efficiency, and equity perspectives.

Not only is cost sharing for prescription drugs widely applied across insurance types in the US, but the level of cost sharing faced by insured individuals is dynamic over time. British Columbia has undergone a recent policy change with the launch of Fair PharmaCare, which targets funding at the lower income groups. Many of the price elasticity estimates from the literature are outdated, particularly because the RAND experiment was conducted over 25 years ago. Other price elasticity estimates are based on less robust estimations, as the authors did not always explore issues such as sample selection, unobserved heterogeneity, or endogeneity. These issues implied the need for current, robust research that would explore the price elasticity of demand for prescription drugs, particularly among older people.

This thesis has addressed some of these existing gaps within the literature, and the purpose of this chapter is to summarize the discussion and findings from this dissertation and to offer suggestions for future research than naturally extends from our work. Specifically, Section 9.2 covers the main points from each of the other seven chapters within this thesis. In addition, we offer avenues for further research that extend beyond the scope of this thesis. Section 9.3 covers these areas that we suggest for further research.

9.2. A brief summary of the dissertation

Chapter 1 introduced the need for updated elasticity estimates for prescription drug consumption. The chapter outlined the various types of cost sharing that exist for prescription drugs and briefly discussed why policymakers implement user fees. While a negative relationship between prescription charges and drug consumption has generally been found across the literature, the first chapter highlighted a number of empirical gaps related to the price elasticity of demand that currently exist. In particular, an updated and more robust analysis would be useful. A study that summarizes the existing literature into one estimate or a few estimates based on the context could better inform policymakers, and analyses and comparisons of particular

populations would be a valuable addition to the traditional analysis of the general population. The need for further research in the area of cost sharing and the usefulness of the price elasticity measure in shedding light on prescription drug consumption in the population were the primary motivations for this dissertation.

Given that our intention was to examine the extent of moral hazard by estimating the elasticity of demand for prescription drugs, Chapter 2 provided the framework of insurance theory as a means of motivating the empirical model. The chapter began with a discussion of insurance in a world of symmetric information and then proceeded to outline insurance under conditions of adverse selection and moral hazard. The main theoretical finding related to moral hazard was that patients increase their consumption of medical care when faced with lower out-of-pocket prices. This causes a welfare loss because of increased premiums and the fact that consumption is diverted away from other goods and services that may have higher net marginal benefits. We then discussed extensions to the traditional model of moral hazard, focusing on the work of Nyman (1999) who postulated that the welfare loss of insurance was not as large as theorized in the traditional model due to the income effect of insurance. Based on these neo-classical and extended theories, we discussed how the economic theories would likely translate into an empirical analysis of the demand for prescription drugs.

Chapter 3 included a literature review of studies that examined the link between cost sharing for medical services in general, physician visits, and hospital visits and the demand for these particular services. The chapter also provided a more comprehensive literature review of the effect of prescription charges on the volume of drugs purchased, the covariates that are important predictors of prescription demand, and the price elasticity of demand for prescription drugs. While there was a consensus that prescription charges reduced the demand for prescription drugs, there was a large range of price elasticity estimates in the literature, perhaps due to the varying quality of studies and the different research settings. Not only did the literature review highlight the need for more research in the area, but in some cases it allowed us to see what results we might expect from our own analysis in terms of the dependent and independent variables.

Chapter 4 extended the literature review by statistically summarizing the widely varying elasticity estimates from the literature. The intent was to provide a benchmark price elasticity value for comparison against the estimates from the United States and British Columbia. We used a meta-regression analysis, which involved collating the existing price elasticity estimates into a dataset and running a regression on this constructed dataset. The analysis provided a "composite" or "adjusted" elasticity estimate that accounted for the heterogeneity that exists between elasticity values. The resulting "adjusted" estimate of –0.16 (not significant) indicated that across most populations and institutional settings, the demand for prescription drugs is highly inelastic. The analysis also revealed that other factors, such as the quality of the medium in which the estimate was published, characteristics of the dataset from which the estimate was pulled, and the institutional setting associated with the estimate were all important predictors of the price elasticity value.

The intent of Chapter 5 was to set the scene for the empirical analyses of prescription drug cost sharing in the US and BC and the subsequent policy discussion in Chapter 8. The overview of the American health care system revealed the fragmented nature of health care and the high levels of cost sharing faced by individuals across most types of insurance coverage. In contrast, core health services in British Columbia can only be funded by the public insurance system, but a large proportion of prescription drug funding for the non-elderly is private. The implication was that price elasticity values would likely differ between the US and Canada.

Chapter 6 highlighted the need for more robust price elasticity estimates among different age and income groups within the American population. The chapter employed data from the Medical Expenditure Panel Survey (MEPS) and provided estimates of the price elasticity of demand for prescription drugs among the adult, elderly, and low-income populations in the United States. An empirical model developed by Semykina and Wooldridge (2006) that accounted for sample selection, endogeneity, and unobserved heterogeneity was used to obtain these estimates. The price elasticity estimate was highest among adults (-0.26), followed by low-income individuals (-0.20), and older people (-0.11). Even though the elasticity value of -0.11 for the elderly was not significantly different from zero at conventional levels, it was well within the range of elasticity values given in the literature review and our meta analysis and was part of a trend of decreasing elasticity values for this less price sensitive group.

Chapter 7 offered another analysis of the price elasticity of demand using a relatively similar population from British Columbia that faced more generous drug insurance coverage than individuals in the United States. The dataset was the British Columbia Linked Health Database. The sample was limited to individuals over the age of 65 in British Columbia, Canada because of our inability to observe private insurance purchases among PharmaCare recipients younger than 65. The empirical model was a variation of the Semykina and Wooldridge (2006) model that accounted for individual-specific effects and sample selection. We obtained a significant and inelastic price elasticity of demand of –0.30. While this indicates that the elderly are relatively insensitive to out-of-pocket price changes, perhaps because of their perceived need for medications and the historically low user fees for the elderly in the province, the value is somewhat higher than we might expect among this population.

Chapter 8 brought together the results from the three analysis chapters and offered a comparison of the different price elasticity results. The meta-regression estimate provided a useful benchmark against which to assess the other price elasticity values. Surprisingly, seniors in British Columbia were the most sensitive to user fees for prescription drugs followed by the general population in the United States. US seniors were the least sensitive to demand-side cost sharing. We also extended the analysis and discussed the policy implications, focusing on the effects of cost sharing on economic efficiency (Pareto efficiency), health care efficiency, and equity. We determined that demand-side cost sharing may lead to greater economic efficiency, but cost sharing may have a detrimental effect on health care efficiency and equity.

The implication is that policymakers in both the United States and Canada should set clear policy goals and openly discuss whether any detrimental effects of cost sharing are considered acceptable from a policy standpoint.

9.3. Further research

There are a number of areas for further research that naturally follow upon the work of this thesis: one area of study relates to research that extends the work of this thesis, and the second type of research correlates with work that is beyond the scope of this dissertation.

In terms of research that extends what has been done in this thesis, this involves work on the differences between generic and brand-name drug consumption and research that further explores the welfare loss of moral hazard in prescription drug consumption.

Beyond the price elasticity of demand for prescription drugs, further research could determine whether the price elasticity differs between multi-source and single-source medications. For drugs where generic competitors exist, it would also be informative to investigate whether the elasticity differs between the generic and brand-name versions. In essence, this research would explore the "generic competition paradox"[1] (Frank and Salkever, 1992; Scherer, 1993) from the consumer side of the market. This work could have important implications for third-party payers that are interested in the potential for reducing drug expenditures through generic drug use. For instance, if research indicated that consumers were more sensitive to prices of brand-name drugs when more competitors existed in the market[2], this would indicate that a supply-side policy of encouraging more generic competition could help reduce overall drug expenditures.

Analysts often expect consumers to behave rationally, foregoing the health services of least benefit to them, but this begs the question of how people decide which drugs they value least when faced with a price barrier. Studies that examined changes in the use of essential drugs as a proxy for poor health outcomes found that individuals were unable to distinguish 'necessary' from 'unnecessary' prescription drugs (Foxman et al., 1987; Soumerai et al., 1991). Other studies found that higher cost sharing increased the risk of adverse events such as being hospitalized or admitted to a nursing home (Soumerai et al., 1991; Tamblyn et al., 2001), and prescription charges

[1] According to economic theory, as more firms enter a competitive market, the market price should fall. Interestingly, in the pharmaceutical off-patent market, researchers have observed that the prices of brand-name medications do not always fall when more generic firms enter the market. In fact, some researchers have found that brand-name prices have risen (Frank and Salkever, 1992). The argument for this paradox is that physicians are generally risk averse, insensitive to the costs of treatment, and habitual creatures. From the consumer side, patients are insufficiently informed about their treatments and averse to switching away from medications (Scherer, 1993). Research on the price elasticity of demand for brand-name and generic drugs would thus explore whether patients indeed are averse to switching away from brand-name medications, even in the face of higher prices.

[2] More specifically, when there are more generic competitors in the market, this should drive overall generic prices and thus out-of-pocket prices for generics down. Consumers are thus more sensitive to the prices of brand-name drugs when there is a greater differential between the brand and generic price.

also lowered adherence to treatment, which may have health implications. More comprehensive analyses that consider the implications of cost sharing on the appropriate use of medications, on the use of substitutes and complements, and on adherence and long-term health are still needed and would shed further light on this issue.

As for further research that is beyond the scope of this thesis, a major area that is virtually unexplored is the effect of prescription charges on access to drugs. Most research has instead focused on utilization as a proxy for access. Cost sharing does not have the same effect across all population groups. Surprisingly, elasticity estimates from our work and other did not show that low-income groups are more sensitive to price, but the findings still indicate that poorer people reduced their use of prescription drugs even when co-payment levels were very low. Furthermore, little work has been done on horizontal inequities brought about by regional variations in prescription charges. In countries like Canada and the United States, where prescription charges for low-income populations and older people differ from region to region, access to prescription drugs may vary significantly across regions. Spatial analyses might provide insight into this area, and further research may contribute to lowering inequalities in access to care.

The price elasticity of demand for prescription drugs: An exploration of demand in different settings

Marin Gemmill

Appendix and References

Appendix A: Appendix to Chapter 2

The purpose of this appendix is to expand upon certain points made in Chapter 2. In some cases this translates into more detailed mathematical derivations of a specific concept. In other cases the appendix covers points that were not central to the objectives of Chapter 2 but may be interesting for the reader. Specifically, the appendix offers an explanation and mathematical derivation of adverse selection along with an expansion of aspects related to *ex post* moral hazard. The presentation of both adverse selection and moral hazard is intended to aid the reader in differentiating between the two types of asymmetric information. In line with Chapter 2, this appendix draws heavily upon other work by Cutler and Zeckhauser (2000), Rothschild and Stiglitz (1976), and Zweifel and Breyer (1997).

A.1. Equilibrium in an insurance market with no asymmetric information

The insured individual's expected utility is represented by (Zweifel and Breyer, 1997):

$$EU_{ins} = \pi * u(w_0 - m + \beta_2) + (1-\pi) * u(w_0 - \beta_1) \qquad \text{(A.1).}$$

We also know that the individual's premium β_1 is related to size of a claim if he falls ill: $\beta_1 = \alpha\varphi$ where α represents the percentage of the loss that the individual's premium covers. Assuming that the consumer purchases insurance, if he doesn't fall ill his wealth is $w_1 = w_0 - \beta_1$. If he falls ill his wealth is $w_2 = w_0 - m + \beta_2$, where $\beta_2 = \varphi - \alpha\varphi$.

To solve for the optimal insurance policy, we substitute for β_1 and β_2 and differentiate (A.1) with respect to the claim φ in the event of illness:

$$\frac{\partial EU_{ins}}{\partial \varphi} = \pi * (1-\pi) * u'(w_0 - m + \varphi - \alpha\varphi) + -\pi * (1-\pi) * u'(w_0 - \alpha\varphi) = 0 \qquad \text{(A.2).}$$

Solving for φ we find that $\varphi = m$, indicating that if insurance is actuarially fair, the optimal policy for a risk averse individual is full insurance. The consumer does have the option of foregoing insurance altogether, so he will only purchase a contract if $EU_{ins} \geq EU_{uins}$.

A.2. Adverse selection: illustration of why the high-risk indifference curve is steeper than the low-risk indifference curve

Adverse selection can be represented both mathematically and diagrammatically (Cutler and Zeckhauser, 2000; Rothschild and Stiglitz, 1976; Wilson, 1980), and this section of the appendix derives models of adverse selection and insurance purchase.

A.2.1. Model assumptions

We assume that asymmetry exists in that individuals are aware of their own risk but are not willing to reveal this information to firms. A distinguishing feature of this model is that companies force individuals to choose from particular insurance packages instead of permitting consumers to purchase as much insurance as they would like at a particular price. Let there be two kinds of consumers: low-risk individuals with illness probability π_{LO} and high-risk individuals with illness probability $\pi_{HI} > \pi_{LO}$.

Each consumer begins with income W and faces an exogenous loss m in the event of illness. Net income is y_i^j, where i represents the individual's risk group $(i = LO, HI)$ and j indicates the state of the world $(j = s, h)$, i.e. sickness or health. The consumer's utility is given by $u\lfloor y_i^j \rfloor$ such that his expected utility is:

$$EU_i = \pi_i * u\lfloor y_i^s \rfloor + (1-\pi_i) * u\lfloor y_i^h \rfloor \qquad \text{(A.3).}$$

A.2.2. Equilibrium with two classes of consumers

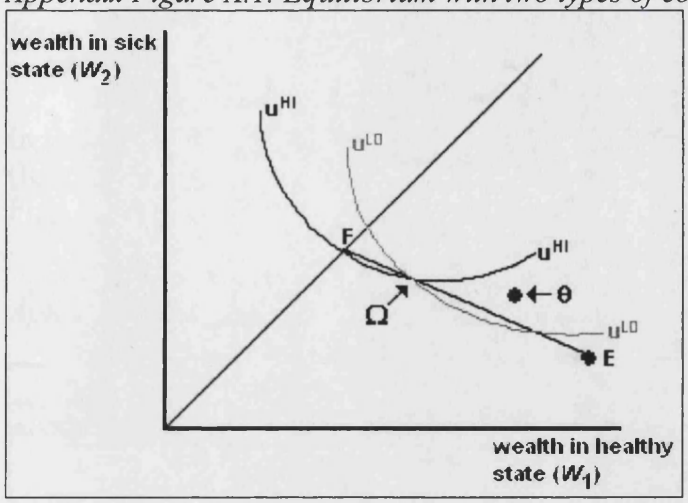
When there are different risk types, a pooling equilibrium will not occur, which can be illustrated through Appendix Figure A.1.

Because there are two risk types in the market, each risk group has its own indifference curve: u_{HI} for the high-risk group and u_{LO} for the low-risk group. The slope of the high-risk indifference curve is less steep than the slope of the low-risk indifference curve (Rothschild and Stiglitz, 1976)[1]. The high-risk indifference curve is represented by u_{HI}, and the low-risk indifference curve is represented by u_{LO}. For high-risk persons the marginal rate of substitution between wealth in the healthy state and wealth in the sick state is:

$$MRS^{HI}_{W_1,W_2} = -\frac{dw_2}{dw_1} = \frac{u'(w_0 - \beta_1) * (1-\pi_{HI})}{u'(w_0 - m + \beta_2) * \pi_{HI}} \qquad \text{(A.4).}$$

[1] Intuitively, since the probability of loss for a low-risk individual is lower, the low-risk person must receive more income than the high-risk person in the unhealthy state to compensate for income taken from the healthy state.

Appendix Figure A.1. Equilibrium with two types of consumers



Similarly, for low risk individuals the marginal rate of substitution between wealth in the healthy and the sick state is:

$$MRS^{LO}_{W_1,W_2} = -\frac{dw_2}{dw_1} = \frac{u'(w_0 - \beta_1) * (1 - \pi_{LO})}{u'(w_0 - m + \beta_2) * \pi_{LO}} \qquad \text{(A.5).}$$

Given the assumption that high-risk and low-risk individuals are otherwise identical, we know that the utility of wealth at a given level of wealth is the same for both types of consumers: $u_{HI}(w) = u_{LO}(w)$. Thus, the ratio of the slope of the high-risk indifference curve to the slope of the low-risk indifference curve is:

$$\frac{MRS^{HI}}{MRS^{LO}} = \frac{u'(w_0 - \beta_1) * (1 - \pi_{HI})}{u'(w_0 - m + \beta_2) * \pi_{HI}} * \frac{u'(w_0 - m + \beta_2) * \pi_{LO}}{u'(w_0 - \beta_1) * (1 - \pi_{LO})}$$
$$= \frac{\pi_{LO}}{\pi_{HI}} * \frac{1 - \pi_{HI}}{1 - \pi_{LO}} \qquad \text{(A.6).}$$

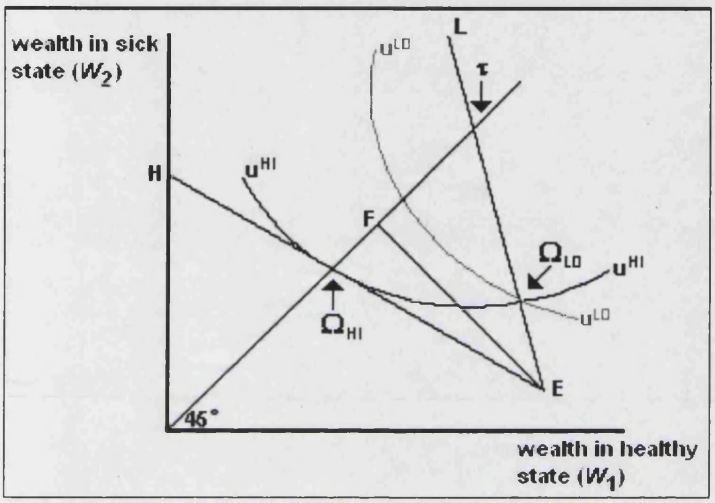
Because both $\frac{\pi^{LO}}{\pi^{HI}}$ and $\frac{1-\pi^{HI}}{1-\pi^{LO}}$ are less than one, it follows that $\frac{MRS_{HI}}{MRS_{LO}} < 1$, indicating that the slope of the high-risk indifference curve is less steep than the slope of the low-risk indifference curve.

In Appendix Figure A.1 the point *E* is the initial endowment, and the line *EF* is the aggregate fair-odds line. The pooling contract Ω, which must lie on the fair-odds line because of the zero-profit constraint, involves a cross-subsidy from low-risk to high-risk individuals. This is because both groups pay the same premium, but high-risk persons make more claims. A contract like θ, however, would be strictly preferred by

low-risk individuals and not preferred by high-risk individuals. Yet, when low-risk consumers switch to θ, Ω becomes unprofitable. This process can continue infinitely for various "pooling" contracts on the market, and thus no pooling equilibrium can exist in a market with two types of customers (Rothschild and Stiglitz, 1976).

In fact, if there is an equilibrium, each risk type will purchase a separate contract (Rothschild and Stiglitz, 1976). This is called a separating equilibrium (see Appendix Figure A.2).

Appendix Figure A.2. Separating equilibrium

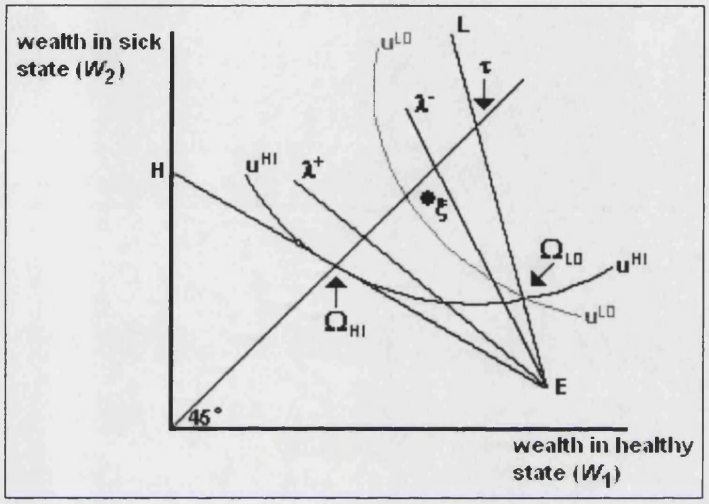


In Appendix Figure A.2 the two contracts offered are: the low risk contract Ω_{LO}, which lies on the line *EL*, and the high-risk contract Ω_{HI}, which lies on the line *EH*. The high-risk contract Ω_{HI} is associated with full insurance[2], while the low-risk contract is partial insurance. Suppose that insurers offer the set of contracts (τ,Ω_{HI}) instead of $(\Omega_{LO},\Omega_{HI})$. The full insurance contract τ would be preferred to both Ω_{LO} and Ω_{HI} by both low-risk and high-risk individuals. The problem is that insurance companies would not be able to distinguish between high- and low-risk customers if τ were offered, and there would be negative profits as τ lies above the fair-odds line for all customers in the market. In order for an equilibrium to exist, all low-risk contracts must lie to the southeast of the high-risk indifference curve u_{HI}; in fact, Ω_{LO} is the best policy than an insurance company could offer to the low-risk types that would not attract the high-risk types.

[2] This is because the high-risk contract lies on the intersection of the fair-odds line and the 45°-line.

Nonetheless, whether $(\Omega_{LO}, \Omega_{HI})$ always constitutes an equilibrium set of contracts depends on λ, the proportion of high-risk individuals in the market. Appendix Figure A.3. demonstrates the importance of λ.

Appendix Figure A.3. Separating equilibrium and the proportion of high-risk individuals



Both low- and high-risk customers would prefer the contract ξ because it lies above the indifference curves that correspond to Ω_{LO} and Ω_{HI} for low-risk and high-risk individuals, respectively. If a greater proportion of the population was high-risk, corresponding to the pooling fair-odds line $E\lambda^+$, then offering a contract like ξ would be unprofitable because it lies above the pooling fair-odds line. However, if the opposite were true, then the pooling policy ξ that would break the separating equilibrium is profitable and would be offered. When a pooling policy is offered, a separating policy that attracts the low-risk types will break the equilibrium. Thus, for a separating equilibrium to occur, the low-risk indifference curve running through the initial endowment must lie completely above the fair-odds line. The lower the share of high-risk individuals in the market, the greater the chance that this requirement will be fulfilled (Rothschild and Stiglitz, 1976).

Had the market only consisted of one risk type, the equilibrium contract would be full insurance. This indicates that according to the neo-classical theory, the presence of high-risk customers in a heterogeneous market exerts a negative externality on the low-risk individuals.

A number of studies have investigated adverse selection in health insurance markets, and a summary of the results can be found in the *Handbook of Health Economics* (Cuter and Zeckhauser, 2000). Nearly all of the studies have found that adverse selection is a significant force in insurance markets. There is adverse selection in the

choice between having insurance or no insurance, between having a generous or less generous insurance plan, and between joining a fee-for-service or managed care plan.

A.3. Mathematical derivation of ex *post* moral hazard

Because medical services are assumed to be useless to a healthy individual in the most basic model, a consumer faces two possible utilities depending on the state of the world: $u^s[m, y^s]$ and $u^h[m, y^h]$. Certain assumptions can be made about these two utility functions (Zweifel and Breyer, 1997):

ASSUMPTION 2A.1

The healthy person's utility only depends on other consumption, meaning that medical care m has no effect on his utility.

$$u_m^h := \frac{\partial u^h[m, y]}{\partial m} = 0$$

ASSUMPTION 2A.2

Both utility functions for each state of the world are strictly increasing and strictly concave with respect to the consumption good. Mathematically:

$$u_y^s := \frac{\partial u^s[m, y]}{\partial y} > 0, \; u_{yy}^s := \frac{\partial^2 u^s[m, y]}{\partial y^2} < 0 \text{ and}$$

$$u_y^h := \frac{\partial u^h[m, y]}{\partial y} > 0, \; u_{yy}^m := \frac{\partial^2 u^h[m, y]}{\partial y^2} < 0$$

ASSUMPTION 2A.3

For the individual who is sick, utility is a strictly concave function of medical care m when we hold consumption constant:

$$u_{mm}^s := \frac{\partial u^s[m, y]}{\partial m^2} < 0$$

The "satiation quantity" is the quantity of treatment m^* at which the marginal utility of consumption is zero.

$$u_m^s[m^*, y] = 0$$

ASSUMPTION 2A.4

Holding consumption constant, the marginal utility of consumption is always lower in the sick state than in the healthy state:

$u_y^s[m, y] < u_y^h[0, y]$ for all values of m.

ASSUMPTION 2A.5

Consumption and medical care are weakly complementary goods in the sick state. This means that the marginal utility of consumption does not fall with increasing utilization of medical care provided that the amount of medical care is below the satiation level.

$$u^s_{my} := \frac{\partial^2 u^s[m,y]}{\partial m \partial y} \geq 0 \text{ if } m < m^*.$$

These assumptions are useful for developing models of the demand for medical services and the optimal amount of insurance coverage in the presence of *ex post* moral hazard.

We assume that the insurer is unable to observe the individual's health status and can only observe medical expenditures (Zweifel and Breyer, 1997). To combat moral hazard the insurer uses a constant coinsurance rate (c). The insurance payout can be expressed as:

$$I(m) = (1-c)^* m \qquad \text{(A.7)},$$

and

$$I'(m) = 1-c \qquad \text{(A.8)}.$$

The optimization problem occurs in two stages[3]. Before the individual falls ill, the first stage is for him to determine the utility-maximizing consumption of medical care and other goods in the event of illness, assuming that the coinsurance rate is exogenous. In the second stage, the individual chooses the rate of coinsurance that maximizes his expected utility, taking this established behaviour into account (the existence of *ex post* moral hazard).

In the first stage the consumer optimizes his demand for medical care in the event that he becomes ill. His income in the ill state is given by:

$$y^s = W - \beta - m + (1-c)^* m \qquad \text{(A.9)}.$$

He then chooses the quantity of medical care that satisfies the necessary first-order condition:

$$\frac{du^s}{dm} = u^s_m[m, y^s] - c^* u^s_y[m, y^s] = 0 \qquad \text{(A.10)}.$$

Based on this condition, we can derive the demand function for medical care[4]:

$$m = m(c) \qquad \text{with } m(0) = m^* \qquad \text{(A.11)}.$$

[3] This is in line with the model presented in Zweifel and Breyer (1997).
[4] This follows from assumption 2A.3.

To find the relationship between medical expenditures and the coinsurance rate, we totally differentiate $\frac{du^S}{dm}$ with respect to *m* and *c* and solve for $\frac{dm}{dc}$, yielding:

$$d\left(\frac{du^s}{dm}\right) = \frac{\partial^2 u^s}{\partial m^2} dm + \frac{\partial^2 u^s}{\partial m \partial c} dc = 0 \qquad \text{(A.12).}$$

Solving for $\frac{dm}{dc}$ results in:

$$\frac{dm}{dc} = -\frac{\partial^2 u^s / \partial m \partial c}{\partial^2 u^s / \partial m^2} \qquad \text{(A.13).}$$

The numerator can be written as:

$$\frac{\partial^2 u^s}{\partial m \partial c} = -u^s_{my} * m + c * u^s_{yy} - u^s_y < 0 \qquad \text{(A.14).}$$

The negative value of $\frac{\partial^2 u^s}{\partial m \partial c}$ (the numerator of $\frac{dm}{dc}$) follows from assumptions 2A.5 $\left(u^s_{my} \geq 0\right)$ and 2A.2: $\left(u^s_{yy} < 0 \text{ and } u^s_y > 0\right)$.

The denominator can be written as:

$$\frac{\partial^2 u^s}{\partial m^2} = u^s_{mm} - 2 * c * u^s_{my} + c^2 * u^s_{yy} < 0 \qquad \text{(A.15).}$$

The negative sign of $\frac{\partial^2 u^s}{\partial m^2}$ (the denominator of $\frac{dm}{dc}$) follows from assumptions 2A.3 $\left(u^s_{mm} < 0\right)$, 2A.5 $\left(u^s_{my} \geq 0\right)$, and 2A.2 $\left(u^s_{yy} < 0\right)$.

Overall, based on the signs of the numerator and the denominator, $\frac{dm}{dc} < 0$. In other words, decreasing the coinsurance rate increases the utility-maximizing individual's demand for medical care in the event of illness (Zweifel and Breyer, 1997).

Once the consumer has determined his optimal choice of medical care based on an exogenous coinsurance rate, he enters the second stage of optimization where he finds the value of *c* that maximizes his expected utility. This optimization problem occurs *ex ante*, so that his expected utility is based on the possibilities of being healthy or ill:

$$EU(c) = \pi * u^s[m(c), W - \beta(c) - c * m(c)] + (1-\pi) * u^h[0, W - \beta(c)] \tag{A.16}.$$

Given that $I(m) = (1-c) * m$ the premium depends on the coinsurance rate. The next step in the process is for the individual to maximize his expected utility subject to the coinsurance rate:

$$\frac{dEU}{dc} = \pi * u_m^s * m'(c) - \pi * u_y^s * [\beta'(c) + c * m'(c) + m(c)] - (1-\pi) * u_y^h * \beta'(c) \tag{A.17}.$$

Solving $\frac{du^s}{dm}$ for u_m^s yields:

$$u_m^s = c * u_y^s \tag{A.18}.$$

This can be substituted into the consumer's utility maximization problem and collecting terms results in:

$$\beta'(c) * \{\pi * u_y^s + (1-\pi) * u_y^h\} = -\pi * u_y^s * m(c) \tag{A.19}.$$

Substituting for $\beta'(c)$[5] and solving for c, the final equation is:

$$c = \frac{-m(c)}{m'(c)} * \left[1 - \frac{u_y^s}{\pi * u_y^s + (1-\pi) * u_y^h}\right] + 1 \tag{A.20}.$$

The expression $\frac{-m(c)}{m'(c)}$ must be positive because $m(c)$ is positive and because the earlier analysis demonstrated that $\frac{dm}{dc} < 0$. Additionally, since $0 < \frac{u_y^s}{\pi * u_y^s + (1-\pi) * u_y^h} < 1$ we conclude that the optimal rate of coinsurance is

[5] Assuming that there is no loading, the expression for the premium is:
$\beta(c) = \pi * (1-c) * m(c)$, where
$\beta'(c) = \pi * \{(1-c) * m'(c) - m(c)\}$.
Note that $m'(c)$ is from equation (A.13).

positive[6].

Based on equation (A.20), we observe that an increase in the health risk (π) translates into an increase in the optimal coinsurance rate. This causes $\pi * u_y^s + (1-\pi) * u_y^h$ to increase. In turn, $\frac{u_y^s}{\pi * u_y^s + (1-\pi) * u_y^h}$ increases, and thus the optimal coinsurance rate must rise (Zweifel and Breyer, 1997).

[6] The proof is as follows:

$u_y^s = (\pi + 1 - \pi) * u_y^s = \pi * u_y^s + (1-\pi) * u_y^s$

if $u_y^s < u_y^h$ (assumption 2A.4), then $u_y^s < \pi * u_y^s + (1-\pi) * u_y^h$

since $u_y^s > 0$ (assumption 2A.2), $0 < \frac{u_y^s}{\pi u_y^s + (1-\pi) u_y^h} < 1$.

Appendix B: Appendix to Chapter 3

This appendix provides supplementary information to Chapter 3. The first section of the appendix covers the main study classifications, for instance experimental/non-experimental and cross-sectional/time-series/panel data. The subsequent sections provide details of the literature that has covered the relationship between cost sharing and other outcome variables besides the use of prescription drugs. Total expenditures and health are two examples of other outcome variables. This description gives the reader an idea of what type of research has been previously performed in the area. The final portion of the appendix provides more detailed information the specific papers that were considered in the literature review.

B.1. The importance of different study classifications

The studies that have investigated cost sharing for a range of medical services can be classified into different types: experimental versus non-experimental, cross-sectional versus time series versus panel, and regression versus non-regression. There are advantages and disadvantages to each classification, and this section discusses these considerations.

In terms of experimental and non-experimental studies, experimental research first attempts decontextualize a single question from a "real world" scenario, studies it under controlled conditions, and then tries to recontextualize the results back on the "real world" scenario. One of the main advantages of this type of research is that it helps overcome problems with self selection, where certain individuals have a greater tendency to enter into specific groups. For instance, within the health insurance market, individuals that are older and sicker are more likely to seek health insurance. A major disadvantage with experimental research is that these experiments are costly and require careful design as poorly designed experiments may have few advantages over non-experimental data. Moreover, because the cost of gathering experimental data is so high, these experiments may be limited to certain regions or subpopulations, and the results may not be generalizable to other populations.

Perhaps because of the prohibitive cost, most available datasets are non-experimental. The main problem with non-experimental methods is the lack of control over the situation, particularly in regards to self selection. Within this classification of methods, some studies are natural and some are observational. A natural study is one where the researcher has data for a group of individuals when a specific event has occurred. For instance, the researcher may have data on individuals in the UK from before and after an increase in prescription charges. The advantage of this design is that the researcher can quantify the impact of a specific policy change, although difficulties with natural datasets often occur if more than one policy or insurance change occurred simultaneously and if there were no individuals unaffected by the change. Observational studies track respondents in the absence of a specific event. In this case, the researcher might examine how insurance influences consumption over a given period of time. While this type of data allows the researcher to examine general

changes in out-of-pocket prices or a snapshot of consumption, the difficulty with observational studies is that unobserved heterogeneity may affect the results, and the researcher may be unable to ascertain how specific changes in the price or level of insurance would affect the sample.

The collection of data can occur at one period in time (cross-sectional data) or over a period of time (panel and time-series data). The difference between panel and time-series data is that panel datasets follow the same individual over a number of time periods, while time-series data are typically at the aggregate level. There are a number of problems with cross-sectional datasets, one of these being omitted variable bias, which can lead to biased coefficients and standard errors (Hsiao, 2003). Omitted variable bias occurs when there are one or more variables that the researcher cannot obtain, and these variables influence the dependent variable. These factors might differ between various individuals but are constant over time. Additionally, these variables might be constant over various individuals but differ over time. The advantage of time-series data is that researchers can track changes over time, but the problem is that individual information is lost at the aggregate level.

Panel data allow the researcher to control for unobserved heterogeneity by examining changes in the left-hand side variable over time. Another advantage is the ability to better assess the dynamics of change (Hsiao, 2003); for instance, the probability of participation in an event may fluctuate over time. A cross-sectional snapshot of participation may imply that involvement is static as some individuals always participate in the event and others never participate. Meanwhile, a time-series analysis of participation may indicate that an individual has a probability of participation at any given moment in time and turnover may be frequent. A panel data approach allows the researcher to discriminate between these two possibilities and assess involvement using participation history and the probability of participation during certain periods of the life cycle, the business cycle, or other spans of time.

Another main distinction in the literature occurs between papers that use regression techniques and papers that only use descriptive analysis. Descriptive analysis allows the researcher to investigate whether certain groups differ significantly according to some criteria. For example, the researcher can test whether some groups obtain more prescription drugs than others. However, there are advantages to using regression analysis over simpler statistical modeling. Regression analyses can sometimes handle a large number of predictive factors simultaneously. Regression analysis also allows the researcher to investigate the influence of one specific variable, while holding the influence of all other variables constant. For instance, low-income respondents tend to be less healthy than wealthy individuals, and regression analysis allows the researcher to control for health and wealth.

B.2. Literature covering cost sharing for medical care

B.2.1. Medical care: the effect of cost sharing on total expenditures

Section 3.3.1 in Chapter 3 provided an overview of the literature on the effect of cost sharing for medical care on the number of goods and services purchased. While there is a general consensus among researchers that this relationship is negative, an extension to this question is whether this reduction in volume is accompanied by a reduction in overall medical expenditures. Expenditures are determined by both a price effect and the volume effect where the price effect can be manifested in a number of ways. One issue is that under coinsurance regimes, lower-priced treatments will be less expensive for consumers. However, under certain systems such as co-payments and deductibles (if the consumer is near the deductible level), consumers may have no interest in being price conscious as all treatments may cost the same. Moreover, over a period of time, individuals tend to trade up to newer and more expensive treatments, causing expenditures to rise despite the existence of co-payments. Thus, the hypothesis is that cost sharing will decrease expenditure growth through the volume effect and potentially through the price effect, but in the long run, cost sharing may not quell the rise in medical expenditures.

There were a number of papers which used individual-level data from the United States and the Netherlands and household-level data from Canada to study the impact of user fees or insurance on medical expenditures. The results of these papers are listed in Appendix Table B.1.

Across Canada, the Netherlands, and the United States, user fees for medical care had the same effect. Whether the user fees were in the form of co-payment, coinsurance rates, deductibles, or some other form, higher out-of-pocket costs reduced medical expenditures.

Appendix Table B.1. Medical care: cost sharing and total health care expenditures

Variable	Expenditures	Studies
Co-payment	-	**Fahs** (1992) [US, NS, CD, R]
Coinsurance	-	**Duan et al.** (1983) [US, ES, CD, R]; **Manning et al.** (1981) [US, ES, CD, R]; **Manning et al.** (1987) [US, ES, CD, R]; **Newhouse** (1981) [US, ES, CD, R]; **Newhouse** (1993) [US, ES, CD, R]
Deductible	-	**Van Vliet** (2001) [NE, OS, CD, R]; **Van Vliet** (2004) [NE, OS, CD, R]
Mixed system	-	**Eichner** (1998) [US, OS, CD, R]; **Smart and Stabile** (2005) [CA, NS, CD, R]
Insurance coverage		
Primary (vs. none)	+	**Christensen et al.** (1987) [US, OS, CD, R]
Public primary (vs. none)	+	**Cartwright et al.** (1992) [US, OS, CD, R]

Country: CA = Canada; NE = The Netherlands; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques

B.2.2. Medical care: the expenditure elasticity of demand

As our primary interest in this thesis is the price elasticity of demand for prescription drugs, we reported the price elasticity of demand for medical care in Section 3.3.2 of Chapter 3 to provide a broad comparator. Other researchers have been concerned with the expenditure elasticity of demand given that policymakers are interested in containing medical care budgets, and cost sharing is one tool for achieving this outcome. Appendix Table B.2 lists the main expenditure elasticities that have been found in the literature.

All of the analyses found the expenditure elasticity of demand for medical care to be less than –0.30. With the exception of the estimate from Smart and Stabile (2005), the other estimates were within a relatively small range (-0.14 to –0.04), implying that at least in these settings and using the given statistical techniques, patients appear to be relatively insensitive to changes in the price of medical care.

Appendix Table B.2. Medical care: the expenditure elasticity of demand

Study	Type of cost sharing	Expenditure elasticity
Phelps and Newhouse (1974) [US, OS, CD, NR]	Coinsurance	-0.12[a] to –0.04[a]
Smart and Stabile (2005) [CA, NS, CD, R]	Mixed system	–0.28
Van Vliet (2001) [NE, OS, CD, R]	Deductible	-0.08
Van Vliet (2004) [NE, OS, CD, R]	Deductible	-0.14

[a]unadjusted elasticity estimate (no regression used)
Country: CA = Canada; NE = The Netherlands; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

B.2.3. Medical care: the effect of cost sharing on health

The literature has established that cost sharing reduces both volume and expenditures, at least in the short-run, but another important consideration is how user fees shape health outcomes. If cost sharing leads to worse health outcomes, there may be an increase in long-run costs if patients delay care and eventually need more expensive care, such as emergency room visits and inpatient stays.

A number of studies using individual-level data from the United States have investigated the relationship between these two variables. The different subpopulations investigated include: children, adults, the non-elderly, non-elderly adults, the elderly, the near elderly, and women. These samples also included individuals with various health problems, including hypertension, colectoral cancer, lung cancer, breast cancer, and prostate cancer. Although there are papers that have investigated other specific health outcomes, most of the literature in this area has

considered mortality as the main outcome. A summary of the main results is available in Appendix Table B.3.

Appendix Table B.3. Medical care: cost sharing and health outcomes

Variable	Health Outcome	Effect	Studies
Coinsurance	mortality	+	**Brook et al.** (1983) [US, ES, CD, R]
Insurance coverage			
Primary (vs. none)	mortality	-	**Franks et al.** (1993) [US, OS, SA, R]; **McDavid et al.** (2003) [US, OS, CD/SA, R]; **McWilliams et al.** (2004) [US, OS, CD/SA, R]
Public primary (vs. private)	mortality	+	**McDavid et al.** (2003) [US, OS, CD/SA, R]
Co-payment	overall health	-	**Lurie et al.** (1984) [US, NS, CD, NR]
Coinsurance	overall health	0	**Valdez** (1986) [US, ES, CD, R]
Insurance coverage			
Primary (vs. none)	overall health	+	**Baker et al.** (2001) [US, OS, CD, R]
Co-payment	blood pressure	+	**Lurie et al.** (1984) [US, NS, CD, NR]
Coinsurance	blood pressure	+	**Brook et al.** (1983) [US, ES, CD, R]; **Keeler et al.** (1985) [US, ES, CD, NR]; **Manning et al.** (1987) [US, ES, CD, R]; **Newhouse** (1993) [US, ES, CD, R]
Coinsurance	hemoglobin levels	+	**Keeler et al.** (1985) [US, ES, CD, NR]
Coinsurance	vision	-	**Brook et al.** (1983) [US, ES, CD, R]; **Lurie et al.** (1989) [US, ES, CD, NR]; **Newhouse** (1993) [US, ES, CD, R]

Country: US = United States
Type of study: ES = experimental study; OS = observational study
Type of model used for analysis: CD = cross-sectional model; SA = survival analysis model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Only one study (Brook et al., 1983) considered how a specific form of cost sharing influences mortality, and the authors determined that individuals with no coinsurance in the RAND experiment had a lower risk of dying, although the authors mainly attributed this fact to the lower blood pressure that the free plan group achieved. Not surprisingly, the existence of primary insurance coverage as opposed to no insurance improved mortality outcomes, but a more interesting finding was that beneficiaries of public insurance coverage had worse mortality outcomes than those with private insurance. If this is the case, it is perhaps indicative of access and quality problems within public insurance. Both studies that found this result regarding public insurance examined a sample of cancer patients. Yet, neither controlled for the possible scenario where individuals with less severe forms of cancer are unable to obtain private health insurance and must obtain public coverage if possible or go without health coverage.

Of the few papers that considered the relationship between cost sharing and overall health, all except for Valdez (1986) found that higher user fees led to a decline in overall health and insurance coverage had the opposite effect. Valdez (1986) found no

significant relationship between coinsurance and overall health, although his sample consisted of children. Given that child health is often considered of utmost importance (Sundelin and Håkansson, 2000) and that guardians are typically making decisions on behalf of children, this may be a reason for the Valdez (1986) result.

Otherwise, there were only a few specific health outcomes where researchers found that cost sharing had an influence. Specifically, higher levels of cost sharing often led to higher blood pressure, higher hemoglobin levels, and worsening vision.

B.2.4. Inpatient care: the effect of cost sharing on expenditures

In contrast to other forms of medical care, consumers of inpatient services may have less control over the types of care they receive. Inpatient procedures are generally more complex than physician services, and patients may not be conscious enough to choose the type of care they are receiving. Although many inpatient procedures are set before the patient enters the hospital, and in these situations patients may have more discretion over the cost of services they receive. Furthermore, there is a question of whether cost sharing can dampen long-run expenditures given advances in medical technology, which are often expensive. It is for these reasons that a number of researchers have considered the relationship between user fees and inpatient expenditures. Appendix Table B.4 lists the results from the literature that has examined this area[1].

Scheffler (1984) determined that increased levels of cost sharing decreased hospital expenditures, while Van Vliet (2001) found that higher deductibles reduced inpatient expenditures among privately insured beneficiaries in the Netherlands. Phelps (1975) considered the quality adjusted out-of-pocket price (based on coinsurance rates) and reached the same conclusion regarding hospital expenses per admission. However, all of these papers used cross-sectional data techniques, and there is a question of whether individuals adjust to changes in the out-of-pocket price over time and whether they shift to newer, more expensive treatments.

Appendix Table B.4. Inpatient care: cost sharing and inpatient expenditures

Variable	Expenditures	Studies
Coinsurance	-	**Phelps** (1975) [US, OS, CD, R]
Deductible	-	**Van Vliet** (2001) [NE, OS, CD, R]
Mixed system	-	**Scheffler** (1984) [US, NS, CD, R]

Country: NE = the Netherlands; US = United States
Type of study: NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques

[1] While Phelps (1975) considered hospital expenses *per* admission, Scheffler (1984) and Van Vliet (2001) considered overall hospital expenditures

B.2.5. Inpatient care: the expenditure elasticity of demand

Although the price elasticity of demand is the primary variable of interest in this dissertation, researchers have also been concerned with the expenditure elasticity of demand for inpatient services. Appendix Table B.5 lists some of the expenditure elasticity estimates from the literature.

Appendix Table B.5. Inpatient care: the expenditure elasticity of demand

Study	Type of cost sharing	Expenditure elasticity
Newhouse and Phelps (1976) [US, OS, CD, R]	Mixed system	-0.30
Phelps and Newhouse (1974) [US, NS, CD, R]	Coinsurance	-0.08 to –0.04
Van Vliet (2001) [NE, OS, CD, R]	Deductibles	-0.01

Country: US = United States
Type of study: NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques

The expenditure elasticity values for inpatient care (-0.30 to -0.01) appear to be in the same range as the expenditure elasticity values for medical care, indicating that patients are relatively insensitive to changes in the out-of-pocket prices of hospital care.

B.2.6. Inpatient care: the effect of cost sharing on health

In addition to examining the relationship between cost sharing and inpatient use, a few papers have considered the association between inpatient user fees and health outcomes. Health is of particular interest as policymakers aim to maximize population health given a budget constraint, and a policy that decreases health outcomes may not contribute to this goal. There are a few studies that have examined mortality among patients that received hospital care, and all of these studies found that uninsured individuals had higher rates of total mortality (Yergan et al., 1988; Young and Cohen, 1991) and inpatient mortality (Haas and Goldman, 1994; Hadley et al., 1991; Young and Cohen, 1991) than individuals with some form of insurance, whether that insurance was Medicare only, fee-for-service, HMO, or any form of insurance. Thus, it appears that insurance does lead to better health outcomes.

B.2.7. Physician and outpatient care: the effect of cost sharing on expenditures

The literature on physician and outpatient expenditures is less extensive than the literature on the volume of services purchased. Van Vliet (2001) and Van Vliet (2004) used individual-level data aggregated to the policy level to investigate the impact of differing deductible levels on physician visits in the Netherlands. Both papers found

that higher deductibles, particularly deductibles above 100 Dfl, led to fewer physician visits.

B.2.8. Physician and outpatient care: the expenditure elasticity of demand

In addition to the price elasticity of demand, another variable of interest in the literature has been the expenditure elasticity of demand as this provides information on the combined effect of volume and price. A number of papers have considered this outcome variable, and Appendix Table B.6 provides an overview of the literature on the expenditure elasticity of demand.

Appendix Table B.6. Physician and outpatient care: the expenditure elasticity of demand

Study	Type of cost sharing	Expenditure elasticity (doctor visits)
Phelps and Newhouse (1974) [US, NS, CD, R]	Coinsurance	-0.14
Van Vliet (2001) [NE, OS, CD, R]	Deductible	-0.09 to –0.07
Van Vliet (2004) [NE, OS, CD, R]	Deductible	-0.40

[a]calculated by this author using the arc elasticity formula:

$$e_d = ((Q_2 - Q_1)/(Q_2 + Q_1))((P_2 + P_1)/(P_2 - P_1)).$$

Country: NE = The Netherlands; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of model used for analysis: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques

The results from the literature indicate that the expenditure elasticity of demand varies according to the context of the study. The reason for the large elasticity estimate from Van Vliet (2004) is likely due to health care in the Netherlands, which operates on a system of referrals. The patient has the largest and most direct effect on the number of visits to his chosen GP, and thus he is likely to be more sensitive to changes in the prices of physician services. In an earlier paper Van Vliet (2001) found a much lower value for GP elasticity, but the author indicates in Van Vliet (2004) that this was likely due to his inability to distinguish specific deductible levels in the 2001 paper.

B.2.9. Physician and outpatient care: the effect of cost sharing on health

We did not identify any studies that examined the impact of cost sharing for physician or outpatient services on health outcomes.

B.3. Literature covering cost sharing for prescription drugs

B.3.1. Prescription drugs: the effect of cost sharing on the probability of prescription drug use

The factors which induce an individual to purchase at least one prescription in a given time period may be different from the factors which determine the number of prescriptions he consumes. Additionally, there is a question of whether the primary effect of cost sharing is to deter the probability of any use or to reduce the consumption of prescriptions. This possibility has led some studies to consider sample selection issues and estimate the volume of prescription drugs obtained conditioned upon an individual having consumed at least one prescription. Other studies have attempted to determine whether cost sharing deters the individual from consumption altogether. The results of these papers are listed in Appendix Table B.7.

Appendix Table B.7. Prescription drugs: the effect of cost sharing on the probability of obtaining a prescription drug

Variable	Probability of drug use	Studies
Co-payment	-	**Esposito** (2002) [1] [[US, OS, CD, R]; **Gardner et al.** (1996) [NZ, OS, CD, NR]; **Hillman et al.** (1999) [US, OS, CD, R]; **Stuart and Zacker** (1999) [US, OS, CD, R]; **Watt et al.** (1992) [NZ, OS, CD, NR]
Multi-tier formulary (vs. 1- or 2-tiers)	-	**Huskamp et al.** (2005a) [US, NS, CD, R];
Coinsurance	-	**Lohr et al.** (1986) [US, ES, CD, NR]
Deductible	-	**Blais et al.** (1999) [CA, NS, TD, R]
Mixed system	-	**Goldman et al.** (2004) [US, OS, CD, R]; **Ozminkowski et al.** (2004) [US, OS, CD, R]; **Smart and Stabile** (2005) [CA, NS, CD, R]
Change from:		
deductible and coinsurance to income-based deductible	-	**Kozyrskyj et al.** (2001) [CA, NS, CD, R]
Insurance coverage		
Primary (vs. none)	+	**Smith and Garner** (1974) [US, NS, CD, NR]
Supplementary (vs. none)	+	**Adams et al.** (2001) [US, OS, CD, R]; **Blustein** (2000) [US, OS, CD, R]; **Caussat and Glaude** (1993) [FR, OS, CD, R]; **Coulson and Stuart** (1995) [US, OS, CD, R]; **Genier et al.** (1997) [FR, OS, CD, R]; **Grignon and Perronin** (2003) [FR, NS, CD, R]; **Raynaud** (2002) [FR, OS, CD, R]; **Raynaud** (2005) [FR, OS, CD, R]; **Stuart and Grana** (1995) [US, OS, CD, R]
Supplementary (vs. none)	0	**Christiansen et al.** (2002) [DK, OS, CD, R]
Supplementary public (vs. private)	+	**Raynaud** (2002) [FR, OS, CD, R]; **Raynaud** (2005) [FR, OS, CD, R]

[1] This study examined the probability of using a specific statin compared to the probability of using other statins when there were differing co-payments for each statin

Country: CA = Canada; DK = Denmark; FR = France; NZ = New Zealand; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Every paper found either that individuals who faced user fees were less likely to use prescription drugs or that those with health insurance were more likely to use them. The co-payments studied ranged in price from $0-$3 to about $10, and co-insurance rates ranged from 0 percent to 95 percent. Esposito (2002) also found that when there were differential co-payments for different statins, which ranged in price from $0 to $52.51, patients in the US were more likely to choose the least expensive option.

Two studies compared prescription drug consumption among individuals facing a change in their cost sharing regime (Huskamp et al., 2005a; Kozyrskyj et al., 2001). Kozyrskyj et al.(2001) found that when the Canadian province of Manitoba changed from a CDN $237 deductible and a 40 percent coinsurance rate to an income-based deductible (families with income below CDN $15,000 faced a lower deductible) with 0 percent coinsurance above the deductible, there was no adjustment in consumption among low-income children, but consumption decreased for higher-income children. This result was not surprising in that the income-based deductible probably increased the out-of-pocket burden for higher-income respondents, but it appears that the existence of a deductible was still a deterrent for low-income groups, even if the deductible was lower than before. Additionally, Huskamp et al. (2005a) considered a group of children with attention-deficit disorder that faced a simultaneous change from a one-tier to a three-tier formulary and an across-the-board co-payment increase. Not surprisingly, the authors found that the probability of consumption decreased after the co-payment change.

B.3.2. Prescription drugs: the effect of cost sharing on prescription drug expenditures

Although volume is clearly influenced by higher cost sharing requirements, policymakers are also interested in the impact of user fees on the drug budget. One issue is that under coinsurance regimes, generics are cheaper than brand-name drugs for consumers, and patients may switch to generic alternatives. Another consideration is that co-payments can be tiered so that generics and other preferred drugs (generally based on negotiations with manufacturers) are cheaper than non-preferred brand-name drugs. Although both of these policy options may decrease volume, it is likely that some consumers will switch to cheaper alternatives instead of foregoing prescriptions. Moreover, over a period of time, patients often trade up to newer and more expensive treatments (and new medicines widen the treatment population), causing expenditures to rise despite the existence of co-payments. The overall message from this discussion is that cost sharing will likely lead to lower expenditures in the short-run, but the long-run effect is unclear. See Appendix Table B.8 for the literature that has examined expenditures for prescription drugs.

Most studies found that higher cost sharing lowered prescription drug expenditures, although Grootendorst (1997) determined that the provision of enhanced drug coverage for older people in British Columbia, Canada had no effect on prescription drug expenditures. However, this result may have been related to the construction of the data as the author could only control for the sickest respondents in the earliest year of the sample (Grootendorst, 1997). Individuals who faced a three-tier formulary

instead of a two-tier formulary also had lower expenditures, likely because these respondents switched to the lower-priced therapeutic alternatives in the first tier.

Appendix Table B.8. Prescription drugs: the effect of cost sharing on prescription drug expenditures

Variable	Expenditures	Studies
Co-payment	-	**Atella** (2000) [IT, OS, CD, R]; **Hanau and Rizzi** (1986) [IT, NS, TD, R]; **Joyce et al.** (2002) [US, OS, CD, R]; **Lurk et al.** (2004) [US, NS, CD, R]; **Reeder and Nelson** (1985) [US, NS, TD, R]; **Smith** (1993) [US, OS, CD, R]
Multi-tier formulary (vs. 1- or 2-tiers)	-	**Fairman et al.** (2003) [US, NS, CD, R]; **Gibson et al.** (2005) [US, NS, PD, R]; **Huskamp et al.** (2003) [US, NS, CD, R]; **Huskamp et al.** (2005a) [US, NS, CD, R]; **Motheral and Fairman** (2001) [US, NS, CD, R]; **Kamal-Bahl and Briesacher** (2004) [US, OS, CD, R]; **Motheral and Henderson** (1999) [US, NS, CD, R]; **Thomas et al.** (2002) [US, OS, CD, NR]
Coinsurance	-	**Alignon and Grignon** (1997) [FR, OS, CD, NR]; **Almarsdóttir et al.** (2000) [IC, NS, TD, R]; **Klaukka et al.** (1993) [FI, NS, CD, R]; **Liebowitz et al.** (1985) [US, ES, CD, R]; **Newhouse** (1993) [US, ES, CD, R]
Deductible	-	**Van Vliet** (2001) [NE, OS, CD, R]; **Van Vliet** (2004) [NE, OS, CD, R]
Mixed system	-	**Klick and Stratmann** (2005) [US, OS, CD, R]; **Smart and Stabile** (2005) [CA, NS, CD, R]; **Thomas et al.** (2002) [US, OS, CD, NR]
Mixed system	0	**Grootendorst** (1997) [CA, NS, PD, R]
Change from		
co-payment to coinsurance	-	**Contayannis et al.** (2005) [CA, NS, CD, R]
coinsurance to deductible and coinsurance	-	**Contayannis et al.** (2005) [CA, NS, CD, R]
Insurance coverage		
Primary (vs. none)	+	**Artz et al.** (2002) [US, OS, CD, R]; **Danzon and Pauly** (2002) [US, OS, CD, NR]; **Gianfrancesco et al.** (1994) [US, NS, CD, NR]; **Smith and Garner** (1974) [US, NS, CD, NR]
Supplementary (vs. none)	+	**Davis et al.** (1999) [US, OS, CD, NR]; **Dourgnon and Semet** (2002) [FR, OS, CD, R]; **Federman et al.** (2001) [US, OS, CD, R]; **Lillard et al.** (1999) [US, OS, CD, R]; **Long** (1994) [US, OS, CD, R]; **Poisal and Murray** (2001) [US, OS, CD, NR]; **Raynaud** (2003) [FR, OS, CD, R]; **Raynaud** (2005) [FR, OS, CD, R]; **Stuart et al.** (2000) [US, OS, CD, R]; **Weeks** (1973) [US, NS, CD, NR]
Supplementary (vs. none)	+	**Yang et al.** (2004) [US, OS, CD, R]
Supplementary (vs. none)	0	**Grignon and Perronin** (2003) [FR, NS, CD, R]
Public supplementary (vs. private)	+	**Raynaud** (2003) [FR, OS, CD, R]
Prescription limit	-	**Soumerai et al.** (1994) [US, NS, TD, R]

Country: CA = Canada; FI = Finland; FR = France; IC = Iceland; IT = Italy; NE = The Netherlands; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Contayannis et al. (2005) considered the effect of changing from one cost sharing regime to another based on two separate policy changes in Quebec, Canada; the first was a change from a CDN $2 co-payment to 25 percent co-insurance up to CDN $25

maximum per prescription and the second was the addition of a deductible. After both policy changes, the authors observed a decrease in prescription drug expenditures.

Although having any form of insurance coverage (as opposed to none) had the expected effect on expenditures, there were other interesting findings related to specific types of insurance coverage. For example, we might expect Medicaid beneficiaries to have higher prescription drug expenditures than others because income and health tend to be correlated (Macinko et al., 2003). However, Medicaid recipients were found to have lower prescription drug expenditures than individuals wi|th Medicare only (Yang et al., 2004), perhaps due to cost containment measures imposed by Medicaid, such as prescription restrictions and the use of formularies.

B.3.3. Prescription drugs: the effect of cost sharing on out-of-pocket drug expenditures

Another dependent variable that the literature considered was out-of-pocket prescription drug expenditures. We would expect higher levels of cost sharing to place a greater economic burden on individuals by increasing their out-of-pocket expenditures. However, rising out-of-pocket expenditures may in turn cause patients to lower their use of prescription drugs, so the net effect of cost sharing on out-of-pocket prescription drug expenditures could be positive or negative (see Appendix Table B.9).

Appendix Table B.9. Prescription drugs: the effect of cost sharing on out-of-pocket drug expenditures

Variable	Out-of-pocket expenses	Studies
Co-payment	+	**Lurk et al.** (2004) [US, NS, CD, R]; **Stuart and Zacker** (1999) [US, OS, CD, R]
Multi-tier formulary (vs. 1- or 2-tiers)	+	**Huskamp et al.** (2005a) [US, NS, CD, R]; **Huskamp et al.** (2005b) [US, NS, CD, R]; **Kamal-Bahl and Briesacher** (2004) [US, OS, CD, R]
Insurance coverage		
Supplementary (vs. none)	-	**Alan et al.** (2002) [CS, OS, CD, R]; **Alan et al.** (2003) [CS, OS, CD, R]; **Alan et al.** (2005) [CS, OS, CD, R]; **Blustein** (2000) [US, OS, CD, R]; **Federman et al.** (2001) [US, OS, CD, R]
Reimbursement limit	+	**Tseng et al.** (2003) [US, OS, CD, NR]

Country: CA = Canada; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Stuart and Zacker (1999) found that Medicaid recipients living in states where Medicaid required co-payments ($0.50 to $3) had lower overall out-of-pocket costs for prescription drugs. However, the study was not able to control for restrictions that

Medicaid might place on recipients, such as limits on the number of prescriptions per month, which might explain lower out-of-pocket spending in states with co-payments. Other researchers (Blustein, 2000; Federman et al., 2001) showed that individuals with insurance coverage in addition to Medicare had lower levels of out-of-pocket spending. In addition, Alan et al. (2003) found that the introduction of additional insurance coverage lowered the proportion of an individual's budget spent on prescription drugs for older Canadian households with low and high levels of out-of-pocket spending on prescription drugs. The same authors confirmed this result in a later study (Alan et al., 2005) but also found that among non-elderly households, the introduction of drug benefit programs lowered out-of-pocket spending on prescription drugs more for low-income households than for high-income households.

B.3.4. Prescription drugs: the expenditure elasticity of demand

The expenditure elasticity of demand is another variable of interest from the literature, and Appendix Table B.10 provides information on the limited number of studies that have considered this outcome variable.

Appendix Table B.10. Prescription drugs: the expenditure elasticity of demand

Study	Type of cost sharing	Expenditure elasticity
Contayannis et al. (2005) [CA, NS, CD, R]	Change from co-payment to coinsurance	-0.16 to -0.12
Klick and Stratmann (2005) [US, OS, CD, R]	Mixed system	-1.07
Phelps and Newhouse (1972) [CA/UK, OS, CD, NR]	Coinsurance	-0.07
Smart and Stabile (2005) [CA, NS, CD, R]	Mixed system	-0.29 to -0.28
Van Vliet (2001) [NE, OS, CD, R]	Deductible	-0.06
Van Vliet (2004) [NE, OS, CD, R]	Deductible	-0.08

Country: CA = Canada; NE = The Netherlands; UK = United Kingdom; US = United States
Type of study: NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

The expenditure elasticity results range from an elastic –1.07 to an inelastic –0.06. The elastic estimate from Klick and Stratmann (2005) was unusually high, although this may have been due to the fact that their sample was restricted to the most price sensitive group of the elderly (those without Medicaid or employer-sponsored health insurance). In general, it appears that the expenditure elasticity is relatively low and close to the range of expenditure elasticity values found for medical care, physician visits, and inpatient visits.

B.3.5. Prescription drugs: the effect of cost sharing on the use of substitutes and complements

As discussed in Section 3.5 of Chapter 3, the literature has established that cost sharing for prescription drugs reduces consumption of prescription drugs. Yet, another question that remains to be discussed is whether user fees influence the use of other goods or services related to prescription drugs. There may be health implications if patients substitute less effective forms of care such as over-the-counter drugs for prescription drugs, and there may be expenditure implications if consumers opt for more expensive forms of care such as inpatient stays. A number of articles focused on the relationship between cost sharing for prescription drugs and the demand for substitutes or complements (over-the-counter drugs, physician visits, inpatient visits, emergency mental health services, and nursing homes). Appendix Table B.11 outlines the literature in this area.

Appendix Table B.11. Prescription drugs: the effect of cost sharing on the use of substitutes and complements

Good/service affected	Variable	Effect	Study
OTC drugs	Coinsurance	-	**Liebowitz** (1989) [US, ES, CD, R]
	Insurance coverage Supplementary (vs. none)	+	**Caussat and Glaude** (1993) [FR, OS, CD, R]
	Supplementary (vs. none)	-	**Stuart and Grana** (1995) [US, OS, CD, R]
	Prescription limit	+	**Cox et al.** (2001) [US, OS, CD, R]
physician services	Co-payment	-	**Anis et al.** (2005) [CA, OS, PD, R]; **Balkrishnan et al.** (2001) [US, NS, PD, R]; **Lauterbach et al.** (2000) [DE, OS, CD, R]; **Winkelmann** (2004a) [DE, NS, PD, R]; **Winkelmann** (2004b) [DE, NS, CD, R]
	Co-payment	0	**Gardner et al.** (1997) [US, NS, TD, R]
	Multi-tier formulary (vs. 1- or 2-tiers)	0	**Motheral and Fairman** (2001) [US, NS, CD, R]
	Mixed system	+	**Li et al.** (2006) [CA, NS, PD, R]
	Change from coinsurance to deductible and coinsurance	0	**Pilote et al.** (2002) [CA, NS, CD, R]
	Insurance coverage Public Supplementary (vs. private)	+	**Raynaud** (2005) [FR, OS, CD, R]
	Reimbursement limit	-	**Hsu et al.** (2006) [US, OS, PD, R]
outpatient services	Co-payment	+	**Balkrishnan et al.** (2001) [US, NS, PD, R]
	Insurance coverage Public supplementary (vs. none)	+	**Raynaud** (2005) [FR, OS, CD, R]
inpatient services	Co-payment	+	**Anis et al.** (2005) [CA, OS, PD, R]; **Atella et al.** (2005) [IT, NS, CD, R]; **Balkrishnan et al.** (2001) [US, NS, PD, R]
	Co-payment	0	**Gardner et al.** (1997) [US, NS, TD, R]
	Multi-tier formulary (vs. 1- or 2-tiers)	0	**Motheral and Fairman** (2001) [US, NS, CD, R]

Good/service affected	Variable	Effect	Study
	Insurance coverage		
	Supplementary (vs. none)	-	**Schoen et al.** (2001) [US, NS, CD, NR]
	Public supplementary drug (vs. private)	-	**Lingle et al.** (1987) [US, OS, CD, R]
	Prescription limit	+	**Soumerai et al.** (1994) [US, NS, TD, R]
	Prescription limit	0	**Soumerai et al.** (1991) [US, NS, TD, R]
	Reimbursement limit	+	**Hsu et al.** (2006) [US, OS, PD, R]
ER visits	Multi-tier formulary (vs. 1- or 2-tiers)	0	**Motheral and Fairman** (2001) [US, NS, CD, R]
	Mixed system	+	**Tamblyn et al.** (2001) [CA, NS, TD, R]
	Change from		
	co-payment to deductible and coinsurance	+	**Tamblyn et al.** (2001) [CA, NS, TD, R]
	coinsurance to deductible and coinsurance	0	**Pilote et al.** (2002) [CA, NS, CD, R]
	Reimbursement limit	+	**Hsu et al.** (2006) [US, OS, PD, R]
emergency mental health services	Prescription limit	+	**Soumerai et al.** (1994) [US, NS, TD, R]
nursing home admissions	Prescription limit	+	**Soumerai et al.** (1991) [US, NS, TD, R]

Country: CA = Canada; DE = Germany; FR = France; IT = Italy; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

As the use of prescription drugs requires a doctor's prescription, in most cases we would expect prescription drug charges to decrease the use of doctors. One study found that a reimbursement limit did indeed lead to a reduction in doctor visits, three papers found that prescription drug charges had no effect on doctor visits, and one study found that they had a positive effect. However, two of the three studies finding no relationship between prescription drug charges and doctor visits examined situations in which user charges were designed to encourage the use of lower-cost drugs through multi-tier formularies (Motheral and Fairman, 2001) or differential charges for generics and brand-name medications (Gardner et al., 1997). In the third of the three studies finding no relationship, the insignificant effect result may be explained by the fact that all of the study participants had experienced a heart attack, while those with lower incomes were afforded greater protection from prescription drug charges (Pilote et al., 2002). Consequently, this group was less likely to be sensitive to changes in price and, perhaps more likely to see the doctor for reasons other than to obtain a prescription. The positive result came from a sample of older people with rheumatoid arthritis (Li et al., 2006). As health insurance in Canada fully covers doctor visits, it is not surprising that some patients would substitute physician care for prescription drugs.

Researchers have obtained mixed results for OTC drugs. In the RAND experiment higher co-insurance rates lowered the probability of purchasing an OTC drug but after

controlling for this, cost sharing had no effect on OTC expenditures (Liebowitz, 1989). Additional insurance coverage led to higher use of prescription drugs compared to OTC drugs in another US study (Stuart and Grana, 1995) but had the opposite effect in a French study (Caussat and Glaude, 1993). The French result probably differed because additional health insurance in France covers more than just prescription drugs, and as doctors often recommend the use of OTC drugs, increased OTC drug use may have been prompted by increased doctor visits. Having a limit on the number of free prescriptions an individual is allowed per month (a policy most often associated with Medicaid in the United States) positively influenced the quantity of OTC drugs used (Cox et al., 2001).

The results for outpatient, inpatient, and emergency care are more consistent. User charges designed to encourage the use of lower-cost drugs had no significant effect on the use of inpatient or emergency care. All except two studies found that prescription drug charges increased the use of outpatient, inpatient, and emergency care. Studies also found that prescription limits increased the frequency of partial hospitalisation (Soumerai et al., 1994), nursing home admissions (Soumerai et al., 1991), and emergency mental health services (Soumerai et al., 1994). The first study to find no effect was the one based on patients who had experienced a heart attack (outlined above) (Pilote et al., 2002). The authors of the second study suggested that their insignificant result for inpatient admissions might be due to the fact that the outcome variable they used (time to first hospital admission) would not highlight repeat hospital visits (Soumerai et al., 1991).

B.3.6. Prescription drugs: the effect of cost sharing on adherence to medications

The financial burden imposed by cost sharing may induce patients to adopt strategies that affect adherence to a particular treatment regime; for example, patients may cut pills in half or skip doses of medication. Appendix Table B.12 lists the results from the literature that focused on adherence to medication regimes.

Respondents were less likely to adhere to a treatment when faced with a co-payment even if the co-payment was relatively small (Poirier et al., 1998). Additionally, adherence was more of a problem for patients with a multi-tier formulary (vs. a two-tier formulary) (Landsman et al., 2005) or when patients purchased non-preferred drugs in a multi-tier formulary (Taira et al., 2006) as opposed to generic or preferred drugs. Dor and Encinosa (2004) also found that individuals who faced co-payments were more likely to comply with treatment regimes for diabetes than individuals who faced co-insurance rates. This difference may be due to patients' uncertainty about how changes in the prices of drugs will affect their out-of-pocket spending under co-insurance (Dor and Encinosa, 2004). Individuals facing co-payments may also be able to obtain larger prescriptions to avoid higher out-of-pocket costs, an option unavailable under coinsurance regimes. Having primary or supplementary insurance increased adherence to treatment, while the existence of a limit on the number of reimbursable prescriptions had the opposite effect (Cox et al., 2001; Shulz et al., 1995).

Appendix Table B.12. Prescription drugs: the effect of cost sharing on adherence

Variable	Compliance	Study
Co-payment	-	**Atella et al.** (2005) [IT, NS, CD, R]; **Gibson et al.** (2006) [US, OS, CD, R]; **Poirier et al.** (1998) [CA, NS, TD, NR]
Co-payment	0	**Poirier et al.** (1998) [CA, NS, TD, NR]
Multi-tier formulary (vs. 1- or 2-tiers)	-	**Landsman et al.** (2005) [US, NS, TD, R]; **Taira et al.** (2006) [US, OS, CD, R]
Coinsurance	-	**Reuveni et al.** (2002) [IS, OS, CD, R]
Mixed system	+	**Ellis et al.** (2004) [US, OS, CD, R]; **Goldman et al.** (2006) [US, OS, CD, R]; **Mojtabai and Olfson** (2003) [US, OS, CD, R]; **Piette et al.** (2004) [US, OS, CD, R]
Change from coinsurance to deductible and coinsurance	0	**Pilote et al.** (2002) [CA, NS, CD, R]
Has coinsurance (vs. has co-payment)	-	**Dor and Encinosa** (2004) [US, OS, CD, R]
Insurance coverage		
Primary (vs. none)	+	**Kennedy and Erb** (2002) [US, OS, CD, NR]; **Piette et al.** (2004) [US, OS, CD, R]; **Thomas et al.** (1996) [US, OS, CD, R]
Primary public (vs. private)	-	**Dodrill et al.** (1987) [US, OS, CD, NR]
Supplementary (vs. none)	+	**Col et al.** (1990) [US, OS, CD, R]; **Safran et al.** (2002) [US, OS, CD, R]; **Schoen et al.** (2001) [US, NS, CD, NR]
Prescription limit	-	**Cox et al.** (2001) [US, OS, CD, R]; **Schulz et al.** (1995) [US, NS, CD, NR]

Country: CA = Canada; IS = Israel; IT = Italy; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

B.3.7. Prescription drugs: the effect of cost sharing on health

Another pressing question related to prescription charges is whether there is any effect on health. If user fees worsen health outcomes, long-run health care costs may increase, particularly if patients make more doctor visits, have more inpatient stays, and ultimately end up needing more prescription drugs.

Datasets of sufficient longitude to assess the impact of cost sharing on health are scarce. Although researchers using data from the RAND experiment estimated the impact of cost sharing on health outcomes, the length of time allowed for follow up of participants may not have been adequate to fully assess any effect on health, and few of these studies specifically linked cost sharing for prescription drugs to health outcomes. As a result, many studies use changes in essential drug use as a proxy for poor health outcomes on the grounds that decreases in the use of necessary medications may negatively affect health in the long term (see Appendix Table B.13). The definition of essential drug use varied by study, but essential drugs were generally considered to be those primarily used in the management of chronic medical conditions where the cessation of drug therapy would have potentially serious consequences or drugs that prevent deterioration in health or prolong life.

Appendix Table B.13. Prescription drugs: the effect of cost sharing on the use of essential and discretionary medications

Variable	Use of essential medicines	Use of discretionary medicines	Studies
Co-payment	-	-	**McManus et al.** (1996) [AU, NS, TD, R]
Co-payment	negligible	N/A	**Brian and Gibbens** (1974) [US, ES, CD, NR]
Coinsurance	-	-	**Foxman et al.** (1987) [US, ES, CD, R]
Mixed system	negligible	-	**Gardner et al.** (1996) [NZ, OS, CD, NR]
Mixed system	-	N/A	**Tamblyn et al.** (2001) [CA, NS, TD, R]
Change from co-payment to deductible and coinsurance	-	N/A	**Tamblyn et al.** (2001) [CA, NS, TD, R]
Prescription limit	-	N/A	**Fortress et al.** (2001) [US, NS, PD, R]; **Martin and McMillan** (1996) [US, NS, TD, R]; **Soumerai et al.** (1987) [US, NS, TD, R]; **Soumerai et al.** (1991) [US, NS, TD, R]
Prescription limit	N/A	-	**Soumerai et al.** (1987) [US, NS, TD, R]

Country: AU = Australia; CA = Canada; US = United States
Type of study: ES = experimental study; NS = natural study; OS = observational study
Type of data analyzed: CD = cross-sectional model; TD = time-series model; PD = panel data model
Type of statistical analysis used: R = regression techniques; NR = no regression techniques

Research has indicated that higher out-of-pocket costs lowered the use of essential drugs, implying that individuals are unable to distinguish between necessary and unnecessary prescriptions. For example, Soumerai et al. (1987) determined that Medicaid beneficiaries decreased their use of both types of prescriptions when faced with a prescription limit. However, Brian and Gibbens (1974) and Gardner et al. (1996) found that cost sharing had little impact on drugs that were judged to be important for the treatment of serious illnesses or drugs that were classified as critical or necessary, although both sets of authors only reported descriptive statistics.

A few papers directly or indirectly linked cost sharing and health outcomes in other ways. A Canadian study (Tamblyn et al., 2001) looked at essential drug use and serious adverse events (hospitalizations, nursing home admissions, and mortality) after a change from no co-payment for those receiving social assistance and a CDN $2 co-payment for older people to co-insurance and annual maximum charges of CDN $200-$925. The authors found that higher prescription charges increased adverse events associated with reductions in the use of essential drugs, and greater cost sharing increased hospitalizations and emergency department visits, particularly among mentally ill patients. Another Canadian study examined a sample of older people who had experienced a myocardial infarction (Pilote et al., 2002) and found that a switch from a CDN $2 co-payment to co-insurance with annual maximums based on income (CDN $200, $500, or $750) had no effect on mortality or readmissions for complications. However, this particular group may have been less sensitive to changes in price due to their life-threatening chronic condition.

Schoen et al. (2001) considered a natural experiment where indigent patients with cardiovascular disease that did not have prescription drug coverage received medications free of charge. The authors found that mean blood pressure declined among patients with hypertension, and mean LDL decreased for patients receiving free lipid-lowering drugs. Finally, Atella et al. (2005) looked at the correlation between a co-payment, level of adherence to treatment, and health in a sample of Italian hypertension patients. They found that the abolition of the co-payment lowered the mortality rate for low-compliant patients by 0.7 percentage points but had no effect on the mortality rate for high-compliant patients.

Overall, most articles found that prescription charges lowered the use of essential and non-essential drugs, although reductions in the use of non-essential drugs were usually slightly larger. This suggests that patients may attempt to discriminate on the basis of the usefulness of the prescription drug in question but are not always able to judge appropriately.

B.4. Summaries of cost sharing studies

Appendix Table B.14. Summaries of studies of cost sharing for medical care, inpatient services, physician services, and prescription drugs

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Adams et al. (2001)	Prescription drugs	The United States	1995	4,439 elderly (65+) beneficiaries with self-reported hypertension not enrolled in VA care or Medicare HMO	Employer-sponsored versus state-sponsored versus private supplemental insurance	Seniors with some form of state-sponsored drug coverage were more likely to use antihypertensive medications (odds ratio 1.5) than their counterparts with Medicare only; Among seniors with private supplemental insurance, those with employer-sponsored insurance were more likely to use antihypertensive medications (odds ratio 1.3) than their counterparts with private insurance that does not cover medications	No information on the extent of drug coverage; Cross-sectional study, thus difficult to control for other factors that increase prescription drug utilization
Ahlamaa-Tuompo et al. (1998a)	Inpatient services	(Helsinki) Finland	1989-1994	40,000 injuries of children (<16)	Introduction of FIM 60 co-payment for inpatient visits; then increased to FIM 100	The introduction of the co-payment decreased the annual inpatient visit rates for injuries by about 27% in the 7-15 age group and by about 18% in the 0-6 age group	May not be generalizable because limited to one city in Finland; Unmeasured variables such as income and education of parents
Ahlamaa-Tuompo et al. (1998b)	Emergency room services	(Helsinki) Finland	1989-1994	37,861 injuries for children (<16)	Introduction of FIM 60 co-payment for inpatient visits; then increased to FIM 100	The incidence of visits due to home and leisure injuries decreased after co-payment was introduced, but the incidence of school injuries was unchanged	May not be generalizable because limited to one city in Finland; Unmeasured variables such as income and education of parents
Alignon and Grignon (1998)	Prescription drugs	France	1991	Individuals of all ages (sample size not specified)	Individuals faced different levels of cost sharing	Out-of-pocket payments were below average for poor households due to foregoing treatment; When rich households chose to forego treatments, it was when they had already made high OOP payments	Did not control for other factors with regression; Cross-sectional study, thus difficult to control for other factors that increase prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Alan et al. (2002)	Prescription drugs	(All 10 provinces) Canada	1969, 1974, 1984, 1986, 1990, 1992, 1996	6,322 elderly (65+) urban respondents	Changes in provincial cost sharing requirements and subsidies over time	The incidence of a prescription drug subsidy for seniors was mildly less progressive than a percentage-of-income cash transfer; The reduction in prescription drug budget share upon implementation of a subsidy was only slightly larger for low-income than for high-income households	Unmeasured variables such as changes in numbers of physicians or pharmacists, restrictiveness of drug programs, and preferences for different drugs over time may have influenced results
Alan et al. (2003)	Prescription drugs	Canada	1969, 1986, 1996	Senior- and nonsenior-led households	Changes in provincial cost sharing requirements and subsidies over time	The introduction of drug benefits programs reduced out-of-pocket prescription drug expenditures by a larger amount for high-outlay households than for low-outlay households; Among elderly households, these programs reduced prescription drug budget shares about the same amount for high- and low-outlay households, while the differences are less clear cut for non-elderly households	Unmeasured variables such as changes in numbers of physicians or pharmacists, restrictiveness of drug programs, and preferences for different drugs over time may have influenced results
Alan et al. (2005)	Prescription drugs	(British Columbia, Alberta, Saskatchewan, Manitoba, and Ontario) Canada	1974, 1984, 1990	Non-elderly households not receiving social assistance (598 and 516 for BC, 704 for Alberta, 440 for Saskatchewan, 327 for Manitoba, and 1403 for Ontario)	Drug programs were introduced during the study time period in each of the studied provinces	The introduction of drug benefits programs reduced prescription drug budget shares for households; The budget share reductions for low-income households were larger than for high-income households, suggesting that programs were progressive	Unmeasured variables such as changes in numbers of physicians or pharmacists, restrictiveness of drug programs, and preferences for different drugs over time may have influenced results
Almarsdóttir et al. (2000)	Prescription drugs	Iceland	1993-1998	6 years of data (number of observations not given)	Increase in cost-sharing requirement	Regulation to increase patients' share of drug costs had a weak effect	Unmeasured variables such as changes in supply of pharmacists and GPs could be important

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Anderson et al. (2006)	Prescription drugs	Sweden	1986-2002	17 years of quarterly data on prescription drug volume	Co-payment changes or reforms over time	The introduction of a new reimbursement schedule decreased levels of costs and volume in all indicator groups except for insulin; Subsequent increases in co-payments had almost no effect on volume	Individual information may have been lost at the aggregate level
Anessi Pessina (1997)	Prescription drugs	(Emilia-Romagna) Italy	1989-1993	18 Districts and 60 months of data	Changes in co-payments for prescription drugs over time and different co-payments for drugs based on their classification	The elasticity of demand was generally larger than estimates from other studies; Estimates ranged from -0.75 for vasoprotectives to -0.07 for diuretics	The demographic variables were aggregated and not all could be included in the regression because of correlation
Anis et al. (2005)	Prescription drugs	(British Columbia) Canada	1997-2000	2,968 elderly patients (65+) with rheumatoid arthritis who had paid the maximum amount of dispensing fees in a calendar year	Individuals paid 100% of dispensing fees up to an annual maximum of $200	No difference in the probability of being admitted to the hospital between the cost sharing and free period, but patients with cost sharing had a slightly higher number of admissions conditioned on one admission; During the cost sharing period, more patients had physician visits and fewer patients filled prescriptions	Unmeasured variables such as income and working status may have influenced the results
Artz et al. (2002)	Prescription drugs	The United States	1992-1995	Individuals that were enrolled in Medicare Part A and Part B but not Medicaid	Supplemental drug insurance coverage (none, good, fair, poor)	As prescription generosity increased, per capita prescription fill ratios increased consistently for all insurance groups; however, the ratios peaked at the fair generosity level and declined as generosity became good; As prescription generosity increased, expenditure ratios rose for all insurance groups	There may be a problem with using individuals with no supplementary insurance for the reference group; No information regarding the restrictiveness of the prescription drug formulary

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Atella (2000)	Prescription drugs	Italy	1963-1994	34 years of annual expenditure data	Changes in institutional structure over time and introduction of co-payments in 1978, which changed several times over the course of the study period	In the long run, increasing the co-payment rate by 1% for public drugs only decreased expenditures by 0.40%; In the long run, an increase in the co-payment rate for private expenditures actually led to an increase in private expenditures	Individual information may have been lost at the aggregate level; Unmeasured variables such as changes in prices of substitutes for prescription drugs
Atella et al. (2005)	Prescription drugs	(Treviso) Italy	1993-2004, 1995-2004	36,453 patients with hypertension being treated with ACE-inhibitors	Co-payment abolished in Jan 2001 (was previously 1.5 Euros); co-payment of 1 Euro reintroduced in March 2002	Changes in cost sharing had a larger impact on low compliant patients than on high compliant patients; For low compliant patients, the abolition of the co-payment decreased the hospitalization rate by 1 percentage point and the mortality rate by 0.7 percentage points	The databases contained no information on income and education; Sample limited to individuals in one small region of Italy and may not be generalizable to a larger population
Babazono et al. (1991)	Inpatient services, outpatient services	Japan	1983-1985	12,385,925 individuals	Introduction of 10% coinsurance with an OOP limit of 54,000 yen	Coinsurance decreased the number of individuals that used inpatient and outpatient care in a month; The average age of the individual was the most important determinant of the demand for medical services	Individual information may have been lost at the aggregate level; Unmeasured variables such as preferences for medical care or cultural factors
Baker et al. (2001)	Medical services	The United States	1992, 1994, 1996	7,577 adults who were not elderly (51-61) in 1992	Insurance coverage (continuously insured, intermittently insured, continuously uninsured)	Continuously uninsured participants were 63% more likely than privately insured participants to have an overall decline in their health	No information on the extent of insurance coverage
Balkrishnan et al. (2001)	Prescription drugs	The United States	1997-1999	2,411 elderly (65+) continuously enrolled in Medicare HMO since 1998; 259 enrolled since 1997 were eligible for the first part of the study	1997: $500 annual coverage limit, $6/generic, $12/brand 1998: $200 quarterly deductible, $7/ generic, $15/brand; 1999: unlimited coverage of generic drugs at $5 per item, $15/brand drug up to $25 per month	Policy change in 1998 caused 25.2% increase in annual inpatient admissions, 29% increase in prescriptions costs, and 38% increase in total costs for HMO; Policy change in 1999 caused 27% increase in prescription costs, 4.4% drop in physician visits, no significant changes in inpatient visits, and 6.2% drop in annual total health care costs	May not be generalizable because limited to a single HMO; Small sample for initial policy change

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Barnett et al. (2000)	Physician services	(Christchurch) New Zealand	1995, 1996	202 patients from the Kingdom Free Clinic and 148 patients using traditional fee-for-service providers	Some eligible individuals were able to use the free clinic	The mean GP consultation rates were 2.82 and 2.03 for the Kingdom Clinic and Phillipstown samples, respectively; Despite having free care, a higher percentage of individuals in the Kingdom Clinic sample reported delaying seeking care because of cost than in the Phillipstown sample	Unmeasured variables such as marital status and employment information; Cross-sectional study, thus difficult to control for other factors that influence physician and clinic utilization rates
Beck (1974)	Physician services	(Saskatchewan) Canada	1963-1968	Approximately 40,000 low-income individuals	Introduction of CDN $1.50 co-payment for physician visits	Co-payment resulted in approximate 18% decline in physician visits	Income was self reported - also reported income often differs from actual income because of the Canadian tax structure
Beck and Horne (1980)	Inpatient services, physician services	(Saskatchewan) Canada	1963-1973	Approximately 40,000 low-income individuals	Introduction of CDN $1.50 co-payment for physician visits and CDN $2.50 charge per day for first thirty days of hospitalization and CDN $1.50 per day thereafter up to 90 day maximum	User fees resulted in 5.66% reduction in use of physicians' services over entire period; No evidence that co-payments shortened lengths of stay in the hospital	Income was self reported - also reported income often differs from actual income because of the Canadian tax structure; Couldn't account for simultaneous changes such as billing changes
Begg (1984)	Prescription drugs	The United Kingdom	1984	1,508 prescriptions for low income and elderly individuals	Co-payment exemption status of patients	3.1% of prescriptions for exempt patients were not filled compared to 9.1% of prescriptions for non-exempt patients that were not filled	May not be generalizable because limited to one group practice; Did not control for other factors with regression
Bhattacharya et al. (1996)	Outpatient services	Japan	1990	Approximately 440,000 individuals; patients visiting physicians for certain reasons were excluded	Individuals enrolled in different health plans had different cost sharing requirements	Increasing expected OOP expenditures resulted in a decreased probability of seeing the doctor on any particular day; Disease type played an important role in the utilization interval between outpatient visits	Unmeasured variables such as preferences for medical care or cultural factors; Cross-sectional study, thus difficult to control for other factors that increase use of outpatient services

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Billings and Tiecholz (1990)	Inpatient services	Washington, DC – the United States	1988	955 individuals admitted to DC hospitals	Insurance coverage (coverage, none)	Almost 20% of the uninsured patients reported delaying an inpatient admission; Almost 1/4 of the uninsured admissions were potentially preventable or avoidable	Did not control for other factors with regression; May not be generalizable because limited to hospitals in one city
Birch (1986)	Prescription drugs	The United Kingdom	1979-1983	NHS beneficiaries not exempt from co-payments	Change in co-payment from £0.20 to £1.60	Consumption of charge prescriptions fell by 35% over the period compared with a 23% increase in the consumption of prescriptions by exempt groups	Did not control for other factors with regression; Individual information may have been lost at the aggregate level
Blais et al. (1999)	Prescription drugs	(Quebec) Canada	1994-1997	5,182 individuals with asthma receiving social assistance	Change from no co-payment to quarterly deductible of $50	In the 18-34 age group there was 40% non-renewable of medication vs. 13% in controls in use of any of the 4 classes in first 11 months after change; In the 35-64 age group, the non-renewable rates were 23% and 9%, respectively in use of any of the 4 classes in first 11 months after change	Cross-sectional study, thus difficult to control for other factors that increase use of prescription drugs
Blais et al. (2001)	Prescription drugs	(Quebec) Canada	1992-1997	Elderly individuals: 49,333 persons on nitrates, 121,298 persons on antihypertensives, 41,118 persons on anticoagulants, 24,112 persons on benzodiazepines	Change in co-payment from CDN $2 to 25% of cost and deductible with maximum contribution	No significant decrease in drug consumption following the implementation of a cost-sharing drug plan for nitrates, antihypertensive agents, anticoagulants, and benzodiazepines	The observation window of one month may have been too short to detect an effect; Unmeasured variables such as family income or the price of medications
Blais et al. (2003)	Prescription drugs	Canada	1991-1997	Non-elderly persons receiving social assistance: 55,890 persons on inhaled corticosteroids, 29,461 persons on neoroleptics, 44,916 persons on anticonvulsants	Change from no co-payment to quarterly deductible of $50	Age group 18-34: 40% non-renewable of medication vs. 13% in controls in use of any of the 4 classes in first 11 months after change; Age group 35-64: non-renewable rates were 23% and 9%, respectively in use of any of the 4 classes in first 11 months after change	No out-of-province control group; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Blendon et al. (1992)	Medical services	Massachusetts, the United States	1989	1,066 households	Insurance coverage (insurance, none)	10% of the uninsured population reported being unable to receive medical care for financial reasons compared to 1% of the insured population experiencing this problem; Insured individuals were more likely than uninsured individuals to receive physician or hospital care for one of twelve serious or chronic health conditions	Didn't control for confounding factors through regression; May not be generalizable because limited to one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Blustein (2000)	Prescription drugs	The United States	1995	4,334 elderly (65+) individuals with hypertension	Supplemental drug insurance coverage (Medicaid, employer-sponsored, individual-purchased, Medicare HMOs, Medicare only)	Lack of drug coverage increased the odds of failing to purchase any antihypertensives by 40%; Drug coverage increased the number of tablets purchased (37 more tablets)	Self-reported information on drug coverage; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Brenna et al. (1984)	Prescription drugs	Italy	1975-1981	7 years of monthly aggregated data	In 1978 pharmaceuticals were divided into two classes (A and B) and user fee imposed on class B drugs	The introduction of co-payments had no effect on total consumption; But consumption shifted from class B products (with co-payment) to class A products	Only had dummy variable for indication of co-payment change; There was a simultaneous introduction of national health insurance around the introduction of co-payments
Brian and Gibbens (1974)	Medical services; Prescription drugs	(San Francisco, Ventura, and Tulare, California) The United States	1971-1972	10,662 low-income Medicaid individuals	Introduction of $1 co-payment for each of first two office visits in month, $0.50 co-payment for first two prescriptions in month	Increased use or small reductions in the use of 'critical' or 'needed' drugs; Individuals with co-payments and those without co-payments were equally likely to have seen a physician for 'significant' illnesses, but co-payers were less likely to seek care for 'intermediate' and 'insignificant' illnesses	Unmeasured variables such as the diagnosis; There could be underlying differences between the use of medical care between the control group and the study group, even if both had no co-payments; Did not control for other factors with regression

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Brook et al. (1983)	Medical services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1977	3,958 non-elderly individuals without disabilities	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Free care had significant positive effect on vision, and almost significant effect on diastolic blood pressure; No other health measure showed a significant difference between the free and the cost-sharing plans; Lower risk of dying for those in free plan, mainly attributable to the improved control of high blood pressure	Unmeasured variables such as marital status and education
Buchmueller et al. (2002)	Physician services	France	1998	8,161 adults (25+)	Supplemental insurance coverage (coverage, none)	Supplemental insurance increased the probability of having at least one physician visit by almost 13 percentage points; The impact of employer-provided insurance was actually slightly larger than the impact of individually-purchased insurance on physician visits	The survey only asked individuals to recall visits in the past month; there may have been a seasonal impact on visits; Cross-sectional study, thus difficult to control for other factors that increase physician visits
Buchmueller et al. (2004)	Physician services	France	1998	8,161 adults (25+)	Supplemental insurance coverage (coverage, none)	Supplemental insurance increased the probability of having at least one physician visit by almost 13 percentage points; Individuals without supplementary coverage were more likely to report having foregone care than those with coverage	Unmeasured variables such as preferences for medical care; Cross-sectional study, thus difficult to control for other factors that increase physician visits
Cameron et al. (1988)	Inpatient services, physician services, prescription drugs	Australia	1977-1978	5,190 adults (18+)	Most individuals received free prescriptions, others received medicines for (AUS) $2.00 which increased to (AUS) $2.50 in 1978, and others paid the full price	Prescription drug and other health care utilization relatively responsive to sex and age but changes less with income; Health status measures typically had a significant impact on prescription drug and other health care utilization	The prescription drug utilization variable only captured use of prescription drugs in the previous 2 days; Unmeasured variables such as employment and use of substitutes or complements

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Carrin and Van Dael (1991)	Inpatient services, physician and outpatient services, prescription drugs	Belgium	1966-1980	15 annual observations, individuals who were employed and their dependents	The out-of-pocket prices of medical care services increased over time	Negative relationship between price and quantity of prescription drugs; The number of GP visits, specialist visits, and hospital bed days all positively influenced the demand for prescription drugs	Individual information may have been lost at the aggregate level; Small sample size
Cartwright et al. (1992)	Medical services	The United States	1977	4,409 elderly (65+)	Supplementary insurance coverage (Medicaid, Medigap, Medicare only) with differing levels of generosity	The Medicaid elderly had the highest levels of medical expenditures; Insurance coverage increased expected medical expenditures	Still contained limited information on specifics of drug coverage; Cross-sectional study, thus difficult to control for other unmeasured factors that influence medical care utilization
Caussat and Glaude (1993)	Prescription drugs	France	1980	16,766 individuals, excluding those with full public coverage or no public coverage, those with high mortality risk, and those with severe handicap	Supplementary health insurance coverage (coverage, none)	Having supplementary coverage increased the probability of consuming prescription drugs and OTC drugs, and it increased the number of prescription and OTC drugs consumed	Possibility that supplementary coverage attracts individuals with higher consumption needs; Cross-sectional study, thus difficult to control for other factors that increase prescription drug utilization
Cherkin et al. (1989)	Physician and outpatient care	(Washington) The United States	1984-1986	30,414 non-elderly (<65) state employees	Introduction of $5 co-payment for outpatient and ambulatory visits	10.9% decrease in primary care visits and 8.2% decrease in total visits per year for state employees; The decrease in medical visits persisted for the 12 months of the study	Did not control for other factors through regression; May not be generalizable because limited to one region in Washington; Employees likely to be healthier and have higher income
Chiappori et al. (1998)	Physician services	France	1993-1994	4,578 individuals with supplementary health insurance (bank and insurance employees and their dependents)	Introduction of 10% coinsurance rate for all ambulatory care expenses	No apparent changes in consumption of GP office visits or specialist visits; Decrease in GP home visits occurred for cost sharing group	Sample population is likely to be wealthier and healthier than the general French population; Unmeasured variables such as income, health status, and education level

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Christensen et al. (1987)	Medical services, inpatient services, physician services	The United States	1980, 1984, 1985	7,799 elderly (65+) individuals	Insurance coverage (Medicaid, private, none)	Medicaid and Medigap recipients were 1.24 and 1.06, respectively time as likely to use some health care services as individuals without supplementary coverage; Out-of-pocket costs were highest for Medigap enrollees and those with no supplemental insurance, and Medicaid beneficiaries had the lowest OOP costs	No information on the extent of insurance coverage Cross-sectional study, thus difficult to control for other factors that increase medical care utilization
Christensen and Shinogle (1997)	Inpatient services, outpatient services	(New York City, Philadelphia, Chicago, Cleveland, Los Angeles, San Francisco, Phoenix, Seattle) The United States	1994	2,363 adults (19+)	Supplemental insurance coverage (HMO, Medigap, employer-sponsored)	Those with Medigap and employer-sponsored insurance used about 20% more inpatient and outpatient services than those with no supplemental insurance; Although HMO enrollees used more outpatient services than those with no supplemental insurance, they used fewer inpatient days	No information on the extent of insurance coverage; Cross-sectional study, thus difficult to control for other unmeasured factors that influence inpatient and outpatient utilization
Christiansen et al. (2002)	Prescription drugs	Denmark	1994	4,668 adults (16+) with private insurance coverage	'Danmark': Private insurance coverage (coverage for co-payments, no coverage for co-payments)	Membership in 'Danmark' had no significant effect on the likelihood of prescription drug consumption; Gender, education, age, and health were important predictors of use	Cross-sectional study, thus difficult to control for other factors that increase prescription drug utilization; Prescription drug usage indicator only covered two-week period
Cockx and Brasseur (2003)	Physician services	Belgium	1993-1994	Groups of individuals in a Belgian sickness fund	Co-payment increases of 48% for GP office-based visits, 35% for GP home visits, 60% for specialist visits (in real terms)	For both men and women, GP office visits were necessities, while GP home visits were luxuries; Specialist visits were luxuries for men and necessities for women	Unmeasured variables such as health status; Cross-sectional study, thus difficult to control for other unmeasured factors that influence physician utilization
Col et al. (1990)	Prescription drugs	The United States	1987	315 elderly (65+) patients in a single hospital	Supplemental insurance coverage (Medicaid, other health insurance, or Medicare only)	Non-compliance for those with insurance was 31% vs. 52% for those with no insurance	Usual non-compliance questionnaire problems; Small sample; May not be generalizable because limited to data from one hospital

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Colle and Grossman (1978)	Physician services	The United States	1971	839 children (1-5)	Childrens' parents faced different quality-adjusted OOP prices for pediatric care	Main determinants of childrens' medical use were mother's schooling and number of children in the family; No evidence of a negative time cost coefficient in the demand for visits	Unmeasured variables such as marital status and age of parents; Cross-sectional study, thus difficult to control for other unmeasured factors that influence use of physician services
Contayannis et al. (2005)	Prescription drugs	(Quebec) Canada	1993-1997	48,027; 60,909; and 64,490 elderly in three pre- and post-policy comparisons	Change from CDN $2 co-payment for middle- and high-income persons to 25% coinsurance up to maximum; changed to CDN $25 deductible and 25% co-payment up to maximum	Price elasticity of expenditure estimates from -0.164 to -0.124; Age and being female led to higher rates of increases in levels of prescription drug consumption	Individual information may have been lost when using neighborhood income and education values rather than individual values
Coulson and Stuart (1995)	Prescription drugs	(Pennsylvania) The United States	1990	4,066 elderly (65+) individuals not enrolled in an HMO	Introduction of $4 co-payment in supplemental state drug subsidy program for low income	Individuals who are aged 85 and older or in better health fill fewer prescriptions; Persons with more health problems or a higher income fill more prescriptions	May not be generalizable because limited to one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Coulson et al. (1995)	Prescription drugs	(Pennsylvania) The United States	1990	4,509 elderly (65+) individuals not enrolled in an HMO	Supplemental drug insurance coverage (Medicaid, PACE, employer-sponsored, prescription coverage, physician coverage, other insurance, Medicare only)	Those with supplemental drug and doctor insurance refilled 1.42 more prescriptions over two-week period than those with no coverage; Those with just supplemental drug insurance refilled 1.05 more prescriptions	May not be generalizable because limited to one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Cox et al. (2001)	Prescription drugs	(Arizona) The United States	Not given	387 elderly (65+), enrolled in a Medicare HMO plan who had reached >=60% of their yearly prescription cap	Some individuals had capped prescription benefits of $1,500 per year, others had caps of $3,000 per year, and others had caps of $750 per year	15% of respondents went without necessities and 12% borrowed money to pay for their prescriptions; Those who reached their prescription cap were more likely to take less medication than prescribed and discontinue medication compared to those who had not reached their prescription cap	Small sample; Does not account for individuals that chose not to consume more 60% of their yearly prescription cap; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Danzon and Pauly (2002)	Prescription drugs	The United States	1987, 1996	Adults (25+) that did not have Medicaid or other public insurance	Insurance coverage (prescription and health insurance coverage, health insurance coverage only, none)	The population with drug coverage increased prescriptions per capita from 10.2 in 1987 to 12.6 in 1996, while volume decreased from 5.5 to 4.6 over the same period for those without drug coverage; Estimated that approximately 1/4 to 1/5 of drug spending growth due to increased insurance coverage	Did not control for other factors with regression; Imperfect measure of drug insurance coverage as the insurance coverage for those with no drug spending could not be determined
Davis and Russell (1972)	Outpatient services	The United States	1969	48 states' not-for-profit hospitals (aggregate data)	Patients faced different out-of-pocket costs of hospital care	Significant cross-price elasticities between prices of inpatient and outpatient care; Demand for outpatient care was sensitive to occupancy rate of inpatient care	Individual information may have been lost at the aggregate level
Davis et al. (1999)	Prescription drugs	The United States	1995	Approximately 12,000 elderly (65+) individuals	Supplemental drug insurance coverage (Medicaid, employer-sponsored, individually-purchased, Medicare HMO, Medicare only)	Those with supplementary coverage filled 33% more prescriptions and had 66% higher prescription drug expenditures than those without; Supplemental insurance increased utilization rates for and access to most types of health services	Did not control for other factors with regression; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Delnoij et al. (2000)	Prescription drugs	The Netherlands	1995-1997	Individuals who were referred to medical specialists	Increase in co-payment rates for people covered by the public health insurance	Individuals who were covered by public health insurance did not significantly reduce the use of drugs compared to those who were covered by private insurance	Only used data from three general practitioners; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Dodrill et al. (1987)	Prescription drugs	(Washington) The United States	Not given	282 nonelderly (<67) patients of an epilepsy center	Supplemental drug insurance coverage (Medicaid, private insurance, no insurance)	Non-compliance is more related to general self-reported financial distress than to whether or not patients have drug insurance	Did not control for other factors with regression; May not be generalizable because limited to one epilepsy center; Small sample
Dor and Encinosa (2004)	Prescription drugs	The United States	1999-2000	27,057 adults (18+) receiving anti-diabetic medicines and covered for prescription drugs by employer-sponsored health plans	Individuals with co-payment requirements vs. individuals with coinsurance requirements	By the end of 90 days, about 58% of individuals with co-payments were compliant; By the end of 90 days, about 48% of individuals with coinsurance were compliant	Unmeasured variables; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Dourgnon and Sermet (2002)	Prescription drugs	France	1998	15,191 individuals	Supplementary health insurance coverage (mutual, private, employer, none)	Individuals without supplementary coverage spent 15% less than the population average; When individuals without supplementary coverage consumed drugs, their expenditures were 10% higher than individuals with supplementary coverage	Cross-sectional study, thus difficult to control for other factors that increase prescription drug utilization
Duan et al. (1983)	Medical services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1977	8,765 non-elderly (<62) individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%) and the individual deductible plan	Under all model specifications, individuals with no coinsurance had higher medical expenses than individuals with cost sharing; Individuals with free care spent $414 on average compared with the $285.73 on average that individuals spent on the 95% plan	Unmeasured variables such as marital status and education
Eichner (1998)	Medical services	The United States	1990-1992	16,989 employees (25-55) with employer-sponsored insurance, restricted to injury and poisoning claims	Different employer-sponsored plans with differences in deductibles, co-payments, and stop-loss limits	Increasing out-of-pocket costs decreased medical care expenditures	May not be generalizable because limited to one firm; Employees likely to be healthier than general population
Ellis et al. (2004)	Prescription drugs	The United States	1998-2001	4,802 adult (18+) patients from a managed care organization receiving statin therapy	Individuals faced different levels of cost sharing depending on the generosity of their prescription drug insurance coverage	76.2% of patients with a co-payment >=$20 were non-adherent compared with 49.4% of patients with a co-payment <=$10; Patients facing co-payments >=$20 were four times more likely to discontinue statin therapy than patients with co-payments <=$10	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Elofsson et al. (1998)	Medical services	Sweden	1995	7,983 adults (18+)	Individuals in different county councils faced different user fees for health care	Individuals that classified their financial situation as poor were almost ten times as likely to forego care an individuals that assessed their financial situation as good	May not be generalizable because limited to two healthcare regions in Sweden; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Esposito (2002)	Prescription drugs	The United States	1997-1998	35,224 patients with coronary heart disease diagnosis, statin use, and continuous enrollment	Individuals faced different co-payment levels based on their health plan	The patient's co-payment level relative to the co-payment levels of alternative statins was a highly significant predictor of statin use; There were significant cross-price effects between statins	Unmeasured variables such as income and race; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Fahs (1992)	Medical services	(New Kensington, Pennsylvania) The United States	1976-1979	1,089 individuals enrolled in the United Mine Workers Health and Retirement Funds with visit for diabetes, urinary tract infection or sore throat	Introduction of $7.50 co-payment for physician visits	Evidence to support physician-induced demand such as an increase in total fees per illness episode; The source of price increase came from physician-initiated characteristics such as ambulatory fees, inpatient fees and increased length of stay	May not be generalizable because limited to one region in Pennsylvania; Unmeasured variables such as income
Fairman et al. (2003)	Prescription drugs	(Midwest region) The United States	1998-2000	4,132 adults (18+) with private insurance (3,577 in the control group)	Individuals in the intervention group faced a 3-tier co-payment ($8, $15, $25) while individuals in the comparison group faced a 2-tier co-payment ($7, $12)	No significant differences in office visits, emergency department visits, or hospitalizations between the intervention and control groups; The 3-tier structure significantly reduced the use of third-tier medications over the long term	The effects on other types of visits may be different for other populations; The mix of drugs within each tier may also affect utilization of other health services
Federman et al. (2001)	Prescription drugs	(New Hampshire) The United States	1997-1999	1,908 elderly (66+), individuals who reported a history of myocardial infarction or coronary heart disease, enrolled in Medicare Part B	Supplemental drug coverage (Medicaid, other public program, employer-sponsored coverage, self-purchased plans with drug coverage, HMO plans, none)	Patients with Medicare only were less likely to use statins; Patients with Medicare only or Medigap without drug coverage were less likely to use nitrates; Patients with Medicaid were the only group less likely to use B-blockers than those with employer-sponsored coverage	May not be generalizable because limited to one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Feldstein (1970)	Physician services	The United States	1948-1966	Aggregates of private physician services	Patients faced different average and net OOP costs of physician care	Doctors seemed to use their discretionary pricing power to maintain permanent excess demand	Individual information may have been lost at the aggregate level
Feldstein (1971)	Inpatient services	The United States	1958-1967	Annual state aggregates of all hospitals (aggregated by state) and patients	Patients faced different out-of-pocket costs of hospital care	Rising demand was induced by increases in insurance coverage, personal income, availability of hospital oriented specialists, and other factors	Individual information may have been lost at the aggregate level

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Feldstein (1977)	Inpatient services	The United States	1958-1973	All individuals admitted to hospitals	Patients faced different out-of-pocket costs of hospital care	An increase in the quality of care increased the demand for hospital admissions but decreased mean bed stay per care; Higher out-of-pocket prices for hospital care decreased inpatient admissions	Individual information may have been lost at the aggregate level; Unmeasured variables such as preferences for care
Fillenbaum et al. (1993)	Prescription drugs	(North Carolina) The United States	1986-1987	4,163 elderly (65+) individuals	Supplemental drug insurance coverage (Medicaid, other drug insurance, or Medicare only)	Medicaid recipients had 25% higher drug use than those with other drug insurance or Medicare only; Total 3rd-party payments rose more rapidly than co-payments only, suggesting that insurers were reluctant to increase co-payments at the same rate for beneficiaries	Not generalizable because only the Piedmont area of North Carolina; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Fleishman and Mor (1993)	Outpatient services, inpatient services, emergency room services	(Northeast and South regions, Florida, Washington) The United States	1988-1989, 1990	937 adults (>18) with AIDS	Insurance coverage (public, private, none)	The uninsured had significantly fewer inpatient admissions per month, inpatient nights per month and outpatient visits per month than the privately insured; No significant differences in medical care use between publicly and privately insured except publicly insured individuals had more emergency room visits	The sample may under represent individuals without insurance because they are less likely to contact a medical provider; Cross-sectional study, thus difficult to control for other unmeasured factors that influence medical care utilization
Fortress et al. (2001)	Prescription drugs	(New Hampshire) The United States	1980-1983	343 elderly (60+), low-income individuals on Medicaid and under treatment for specific chronic illnesses	Introduction of a cap of 3 reimbursable prescriptions per month	34.4% decrease in standard doses of essential medications; The comorbidities associated with largest relative reduction were psychoses/bipolar disorders, anxiety/sleep problems, and chronic pain	May not be generalizable because limited to one state; Small sample; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Foxman et al. (1987)	Prescription drugs	The United States	1974-1982	5,765 non-elderly (14-61) individuals	Insurance for health services and prescription drugs with different cost sharing (0%, 25%, 50%, 95%)	Use of prescription drugs increased by 85% in free plans relative to cost sharing plans; Antibiotic use was greater on the free than on the cost-sharing plans across all diagnoses; Cost sharing decreased both inappropriate and appropriate use of antibiotics	Unmeasured variables such as income may influence demand for prescriptions; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Franks et al. (1993)	Medical services	The United States	1975-1987	4,694 adults (25-74) who were uninsured or privately insured	Insurance coverage (insurance, none)	The risk of dying for uninsured individuals was 1.25 times the risk of dying for insured individuals; The adverse association between lacking insurance and mortality was observed in all subgroups	No information on the extent of insurance coverage; Cross-sectional study, thus difficult to control for other unmeasured factors that influence medical care utilization
Freeman et al. (1990)	Medical services, physician services	The United States	1986	10,130 individuals	Insurance coverage (insurance, none)	Uninsured individuals had 1.2 fewer ambulatory visits in a year than insured individuals Uninsured individuals were more than twice as likely as insured individuals to report foregoing needed medical care	Didn't control for confounding factors through regression; Little information on the extent of insurance coverage
Freiberg and Scutchfield (1976)	Inpatient services	(Kentucky) The United States	1972	Individuals in 13 group-family insurance plans	Because of differing coinsurance rates between plans, individuals faced different out-of-pocket costs for inpatient care	A decrease in the out-of-pocket price of care led to a small but significant increase in hospital admissions and an increase in average lengths of hospital stays; No support for the hypothesis that as the out-of-pocket cost of inpatient services decreases, more patients substitute inpatient for outpatient care	Chose not to control for covariates such as income and sex, possibly causing omitted variable bias; Cross-sectional study, thus difficult to control for other unmeasured factors that influence hospital utilization
Friis et al. (1993)	Prescription drugs	(Zealand) Denmark	1987, 1990	5,765 patients prescribed antibiotics by 553 general practitioners	Change from 25% coinsurance rate to patient paying full price up to 800 DKr for most commonly used antibiotics	The cost sharing change decreased the total number of patients treated for diagnoses where antibiotics are typically used; Also a shift from more expensive to less expensive antibiotics	Did not control for other factors with regression
Fuchs and Kramer (1972)	Physician services	The United States	1948-1956, 1956-1966	Aggregates of physician services (aggregates of 33 states)	Patients faced different average and net OOP costs of physician care	The demand for physicians' services appeared to be significantly influenced by the number of physicians available; But, the demand for physicians' services did not appear very sensitive to differences in income	Individual information may have been lost at the aggregate level

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Gardner et al. (1996)	Prescription drugs	New Zealand	1992	19,299 patients	Different levels of government drug subsidies depending on income status (these were not stated)	10.5% of prescriptions were for those with highest subsidy rate (lowest income) and 15.4% were for those with no subsidy (highest income); For essential drug categories, no difference in non-dispensing rates; For discretionary drug categories, lower non-dispensing rates for those with highest subsidy rate	Did not control for other factors through regression
Gardner et al. (1997)	Prescription drugs	The United States	1988-1994	18,000 elderly (65+) public employees with state-funded Medicare supplemental benefit program	Initial co-payment of $5 and increased to $8 (generics), $10 (brand), second increase to $10 and $15 respectively, third increase to coinsurance of 50% to a max of $50	Generic share of total days drug therapy per month unchanged after first two price increases; Increased 20% after third price increase	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Genier et al. (1997)	Prescription drugs	France	1991-1992	11,500 households with adjustment to be representative of French population	Generosity of supplementary health insurance coverage	Pharmaceutical consumption varied according to number of illness episodes and insurance coverage; Difference between insurance coverage with social security alone or with social security and supplementary coverage was significant	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Gianfrancesco et al. (1994)	Prescription drugs	(Pennsylvania) The United States	1990-1992	1,818 retired mine workers and dependents	Extension of prescription drug benefits to previously uninsured beneficiaries	Drug use and expenditures of the newly insured converged to that of the previously insured	Unmeasured variables such as income; Not generalizable because specific population of retired mine workers
Gibson et al. (2005)	Prescription drugs	The United States	1995-1998	Non-elderly adults between 18 and 64 with employer-sponsored health insurance; 16,783 in intervention and 1,984 in control group	The intervention employer increased the co-payment from $2 for all drugs to $7 for brand-name drugs in 1996	An increase in the co-payment led to a drop in prescription drug utilization; An increase in the brand-name co-payment led to an increase in generic drug expenditures	May not be generalizable because limited to population of employees for one firm; Unmeasured variables such as health status and income

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Goldman and Grossman (1978)	Physician services	(Mott Haven and Westchester, New York) The United States	1956-1966	568 infants and children	Children's' parents faced different quality-adjusted OOP prices for pediatric care	Pediatric visits more sensitive to income than quality of visits; The number of visits and the quality of visits were sensitive to fixed travel cost	May not be generalizable because limited to parts of New York; Unmeasured variables such as health status of the child
Goldman et al. (2004)	Prescription drugs	The United States	1997-2000	960,791 beneficiaries continuously enrolled for up to 4 years	Private drug insurance coverage differed among individuals	Significant changes in utilization for NSAIDs and antihistamines when co-payment was predicted to change; Lower responsiveness among chronically ill patients to predicted change in co-payments	Sample consisted of primary beneficiaries who may be healthier because they are employed; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Goldman et al. (2006)	Prescription drugs	The United States	1997-2002	62,274 adults (20+) from 88 health plans who initiated cholesterol-lowering therapy between 1997 and 2001	Different individual faced different co-payments for cholesterol drugs	For each $10 increase in co-payments, average compliance in a given year fell by 5 percentage points; There would be a projected increase in hospitalizations if co-payments increased for individuals at high risk	Study only examined patients who initiated therapy, and co-payments may have deterred some from initiating therapy in the first place; The co-payment may be endogenous as unmeasured variables may influence co-payment and compliance
Grana and Stuart (1996)	Physician services	The United States	1992	5,543 elderly (65+) individuals with arthritis	Supplemental insurance coverage (individual supplement, group supplement, Medicaid, supplement of unknown origin, none)	Individuals with supplementary insurance were more likely to receive arthritis treatment from physicians than those with none; Those with individual supplementary insurance were more likely to have treatment than those with group coverage	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Greene and Gunselman (1986)	Inpatient services	North Carolina, the United States	1981-1982	40 large (200+) employer groups for a total sample size of 33,882 individuals	Different levels of insurance coverage (full inpatient coverage, medical coverage with cost sharing); deductibles ranging from $100-$200; coinsurance ranging from 15-20%	The groups that switched to the medical plans with cost sharing experienced an 11.3% decline in hospital admission rates, 14.4% decline in days/1000 in the hospital, and a decrease in the average length of stay of 0.3 days	Did not control for other factors through regression; May not be generalizable because limited to one state; Employed individuals are likely to be healthier on average than general population and may be differences between individuals in small and large employer groups

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Greenlick and Darsky (1968)	Prescription drugs	(Windsor, Ontario) Canada	1962-1963	Approximately 3,400 prescriptions dispensed	Prescriptions dispensed under Prescription Services, Incorporated plan compared with prescription dispensed to people paying out-of-pocket	4.20 prescriptions per person dispensed to individuals with PSI, while 2.19 prescriptions dispensed to those without PSI; Annual expenditures per person in the PSI plan were $16.64 and $8.29 for those not in PSE plan	Did not control for other factors with regression; Analysis limited to small area and results may not be applicable to wider population
Gribben (1998)	Physician services	(Dargaville, Pukekohe, Matamama, Kawerau, Piopio, Taumaranui, and Featherston) New Zealand	1993-1994	5,367 patient records	Some individuals received subsidies from the government for medical care	The GP consultation rate for subsidized individuals was 4.00 visits per year, while the visit rate was 3.46 for non-subsidized individuals	Unmeasured variables such as income and marital status If the patient did not visit the doctor, the authors had to estimate whether the person was a subsidy cardholder
Grignon and Perronin (2003)	Prescription drugs	France	1998-2000	Individuals benefiting from CMU out of permanent sample of social Insured (absolute numbers not specified)	Introduction of supplementary (CMU; Couverture Maladie Universelle) coverage on 1 Jan 2000	CMU coverage increased probability of prescription by 5.2 percentage points; CMU increased expenditures (non-significant) 6.3 percentage points for individuals with at least one prescription and 12 percentage points for the whole population	The covariates that the authors considered are unclear, and there may have been unmeasured and omitted variables
Grootendorst (1997)	Prescription drugs	(British Columbia) Canada	1985-1992	18,000 individuals who turned 65 during the study time period	Provision of enhanced public drug insurance coverage at 65	Availability of prescription drug coverage from the state for elderly contributed relatively little to overall increase in drug expenditures; Prescription drug claims by low-income males seemed to increase substantially after provision of insurance	May not be generalizable to individuals not living in single person households; No out-of-province control group
Grootendorst and Levine (2001)	Prescription drugs	(All 10 provinces) Canada	1994-1995, 1995-1996	3 categories of non-institutionalized persons: 3,195 elderly (65-85), social assistance recipients (unknown sample size), and non-elderly (<65) (unknown sample size)	Different deductibles, co-payments, and coinsurance rates, depending on the individual's province, age, income, and type of drug coverage	Seniors' drug use was relatively insensitive to price and a small positive correlation between price and volume; Social assistance recipients somewhat more sensitive to price; Among the general population, insurance had a small positive impact on the volume of drugs consumed	Problems with measuring drug coverage forced the authors to reduce the sample size; Cross-sectional study, thus difficult to control for other factors that increase prescription drug use

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Grootendorst, O'Brien, and Anderson (1997)	Prescription drugs	(Ontario) Canada	1990	9,370 near elderly (55-64) and elderly (65-75)	When individual turned 65, the province offered full drug coverage (equivalent to comparing those with and without supplemental insurance)	Increased use of prescription drugs upon eligibility, primarily among persons with lower health status; Increases in drug use were concentrated primarily among individuals with lower health status	Unmeasured variables such as the value of time because individuals may retire upon turning 65; Consumption is self-reported
Haas and Goldman (1994)	Inpatient services	(Massachusetts) The United States	1990	Non-elderly (15-64) individuals hospitalized for an emergency	Insurance coverage (Medicaid, private, none)	Individuals who were uninsured or had Medicaid were more likely to receive care in an urban hospital or level 1 trauma center; Patients who were uninsured received fewer resources and had higher in-hospital mortality rates	Unmeasured variables such as income and sex; May not be generalizable because limited to part of one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Hadley et al. (1991)	Inpatient services	The United States	1987	592,598 non-elderly (1-64) patients admitted to hospital	Insurance coverage (private insurance, none)	The length of stay for uninsured individuals was significantly shorter than that of the privately insured patients by 12% - 38%; The uninsured faced a higher relative probability of in-hospital mortality than the insured	Unmeasured variables such as health status and income; Cross-sectional study, thus difficult to control for other factors that influence hospital admissions, procedures, and outcomes
Hahn (1994)	Medical services	The United States	1987	16,430 non-elderly adults (18-64)	Insurance coverage (Medicaid, private, none)	Individuals with Medicaid had significantly more hospital stays and physician visits than the uninsured, although there were not significant differences for visits between uninsured individuals and those with private insurance	Unmeasured variables such as marital status and region; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Hanau and Rizzi (1986)	Prescription drugs	(Emilia-Romagna) Italy	1980-1984	5 years of monthly aggregated data	Various changes in co-payment regime over the period	Each new co-payment regime reduced total prescription drug expenditures and expenditures per prescription; The effect of each regime decreased over time as consumption shifted to fully reimbursed drugs, exemptions were granted, and co-payment evasion became widespread	Regression only had dummy variable for indication of co-payment change; A number of other policy changes were also introduced with co-payment changes

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Harmon and Nolan (2001)	Living in Ireland Survey	Ireland	1994	4,048 households	Insurance coverage (insurance, none)	The presence of insurance increased the probability of having at least one hospital stay by about 3% (not correcting for endogeneity) and about 6% (correcting for endogeneity)	Cross-sectional study, thus difficult to control for other factors that increase inpatient services
Harris et al. (1990)	Prescription drugs	(Washington) The United States	1982-1986	19,982 non-elderly state of Washington employees enrolled in an HMO	Co-payments increased from $0-$1.50 and again from $1.50 to $3	Greater decline in use of discretionary compared to use of nondiscretionary drugs; The effect of co-payments on reducing drug costs was smaller than the effect of co-payments on reducing drug utilization	May not be generalizable because only one state and one HMO; Did not control for other factors with regression
Helms et al. (1978)	Inpatient services, physician services	(California) The United States	1971-1972	10,687 Medicaid individuals with the co-payment; 29,975 Medicaid individuals without the co-payment	Introduction of $1 co-payment for each of first two office visits in month, $0.50 co-payment for first two prescriptions in month	8% decline in physician office visits and 17% increase in hospital days among co-payment group; Total program costs actually increased 3-8%	Unmeasured variables such as the diagnosis; There could be underlying differences between the use of medical care between the control group and the study group, even if both had no co-payments
Hill and Veney (1970)	Inpatient services	Sedgwick County, Kansas, the United States	1968	5,000 contracts for groups of employees that were enrolled in Blue Cross / Blue Shield of Kansas	Certain outpatient and ambulatory services were offered for free in the experiment	No significant reductions in inpatient utilization rates for those with free care; Inpatient short stays were reduced in experimental group; Evidence that free out-of-hospital care created admissions which resulted in stays longer than 10 days	May not be generalizable because limited to one region in Kansas; Employees and dependents likely to be healthier and have higher income; Did not control for other factors with regression
Hillman et al. (1999)	Prescription drugs	The United States	1990-1992	134,937 non-elderly members of nine US managed care plans	Variation in co-payment from $1 to $20 between different between employer health plans	Higher co-payments associated with lower drug spending in insurance models where physicians not at risk for drug costs, but have little effect in insurance models where physicians bear financial risk for prescribing	Unmeasured variables such as education, marital status, and race may influence drug spending; Individuals in private health insurance plans likely to be healthier

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Holly et al. (1998)	Inpatient services	Switzerland	1992-1993	15,288 individuals aged 15 and older living in private households	Supplemental insurance coverage (coverage, none)	Given that an individual has used some medical service, the existence of supplemental insurance coverage increases the probability that he will have at least one inpatient stay	Cross-sectional study, thus difficult to control for other factors that increase inpatient services
Hsu et al. (2006)	Prescription drugs	The United States	2002-2003	199,179 elderly (65+) Medicare+Choice beneficiaries who were enrolled in a 2-tier drug plan	All individuals faced 2-tier co-payments for drugs, but individuals in one group faced a $1000 maximum for drug coverage	Subjects with capped benefits had higher LDL cholesterol and more emergency department visits, non-elective hospitalizations, and deaths than subjects without capped benefits; They also had relatively fewer office visits	Differences between insurance coverage groups may be non-random
Hughes and McGuire (1995)	Prescription drugs	(England and Wales) The United Kingdom	1969-1992	24 annual observations, NHS beneficiaries not exempt from co-payments	Change in co-payment from £0.125 to £3.75	The price elasticity of demand increased over time; Raising the charge from £3.75 in 1992 to £4.25 in 1993 increased revenue by approximately £17.3 million	Unmeasured variables such as changes in supply of pharmacists and GPs could be important
Hurd and McGarry (1997)	Inpatient services, physician services	The United States	1993-1994	7,327 elderly individuals (70+)	Insurance coverage (private, Medicare A&B only, Medicare A only, no insurance)	Individuals without Medicare Part B and individuals with no insurance coverage were 3.7% and 15%, respectively, less likely to have at least one doctor visit than individuals with Medicare Parts A&B	Respondents may have had difficulty recalling health utilization and out-of-pocket payments for the past year; Cross-sectional study, thus difficult to control for other factors that increase physician visits and inpatient stays
Huskamp et al. (2003)	Prescription drugs	The United States	1999-2001	134,937 non-elderly members of nine US managed care plans	Employer 1: change from a 1-tier to a 2-tier formulary and increased levels of co-payments for all tiers, Employer 2: change from a 2-tier to a 3-tier formulary and increased levels of co-payments for tier 3	Enrollees covered by Employer 1 were twice as likely as the comparison group to discontinue the use of drugs in a given class altogether; But enrollees covered by Employer 2 were not as likely as the comparison group to discontinue the use of drugs in a given class altogether	May not be generalizable because limited to two employers; Individuals in employer health insurance plans likely to be healthier

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Huskamp et al. (2005)	Prescription drugs	The United States	1999-2001	11,653 non-elderly (<65) individuals with employer-based managed care insurance	Change from 2-tier formulary with $6 co-pay for generics and $12 co-pay for brand-name to $6 co-pay for generics, $12 co-pay for preferred, and $24 for no-preferred	For ACE inhibitors, there was a 22.7% decline in the use of non-preferred tier 3 drugs; Increase in the use of preferred tier 2 drugs but no change in the use of tier 1 generic drugs	Unmeasured variables such as health status and income; May not be generalizable because limited to population of employees for one firm
Hux et al. (1997)	Prescription drugs	(Ontario) Canada	1996-1997	Elderly individuals (65+)	Introduction of income-graded cost sharing: CDN $2 co-payment for low-income persons and CDN $100 deductible and CDN $6.11 co-payment for higher-income persons	Drop in prescription drug use in the few months after the user fee introduction; In the first few months, the number of essential prescriptions, discretionary prescriptions, and preventative prescriptions fell, although the volume per prescription rose	Unmeasured socioeconomic and demographic variables; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Johnson et al. (1997a)	Prescription drugs	(Oregon) The United States	1987-1991	Between 3,352 and 3,981 elderly (65+) Medicare HMO enrollees	In one group, increase in co-payment from $1 to $3 (1987-1988) and $3 to $5 (1988-1989); In other group, 50% coinsurance with $25 max per prescription (1987-1989) and rose to 70% with a $30 max in 1990	Inconsistent results, although when the largest increase in co-payment occurred, beneficiaries were less likely to get exposure to 3 essential classes of medication and 2 nonessential classes of medication and the total days of use declined in 5 of the 7 essential classes and 1 nonessential class	May not be generalizable because limited to HMO elderly population in one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Johnson et al. (1997b)	Prescription drugs	(Oregon) The United States	1987-1991	Between 6,704 and 7,962 elderly (65+) Medicare HMO enrollees	In one group, increase in co-payment from $1 to $3 (1987-1988) and $3 to $5 (1988-1989); In other group, 50% coinsurance with $25 max per prescription (1987-1989) and rose to 70% with a $30 max in 1990	Little evidence that exposure to, costs and annual days of drug use for discretionary and essential drug use was affected; Increased co-payments reduced total number of days of use for cardiac agents and diuretics in 1988-1990, 1989-1990	May not be generalizable because limited to HMO elderly population in one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Joyce et al. (2002)	Prescription drugs	The United States	1997-1999	420,786 non-elderly employees (18-64) at large firms with health insurance benefits that included outpatient drugs	Plan A: change from $5 to $7 co-payment Plan B: change from $4 to $5 brand co-payment Control group: $10 brand co-payment and $5 generic co-payment	Doubling the co-payment in a 1-tier plan for all drugs reduced average annual spending from $725 to $563 per member; Adding an additional co-payment of $30 for non-preferred brand drugs lowered overall drug spending by 4%	Unmeasured variables such as income may influence spending; Individuals in employer health insurance plans likely to be healthier
Kamal-Bahl and Briesacher (2004)	Prescription drugs	The United States	1999	149,243 adults (18+) with a diagnosis of hypertension with prescription drug benefits	18 single-tier prescription drug plans, 20 2-tier plans, and 4 3-tier plans	As the co-payment increased in the all plans, the probability of getting a more expensive medication (like ACE inhibitor) declined; Regardless of the co-payment amount, no differences in the types of antihypertensives that enrollees obtained in single-tier plans	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization; Unmeasured variables such as income may influence demand for prescriptions
Keeler et al. (1985)	Medical services	The United States	1974-1982	3,495 non-elderly (14-61) individuals with hypertension	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	For the average adult, diastolic blood pressure was significantly lower with free care than with cost sharing; Hypertensives with free care received a better quality of care than their counterparts on the cost-sharing plans, although for many measures of quality, no difference	Unmeasured variables such as income which may influence medical service use
Kennedy and Erb (2002)	Prescription drugs	The United States	1994-1995	11,272 individuals with disabilities	Insurance coverage (private only, public only, mix of private and public, no insurance)	2% of adults 65-74 and 1% of adults 75+ reported non-compliance because of cost (these rates were much lower than those of younger age groups); More than 50% of individuals who reported non-compliance due to costs reported adverse health outcomes	Did not control for other factors through regression; Some of the reasons they included for non-compliance may not be related to cost (may be related to side effects, doctor-patient relationship, etc)

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Klaukka et al. (93)	Prescription drugs	Finland	1992	399 individuals receiving treatment for high blood pressure	Reimbursement for the special compensation class of drugs was lowered from 90% to 80% in 1992	Every tenth individual who took part in the survey said that they had decreased the consumption of blood pressure medication due to the increased costs; Expenditures for drugs in the 80% class were 2.3% below the previous year	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization; Only examined individuals from one pharmacy, so there may have been sample selection issues
Klick and Stratmann (2005)	Prescription drugs	The United States	1996-1998	Elderly individuals (65+) that had not spent at least 1/2 of the year in a nursing home, excluded those with Medicaid and employer-sponsored insurance	Individuals with different types of supplemental insurance coverage face different out-of-pocket expenses	A $1 increase in the out-of-pocket price of a prescription led to a 66% decline in expenditures for prescription drugs and a 43% decline in the number of prescriptions	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Kozyrskyj et al. (2001)	Prescription drugs	(Manitoba) Canada	1995-1998	10,703 low-income children (5-15) with asthma	Change from a fixed deductible of CDN $237 per family and 40% co-payment system to income-based deductible system	Decrease in use of corticosteroids by higher-income group with severe asthma compared to control group; No change in use by low-income children compared to control group	Some children may have a higher probability of being diagnosed with asthma because of access to physicians; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Kupor et al. (1995)	Inpatient services, outpatient services	Japan	1984, 1989	Subscribers to the *Kukoho* insurance fund	Main subscribers and dependents had 30% coinsurance and retirees had 20% for all medical services; retiree dependents had 20% coinsurance for inpatient and 30% coinsurance for outpatient care	Cost sharing had small but negative and significant effect on medical services utilization; Inpatient utilization was most sensitive to co-payments in the lowest income group, while it was least sensitive to co-payments in the higher income group	Individual information may have been lost at the aggregate level; Unmeasured variables such as preferences for medical care
Landsman et al. (2005)	Prescription drugs	(Northeast, South, and Southeast regions) The United States	1999-2001	Approximately 630,000 cases and 1 million controls enrolled in managed care plans	Co-payments ranged from $5 to $20 in 2-tiers for generic and brand-name drug in the pre-period and from $5 to $20 in 3-tiers in the post-period	A larger proportion of cases than controls switched to a product with a lower co-payment for statins, ACE inhibitors, and triptans; For most medications considered, discontinuation rates increased significantly in the 6 months following the benefit change	Did not control for other factors with regression; Information may have been lost at the aggregate level

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Lauterbach et al. (2000)	Prescription drugs	(Cologne) Germany	1998	Approximately 700 adults (18+) that visited the chosen pharmacies who were not exempted from the co-payment	In 1997 the government increased co-payments by 6 DM (co-payments still differed by pack size, though)	The co-payment increase reduced physician visits by 4.5% and drugs by one pack on average; Most people covered by public health insurance slightly changed their consumption of drugs due to an increase in co-payments	Sampling issue because there was a probability of being included in the sample as the individual had to visit the pharmacy; Retrospective self-assessment may have been biased
Lavers (1989)	Prescription drugs	(England and Wales) The United Kingdom	1971-1982	12 annual observations, NHS beneficiaries not exempt from co-payments	Change in co-payment from £0.20 to £1.30	No significant change in prescription size with the increase in co-payment; No significant change in morbidity with the increase in co-payment	Unmeasured variables such as changes in supply of pharmacists and GPs could be important
Lewis and Keairnes (1970)	Inpatient services, physician services	(Sedgwick County, Kansas) The United States	1968	5,000 contracts for groups of employees that were enrolled in Blue Cross / Blue Shield of Kansas	Certain outpatient and ambulatory services were offered for free in the experiment	No significant differences in hospital admission rates between experimental and control groups; 38.8% of individuals in the experimental group and 34.4% of individuals in the control group visited a physician at some time during the five two-week periods	May not be generalizable because limited to one region in Kansas; Employees and dependents likely to be healthier and have higher income; Employee groups, not individuals, had to be selected for the study
Li et al. (2006)	Prescription drugs	British Columbia, Canada	2001-2002	8,017 elderly individuals with rheumatoid arthritis	In 2002 co-payments increased to max of CDN $25 for higher income groups and CDN $10 for lower income groups. Annual maximums also increased from CDN $200 to CDN $275 for higher-income groups	The co-payment increase decreased prescription drug consumption among both groups, although the lower-income group was more sensitive to the price change; Both groups also substituted more physician visits for prescription drugs	Little demographic information was included as additional controls; Restricted to one disease and the reaction to the price change among the general population of the elderly may be different
Liebowitz et al. (1985)	Prescription drugs	The United States	1974-1982	3,680 non-elderly (14-61) individuals	Insurance plans for prescription drugs varying by level of cost sharing (0%, 25%, 50%, 95%)	No change in drug quantities per prescription; No change in use of generic drugs	Unmeasured variables such as income may influence demand for prescriptions

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Liebowitz (1989)	Prescription drugs	The United States	1974-1982	3,057 non-elderly (14-61) individuals	Insurance plans for prescription drugs varying by level of cost sharing (0%, 25%, 50%, 95%)	Decreased probability of OTC use (31% used OTCs in free plan vs. 22% in plan with 95% co-payment); No evidence of substitution of OTC for prescription drugs by consumers with less generous insurance for prescription drugs	Unmeasured variables such as income and prices of OTC medications may influence demand for prescriptions
Lillard et al. (1999)	Prescription drugs	The United States	1990	1,082 elderly (65+) individuals not enrolled in an HMO	Supplemental insurance coverage (Medicaid, private drug coverage, private physician coverage, Medicare only)	Privately insured individuals had 44% higher odds of drug use; Privately insured individuals had $83 more in drug expenditures; Medicaid insurance had similar but smaller effects	Some variables self-reported (such as total and OOP drug expenditures and prescription drug coverage); Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Lingle et al. (1987)	Prescription drugs	(New Jersey, and Pennsylvania) The United States	1975, 1979	9,966 elderly (65+) individuals not eligible for Medicaid	Introduction in 1977 of state drug subsidies for low-income elderly	Decrease of $238.50 in inpatient expenses (likely due to less intensive care per hospital admission)	Unmeasured variables such as income may influence demand for prescriptions; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Link et al. (1980)	Inpatient services, physician services	The United States	1976	8,239 elderly (65+)	Supplementary insurance coverage (Medicaid, private insurance, no insurance)	Those with chronic conditions and private supplementary insurance or Medicaid had 42% and 50%, respectively, more physician visits than those with Medicaid only; Those with private supplementary insurance or Medicaid had 33% and 47%, respectively, more hospital days than those with Medicaid only	Cross-sectional study, thus difficult to control for other unmeasured factors that influence use of inpatient and physician services
Lohr et al. (1986)	Medical services, prescription drugs	The United States	1974-1977	5,554 non-elderly individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Cost sharing lowered use for both effective and non-effective drugs; Cost sharing decreased the probability of any use of medical care and prescription drugs among adults for almost all drugs studied	Did not control for other factors with regression

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Long (1994)	Prescription drugs	The United States	1990	5,300 elderly (65+) individuals	Supplemental drug insurance coverage (employer-sponsored, Medigap, or Medicare only)	Those with supplemental drug coverage had 26% higher spending than those without; Evidence of adverse selection into the prescription drug insurance market	Unmeasured demographic information such as sex and age which may influence prescriptions; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Lundberg et al. (1998)	Prescription drugs	(Uppsala County) Sweden	1995	2,008 individuals (20-84)	Hypothetical increases of 9%, 25%, 56%, 88%, and 150% in cost sharing requirements	Price sensitivity greatest for antitussives (40%) and least for climacteric drugs (11%); Price sensitivity decreased with more education, age, and income	Study based on hypothetical rather than observed changes in user charges
Lurie et al. (1984)	Medical services	(Los Angeles, California) The United States	1984	186 medically indigent adults who were not eligible for federal assistance programs	Termination of medical care that was free of charge (patients could pay a fee of $20 or $30 or choose to undergo a screening to determine their eligibility for free care	There was a deterioration in the health status of medically indigent individuals at the six month follow-up; There was a mean increase in diastolic blood pressure of 10 mm Hg from base line to the six month follow-up	May not be generalizable because limited to one region in California; Did not control for confounding factors through regression
Lurie et al. (1989)	Medical services	The United States	1974-1982	3,958 non-elderly (<62) individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Of the individuals that had perceived vision problems at enrollment in the experiment, 90% on the free plan and 76% on cost sharing plans received an eye examination; Once individuals received an eye examination, enrollees on all plans obtained lenses with similar frequency	Did not control for other factors with regression; Examined only vision services, while co-payments could affect use of other services differently
Lurk et al. (2004)	Prescription drugs	(Kansas City, Missouri) The United States	1999-2002	Approximately 42,000 patient visits for low-income patients	Co-payments increased from $5 for generic and $10 for brand-name drugs to $7.50 for generic and $15 for brand-name drugs	A $1 increase in the co-payment led to a $26.07 drop in prescription drug expenditures and a drop in the number of prescriptions of 0.42; No significant change in the number of clinic visits after the co-payment increase	Individual information may have been lost at the aggregate level; May not be generalizable because limited to one clinic in Kansas City

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Manning and Marquis (1996)	Medical services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1977-1982	2,138 non-elderly (<62) individuals	Insurance for health services with different cost sharing (200%, 25%, 50%, 95%)	Increasing out-of-pocket costs decreased medical care use; As the anticipated expenditures for medical care increased, the demand for health care increased	Unmeasured variables such as marital status and education
Manning et al. (1981)	Medical services	(Dayton, Ohio) The United States	1974-1977	2,202 non-elderly (<62) individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Higher coinsurance reduced both the probability of seeking medical care and the amount of care consumed; The largest coinsurance response occurred in the free and 25% coinsurance plans	Unmeasured variables such as marital status and education
Manning et al. (1987)	Medical services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1977	5,809 non-elderly (<63) individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	The likelihood of any use was 86.7% on the free plan, 78.8% on the 25% plan, 74.3% on the 50% plan, and 68% on the 95% plan; The mean predicted expenditure in the free plan was 46% higher than in the 95% plan	Unmeasured variables such as marital status and education
Martin and McMillan (1996)	Prescription drugs	(Georgia) The United States	1991-1992	1,884 non-elderly and elderly low income individuals who filled at least six prescriptions per month before policy change	Reduction in monthly limit from six to five reimbursable prescriptions	Decrease of 6.6% in total prescription use, decrease of 9.9% in prescriptions reimbursed by Medicaid, increase of 9.7% in prescriptions paid OOP; Decrease in use of some essential therapeutic groups but not others	May not be generalizable because limited to one state; Does not account for individuals that chose not to consume more than six prescriptions
McAvinchey and Yannopoulos (1993)	Inpatient services	The United Kingdom	1955-1987	Individuals in the UK	Price difference between public and private care	The demand for public sector care was less elastic in the short term, but the opposite was true in the longer term; Cross elasticities indicated that private and public acute care could be substitutes or complements with substitutability dominant in long run	Unmeasured variables such as changes in the supply of doctors or changes in benefits for private insurance

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
McCall et al. (1991)	Inpatient services, outpatient and physician services	(California, Florida, Michigan, New Jersey, Washington, Wisconsin) The United States	1982	2,335 elderly (65+) individuals	Supplemental insurance coverage (basic coverage, first-dollar coverage, none)	Those who characterized their health as fair or poor and had supplemental insurance had 31% more hospital days; Those who characterized their health as fair or poor and had supplemental insurance used 42% more Medicare Part B services	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization; May not be generalizable because limited to six states
McDavid et al. (2003)	Medical Services	(Kentucky) The United States	1995-1999	Adults (15+): 7,661 with colectoral cancer; 12,477 with lung cancer; 8,758 with breast cancer; and 6,959 with prostate cancer	Insurance coverage (Medicaid, Medicare, Medicare + supplementary, other federally funded, private, unknown, none)	Individuals with private insurance had higher rates of colectoral cancer survival than individuals with no or unknown insurance; Individuals with private insurance also had higher rates of lung cancer survival than individuals with all other insurance types	Unmeasured variables such as income, number of children, education, quality of cancer treatment; May not be generalizable because limited to one state
McDonald et al. (1974)	Physician services	Montreal, Quebec - Canada	1969-1972	Approximately 22,500 individuals	Introduction of health insurance	After the introduction of insurance, physician consultations for 13 of 14 selected symptoms increased; Little change in physician consultations for trivial complaints	Did not control for confounding factors through regression
McManus et al. (1996)	Prescription drugs	Australia	1989-1994	Beneficiaries of Australian National Pharmaceutical Benefits Scheme, subgroup of elderly (retired servicemen and women – Repatriation group)	Increase in co-payment from $11 to $15 for general population; Introduction of $2.50 co-payment for seniors and low income	For Repatriation group, smaller decrease in use of both classes of drugs and more rapid return to pre-co-payment levels	Unmeasured variables such as changes in supply of pharmacists and GPs could be important
McWilliams et al. (2004)	Medical services	The United States	1992, 2000	8,736 adults who were near elderly (55-64) in 1992 and did not have public insurance coverage	Insurance coverage (continuously insured, intermittently uninsured, continuously uninsured)	Mortality was significantly greater for uninsured adults; Uninsured individuals with low incomes or with diabetes or cardiovascular disease were at higher risk of mortality	No information on the extent of insurance coverage; Did not account for gains or losses in insurance over the study period
Mojtabai and Olfson (2003)	Prescription drugs	The United States	2000	10,413 elderly (65+)	Individuals faced different levels of cost sharing depending on the generosity of their insurance coverage	While only 7% of all Medicare beneficiaries reported cost-related non-adherence, more than 20% of low-income beneficiaries with OOP drug spending greater than $1000 reported this	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Monheit et al. (1985)	Physician services, inpatient services	The United States	1977, 1980	Non-elderly (16-64) individuals (sample size not given)	Insurance coverage (private, public, none)	About 62% of uninsured individuals visited the physician compared to almost 77% of the insured Fewer than 5% of the uninsured were hospitalized compared to more than 11% of the insured	Didn't control for confounding factors through regression
Mortimer (1997)	Prescription drugs	The United States	1991-1993	3,397 individuals receiving antidepressants and 1,426 receiving beta blockers	Insurance coverage (Medicaid, HMO, commercial insurance, uninsured)	For both antidepressants and beta blockers, price and quantity were negatively related; The most negative coefficient was for Medicaid patients, followed by HMO patients, commercial plan patients, and self-pay patients in both groups	Unmeasured variables such as income; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Motheral and Fairman (2001)	Prescription drugs	(Midwest region) The United States	1997-1998, 1998-1999	6,811 enrollees with employer-sponsored insurance as group with change, 13,279 enrollees in comparison group with no change	Change from 2-tier system with $7 co-payment for generic and $12 for brand drug to 3-tier system with $15 co-payment for formulary brand drug and $25 for non-formulary drug	The group with a 2-tier co-payment had larger increases in total prescription claims and tier 2 and 3 claims than the group with a 3-tier co-payment; No differences in office visit rates, emergency room visits, or inpatient visits between groups	Analysis was limited to enrollees with employer-sponsored insurance who may be healthier and wealthier than the general population; Information may be lost at the aggregate level
Motheral and Henderson (1999)	Prescription drugs	The United States	1996-1997	4,091 adults (18+) enrolled in two employer-sponsored plans	Increase in co-payment for brand name from $10-$15, smaller co-payment increase for generic drugs ($4-$5 for one group, and $5-$7 for another) for individuals in employer plans	No change in overall utilization but decrease use of brand drugs (discretionary only) and increased use of generic drugs (discretionary and essential)	Individuals in employer health insurance plans likely to be healthier; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Nelson et al. (1984)	Prescription drugs	(Tennessee) The United States	1976-1979	17,811 low-income individuals (Medicaid recipients) using 5+ prescriptions in year prior to co-payment	Introduction of $0.50 co-payment	26% decrease in number of prescriptions obtained; 39% decrease in average cost for prescriptions for the state	Differences between control groups; Does not account for individuals that chose not to consume more than five prescriptions

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Newhouse (1981)	Medical services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1977	7,706 non-elderly (<62) individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Expenditure per person with full coverage approximately 60% greater than those with 95% coverage plan, and expenditure in the other plans fell between these two extremes; Cost sharing reduced inappropriate and appropriate hospital days by about the same; Individuals with free care were more likely to make at least one physician visit and have at least one hospital admission	Unmeasured variables such as marital status and education
Newhouse (1993)	Medical services, inpatient services, prescription drugs	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1977-1982	3,988 non-elderly individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	The mean predicted expenditure in the free plan was 46% higher than in the 95% plan; The outpatient-only cost sharing plan reduced expenditures, mainly by reducing the probability of any use; The variation in prescription drug expenditures mainly due to the rate of provider visits, not from the expenditure on drugs per visit	Unmeasured variables such as marital status and education
Newhouse and Phelps (1974)	Physician visits, inpatient services	The United States	1963	854 employed individuals	Individuals faced different coinsurance rates and deductibles	Individuals with complete coverage chose hospitals with more expensive room and board rates; Individuals with complete coverage also chose physicians with higher charges	Unknown bias from excluding non-labor force participants; Cross-sectional study, thus difficult to control for other unmeasured factors that influence inpatient and physician utilization
Newhouse and Phelps (1976)	Physician visits, inpatient services	The United States	1963	4,552 individuals without deductibles in their health insurance policies	Individuals faced different OOP prices for medical care	Elasticity of demand for physician services was higher than for inpatient services; Larger families were more sensitive to changes in the prices of physician services than to changes in the prices of inpatient services	Self-reported data on health care utilization; Cross-sectional study, thus difficult to control for other unmeasured factors that influence inpatient and physician utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Nolan (1993)	Inpatient services, physician services	Ireland	1987	3,294 households	Full care was free of charge, free inpatient services but not free primary care, no public coverage for hospital care; Some individuals have private insurance coverage	Individuals with free GP care had more visits than those who had to pay OOP; Individuals with health insurance were more likely to have an inpatient visit and had longer average inpatient stays than those without insurance	Cross-sectional study and thus difficult to control for other confounding factors
O'Brien (1989)	Prescription drugs	(England and Wales) The United Kingdom	1969-1986	216 monthly observations, NHS beneficiaries not exempt from co-payments	Change in co-payment from £0.125 to £2.20	A negative relationship between the prescription charge and the number of prescriptions dispensed that were not exempt from prescription charges	Unmeasured variables such as changes in supply of pharmacists and GPs could be important
O'Grady et al. (1985)	Emergency department services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1977	3,973 non-elderly (<62) individuals	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Individuals with 95% cost sharing were 70% more likely to visit the emergency department than those on the free plan; Those with coinsurance were less likely to visit the emergency room both for diagnoses categorized as more urgent and diagnoses categorized as less urgent	Unmeasured variables such as marital status and education
Ong et al. (2003)	Prescription drugs	(Stockholm) Sweden	1990-1999	Individuals of all ages (size of sample not specified)	Co-payment changes or reforms over time	In most cases, pharmaceutical consumption did not decrease as consumer costs increased; Only antidepressant use among women was permanently reduced after the 1997 reforms	Unmeasured variables such as changes in supply of pharmacists and GPs could be important
Overpeck and Kotch (1990)	Medical services	The United States	1988	17,110 children (<18)	Insurance coverage (coverage, none)	Compared to those with coverage, rates of totally medically attended injuries ranged from 1.70 at ages 12-17 and 0.80 at ages <6 for those without coverage	Unmeasured variables such as income and family size; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Ozminkowski et al. (2004)	Prescription drugs	The United States	1996-2000	1,807 individuals with Multiple Sclerosis under employer-sponsored plans	Individuals faced different levels of cost sharing depending on the generosity of their insurance coverage	A 1% increase in the share of drug expenditure accounted for by drug co-payments led to an approximate 14% decrease in the rate of new drug use	The results may be more dramatic if extended to populations that are not privately insured; Limited to those with MS so results may differ for individuals that do not have MS

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Patrick et al. (1992)	Inpatient services, physician and outpatient visits	(Washington) The United States	Not given	1,127 low-income families	Insurance coverage (has insurance, no insurance)	Uninsured families made fewer ambulatory visits and had fewer hospitalizations in the 3 months prior to the interview; Uninsured families reported more often that the emergency room was their usual source of care	May not be generalizable because limited to parts of Washington; Cross-sectional study, thus difficult to control for other unmeasured factors that influence inpatient and physician utilization
Phelps and Newhouse (1972)	Physician services, outpatient services	(California) The United States	1966-1968	5,134 observations for all members of the Palo Alto Group Health Plan	Introduction of 25% coinsurance	Evidence that time costs influenced the demand for medical visits (female workers used less than female dependents)	Unable to determine if patients purchased supplementary insurance; Unmeasured variables such as income and substitutes like non-clinic doctors
Phelps and Newhouse (1974)	Inpatient services, physician services, prescription drugs	Multiple countries	1962	All ages	Introduction of coinsurance	Services with high time price have low coverage elasticities and relatively high time price elasticities; Services with high money price have higher own price elasticities	Cross-sectional study, thus difficult to control for other unmeasured factors that influence inpatient, physician, and prescription drug utilization
Phelps (1975)	Inpatient services, physician services	The United States	1971	11,882 individuals	Individuals faced different coinsurance rates	Negative relationship between coinsurance and hospital length of stay and hospital expense per admission; Demand for physician visits is over twice as high at full coverage as with no insurance	Unmeasured variables such as marital status and household size; Cross-sectional study, thus difficult to control for other unmeasured factors that influence inpatient and physician utilization
Piette et al. (2004)	Prescription drugs	The United States	2002	4,055 adults that were chronically ill	Individuals faced different out-of-pocket costs for prescription drugs and had prescription drug insurance or none	Individuals with higher out-of-pocket medication costs had greater odds of underuse of medicines in 9 of 10 medicine classes; Cost-related adherence problems most prevalent among individuals taking medication for arthritis, depression, back pain, asthma, migraines, and stomach ulcers	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization; Problems with reporting of compliance (recall bias and social desirability)

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Pilote et al. (2002)	Prescription drugs	(Quebec) Canada	1994-1998	22,066 elderly (65+) individuals who had been admitted to acute care hospitals with discharge of myocardial infarction	Change from CDN $2 co-payment to 2.5% coinsurance fee with annual ceilings depending on income; Income-based deductible added in 1997	Policy reform had no effect on prescription rates, persistence of drug therapy, adherence to drug therapy, mortality rates, readmissions for complications, or outpatient physician and emergency department visits	Results only applied to use of prescriptions after a myocardial infarction and response to co-payments could differ for other ailments
Poirier et al. (1998)	Prescription drugs	(Quebec) Canada	1991-1993	Elderly (65+): 9,336 users of antihypertensives, 19,457 users of benzodiazepines	Introduction of CDN $2 co-payment up to CDN $100 annual maximum	Small decrease in refill rate for antihypertensives; No change for benzodiazepines	Did not control for other factors with regression
Poisal and Chulis (2000)	Prescription drugs	The United States	1996	Elderly (65+) individuals (sample size not given)	Supplemental drug insurance coverage (Medicaid, employer-sponsored, individual-purchased, Medicare HMOs, other insurance, Medicare only)	Compared to those without coverage, those with coverage filled 19%-43% more prescriptions and incurred 45%-100% higher drug expenditures, depending on level of health status	Did not control for other factors with regression
Poisal and Murray (2001)	Prescription drugs	The United States	1997-1998	Elderly (65+) individuals	Supplemental drug insurance coverage (Medicaid, employer-sponsored, individual-purchased, Medicare HMOs, other public, Medicare only)	Medicaid beneficiaries without drug coverage used 18 fewer prescriptions than Medicaid beneficiaries with coverage; Beneficiaries without drug coverage spent $546 OOP compared with $325 OOP spent by beneficiaries with coverage	Total drug prices sometimes had to be estimated; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Puig-Junoy (1988)	Prescription drugs	Spain	1967-1983	17 annual observations, aggregate country data	Price changes of prescription drugs over time	Evidence that pensioners purchased prescriptions on behalf of individuals facing coinsurance	Individual information may have been lost at the aggregate level
Raynaud (2002)	Prescription drugs	France	1992, 1995 and 1997	9,000 households	Supplementary insurance coverage (CMU, other coverage, none)	The probability of pharmaceutical consumption in a year was 85% for those with supplementary coverage; The same probability was only 73% for those without supplementary coverage	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Raynaud (2003)	Prescription drugs	France	2000	9,000 households, including 500 benefiting from CMU coverage	Supplementary insurance coverage (CMU, other coverage, none)	Pharmaceutical spending was 32% higher for those with CMU coverage compared to those with no supplementary coverage and 16% higher compared to those with other types of supplementary coverage	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Raynaud (2005)	Prescription drugs	France	2000, 2002	18,500 individuals	Supplementary prescription drug coverage (CMU, other coverage, none)	Individuals with CMU had a higher probability of incurring drug expenditures (90%) compared to those with other types of supplementary coverage (85%) and those with no supplementary coverage (73%); Those with CMU had 21% higher pharmaceutical spending than those without supplementary coverage	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Rector et al. (2003)	Prescription drugs	The United States	1998-1999	Members of four employer health plans: 1,874 using ACEI inhibitors, 2,826 using PPIs, 4,443 using statins	Introduction of a tiered co-payment plan where patients paid a different co-payment based on whether the drug was preferred or not preferred	Use of preferred brands did not increase as much in the non-tiered group; Effect of tiered co-payments did not depend on size of co-payment differential between preferred and non-preferred groups	Did not control for amount of co-payment or differences in co-payments between plans; May not be generalizable because limited to four employers in one state
Reeder and Nelson (1985)	Prescription drugs	(South Carolina) The United States	1976-1979	62,176 low-income individuals (Medicaid recipients) using 6+ prescriptions in year prior to co-payment	Introduction of $0.50 co-payment	With the exception of the analgesic and sedative groups, a significant decline in the level of drug expenditures; Decrease in long-term use and costs in 4 of 10 groups: cardiovascular, cholinergic, diuretic, and psychotherapeutic	Does not account for individuals that chose not to consume more than six prescriptions
Reuveni et al. (2002)	Prescription drugs	Israel	1999	779 children and adolescents ages 0-18 diagnosed with acute infectious disease for which drugs were prescribed	Individuals facing different cost sharing requirements	One of the main reasons for poor compliance with medical treatment was the income level of the patient's family; Families with low income, overcrowded living conditions, and more drugs per prescription were less likely to purchase drugs	May not be generalizable because limited to one health care center; Unmeasured variables such as amount of cost sharing requirement would have added more information

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Roemer et al. (1975)	Physician services, inpatient services	San Francisco, Ventura, and Tulare, California - the United States	1971-1972	10,687 Medicaid individuals with the co-payment; 29,975 Medicaid individuals without the co-payment	Introduction of $1 co-payment for first two doctor visits each month; $0.50 co-payment for first two drug prescriptions per month	Individuals with co-payments made fewer doctor visits than individuals without co-payments; An increase in hospitalizations in the co-payment group compared to the no co-payment group	May not be generalizable because limited to the state of California; There could be underlying differences between the use of medical care between the control group and the study group, even if both had no co-payments; Did not control for other factors through regression
Rogowski et al. (1997)	Prescription drugs	The United States	1990	996 elderly (66+) individuals	Supplemental drug insurance coverage (Medicaid, prescription coverage, physician coverage, Medicare only)	Those with drug coverage: 4 times greater odds of prescription drug use than for those with no insurance; Those with drug coverage spent 50% less as a share of household income on prescription drugs compared to those with no insurance	No information on the extent of drug coverage; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Rosenthal (1964)	Inpatient services	The United States	1950, 1960	Non-federal short-term general and specialist hospitals	Individuals faced different prices for inpatient care	The price of care had a significant negative effect on the demand for hospital care in 1960; The variable indicating the percent of the population with insurance coverage was significantly and positively related to the demand for inpatient care	The price variable included was not the out-of-pocket price to the patient and may have been unrelated to what the consumer paid; Individual information may have been lost at the aggregate level
Rosenthal (1968)	Inpatient services	(Maine, New Hampshire, Vermont, Massachusetts, Rhode Island) The United States	1962	15,685 hospital admissions	Patients faced different total inpatient bills and average daily room charges	The results suggested that there is likely to be a lower price elasticity of demand for short hospital lengths of stay; The price elasticity of demand differed across categories of admissions	Cross-sectional study, thus difficult to control for other unmeasured factors that influence inpatient utilization; Did not use out-of-pocket price but rather the total price of the service
Rosett and Huang (1973)	Medical services	The United States	1960	2,602 households with positive income	Individuals faced different prices for medical care	Low-income individuals at risk of illness are likely to purchase insurance for the worst and least probable risks but self-insure against more probable smaller losses; At higher incomes, the elasticity of income was greater	Unmeasured variables such as health status of individuals in household; Cross-sectional study, thus difficult to control for other unmeasured factors that influence medical care utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Ryan and Birch (1991)	Prescription drugs	(England and Wales) The United Kingdom	1979-1985	NHS beneficiaries not exempt from co-payments	Change in co-payment from £0.20 to £2.00	From 1979-1985, prescription charged increased by 490% in real terms, while rate of prescriptions dispensed per capita in the population not exempt from charges decreased by 33%	Unmeasured variables such as changes in supply of pharmacists and GPs could be important
Safran et al. (2002)	Prescription drugs	(Illinois, Michigan, New York, Pennsylvania, California, Colorado, Ohio, and Texas) The United States	2001	10,416 elderly (65+) individuals	Different types of prescription drug coverage	Patients without drug coverage were 2.8 times more likely to skip doses and 2.3 times more likely to spend less on basic necessities; 25% of low-income seniors with Medigap or HMO drug coverage reported not filling prescriptions, and >20% skipped doses	Self-reported information on drug coverage; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Scheffler (1984)	Inpatient services, physician services	(Pennsylvania) The United States	1977	5,928 non-elderly (<65) individuals	Introduction of a $250 inpatient deductible, 40% coinsurance rate, and family maximum liability of $500	45% decline in the probability of hospital admission after cost sharing while length of inpatient stays and hospital expenditures per admission increased; 35% decline in the probability of having a physician visit, and the number of physician visits physician expenditures decreased	May not be generalizable because limited to one area; There was a rumor that the cost sharing requirements were only temporary (during the time period of the study), and this could have influenced consumption
Schoen et al. (2001)	Prescription drugs	Chicago, Illinois – the United States	N/A	163 patients with cardiovascular disease who did not have prescription drug coverage	Patients without prescription drug coverage were given assistance for prescription drugs	The mean LDL cholesterol level decreased for patients on lipid-lowering drugs after they received assistance with prescriptions; Patient drug adherence improved from 49% at baseline to 73% at six months	Did not control for other factors through regression; Study limited to group of ill patients in one city – results may be different for less disadvantaged patients
Schulz et al. (1995)	Prescription drugs	(South Carolina) The United States	Not given	19 low-income individuals who were "affected by prescription cap"	Cap of three prescriptions per month	7 patients reduced frequency of dosing; 8 patients did not obtain a prescription at some point	Very small sample (19 individuals); May not be generalizable because limited to small site; Did not control for other factors with regression

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Scitovsky and McCall (1977)	Physician services, outpatient services	California, the United States	1966-1968	3,819 non-elderly (<65) members of the Palo Alto Group Health Plan	Introduction of 25% coinsurance	Some evidence that lowest socioeconomic group responded more to the increase in cost sharing	Did not control for other factors with regression; Unable to determine if patients purchased supplementary insurance; Unmeasured variables such as income and substitutes like non-clinic doctors
Scitovsky and Snyder (1972)	Physician services, outpatient services	California, the United States	1966-1968	2,567 non-elderly (<65) members of the Palo Alto Group Health Plan	Introduction of 25% coinsurance	Some evidence that lowest socioeconomic group responded more to the increase in cost sharing; Male subscribers reduced utilization markedly less than other groups	Did not control for other factors with regression; Unable to determine if patients purchased supplementary insurance; Unmeasured variables such as income and substitutes like non-clinic doctors
Scott et al. (1990)	Prescription drugs	(Minneapolis, Minnesota) The United States	1983	145 ear infection episodes from near-poor Medicaid ineligible patients at an urban health center	Introduction of co-payment for prescription drugs (unknown size)	Decreases in antibiotics were greater for the self-paid group than for the Medicaid group; For the self-paid patients, physician prescribing of the higher-cost antibiotics declined, while prescribing of the lower-cost antibiotics increased	May not be generalizable because limited to one urban health clinic; Small sample; Did not control for other factors with regression
Scott et al. (2003)	Physician services	New Zealand	1996-1997	7,862 adults	Individuals with CSC card paid NZ $20 to NZ $30 per physician visit, while everyone else paid NZ $35 to NZ $45 per physician visit	Individuals subsidized by the government were more likely to visit the physicians once, but not more likely to visit the physician frequently; Unemployed individuals were not more likely to make at least one physician visit but were more likely to be frequent users	Cross-sectional study, thus difficult to control for other unmeasured factors that influence physician utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Selby et al. (1996)	Emergency department care	(California) The United States	1992-1993	30,276 non-elderly (<64) employees and dependents with HMO insurance	Introduction of $25-$35 co-payment for emergency department care	Emergency visits were 27% higher in control group 1 and 7% higher in control group 2 than in study group; For visits defined as "always an emergency", little decline in emergency visits, but for visits defined as less severe, greater declines in the co-payment group than in the control group	May not be generalizable because limited to one region in California; Employees and dependents likely to be healthier and have higher income
Shapiro et al. (1986)	Physician services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1977	3,539 non-elderly, adult individuals (17-61)	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Individuals assigned to cost sharing plans 1/3 less likely to visit a physician for a minor symptom; Among those reporting a serious symptom, the percentage seeking care was only significantly different for cost sharing and free plans at the 10% level	Unmeasured variables such as marital status and education; Cross-sectional study, thus difficult to control for other unmeasured factors that influence physician utilization
Shih (1999)	Prescription drugs	The United States	1993-1997	10,214 elderly (65+) individuals enrolled in Medicare End Stage Renal Disease program	Supplemental drug insurance coverage (Medicaid, employer-sponsored, Medicare HMOs, other insurance, Medicare only)	9-10% increase in number of prescription drugs per person with supplemental drug insurance coverage	Cross-sectional study, thus difficult to control for other unmeasured factors that influence physician utilization
Siu et al. (1986)	Inpatient services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1977	1,132 hospitalized adults (17-61)	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	Cost sharing decreased both appropriate and inappropriate admissions and hospital days by about the same amount; Cost sharing for outpatient services did not cause a higher rate of inappropriate admissions or hospital days	Unmeasured variables such as marital status and education; Cross-sectional study, thus difficult to control for other unmeasured factors that influence physician utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Smart and Stabile (2005)	Prescription drugs	Canada	1986, 1988, 1990, 1992, 1994, 1996, 1998, 2000	91,327 individuals over 8 years	Change in 1987 from tax deductions to tax credits for medical care costs exceeding a pre-defined threshold (in 2000, CDN $1637 or 17% of the individual's net income, whichever is less)	As the after-tax price of health care rose, the probability of any spending on health care and prescription drugs fell; As the after-tax price of medical care rose by CDN $1, spending on prescription drugs fell by 26.4%	Unmeasured variables such as health status and employment
Smith (1993)	Prescription drugs	The United States	1989	212 individuals in employer groups covered by one national managed care company	Variation in co-payment from $1 to $8 between different employer groups	Changing the co-payment from $3-$5 led to little change in total drug costs, but total prescriptions per person decreased by 5% and ingredient costs per prescription increased by about 5%; Changing the co-payment from $3-$5 also decreased employer costs by 10%	Unmeasured variables such as income and education; Small sample; Individuals with employment more likely to be healthy
Smith and Garner (1974)	Prescription drugs	(Mississippi) The United States	1970-1971	241 individuals with Medicaid	Introduction of Medicaid program in Mississippi with free prescriptions	Prior to Medicaid, the average number of prescriptions was 5.43 per person, and after the program began, the average number of prescriptions was 9.48 per person; Little evidence that physicians increased the size of prescriptions after implementation of Medicaid	Did not control for other factors with regression; May not be generalizable because limited to one area in Mississippi; Small sample
Smith and Watson (1990)	Prescription drugs	The United Kingdom	1979-1984	42,901 NHS beneficiaries not exempt from co-payments	Change in co-payment from £0.45 to £1.60	A negative relationship between the prescription charge and the number of prescriptions dispensed that were not exempt from prescription charges; As the price of substitute proprietary medicines increased, the number of prescription dispensed increased	Unmeasured variables such as changes in supply of pharmacists and GPs could be important
Soumerai et al. (1987)	Prescription drugs	(New Hampshire) The United States	1980-1983	10,734 elderly (60+), low-income Medicaid recipients	Introduction of cap of 3 reimbursable prescriptions per month; Replacement of cap by $1 co-payment	After cap: 30% decrease in number of prescription, 58% decrease in discretionary drugs, 28% decrease in essential drugs; After co-payment: return to just below precap levels	May not be generalizable because limited to one state

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Soumerai et al. (1991)	Prescription drugs	(New Hampshire) The United States	1980-1983	411 non-elderly, low-income Medicaid recipients that were chronically ill	Introduction of cap of 3 reimbursable prescriptions per month; Replacement of cap by $1.00 co-payment	After the introduction of the cap, there was a 30% decrease in number of prescriptions, 58% decrease in discretionary drugs, 28% decrease in essential drugs; After the introduction of the co-payment, there was a return to just below precap levels	May not be generalizable because limited to one state
Soumerai et al. (1994)		(New Hampshire) The United States	1980-1983	10,734 non-elderly (19-60), low-income individuals with schizophrenia	Introduction of cap of 3 reimbursable prescriptions per month; replacement of cap by $1 co-payment	After cap: decrease of 15%-49% in use of psychotropic drugs; After cap: increase in use of emergency mental health services and partial hospitalization, increase in mental health care costs 17 times greater than drug savings; After co-payment: drug use and services reverted to precap level	May not be generalizable because limited to one state
Spillman (1992)	Medical services, inpatient services, emergency room services	The United States	1980	10,009 non-elderly (<65) individuals	Insurance coverage (insurance, none)	Uninsured individuals were less likely to use at least one nonemergency service and used fewer nonemergency services; Uninsured adults were less likely to use any emergency services, but among individuals with at least one emergency visit, only uninsured men had fewer visits than insured men	Unmeasured variables such as usual source of care; Cross-sectional study, thus difficult to control for other unmeasured factors that influence medical care utilization
Starmans et al. (1994)	Prescription drugs	The Netherlands	1978-1986	760,000 beneficiaries in four Sickness Funds using antihypertensives	Introduction of co-payment of NLG 2.50 for; Removal of 30 day limit on prescriptions	No effects on drug use (decrease in prescriptions, but simultaneous increase in number of units per prescription)	Unmeasured variables such as changes in supply of pharmacists, changes in average age and sex of GPs could be important; Cost sharing may have different effect on other drug classes
Steffensen et al. (1997)	Prescription drugs	(North Jutland) Denmark	1993-1996	All prescriptions of antibiotics	Increase in co-payment for tetracyclines from 50% to 100% and increase in co-payment for other antibiotics from 25% to 50% in Jan 1996	Prescriptions of antibiotics decreased 13% from the previous year after the increase in co-payments; Prescriptions of tetracyclines dropped 42% after the loss of reimbursement	Did not control for other factors with regression; Individual information may have been lost at the aggregate level

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Steinman et al. (2001)	Prescription drugs	The United States	1995-1996	4,896 elderly (70+) individuals who regularly used prescriptions	Supplemental drug insurance coverage (none, some, full)	Whereas only 2% of individuals with full coverage reported non-compliance, 3% of individuals with partial coverage and 7.7% of individuals with no drug coverage reported non-compliance	Self-reported information; Unmeasured variables may account for some of the variance in rates of medication restriction (such as depression)
Stuart and Grana (1995)	Prescription drugs	(Pennsylvania) The United States	1990	2,962 elderly (65+) individuals enrolled in Medicare Part A and B, restricted to individuals reporting a serious health problem and receiving at least one medication for this	Drug insurance coverage (Medicaid, PACE, prescription coverage, physician coverage, none or other)	10%-15% increase in the probability of use of prescription drugs (vs. OTC) with drug insurance coverage	No price information for OTC drugs; May not be generalizable because limited to one state; Cross-sectional study, thus difficult to control for other unmeasured factors that influence physician utilization
Stuart and Grana (1998)	Prescription drugs	(Pennsylvania) The United States	1990	1,302 elderly (65+) low-income, Medicaid eligible individuals not enrolled in an HMO	Drug insurance coverage (employer-sponsored, Medicaid, or state-sponsored)	Co-payment recipients in fair health reported 40% fewer prescriptions than their counterparts in non-co-payment states; Co-payment recipients in poor health reported 27% fewer prescriptions than their counterparts in non-co-payment states	May not be generalizable because limited to one state; Limited sample of Medicaid beneficiaries; Cross-sectional study, thus difficult to control for other unmeasured factors that influence physician utilization
Stuart and Zacker (1999)	Prescription drugs	The United States	1992	1,302 elderly (65+) low-income, Medicaid eligible individuals not enrolled in an HMO	Variation in state-specific Medicaid co-payments; 18 states without co-payment and 21 with ($0.50-$3)	12% decrease in probability of prescription drug use and 7% decrease in prescriptions filled among users in co-payment states compared to states without co-payments; Coverage increased the odds of drug use for 10 of 22 conditions	Limited sample of Medicaid beneficiaries; Limited number of control variables for health status; No information on the extent of drug coverage
Stuart et al. (2000)	Prescription drugs	The United States	1996	Elderly (65+) individuals	Supplemental drug insurance coverage (Medicaid, employer-sponsored, individual-purchased, Medicare HMOs, other insurance, Medicare only)	Among those in poor health, those with no coverage filled 35% fewer prescriptions than those with coverage; Continuous prescription drug coverage was associated with higher use of prescription drugs and higher unit costs	No information on the extent of drug coverage; Did not control for other factors with regression

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Swedish National Board of Health and Welfare (Socialstyrelsen) (1997)	Prescription drugs	Sweden	1997	5,975 adults (18-84)	New medical bill passed in 1996 capping total yearly out-of-pocket prescription drug costs at 1300 SKr and adding deductibles for prescription drugs	A little more than half of households reported foregoing prescriptions because of price; Those who were more likely to report price as a reason for foregoing a prescription were unemployed, students, on long-term sick leave, early retired, or working at home	Did not control for other factors with regression; Did not attempt to look at how new cost sharing requirements influenced Swedish individuals
Taira et al. (2006)	Prescription drugs	The United States	1999-2004	patients with a 114,232 with managed care and a diagnosis of hypertension that filled at least one prescription	Co-payments were $5 for generic drugs, $20 for preferred brand-name drugs, and $20-$265 for non-preferred drugs	Compliance for antihypertensive medications was 67% for tier 1 drugs, 66% for tier 2 drugs, and 55% for tier 3 drugs; There were additional disparities in compliance between the most and least expensive drugs within a therapeutic class	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization; Compliance rates for individuals without managed care may be different
Tamblyn et al. (2001)	Prescription drugs	(Quebec) Canada	1993-1997	120,000 elderly (65+) and low-income recipients of social assistance	For elderly: CDN $2 co-payment to coinsurance and deductibles with max annual charge of CDN $200-$925; For social assistance: no co-payment to coinsurance and deductibles with max quarterly charge of CDN $50	The incidence of a prescription drug subsidy for seniors is less progressive than a percentage-of-income cash transfer, though at most only mildly; The reduction in prescription drug budget share upon implementation of a subsidy is only slightly larger for low-income than for high-income households	Individual information may have been lost at the aggregate level
Thomas et al. (1996)	Prescription drugs	(Northeast region) United States	1993	1,386 patients who had experienced abdominal pain, asthma, chest pain, hand lacerations, head trauma, or first-trimester vaginal bleeding	Insurance coverage (insurance, none)	Individuals without insurance were less likely to fill a prescription after an emergency department discharge	May not be generalizable because limited to five urban teaching hospital emergency departments in the northeastern US; No information on the extent of insurance coverage

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Thomas et al. (2002)	Prescription drugs	The United States	2001	29,435 elderly (65+) individuals with employer-sponsored prescription drug insurance administered by a national PBM	Individuals faced different levels of cost sharing depending on the generosity of their prescription drug insurance coverage	Members in plans with higher cost sharing had higher out-of-pocket costs as a percentage of total expenditures; Co-payment incentives led plan members to purchase less costly generic drugs	Did not control for other factors with regression; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Tseng et al. (2003)	Prescription drugs	The United States	2001	438,802 individuals with Medicare+Choice who filled at least one prescription	Individuals faced drug reimbursement caps of $750 to $2000 per year	After exceeding the cap, patient average OOP costs increased from $79-$100 per month to $179-$305 per month; Of the twenty medications with the highest total prescription expenditures for patients, 15 were for chronic conditions	Did not control for other factors with regression; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Valdez (1986)	Medical services	(Areas in Washington, Ohio, Massachusetts, and South Carolina) The United States	1974-1982	1,844 children (<14)	Insurance for health services with different cost sharing (0%, 25%, 50%, 95%)	No differences in health status between those with free care and those with cost sharing for the typical child participant; For most measures of health status, no differences in health status between poor children with free care and poor children with cost sharing	Unmeasured variables such as marital status and education
Van de Voorde et al. (2001)	Physician services	Belgium	1986-1995	Individuals from the largest sickness fund, the Federation of Christian Mutualities	Large increase in co-payment rates for public health insurance system in 1984	In the short run, not all of the price-induced demand reduction could be countered by physician-induced demand for additional services; The general active population seemed to be more price sensitive than the subsidized (low income) group	There may be underlying differences between the experiment group and the control group; Unmeasured variables such as prices of complements/substitutes
Van der Gaag and Wolfe (1991)	Medical services, emergency room services, outpatient services, physician services	(New York) The United States	1975	2,163 individuals	Insurance coverage (Medicaid, private insurance, HMO insurance, none)	Individuals with Medicaid visited the emergency room and hospital outpatient clinics more often than privately insured individuals; Adults with Medicaid or HMO coverage had more physician home or office visits than privately insured individuals	Cross-sectional study, thus difficult to control for other unmeasured factors that increase medical care utilization

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Van Doorslaer (1984)	Prescription drugs	Belgium	1977-1981	Belgian National Health Insurance beneficiaries	Replacement of fixed co-payment with proportional coinsurance differentiated by therapeutic and beneficiary class	The active part of the insured population was more responsive than the non-active portion to an increase in cost sharing; Lower income individuals responded more to an increase in cost sharing	Small sample size; Individual information may have been lost at the aggregate level
Van Vliet (2001)	Inpatient services, physician services, prescription drugs	The Netherlands	1990-1994	13,362 privately insured individuals	Insurance coverage with differing levels of generosity	Physiotherapy visits were the most sensitive to prices; Prescription drugs were not significantly sensitive to changes in price	Unmeasured variables such as income and age
Van Vliet (2004)	Medical services, physician and outpatient services, prescription drugs	The Netherlands	1996	100,048 privately insured individuals	Insurance coverage with different deductible levels: one older policy had deductibles that were a fixed percentage of the premium per year (0, 20, 50, 100, 0r 150), and one policy with fixed deductibles of 0, 200, 500, 1000, 1500, or 2000 Dfl per year	With no deductibles, expenses would have been Dfl 2510 per policy, and deductibles appeared to reduce expected expenses by about 6% in this situation; Deductibles between 0-100 Dfl increased health care and prescription drug expenses, but above this level, deductibles had a negative impact on health care and prescription drug expenses	Unmeasured variables such as income may have led to an underestimation of the deductible effect; Cross-sectional study, thus difficult to control for other unmeasured factors that medical care utilization
Van Vliet et al. (1999)	Prescription drugs	The Netherlands	1990-1994	40,278 individuals; one group insured under the 'civil servant' scheme; one group insured under the private health insurance	No deductibles applied for the 'civil service' scheme; privately insured had a choice of health care provider, which offered different packages and a choice of deductibles	No significant coinsurance effect for those insured under the 'civil servant' health scheme; A significant negative effect of deductibles on the utilization of privately insured persons	Unmeasured variables such as education; Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Vera-Hernández (1999)	Physician services	(Catalonia) Spain	1994	7,281 individuals	Supplementary insurance coverage (coverage, none)	Supplementary insurance led to an approximate 27% increase in the number of specialist visits; Health status had a significant impact on the number of specialist visits	Cross-sectional study, thus difficult to control for other factors that increase inpatient services

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Watt et al. (1992)	Prescription drugs	(Wellington) New Zealand	1991	669 prescriptions for asthma patients from 30 pharmacies	Increase in co-payment from $2-$5 for children, chronically ill, and low income; increase from $5-$15 for all others	Only 0.75% of asthma patients failed to collect their medications within the study period; No patients that were exempt from prescription fees failed to collect their prescriptions or delayed their collection for more than seven days	Did not control for other factors through regression; May not be generalizable because limited to one area of New Zealand
Wedig (1988)	Physician services	The United States	1980	5,322 adults (17+)	Individuals faced different OOP prices and time prices for visits	An increase in the price for physician visits decreased initial use of care and total utilization of care; Better health status, decreased initial use of care and total utilization	Price estimates likely to be somewhat biased; Unmeasured variables such as preferences for care
Weeks (1973)	Prescription drugs	(Michigan) The United States	1969	Employees of the United Auto Workers (UAW) association and their dependents (sample size not given)	The UAW paid for most of the cost of prescription drugs with a $2 co-payment; this was later reduced to a $1.07 co-payment	Individuals with the $2 co-payment were more likely to receive a prescription than individuals without this benefit; The proportion of individuals receiving more expensive prescriptions increased when cost sharing decreased	Did not control for other factors with regression; May not be generalizable because limited to one area in Michigan
Williams (1966)	Inpatient services	The United States	1964	individuals enrolled in Blue Cross plans	Generosity of Blue Cross insurance coverage, ranging from 30 to 150 days of coverage per hospital admission, deductibles (if present) ranging from $20 to $25, and co-payments (if present) of $4	Hospital admission rates were lower for plans with deductibles and plans with co-payment requirements than for full coverage plans; Average lengths of stay were somewhat longer in the plans with deductibles compared to the full coverage plans	Didn't control for confounding factors through regression; Cross-sectional study, thus difficult to control for other unmeasured factors that inpatient utilization
Winkelmann (2004a)	Prescription drugs	Germany	1995-1999	37, 319 individuals	6 DM increase in co-payments (which depended on pack size), leading to increases in co-payments up to 200%	9-10% reduction in the expected number of doctor visits in the post-reform period; 13% reduction in the expected number of visits of the treatment group relative to the control group	Imperfect difference-in-difference comparison (stated by author)

Author (Year)	Outcome variable	(Region) Country	Study dates	Study population	Price variation	Main results	Limitations
Winkelmann (2004b)	Prescription drugs	Germany	1995-1999	Individuals of all ages (no information on the sample size given)	6 DM increase in co-payments (which depended on pack size), leading to increases in co-payments up to 200%, co-payments later lowered between DM 1 and DM 3	The probability of having no doctor visits decreased by 6.7% between 1996 and 1998; But, conditional on use, the number of doctor visits only decreased by 2.6%	Unmeasured variables, such as employment, which could have measured the time cost of visits; Changes may not have solely been due to the increase in co-payments as a number of other policy changes occurred simultaneously
Wolfson et al. (1982)	Medical services	(Unknown state) The United States	1977-1980	Children (<22) enrolled in the state's Crippled Children's Division (CCD) (sample size not given)	Introduction of co-payment ranging from $10 to full cost of service, depending on family size and income	No statistically significant changes in the distribution of services provided to program users; Lower-income, medically needy individuals were not deterred from using services	Pre-intervention period may have been too short for testing of differences; Unmeasured variables such as waiting times and distance to provider
Yang et al. (2004)	Prescription drugs	The United States	1992-1998	14,439 elderly (65+) individuals	Supplemental drug insurance coverage (Medicaid, private drug coverage, private physician coverage, Medicare only)	Drug coverage had no effect on whether an individual purchased any prescription drugs, but did effect his expenditures	Cross-sectional study, thus difficult to control for other unmeasured factors that influence prescription drug utilization
Yergan et al. (1988)	Inpatient services	The United States	1972	4,369 patients with a diagnosis of pneumonia	Insurance coverage (Medicaid, Medicare, Blue Cross, none)	Controlling for the hospital where the patient received the treatment, no differences in services by insurance status; Self-pay patients had the highest mortality rate followed by Medicare patients, while Blue Cross patients had the lowest mortality rate	Unmeasured variables such as income and marital status; No information on the extent of insurance coverage
Young and Cohen (1991)	Inpatient services	(Massachusetts) The United States	1987	4,972 non-Medicaid, non-elderly (<65) patients admitted to a hospital on an emergency basis and diagnosed with acute myocardial infarction	Insurance coverage (FFS coverage, HMO coverage, none)	The length of inpatient stay was significantly shorter for HMO patients than for FFS and uninsured patients; The odds of death for uninsured individuals were 57% greater than for FFS patients and 48% greater than for HMO patients	May not be generalizable because limited to one Massachusetts hospital; May not have sufficiently controlled for health status, as healthier individuals are more likely to obtain HMO insurance than FFS insurance

Appendix C: Appendix to Chapter 5

This appendix provides additional background information for Chapter 5. Because many of the values for premiums and levels of cost sharing reported throughout Chapter 5 are adjusted for inflation, we first provide a table of the inflation adjustment factors. We also provide a table of state-specific information on the size and depth of Medicaid coverage for a more detailed picture of Medicaid coverage in the US. Finally, we offer a description of the main types of health insurance providers in the US.

C.1. Deflation factors from the consumer price indices used in Chapter 5

Appendix Table C.1 lists the consumer price indices from the United States (US-CPI), Canada (CA-CPI), and British Columbia (BC-CPI) for all expenditure classes (Council of Economic Advisors, 2007; Statistics Canada, 2007). To calculate the deflation factor, the CPI value for 2005 is used as the base for all three indices.

Appendix Table C.1. Deflation factors from the US-CPI, CA-CPI, and BC-CPI

Year	US-CPI	US-CPI deflation factor[b]	CA-CPI	CA - Deflation factor[b]	BC-CPI	BC - Deflation factor[b]
1989	124.0	1.58	89.0	1.43	87.7	1.43
1990	130.7	1.49	93.3	1.36	92.4	1.36
1991	136.2	1.43	98.5	1.29	97.4	1.29
1992	140.3	1.39	100.0	1.27	100.0	1.25
1993	144.5	1.35	101.8	1.25	103.5	1.21
1994	148.2	1.32	102.0	1.25	105.5	1.19
1995	152.4	1.28	104.2	1.22	107.9	1.16
1996	156.9	1.24	105.9	1.20	108.9	1.15
1997	160.5	1.22	107.6	1.18	109.7	1.14
1998	163.0	1.20	108.6	1.17	110.0	1.14
1999	166.6	1.17	110.5	1.15	111.2	1.13
2000	172.2	1.13	113.5	1.12	113.3	1.11
2001	177.1	1.10	116.4	1.09	115.2	1.09
2002	179.9	1.09	119.0	1.07	117.9	1.06
2003	184.0	1.06	122.3	1.04	120.4	1.04
2004	188.9	1.03	124.6	1.02	122.8	1.02
2005	195.3	1.00	127.3	1.00	125.3	1.00
2006	201.8[a]	0.97	129.9	0.98	127.5	0.98

[a]estimated using a trend line, [b]computed by: CPI_{2005}/CPI_t

C.2. State-specific information related to the Medicaid program

Appendix Table C.2 includes the latest state-level information related to the number of Medicaid enrollees, Medicaid payments per enrollee, co-payments for physician and inpatient visits, and median incomes for each of the 50 states.

Appendix Table C.2. State-specific information related to the size and depth of Medicaid coverage, 2004

State	Enrollees as % of state population[a]	Medicaid payments per enrollee[b]	Physician visit co-payment[a]	Inpatient visit co-payment[a]	Median state income
Alabama	13	$2,983	$1	$50/admission	$34,135
Alaska	15	$5,568	$3	$50/day up to lesser of $200/admission or 50% of first day's payment	$51,571
Arizona	14	$2,723	$1	None	$40,558
Arkansas	16	$3,276		10% of first day's per diem rate up to specified limit	$32,182
California	16	$2,472	$1	None	$47,493
Colorado	8	$4,653	$2	Lesser of $10/day or 50% of average allowable daily rate	$47,203
Connecticut	11	$6,740	None	None	$53,935
Delaware	10	$4,333	None	None	$47,381
District of Columbia	19	$4,436	None	None	$40,127
Florida	11	$3,337	$2	$3/admission	$38,819
Georgia	13	$3,079	$2	$12.50/non-emergency admission	$42,433
Hawaii	10	$3,241	None	None	$49,820
Idaho	12	$3,996	None	None	$37,572
Illinois	9	$4,153	$2	$2-$3/day unless per diem less than $275	$46,590
Indiana	11	$4,199	None	None	$41,567
Iowa	10	$5,078	$3	None	$39,469
Kansas	9	$4,846	$2	$48/admission	$40,624
Kentucky	14	$4,349	$2	None	$33,672
Louisiana	15	$3,204	None	None	$32,566
Maine	19	$4,910	None	$3/day up to $30/month	$37,240
Maryland	8	$5,870	None	None	$52,868
Massachusetts	13	$5,240	None	$3/admission	$50,502
Michigan	13	$2,877	None	None	$44,667
Minnesota	9	$6,345	$3	None	$47,111
Mississippi	19	$3,505	None	$10/day up to half of first day's per diem/admission	$31,330
Missouri	13	$3,694	$1	$10/admission, except emergencies and transfers	$37,934
Montana	14	$4,810	$4	$100/admission	$33,024
Nebraska	10	$4,551	$2	None	$39,250
Nevada	7	$3,133	None	None	$44,581
New Hampshire	6	$6,432	None	None	$49,467

State	Enrollees as % of state population[a]	Medicaid payments per enrollee[b]	Physician visit co-payment[a]	Inpatient visit co-payment[a]	Median state income
New Jersey	8	$5,516	None	None	$55,146
New Mexico	18	$3,501	$7	for certain groups: $30/admission with annual maximum across all services based on income	$34,133
New York	16	$7,506	None	$25/admission	$43,393
North Carolina	12	$4,312	$3	None	$39,184
North Dakota	8	$5,761	$2	$75/admission	$34,604
Ohio	11	$5,211	None	None	$40,956
Oklahoma	11	$3,071	$1	$3/day	$33,400
Oregon	11	$3,326	$3	for certain groups: $3/admission	$40,916
Pennsylvania	10	$4,965	$0.50-$3	$3/day up to $21/admission	$40,106
Rhode Island	16	$6,072	None	None	$42,090
South Carolina	14	$3,009	$3	$25/admission	$37,082
South Dakota	11	$4,329	$2	None	$35,282
Tennessee	16	$2,624	$5-$25	for certain groups: $100/admission, B2 - $200/admission	$36,360
Texas	12	$3,428	None	None	$39,927
Utah	9	$3,918	$3-$5	for certain groups: $220/admission	$45,726
Vermont	18	$3,839	None	None	$40,856
Virginia	7	$4,110	$1-$3	$100/admission	$46,677
Washington	13	$2,650	None	None	$45,776
West Virginia	15	$4,013	None	None	$29,696
Wisconsin	11	$4,614	$0.50-$3	$3/day up to $75/admission	$43,791
Wyoming	11	$4,000	$1	None	$37,892

Sources: Academy Health (2006), KFF (2006d), US Census Bureau (2007a)
[a]for the year 2004, [b]for the year 2002 (the latest available year)

Enrollment as a percent of the state population ranged from 6 percent of the state population (New Hampshire) to 19 percent of the state population (Maine). On average 12.25 percent of the state population was enrolled in Medicaid, while the median enrollment was 12 percent. An interesting observation is that 16 of the states with income below the median level ($40,624) enrolled 12 percent or more of the state population in Medicaid, while only eight states with income above the median level covered 12 percent of the state population. Meanwhile, Medicaid payments per enrollee ranged from $2,472 (California) to $7,506 (New York). The average Medicaid payment per enrollee was $4,271, and the median payment per enrollee was $4,153. There were 10 states with income below the median level that provided Medicaid payments above the median state payment, and five of these states had Medicaid enrollments of less then 12 percent of the population. There were 13 states with income above the median level that provided Medicaid payments at or above the state payment, and 10 of these states had Medicaid enrollments of less then 12 percent of the population. Thus, it appears that many states make a tradeoff between the

percentage of the population covered and the amount of insurance coverage offered to Medicaid beneficiaries.

In 2004 there were 28 states that imposed co-payments for physician services. Most of these co-payments ranged from $0.50 to $1, although Tennessee charged co-payments up to $25 for certain Medicaid beneficiaries and certain physician services (KFF, 2004). Cost sharing for inpatient hospital services was even higher, although fewer states (24) charged co-payments for hospital services. The out-of-pocket requirements for inpatient services ranged from $3 per hospital admission in many states to $220 per admission for certain beneficiaries in Utah (KFF, 2004).

C.3. The main types of private health insurance providers in the US

Commercial health insurers, otherwise known as indemnity plans, are generally organized as stock companies (owned by stockholders) or as mutual insurance companies (owned by their policyholders). A prominent example of a commercial health insurer is Aetna, a publicly traded health insurance company. HMOs, PPOs, and POSs are all forms of managed care plans. A managed care plan entails an arrangement between a selected group of medical providers and the insurer. Individuals who are insured under managed care plans are offered financial incentives to choose health care providers within this selected network. In health maintenance organizations the insurer pays the provider a fixed monthly fee for each insured patient that the provider has agreed to cover, regardless of the level of care provided. Patients insured by an HMO generally must seek care from a selected network of providers if they are to receive reimbursement. In a PPO there is also a group of network providers and patients pay less out-of-pocket to visit these providers, giving patients the option to visit providers outside of their network. Reimbursement for medical providers in a PPO is based on actual visits and use rather than a fixed monthly fee per covered patient. Finally, a POS is similar to an HMO in that patients pay very little out-of-pocket for in-network providers. However, if the patient's primary physician refers the patient to an out-of-network provider, the patient can still receive substantial reimbursement. The patient also has the option of referring himself to an out-of-network provider, although his out-of-pocket fees for this option will be greater.

Appendix D: Appendix to Chapter 6

As a supplement to Chapter 6, this appendix provides additional information on issues such as the econometric specification, the code used to run the Semykina and Wooldridge (2006) model in STATA, and the full results from the empirical analyses. The first few sections provide detailed information on relevant considerations for the econometric specification, mainly sample selection, endogeneity, and unobserved heterogeneity. With these considerations in mind, we developed an econometric model in Chapter 6 based on Semykina and Wooldridge (2006). Because there is no command in STATA yet available to run this model, this appendix provides the STATA program that we coded for this purpose. The full results of the Semykina and Wooldridge (2006) model in addition to the specification tests, the first-stage probits, and the equation to predict the endogenous (co-payment) variable are also included in Appendix Sections D.6 to D.9.

D.1. Heckman sample selection regression model

The following section outlines the Heckman sample selection model. In the first stage of this method, the individual determines whether not to participate. In the second stage, he decides how much to consume. The first stage of the model is represented by:

$$b_i^* = w_i\gamma + \varepsilon_i \qquad \text{(D.1)},$$

where b_i is the net benefit of participation, w_i are the explanatory variables for the participation decision, and ε_i is the random error term. The second stage of the model is represented by:

$$y_i = x_i\beta + u_i \qquad y_i = y_i^* \text{ for } b_i^* > 0 \qquad \text{(D.2)}.$$
$$y_i \text{ is not observed for } b_i^* \le 0$$

In equation (D.2) y_i is the outcome variable (the total number of prescriptions that the individual obtains in a given year including initial purchases and refills), x_i are the explanatory variables, and u_i is the random error term. Based on equations (D.1) and (D.2):

$$E(u_i | b_i^* > 0) = E(u_i | \varepsilon_i > -w_i\gamma) \qquad \text{(D.3)}.$$

If u_i and ε_i are distributed independently, the above expression reduces to $E(u_i)$, and the selection process does not interfere with the regression model (Dougherty, 2002). However, if u_i and ε_i are correlated, then OLS is inconsistent. Heckman (1979) developed a procedure to account for this bias, and he used the result that:

$$E(u_i|\varepsilon_i > -w_i\gamma) = \frac{\sigma_{u\varepsilon}}{\sigma_\varepsilon}\lambda_i \qquad \text{(D.4)}$$

to develop an estimator. In equation (D.4) $\sigma_{u\varepsilon}$ is the population covariance of u_i and ε_i, σ_ε is the standard deviation of ε_i, and λ_i is the inverse of Mill's ratio, given by:

$$\lambda_i = \frac{f(v_i)}{F(v_i)} \qquad \text{(D.5).}$$

The variable v_i is:

$$v_i = \frac{\varepsilon_i}{\sigma_\varepsilon} \qquad \text{(D.6),}$$

and the function $f(v_i)$ is the density function for ε_i normalized by its standard deviation. $F(v_i)$ is the cumulative density function, i.e. the probability that $b_i^* > 0$. Substituting equation (D.4) into equation (D.2), we obtain:

$$E(y_i|\varepsilon_i > w_i\gamma) = x_i\beta + \frac{\sigma_{u\varepsilon}}{\sigma_\varepsilon}\lambda_i \qquad \text{(D.7).}$$

Therefore, the sample selection problem can be viewed as one of omitted variable bias where λ_i is the omitted variable.

Testing for the presence of sample selection is generally straightforward: if the t-statistic on the inverse Mill's ratio is significant, then the sample selection correction is needed. Statistical packages incorporate a likelihood ratio test as well. Alternatively, the double hurdle model is sometimes employed to account for unobserved values of the dependent variable, but this specification is not appropriate for our analysis as the double hurdle model assumes that the observed zeros are true zeros (Jones, 2001). Another alternative to the Heckman methodology is the two-part model developed by Duan et al. (1983). This specification was created to model the demand for health care and is motivated by the conditional mean independence assumption:

$$E(y_i|y_i > 0, x_i = x_i\beta) \qquad \text{(D.8).}$$

There has been extensive debate in the literature regarding the choice between the two-part model and the sample selection model (Jones, 2001). One argument has been that two-part models are more appropriate for sequential decisions, although Maddala (1985) argues that even when decisions are sequential, the decisions will be correlated if there are omitted variables common to both. Leung and Yu (1996) used Monte Carlo simulations to compare these two differing methods and determined that the

choice of model depends on the empirical context. Specifically, the sample selection model performs poorly when there is collinearity, which can arise in certain contexts: when there is a large degree of censoring, when there are few exclusion restrictions, when there is little variability between regressors, or when there are weak instruments (Leung and Yu, 1996). In the absence of collinearity, which can be verified using the condition number, the t-test on the inverse Mills ratio is an indicator of which specification is more appropriate.

D.2. Testing for multicollinearity

Two methods for detecting multicollinearity are the condition index and the variance inflation factor (VIF). The condition number (κ_i) is the condition index with the largest value, which is given by the equation:

$$\kappa_i = \sqrt{\frac{\varphi_{\max}}{\varphi_{\min}}} \qquad \text{(D.9)},$$

where $\varphi_{\max}$ and $\varphi_{\min}$ are the maximum and minimum eigenvalues[1], respectively. When multicollinearity is non-existent, the eigenvalues, condition indices, and condition number will all equal one, where the condition index summarizes the findings from the condition numbers. The greater the collinearity, the higher the condition numbers and the condition index. An informal rule is that if the condition number is greater than 20, multicollinearity is likely a problem (Belsley et al., 1980).

Another way to diagnose multicollinearity is to use the Variance Inflation Factor. The value of this statistic is given by:

$$VIF(\beta_i) = (1 - R_i^2)^{-1} \qquad \text{(D.10)},$$

where R_i^2 is the unadjusted R^2 obtained when we regress x_i against all other explanatory variables that are included in the model. The higher the VIF, the greater the multicollinearity in the model. Generally, a VIF greater than 10 indicates a serious multicollinearity problem (Belsley et al., 1980).

D.3. Instrumental variables methods to account for endogeneity

When the error term in the regression is not independent of x_i, there is a problem of endogeneity, which can be represented by:

$$y_i = x_i\beta + c_i\delta + u_i \qquad \text{(D.11)}$$

[1] An eigenvalue, φ, is the scalar that solves the matrix equation:
$AX = \varphi X$,
where A is a [aXb] matrix and X is a [bX1] vector known as the eigenvector.

$$c_i = z_i\alpha + y_i\kappa + \varpi_i \quad \text{(D.12)},$$

where y_i is the outcome variable (the total number of prescriptions purchased), x_i are the variables that explain consumption, and c_i is the endogenous variable (the co-payment), which is determined by z_i and y_i. The reduced form equation is:

$$c_i = \frac{z_i\alpha + (x_i\beta + u_i)\kappa + \varpi_i}{1-\delta\kappa} \quad \text{(D.13)}.$$

The reduced form equation illustrates that c_i is not independent of the error term u_i in equation (D.11), indicating that OLS estimates will be inconsistent (Greene, 2003). To account for this endogeneity, one option is to use an instrumental variables (IV) regression. IV methods involve estimating the equation:

$$c_i = z_i\alpha + \varpi_i \quad \text{(D.14)},$$

calculating the predicted value of c_i, plugging this predicted value back into (D.11) for c_i, and running an OLS regression to obtain the parameter values in (D.11) (Dougherty, 2002). The variances need to be adjusted by the formula:

$$Var_{adj} = Var_{unadj}\frac{RMSE_{adj}}{(RMSE_{unadj})^2} \quad \text{(D.15)}.$$

The Durbin-Wu-Hausman test can be used to test whether a specific variable is endogenous to the regression. To carry out this test, we estimate:

$$\chi^2\text{-}statistic = (\beta_{OLS} - \beta_{IV})'(VC_{OLS} - VC_{IV})^{-1}(\beta_{OLS} - \beta_{IV}) \quad \text{(D.16)},$$

and the χ^2-statistic is distributed with k degrees of freedom[2]. Alternatively, we can regress all of the instruments on the suspected endogenous variable, calculate the residuals from this regression, and then run a regression of the residuals, the potentially endogenous variable, and the exogenous variables on the main explanatory variable of interest. If the coefficient on the residuals is significant, then an IV regression is appropriate.

D.4. Panel data regression models

This section develops the basic model for panel data. Start by assuming that we have a sample of N individuals over T time periods, where the dependent variable is y_{it}, the independent variables are represented by x_{kit}, and $i = 1,...,N$, $t = 1,...,T$, and

[2] In this chapter, k always represents the number of explanatory variables in the main regression (and doesn't include the constant)

$k = 1,..., K$ (Hsiao, 2003). In its most general form, the linear model for panel data is represented by:

$$y_{it} = g_{it} + x_{it}\beta + v_{it} \qquad \text{(D.17)}$$

where u_{it} represents the non-random component of y_{it}. The simplest model assumes that the intercept and slope coefficients are constant across cross-sectional units for all time periods ($g = g_{it}$), and the researcher can simply run a pooled OLS regression. If this assumption does not hold, the pooled least-squares estimator may lead to biased and inconsistent estimates.

The assumptions that we make regarding g_{it} are important as this determines whether a fixed or random effects framework is more appropriate. If we believe that g_{it} represents unmeasured individual-specific variables, such as preferences for types of health care or risk-aversion, then a fixed effects framework is more appropriate. If we believe that g_{it} is instead some random variable that influences all individuals in each year, then random effects is more appropriate. In a simple linear situation, the assumption regarding g_{it} is testable, and this test is discussed below.

Before proceeding with a panel data model, it is important to determine if a pooled estimator is more efficient. One option is to test whether the intercept coefficients are constant across cross-sectional units, which would indicate that pooled OLS is more efficient than fixed effects. This is carried out with an F-test:

$$F\text{-}statistic = \frac{\left(R^2_{LSDV} - R^2_{pooled}\right)/(n-1)}{\left(1 - R^2_{LSDV}\right)/(nT - n - k)} \qquad \text{(D.18)},$$

where n is the number of observations in each time period, T is the number of time periods, and k is the number of regressors. The F-statistic is distributed with $n-1$ and $nT-n-k$ degrees of freedom.

Once it is established that pooled OLS is less efficient than a panel data estimator, we need to examine the appropriateness of a fixed effects over a random effects framework. One test for this comparison is the Hausman test, where the null hypothesis is that the coefficients from the random effects and fixed effects models are similar and thus both models are consistent. If the null hypothesis is rejected, the explanatory variables in the model are correlated with the error terms such that the random effects estimator produces biased coefficients, and a fixed effects model is more appropriate. The formula for the Hausman test is:

$$\chi^2\text{-}statistic = \left(\beta_{FE} - \beta_{RE}\right)'\left(VC_{FE} - VC_{RE}\right)^{-1}\left(\beta_{FE} - \beta_{RE}\right) \qquad \text{(D.19)},$$

and the χ^2 -statistic is distributed with k degrees of freedom (Baltagi and Li, 1990).

A problem with the Hausman test is that if we reject the null hypothesis, it is not clear whether the difference between the specifications is caused by misspecification of the model or whether this is caused by the assumption of no correlation between the individual-specific error term and the explanatory variables. Another way to compare random and fixed effects is to consider the fact that random effects constrains the within- and between-effects to be the same. The null hypothesis is that the between- and within-effects are equal. This test is performed by decomposing each explanatory variable into its within- and between-effects, running a random effects regression, and testing whether each of the decomposed effects are equal using a t-test[3].

When the intercept varies over individuals but not time, the fixed effects model is:

$$y_{it} = g_i + x_{it}\beta + u_{it}, \qquad \text{(D.20)},$$

where $i = 1,...,N$ and $t = 1,...,T$. An important assumption of the model is that u_{it} is uncorrelated with the explanatory variables, including the fixed effect g_i and is an independently and identically distributed random variable with a mean of zero and variance σ_u^2. The simplest method of estimating the fixed effects model is to include a dummy variable for each of the individual cross-sectional units and run an OLS regression, otherwise known as the least-squares dummy-variable (LSDV) model. Alternatively, we can estimate the deviations from the group means as $\left[y_{it} - \overline{y_i}\right]$ and $\left[x_{it} - \overline{x_i}\right]$ and run an OLS regression of $\left[y_{it} - \overline{y_i}\right]$ on $\left[x_{it} - \overline{x_i}\right]$. The parameter estimates from both methods will be identical (Greene, 2003; Hsiao, 2003). A third possibility is the difference-in-difference estimator, which is an OLS regression on:

$$\Delta y_{it} = \Delta x_{it}\beta^* + \Delta u_{it} \qquad \text{(D.21)}.$$

For T=2 periods, the difference-in-difference model is identical to the first two methods (Wooldridge, 2002). Finally, a fourth option is to regress the explanatory variables along with their time means, x_i, on the dependent variable.

D.5. STATA code to implement FE-2SLS correcting for sample selection bias

The section provides the code that was used to run Semykina and Wooldridge (2006) model (SS FE-2SLS). Inside of the following symbols, there are comments on the different aspects of the code to help the user better understand the program:

[3]Testing whether a random or fixed effects framework is more appropriate is not a straightforward for the preferred model. We assume that if individual-specific effects appear to be more appropriate in the linear case, then by extension fixed effects is more appropriate than random effects in a non-linear case. Thus, we still provide the results of the fixed and random effects specification tests for a simple linear panel data model.

```
/*************************
*                                                    (a)
*************************/

//                                                   (b)
```

```
/*********************************************************************
* PROGRAM TO RUN THE 'SS FE-S2LS' MODEL
*********************************************************************/

// generates the base variables used in the model
scalar time_lambdas = 1
scalar num_time_pers = 9
gen selection_indicator=0
replace selection_indicator=1 if rxtot>0

// # periods the person had positive drug spending
by pid: egen keep_obs = sum(selection_indicator)

// defines all of the variable lists
local varlist_ins age_30to39 age_40to49 age_50to64 age_65to74 age_gt74
                  ln_income_pp bad_hlth morb non_mcr_pub self_employed
local varlist_main age_30to39 age_40to49 age_50to64 age_65to74 age_gt74
                   ln_income_pp bad_hlth morb

// generates the time dummies
local i=1997
while `i'<2005 {
 quietly gen T_`i'=0
 quietly replace T_`i' = 1 if year==`i'
 local i = `i'+1
}

// generates the mean variables for the selection probit estimations
local j=1
foreach var of varlist `varlist_ins' {
 quietly egen ms_`var' = mean(`var'), by(pid)
 local j = `j'+1
}
```

```
/*****************************************************************
* PROCEDURE 1: RUN THE FIRST STAGE PROBITS
*****************************************************************/

// generates the inverse Mills ratio for each year
gen lambda = .
local i = 1996
while `i'<2005 {
  quietly probit selection_indicator `varlist_ins' ms_ if year==`i'
  quietly predict rhat, xb
  quietly replace lambda = normden(rhat)/norm(rhat) if selection_indicator==1 &
                                year == `i'
  drop rhat
  local i = `i'+1
}

// generates interaction terms for lambda
if time_lambdas == 1 {
  local i = 1997
  while `i'<2005 {
    quietly gen lambda_`i' = T_`i'lambda
    local i = `i'+1
  }
}


/*****************************************************************
* PROCEDURE 2: RUN THE SECOND STAGE AND CORRECT THE
* STANDARD ERRORS
*****************************************************************/

// generates the mean variables (of the instruments)
local j = 1
foreach var of varlist `varlist_ins' {
  quietly egen mi_`var' = mean(`var'), by(pid)
  local j = `j'+1
}

// runs the regression without correcting for the Heckman standard errors
regress ln_rxtot ln_rxcopay `varlist_main' lambda T_* mi_* (`varlist_ins' lambda T_*
mi_) if keep_obs>1 & selection_indicator==1, robust cluster(pid)

// obtain the coefficient on the Mills ratio
if time_lambdas==1 {
  scalar b_mills1996 = _b[lambda]
  local i = 1997
  while `i'<2005 {
```

```
   scalar b_mills`i' = _b[lambda_`i'] + b_mills1996
   local i=`i'+1
  }
}
if time_lambdas == 0 {
 local i = 1996
 while `i'<2005 {
   scalar b_mills`i' = _b[lambda]
   local i=`i'+1
  }
}


*****************************************************************/
* Generates the diagonal matrix with Hessians
*****************************************************************/

// count the number of Heckman regressors
local c=0
foreach var of varlist `varlist_ins' {
 local c = `c'+1
}
scalar stage_1 = `c'
gen cons = 1

// defines the list of regressors used in the first stage
local varlist_i1 `varlist_ins' ms_ cons
local varlist_i3
local varlist_i4

// generates matrix H, a square matrix of dimension [# regressors in 1st stage
   probit --BY-- # time periods]
mat H = I((2stage_1+1)*num_time_pers)

local i = 1996
while `i'<2005 {
 quietly probit selection_indicator `varlist_ins' ms_ if year == `i'
 predict rhat, xb
 mat H`i' = e(V)
 quietly generate tempvar1 = normden(rhat) / norm(rhat) if selection_indicator == 1
                             & year == `i'
 quietly generate tempvar2 = -normden(rhat) / (1 - norm(rhat)) if
                             selection_indicator == 0  & year == `i'
 assert lambda = tempvar1 if selection_indicator == 1 & year == `i'
 local j = `i' - 1996
 mat H[(2stage_1 + 1)`j' + 1,(2stage_1 + 1)`j' + 1] = H`i'
```

```
 foreach var of varlist `varlist_i1' {
  quietly generate g_`var'`j' = 0 if selection_indicator == 1
  quietly replace g_`var'`j' = -lambda  (lambda + rhat)b_mills`i'`var' if
                               selection_indicator == 1 & year == `i'

  quietly generate q_`var'`j' = .
  quietly replace q_`var'`j' = tempvar1`var' if selection_indicator == 1 &
                               year == `i'
  quietly replace q_`var'`j' = tempvar2`var' if selection_indicator == 0 & year == `i'

  sort pid year
  quietly by pid: replace q_`var'`j' = q_`var'`j'[`j'  + 1] if year ~= `i'
  local varlist_i3 `varlist_i3' g_`var'`j'
  local varlist_i4 `varlist_i4' q_`var'`j'
 }

 drop rhat tempvar1 tempvar2
 mat drop H`i'
 local i = `i' + 1
}

foreach var of varlist `varlist_i4' {
 quietly replace `var'=0 if `var' == .
}

keep if keep_obs>1 & selection_indicator == 1


*****************************************************************/
* Replicates the second stage equation using matrices
*****************************************************************/

*****************************************************************/
* W is a matrix of the second-stage regressors
*       # vars in W = 1(rxcopay) + count(varlist) + 1(for lambda) +
*       7(time_lambda) + 7(time) + count(m_varlist) + 1(constant)
* Z is a matrix of the second-stage instruments
*
* WZ is the upper right (or lower left) corner of the temp matrix
 * It is chosen as:
 *       rows:   1..<# regressors in the 2nd stage>
 *       columns: <# regressors in the 2nd stage> + 1 ..
 *
 * Here and everywhere below, the # regressors includes the constant
*****************************************************************/

// counts the number of instruments
```

```
local c = 0
foreach var of varlist `varlist_ins' {
  local c = `c'+1
}
scalar INST = `c'

// counts the number of regressors that are in the main part of the regression
local c = 0
foreach var of varlist `varlist_main' {
  local c = `c'+1
}
scalar MAIN = `c'

matrix accum TEMP = ln_rxcopay `varlist_main' lambda T_* mi_* cons `varlist_ins'
                            lambda T_* mi_* cons, nocons

scalar M = 1 + MAIN + 1 + time_lambdas(num_time_pers-1) + (num_time_pers-1) +
              INST + 1

matrix WZ = TEMP[1..M, M + 1...]
matrix drop TEMP


*****************************************************************/
* matrix ZZ = Z'Z
* matrix Zy = Z'y
*****************************************************************/

matrix accum ZZ = `varlist_ins' lambda* T_* mi_* cons, nocons
matrix vecaccum yZ = ln_rxtot `varlist_ins' lambda* T_* mi_* cons, nocons
matrix IV_BETA = inv(WZinv(ZZ)WZ')WZinv(ZZ)yZ'

quietly regress ln_rxtot ln_rxcopay `varlist_main' lambda* T_* mi_* `varlist_ins'
lambda mi_* T_*
predict ehat, res

*****************************************************************/
* Replicates the robust variance matrix using matrices

* Define a new varlist_1r, which is the list of variables used as instruments at  the
* second stage
* varlist_2r is the list of interaction terms
*****************************************************************/

local varlist_1r `varlist_ins' lambda T_* mi_*  cons
local varlist_2r
```

```
local j = 1
foreach var of varlist `varlist_1r' {
  quietly gen eh_`var' = `var'ehat
  quietly egen t_`var' = sum(eh_`var'), by(pid)
  local varlist_2r `varlist_2r' t_`var'
  local j = `j' + 1
}
drop eh_*

// scalar g is the number of individuals in the selected sample
sort pid year
by pid: gen num=_n

gen countid = (num == 1)
sum countid
scalar g = r(sum)
drop countid

matrix accum ZEEZ = `varlist_2r' if num == 1, nocons

// obtain standard errors corrected for the first stage estimation
matrix A = WZinv(ZZ)WZ'
matrix TERM1 = ZEEZ


**********************************************************************/
* The number of variables in varlist_2r should be equal to the number of
* instruments at the second stage

* The number of variables in varlist_i4 should be equal to # 1st-stage regressors
* # time periods
**********************************************************************/

matrix accum TEMP = `varlist_2r' `varlist_i4' if num == 1, nocons

// extract the upper right hand corner of the TEMP matrix
matrix ZEQ = TEMP[1..INST + 1 + time_lambdas(num_time_pers - 1) +
                  (num_time_pers-1) + INST + 1, INST + 1 +
                  time_lambdas(num_time_pers - 1) + (num_time_pers - 1) +
                  INST + 1 + 1...]
matrix drop TEMP

matrix accum TEMP = `varlist_1r' `varlist_i3', nocons



// extract the upper right hand corner of the TEMP matrix
```

```
matrix ZG = TEMP[1..INST + 1 + time_lambdas(num_time_pers - 1) +
          (num_time_pers - 1) + INST + 1, INST + 1 +
          time_lambdas(num_time_pers - 1)  + (num_time_pers - 1) +
          INST + 1 + 1...]
matrix drop TEMP

matrix TERM2 = ZEQ*H*ZG'
matrix accum QQ = `varlist_i4' if num == 1, nocons
matrix TERM4 = ZG*H*QQ*H*ZG'
matrix B = WZ*inv(ZZ)*(TERM1 - TERM2 - TERM2' + TERM4)*inv(ZZ)*WZ'

matrix V2 = inv(A)Binv(A)(e(N) - 1)g / ((g - 1)(e(N) - M))
mata:
{
  mata_V2 = st_matrix("V2")
  mata_Beta = st_matrix("IV_BETA")
}
end

drop q_* g_* ttt_*

quietly regress ln_rxcopay `varlist_ins' lambda T_* mi_* if keep_obs>1 &
selection_indicator==1, robust cluster(pid)
quietly predict ln_rxcopay_hat, xb

if time_lambdas == 1 {
  local out_varlist ln_rxcopay `varlist_main' `lambda_varlist' `T_varlist' `mi_varlist'
  _cons
  local pred_varlist ln_rxcopay_hat `varlist_main' `lambda_varlist' `T_varlist'
}
if time_lambdas == 0 {
  local out_varlist ln_rxcopay `varlist_main' lambda `T_varlist' `mi_varlist' _cons
  local pred_varlist ln_rxcopay_hat `varlist_main' lambda `T_varlist'
}

quietly ci ln_rxtot
mata: mata_se_y = st_numscalar("r(se)")
mata: mata_var_y = mata_se_ymata_se_y

local c = 0
foreach var of varlist `varlist_main' {
 local c = `c' + 1
}
scalar MAIN = `c'

local c = 0
foreach var of varlist `mi_varlist' {
```

```
 local c = `c'+1
}
scalar mean_vars = `c'

matrix beta_1 = IV_BETA[1..MAIN + 1 + 1 + ((num_time_pers - 1)time_lambdas)
                + (num_time_pers - 1), .]
matrix beta_2 = IV_BETA[MAIN + 1 + 1 + ((num_time_pers - 1)time_lambdas) +
                (num_time_pers - 1) + mean_vars + 1..MAIN + 1 + 1 +
                ((num_time_pers - 1) time_lambdas) + (num_time_pers  1) +
                mean_vars + 1, .]
mata: mata_beta_1 = st_matrix("beta_1")
mata: mata_beta_2 = st_matrix("beta_2")

mata: beta_new = mata_beta_1 \ mata_beta_2
mata: beta_new

mata: x_varlist_1 = st_local("pred_varlist")
mata: x_varlist_2 = st_data(., tokens(x_varlist_1))
mata: rows_xs = rows(x_varlist_2)

mata: constant = J(rows_xs, 1, 1)
mata: x = (x_varlist_2, constant)

mata: y_pred = xbeta_new
mata: var_y_pred = ((1/rows_xs)colsum(y_pred:y_pred)) - ((colsum(y_pred) /
                   rows_xs)^2)

mata: y_pred_new = st_addvar("float","ln_y_pred")
mata: st_store(., y_pred_new,y_pred)

correlate ln_y_pred ln_rxtot if keep_obs>1 & selection_indicator == 1
mata: mata_corr = st_numscalar("r(rho)")
mata: mata_r2 = mata_corrmata_corr



*****************************************************************/
* Outputs the results
*****************************************************************/

mata: v_a = st_local("out_varlist")
mata: varname = J(0, 0, .)
mata: variable_vector(v_a, varname)

mata:
{
 st_err_adj = sqrt(diagonal(mata_V2))
```

```
t_value_adj = mata_Beta:/ st_err_adj
p_value_adj = get_pvalue(t_value_adj)

printf("Heckman Fixed effects output with standard errors adjusted\n")
printf("\n")
printf("R2 = ")
printf("%8.4g\n", mata_r2)
printf("\n")
printf("{hline 21}{c +}{hline 55}\n")
 printf("ln_rxtot          {c |}Coef.      Std. Err.      t-value
 p-value\n")
printf("{hline 21}{c +}{hline 55}\n")
i = 1

while (i<=rows(t_value_adj)) {
    printf("%-20s {c |}%8.4g     %8.4g     %8.4g     %8.4g\n", varname[i],
    mata_Beta[i], st_err_adj[i], t_value_adj[i], p_value_adj[i])
 i++
}
printf("{hline 21}{c +}{hline 55}\n")

}
end
```

D.6. Results of specification tests

This section discusses the results of the specification tests for the appropriateness of various assumptions related to the model. As we decided to examine three different samples: the adult, elderly, and low-income groups, it was important to determine whether each of these was a random sample. We used the runs test, where a run is a series of similar responses. The null hypothesis of the runs test is that the number of runs is outside the range of runs that we would expect by chance. Appendix Table D.1 lists the z-values and p-values of the various runs tests that we ran on the data.

Appendix Table D.1. Results of runs tests for specific samples

Sample	Number of prescription drugs obtained
adults	-131.60 (p=0.000)
elderly	-54.39 (p=0.000)
low-income	-58.58 (p=0.000)

The results of the test on the three different samples indicated that none of the samples were non-random, and we could proceed with our estimation.

We also employed other tests for the specification of the model, the assumption of an endogenous co-payment variable, and the choice of main variables and instruments (Appendix Table D.2).

Appendix Table D.2. Results from various specification tests

Test	Models compared	Results: adult sample	Results: elderly sample	Results: low-income sample
Wald test for appropriateness of fixed effects	FE-2SLS (with SS) and 2SLS (with SS)	$\chi^2(10) = 1{,}701$ (p=0.000)	$\chi^2(6) = 390$ (p=0.000)	$\chi^2(10) = 456$ (p=0.000)
Durbin-Wu-Hausman test for endogeneity	FE-OLS (with SS) and FE-2SLS (with SS)	t = 9.22 (p=0.000)	t = 1.85 (p=0.065)	t = 10.10 (p=0.000)
Semykina-Wooldridge test (Wald test) for sample selection	FE-2SLS (no SS) and FE-2SLS (with SS)	$\chi^2(9) = 314.7$ (p=0.000)	$\chi^2(9) = 42.93$ (p=0.000)	$\chi^2(9) = 62.40$ (p=0.000)
Condition index to test for multicollinearity		CI = 18.3	CI = 14.4	CI = 14.6
Variance Inflation Factor to test for multicollinearity		VIF = 7.05	VIF = 5.33	VIF = 5.01

Because of the panel nature of our data, we first tested for the appropriateness of a fixed effects model as compared to pooled ordinary least squares. The null hypothesis of the test is that all of the time-means parameters are zero. For each of the three samples, the Wald statistic from this test indicated that we could reject the null hypothesis and conclude that a fixed effects model is more appropriate than a pooled model[4].

We then used a Durbin-Wu-Hausman test to examine the null hypothesis that the co-payment was exogenous[5]. The statistic reported in Appendix Table D.2 is the t-statistic from the error term on the estimated co-payment residual variable, and the results indicate that the co-payment variable is endogenous in the adult and low-income samples. The co-payment residual is only significant at the 10 percent level in the elderly sample. The problem with this test is that it does not distinguish between endogeneity due to the endogenous co-payment variable and endogeneity due to sample selection. If we fail to reject the null hypothesis of no sample selection, then the Durbin-Wu-Hausman test is valid for testing the endogeneity of the co-payment.

[4] In addition, we tested for whether a fixed or random effects specification was more appropriate, although we only provide the results of the linear case (as opposed to the specification that accounts for endogeneity and sample selection). The results of the Hausman specification test for all three samples yielded p-values of 0.000, indicating that a fixed effects framework was more appropriate.

[5] An important note is that because there is potentially correlation between the individual-specific effects and some of the explanatory variables, we used a fixed effects estimator that corrected for sample selection for this test as it would be impossible to disentangle the endogeneity bias from omitted variable bias with the pooled OLS estimators.

As no test yet exists to distinguish between these two possibilities, we choose to treat the co-payment as endogenous.

In terms of sample selection, we used a Wald test proposed by Semykina and Wooldridge (2006). The null hypothesis of the test is that the explanatory variables are not correlated with the error term in the main equation, i.e. $E(x_{it}, u_{it}) = 0$. The reported values in Appendix Table D.2 indicate that for all three samples, sample selection is a problem. Moreover, when we adjust for serial correlation, the joint Wald test on all of the Mills ratio terms further confirms this result.

We also used a condition index where a condition index of 20 or greater generally indicates a possible multicollinearity problem (Greene, 2003). For all specifications, the condition index was less than 20. A second check for multicollinearity is the Variance Inflation Factor (VIF), which indicates that multicollinearity is an issue for VIF values greater than 10. The mean VIF for each specification was less than 10, and again we concluded that multicollinearity is not a significant issue.

D.7. First-stage probit results for probability of any prescription drug use

This section provides the results for each of the individual year probits (1996-2004) that make up the first stage of the FE-2SLS model; the probits for each sample are used to predict the Mills lambda, which is substituted into the main equation of interest. The probit results for each of the three samples (the general population, the elderly, and the low-income group) are provided in separate tables. The probit estimates for the revised elderly sample model are also included as a separate table.

Appendix Table D.3. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (adult sample)[a,b,c]

Explanatory variable	1996	1997	1998	1999	2000
age 30 to 39	-0.339[§]	0.233*	-0.472[§]	-0.023	-0.263*
	(0.161)	(0.122)	(0.147)	(0.138)	(0.139)
age 40 to 49	-0.502[§]	-0.048	-0.541[§]	0.343*	-0.336*
	(0.226)	(0.169)	(0.204)	(0.195)	(0.191)
age 50 to 64	-0.388	-0.069	-0.666[§]	0.423*	-0.556[§]
	(0.284)	(0.214)	(0.257)	(0.253)	(0.249)
age 65 to 74	-0.117	0.105	-0.746[§]	0.228	-0.210
	(0.390)	(0.299)	(0.366)	(0.357)	(0.349)
age greater than 74	0.648	0.137	-0.792	-0.011	-0.490
	(0.511)	(0.410)	(0.492)	(0.474)	(0.485)
(log) income per person in family	0.050[§]	-0.000	0.019	0.005	0.022
	(0.016)	(0.012)	(0.016)	(0.016)	(0.015)
poor health	0.162[§]	0.206[§]	-0.088	0.154[§]	0.109
	(0.076)	(0.059)	(0.072)	(0.075)	(0.073)
diagnosis of at least one of leading causes of death	0.392[§]	0.585[§]	0.483[§]	0.867[§]	0.679[§]
	(0.111)	(0.088)	(0.104)	(0.101)	(0.101)
has public insurance (non Medicare)	0.410[§]	0.377[§]	0.132	0.162	0.404[§]
	(0.117)	(0.089)	(0.108)	(0.110)	(0.104)
self-employed	0.065	0.056	0.235	0.114	-0.050
	(0.259)	(0.178)	(0.200)	(0.199)	(0.192)
(mean) age 30 to 39	0.524[§]	-0.035	0.672[§]	0.285[§]	0.522[§]
	(0.164)	(0.125)	(0.150)	(0.141)	(0.143)
(mean) age 40 to 49	0.733[§]	0.379[§]	0.917[§]	0.013	0.664[§]
	(0.228)	(0.172)	(0.206)	(0.197)	(0.193)
(mean) age 50 to 64	0.873[§]	0.609[§]	1.207[§]	0.147	1.153[§]
	(0.286)	(0.216)	(0.260)	(0.255)	(0.251)
(mean) age 65 to 74	0.919[§]	0.691[§]	1.541[§]	0.698*	1.119[§]
	(0.389)	(0.303)	(0.371)	(0.360)	(0.353)
(mean) age greater than 74	0.106	0.711*	1.743[§]	0.980[§]	1.504[§]
	(0.510)	(0.414)	(0.495)	(0.478)	(0.490)
(mean) (log) income per person in family	-0.018	0.036[§]	0.026	0.040[§]	0.023
	(0.016)	(0.013)	(0.016)	(0.016)	(0.016)
(mean) poor health	0.435[§]	0.487[§]	0.801[§]	0.486[§]	0.587[§]
	(0.090)	(0.068)	(0.086)	(0.087)	(0.086)
(mean) diagnosis of at least one of leading causes of death	0.720[§]	0.504[§]	0.589[§]	0.241[§]	0.478[§]
	(0.115)	(0.093)	(0.111)	(0.105)	(0.107)
(mean) has public insurance (non Medicare)	-0.215*	-0.133	0.174	0.166	-0.074
	(0.124)	(0.092)	(0.113)	(0.117)	(0.109)
(mean) self-employed	-0.007	-0.165	-0.581[§]	-0.286	-0.018
	(0.344)	(0.247)	(0.268)	(0.282)	(0.245)
constant	-0.221[§]	-0.366[§]	-0.404[§]	-0.399[§]	-0.413[§]
	(0.031)	(0.025)	(0.030)	(0.029)	(0.029)
N	15,560	23,456	16,198	16,901	17,354
Log-likelihood	-8,748	-13,253	-9,012	-9,457	-9,620
probability > χ^2	0.000	0.000	0.000	0.000	0.000

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample

[§]significant at the 5% level, *significant at the 10% level

Appendix Table D.3. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (adult sample - continued)[a,b,c]

Explanatory variable	2001	2002	2003	2004
age 30 to 39	-0.226	-0.013	-0.210	-0.023
	(0.127)	(0.117)	(0.130)	(0.180)
age 40 to 49	-0.417§	-0.060	-0.239	-0.402*
	(0.173)	(0.160)	(0.178)	(0.240)
age 50 to 64	-0.041	-0.147	-0.395*	-0.222
	(0.220)	(0.205)	(0.229)	(0.307)
age 65 to 74	-0.142	-0.041	-0.329	0.189
	(0.302)	(0.292)	(0.324)	(0.420)
age greater than 74	-0.476	0.174	-0.131	-0.033
	(0.419)	(0.408)	(0.459)	(0.534)
(log) income per person in family	0.006	-0.022*	0.011	-0.003
	(0.013)	(0.012)	(0.013)	(0.018)
poor health	0.125§	0.124§	0.175§	0.048
	(0.063)	(0.057)	(0.059)	(0.084)
diagnosis of at least one of leading causes of death	0.717§	0.669§	0.538§	0.933§
	(0.086)	(0.084)	(0.091)	(0.129)
has public insurance (non Medicare)	0.222§	0.317§	0.236§	0.356§
	(0.088)	(0.082)	(0.085)	(0.118)
self-employed	-0.224	-0.070	0.060	0.075
	(0.169)	(0.151)	(0.156)	(0.220)
(mean) age 30 to 39	0.452§	0.251§	0.431§	0.251
	(0.130)	(0.120)	(0.132)	(0.182)
(mean) age 40 to 49	0.759§	0.421§	0.624§	0.793§
	(0.175)	(0.162)	(0.180)	(0.242)
(mean) age 50 to 64	0.602§	0.770§	1.015§	0.898§
	(0.222)	(0.207)	(0.231)	(0.309)
(mean) age 65 to 74	0.967§	1.038§	1.270§	0.914§
	(0.304)	(0.296)	(0.327)	(0.424)
(mean) age greater than 74	1.537§	0.892§	1.308§	1.352§
	(0.421)	(0.412)	(0.461)	(0.540)
(mean) (log) income per person in family	0.042§	0.072§	0.048§	0.064§
	(0.014)	(0.013)	(0.014)	(0.018)
(mean) poor health	0.480§	0.499§	0.335§	0.444§
	(0.073)	(0.068)	(0.069)	(0.090)
(mean) diagnosis of at least one of leading causes of death	0.485§	0.547§	0.584§	0.199
	(0.091)	(0.090)	(0.096)	(0.133)
(mean) has public insurance (non Medicare)	0.088	-0.035	0.125	-0.011
	(0.092)	(0.087)	(0.089)	(0.121)
(mean) self-employed	-0.118	-0.085	-0.492§	-0.163
	(0.242)	(0.197)	(0.218)	(0.229)
constant	-0.368§	-0.451§	-0.502§	-0.561§
	(0.025)	(0.023)	(0.025)	(0.025)
N	23,361	26,964	23,271	23,535
Log-likelihood	-12,732	-14,629	-12,713	-12,704
probability > χ^2	0.000	0.000	0.000	0.000

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample

§significant at the 5% level, *significant at the 10% level

Appendix Table D.4. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (elderly sample)[a,b,c]

Explanatory variable	1996	1997	1998	1999	2000
age greater than 74	0.786[§] (0.325)	0.007 (0.278)	0.081 (0.324)	-0.252 (0.308)	-0.245 (0.335)
(log) income per person in family	0.034 (0.049)	0.058 (0.038)	-0.077 (0.052)	0.007 (0.055)	0.024 (0.054)
poor health	0.113 (0.193)	0.160 (0.149)	-0.050 (0.185)	0.311 (0.194)	0.145 (0.203)
diagnosis of at least one of leading causes of death	0.297 (0.279)	0.504[§] (0.222)	-0.048 (0.269)	0.457 (0.247)	0.675[§] (0.279)
has public insurance (non Medicare)	-0.033 (0.322)	0.114 (0.267)	-0.033 (0.339)	-0.240 (0.306)	0.010 (0.300)
changed insurance coverage this year	-0.038 (0.170)	0.026 (0.130)	-0.254 (0.164)	0.098 (0.162)	-0.132 (0.162)
(mean) age greater than 74	-0.825[§] (0.331)	0.059 (0.285)	0.079 (0.331)	0.316 (0.317)	0.329 (0.343)
(mean) (log) income per person in family	-0.017 (0.051)	-0.029 (0.039)	0.130[§] (0.054)	0.034 (0.057)	0.051 (0.055)
(mean) poor health	0.428* (0.219)	0.506[§] (0.171)	0.772[§] (0.220)	0.152 (0.214)	0.584[§] (0.233)
(mean) diagnosis of at least one of leading causes of death	0.788[§] (0.278)	0.463[§] (0.235)	0.837[§] (0.284)	0.466* (0.256)	0.392 (0.294)
(mean) has public insurance (non Medicare)	-0.045 (0.346)	-0.006 (0.275)	0.042 (0.360)	0.259 (0.332)	-0.087 (0.313)
(mean) changed insurance coverage this year	-0.120 (0.228)	-0.059 (0.155)	0.123 (0.206)	-0.281 (0.210)	0.053 (0.199)
constant	0.755[§] (0.101)	0.510[§] (0.080)	0.458[§] (0.099)	0.651[§] (0.101)	0.403[§] (0.099)
N	2,475	3,762	2,598	2,644	2,783
Log-likelihood	-825	-1301	-844	-842	-840
probability > χ^2	0.000	0.000	0.000	0.000	0.000

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 75, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample

[§]significant at the 5% level, *significant at the 10% level

Appendix Table D.4. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (elderly sample - continued)[a,b,c]

Explanatory variable	2001	2002	2003	2004
age greater than 74	-0.441 (0.311)	0.085 (0.292)	0.246 (0.322)	-0.241 (0.435)
(log) income per person in family	0.045 (0.043)	-0.039 (0.039)	-0.032 (0.041)	0.054 (0.064)
poor health	0.028 (0.169)	0.078 (0.164)	0.366[§] (0.167)	-0.256 (0.255)
diagnosis of at least one of leading causes of death	0.571[§] (0.224)	0.645[§] (0.233)	0.295 (0.248)	1.021[§] (0.437)
has public insurance (non Medicare)	-0.276 (0.235)	0.479[§] (0.242)	0.282 (0.327)	-1.181[§] (0.500)
changed insurance coverage this year	-0.235* (0.136)	0.179 (0.126)	-0.166 (0.137)	-0.055 (0.204)
(mean) age greater than 74	0.681[§] (0.317)	-0.005 (0.299)	-0.019 (0.328)	0.451 (0.443)
(mean) (log) income per person in family	0.013 (0.045)	0.071* (0.041)	0.100[§] (0.043)	-0.017 (0.066)
(mean) poor health	0.573[§] (0.197)	0.598[§] (0.191)	0.076 (0.188)	0.628[§] (0.277)
(mean) diagnosis of at least one of leading causes of death	0.260 (0.230)	0.349 (0.243)	0.627[§] (0.259)	-0.043 (0.446)
(mean) has public insurance (non Medicare)	0.302 (0.247)	-0.512 (0.259)	-0.294 (0.335)	1.363[§] (0.512)
(mean) changed insurance coverage this year	0.183 (0.184)	-0.439[§] (0.157)	-0.108 (0.171)	-0.250 (0.218)
constant	0.499[§] (0.087)	0.774[§] (0.085)	0.559[§] (0.092)	0.820[§] (0.092)
N	3,659	4,144	3,572	3,607
Log-likelihood	-1089	-1126	-950	-873
probability > χ^2	0.000	0.000	0.000	0.000

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 75, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample

[§]significant at the 5% level, *significant at the 10% level

Appendix Table D.5. Revised probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (elderly sample)[a,b,c]

Explanatory variable	1996	1997	1998	1999	2000
age greater than 79	-0.381 (0.474)	0.252 (0.358)	0.771 (0.532)	0.506 (0.433)	-0.816[§] (0.394)
(log) income per person in family	0.050 (0.053)	0.055 (0.040)	-0.059 (0.054)	0.005 (0.060)	0.063 (0.057)
retired	0.084 (0.231)	-0.153 (0.185)	0.177 (0.232)	-0.019 (0.246)	-0.296 (0.262)
poor health	0.147 (0.211)	0.187 (0.160)	-0.156 (0.196)	0.307 (0.208)	0.240 (0.220)
limitation to an activity of daily living	-0.162 (0.443)	0.209 (0.308)	0.413 (0.385)	0.094 (0.409)	0.141 (0.556)
pre-defined high-cost and/or high-prevalence disease	0.908[§] (0.260)	0.783[§] (0.225)	0.445* (0.266)	0.906[§] (0.248)	0.843[§] (0.279)
has public insurance (non Medicare)	-0.014 (0.353)	-0.052 (0.291)	0.098 (0.368)	-0.236 (0.327)	0.038 (0.318)
changed insurance coverage this year	0.079 (0.184)	0.002 (0.140)	-0.327* (0.175)	0.097 (0.172)	-0.171 (0.173)
(mean) age greater than 79	0.457 (0.472)	-0.223 (0.368)	-0.747 (0.537)	-0.494 (0.437)	0.852[§] (0.410)
(mean) (log) income per person in family	-0.030 (0.055)	-0.028 (0.041)	0.115[§] (0.057)	0.046 (0.062)	0.018 (0.058)
(mean) retired	0.175 (0.247)	0.248 (0.195)	-0.121 (0.247)	0.094 (0.259)	0.361 (0.273)
(mean) poor health	0.273 (0.240)	0.425 (0.186)	0.895[§] (0.236)	0.094 (0.230)	0.458* (0.253)
(mean) limitation to an activity of daily living	0.688 (0.475)	-0.012 (0.347)	-0.452 (0.403)	0.052 (0.454)	0.601 (0.588)
(mean) pre-defined high-cost and/or high-prevalence disease	0.561[§] (0.261)	0.579[§] (0.235)	0.807[§] (0.278)	0.394 (0.255)	0.511* (0.289)
(mean) has public insurance (non Medicare)	-0.117 (0.379)	0.120 (0.299)	-0.118 (0.390)	0.244 (0.355)	-0.149 (0.331)
(mean) changed insurance coverage this year	-0.180 (0.249)	-0.004 (0.166)	0.215 (0.220)	-0.202 (0.222)	0.111 (0.211)
constant	0.220* (0.123)	0.165* (0.096)	0.135 (0.115)	0.269[§] (0.119)	0.045 (0.117)
N	2,475	3,762	2,598	2,644	2,783
Log-likelihood	-720	-1147	-749	-749	-742
probability > χ^2	0.000	0.000	0.000	0.000	0.000

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 79, individual is not retired, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, individual does not report at least one limitation to activity of daily living
[c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample
[§]significant at the 5% level, *significant at the 10% level

Appendix Table D.5. Revised probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (elderly sample – continued)[a,b,c]

Explanatory variable	2001	2002	2003	2004
age greater than 79	0.329 (0.377)	-0.274 (0.375)	0.002 (0.454)	-0.392 (0.609)
(log) income per person in family	0.030 (0.047)	-0.023 (0.043)	-0.046 (0.045)	0.052 (0.069)
retired	0.397* (0.219)	-0.188 (0.205)	0.256 (0.214)	0.114 (0.311)
poor health	0.001 (0.184)	0.070 (0.177)	0.370§ (0.182)	-0.072 (0.278)
limitation to an activity of daily living	0.169 (0.380)	-0.012 (0.326)	-0.909§ (0.338)	0.691§ (0.601)
pre-defined high-cost and/or high-prevalence disease	1.017§ (0.219)	1.011§ (0.226)	0.765§ (0.257)	0.925§ (0.471)
has public insurance (non Medicare)	-0.390 (0.251)	0.603§ (0.261)	0.296 (0.363)	-1.282 (0.550)
changed insurance coverage this year	-0.176 (0.145)	0.100 (0.136)	-0.158 (0.149)	0.050 (0.218)
(mean) age greater than 79	-0.156 (0.383)	0.332 (0.387)	0.120 (0.464)	0.422 (0.623)
(mean) (log) income per person in family	0.029 (0.049)	0.058 (0.045)	0.114§ (0.046)	-0.015 (0.071)
(mean) retired	-0.335 (0.230)	0.233 (0.216)	-0.060 (0.227)	0.178 (0.320)
(mean) poor health	0.533 (0.214)	0.535§ (0.206)	0.085 (0.204)	0.434 (0.304)
(mean) limitation to an activity of daily living	0.338 (0.402)	0.413 (0.393)	0.846§ (0.402)	-0.691 (0.633)
(mean) pre-defined high-cost and/or high-prevalence disease	0.222 (0.225)	0.325 (0.234)	0.615§ (0.265)	0.570 (0.479)
(mean) has public insurance (non Medicare)	0.368 (0.264)	-0.711§ (0.280)	-0.320 (0.370)	1.435§ (0.563)
(mean) changed insurance coverage this year	0.134 (0.197)	-0.347§ (0.168)	-0.067 (0.185)	-0.266 (0.234)
constant	0.201§ (0.101)	0.415§ (0.099)	0.156 (0.105)	0.344§ (0.107)
N	3,659	4,144	3,572	3,607
Log-likelihood	-966	-991	-821	-733
probability > χ^2	0.000	0.000	0.000	0.000

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 79, individual is not retired, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, individual does not report at least one limitation to activity of daily living
[c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample
§significant at the 5% level, *significant at the 10% level

Appendix Table D.6. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (low-income sample)[a,b,c]

Explanatory variable	1996	1997	1998	1999	2000
age 30 to 39	-0.080 (0.357)	0.246 (0.262)	-0.013 (0.314)	0.265 (0.338)	-0.597* (0.346)
age 40 to 49	0.191 (0.556)	-0.260 (0.397)	-0.077 (0.457)	0.082 (0.477)	-0.714 (0.492)
age 50 to 64	0.307 (0.798)	0.015 (0.591)	0.058 (0.721)	-0.738 (0.760)	0.237 (0.802)
age 65 to 74	0.472 (1.010)	0.868 (0.769)	-0.541 (0.938)	-1.845 (0.978)	0.953 (1.020)
age greater than 74	0.864 (1.207)	0.747 (0.938)	0.254 (1.233)	-2.330* (1.179)	0.219 (1.193)
(log) income per person in family	0.035 (0.038)	0.006 (0.029)	0.005 (0.038)	-0.054 (0.043)	0.108§ (0.042)
poor health	0.367§ (0.138)	0.254§ (0.105)	-0.212 (0.140)	0.171 (0.147)	0.281§ (0.142)
diagnosis of at least one of leading causes of death	0.200 (0.280)	0.493§ (0.218)	0.725§ (0.281)	1.051§ (0.251)	0.551§ (0.265)
has public insurance (non Medicare)	0.323§ (0.175)	0.468§ (0.140)	0.191 (0.178)	0.302§ (0.180)	0.215 (0.175)
changed insurance coverage this year	-1.352 (0.916)	0.130 (0.446)	0.138 (0.451)	0.014* (0.503)	-0.808 (0.559)
(mean) age 30 to 39	0.231 (0.361)	-0.125 (0.266)	0.126 (0.321)	-0.026 (0.344)	0.824§ (0.352)
(mean) age 40 to 49	-0.013 (0.558)	0.455 (0.400)	0.343 (0.463)	0.254 (0.481)	0.942* (0.498)
(mean) age 50 to 64	0.260 (0.799)	0.445 (0.595)	0.388 (0.725)	1.220 (0.764)	0.313 (0.805)
(mean) age 65 to 74	0.360 (1.010)	-0.042 (0.772)	1.485 (0.948)	2.723§ (0.981)	-0.103 (1.026)
(mean) age greater than 74	0.016 (1.207)	0.200 (0.943)	0.917 (1.236)	3.389§ (1.181)	0.831 (1.201)
(mean) (log) income per person in family	0.010 (0.039)	0.031 (0.030)	0.055 (0.039)	0.116§ (0.045)	-0.035 (0.043)
(mean) poor health	0.200 (0.154)	0.465§ (0.117)	0.940§ (0.161)	0.291* (0.162)	0.392§ (0.156)
(mean) diagnosis of at least one of leading causes of death	0.950§ (0.289)	0.550§ (0.224)	0.418 (0.290)	-0.015 (0.256)	0.658§ (0.276)
(mean) has public insurance (non Medicare)	0.149 (0.185)	-0.076 (0.145)	0.310 (0.186)	0.174 (0.189)	0.343§ (0.182)
(mean) changed insurance coverage this year	1.408§ (1.047)	-0.146 (0.525)	-0.208 (0.563)	-0.162 (0.627)	0.513 (0.640)
constant	-0.504§ (0.056)	-0.507§ (0.044)	-0.583§ (0.056)	-0.587§ (0.056)	-0.666§ (0.056)
N	4,289	6,591	4,086	4,173	4,332
Log-likelihood	-2,231	-3,453	-2,060	-2,205	-2,156
probability > χ^2	0.000	0.000	0.000	0.000	0.000

[a]standard errors in parentheses; [b]excluded dummy variables are age less than 75, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death; [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample

§significant at the 5% level, *significant at the 10% level

Appendix Table D.6. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (low-income sample - continued)[a,b,c]

Explanatory variable	2001	2002	2003	2004
age 30 to 39	-0.151 (0.297)	-0.328 (0.244)	-0.188 (0.244)	-0.046 (0.360)
age 40 to 49	-0.507 (0.429)	-0.702* (0.362)	-0.143 (0.363)	-0.439 (0.504)
age 50 to 64	0.428 (0.645)	-1.114§ (0.535)	-0.553 (0.535)	0.111 (0.773)
age 65 to 74	0.128 (0.898)	-0.759 (0.761)	-0.756 (0.763)	0.182 (1.047)
age greater than 74	-0.839 (1.151)	-0.789 (0.933)	0.005 (0.947)	-1.191 (1.290)
(log) income per person in family	-0.002 (0.034)	-0.060§ (0.028)	0.000 (0.027)	-0.023 (0.040)
poor health	0.030 (0.121)	0.054 (0.102)	0.135 (0.100)	-0.051 (0.145)
diagnosis of at least one of leading causes of death	0.973§ (0.226)	0.665§ (0.196)	0.356* (0.198)	1.236§ (0.301)
has public insurance (non Medicare)	0.308§ (0.157)	0.335* (0.137)	0.210* (0.131)	0.378 (0.186)
changed insurance coverage this year	-0.480 (0.458)	0.528 (0.404)	-0.105 (0.364)	-0.013 (0.477)
(mean) age 30 to 39	0.337 (0.302)	0.544§ (0.248)	0.382 (0.249)	0.225 (0.363)
(mean) age 40 to 49	0.696* (0.432)	0.878§ (0.366)	0.442 (0.367)	0.699 (0.508)
(mean) age 50 to 64	0.148 (0.647)	1.650§ (0.538)	1.053§ (0.539)	0.463 (0.777)
(mean) age 65 to 74	0.809 (0.901)	1.649§ (0.765)	1.603§ (0.767)	1.036 (1.053)
(mean) age greater than 74	1.806 (1.155)	1.883§ (0.936)	1.278 (0.950)	2.660§ (1.299)
(mean) (log) income per person in family	0.062* (0.035)	0.121§ (0.030)	0.069§ (0.029)	0.092§ (0.041)
(mean) poor health	0.661§ (0.137)	0.638§ (0.117)	0.439§ (0.112)	0.686§ (0.153)
(mean) diagnosis of at least one of leading causes of death	0.215 (0.230)	0.611§ (0.205)	0.869§ (0.207)	-0.051 (0.307)
(mean) has public insurance (non Medicare)	0.211 (0.163)	0.148 (0.143)	0.406§ (0.136)	0.240 (0.190)
(mean) changed insurance coverage this year	0.414 (0.522)	-0.853 (0.468)	-0.316 (0.419)	-0.202 (0.525)
constant	-0.581§ (0.048)	-0.677§ (0.043)	-0.759§ (0.043)	-0.808§ (0.043)
N	5,907	7,277	7,184	7,273
Log-likelihood	-2,939	-3,631	-3,584	-3,546
probability > χ^2	0.000	0.000	0.000	0.000

[a]standard errors in parentheses; [b]excluded dummy variables are age less than 75, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death; [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample

§significant at the 5% level, *significant at the 10% level

D.8. Estimates of the endogenous co-payment variable

After the Mills lambda is estimated in the first stage of the Semykina and Wooldridge (2006) model, the next step is to estimate the endogenous variable to obtain a prediction that will be used in the main equation. This section provides the results of the estimations to predict the endogenous co-payment variable for each of the three samples (general population, the elderly, and low-income group).

Appendix Table D.7. Estimates for the log of the prescription drug co-payment (all three samples)

Explanatory variable	Adult sample	Elderly sample	Elderly sample (revised)	Low-income sample
age between 30 and 39	0.001* (0.045)			-0.035 (0.132)
age between 40 and 49	0.104§ (0.058)			0.164 (0.168)
age between 50 and 64	0.141§ (0.066)			0.034 (0.201)
age between 65 and 74	0.180* (0.077)			-0.198 (0.224)
age above 74	0.169 (0.090)	-0.031 (0.045)		-0.271 (0.252)
age above 79			-0.015 (0.049)	
(log) income per person in family	-0.001 (0.003)	-0.001 (0.006)	-0.001 (0.006)	0.002 (0.007)
retired			-0.023 (0.026)	
individual reports poor health	-0.008 (0.013)	0.017 (0.022)	0.013 (0.022)	-0.009 (0.027)
individual diagnosed with at least one of leading causes of death	-0.004 (0.019)	0.012 (0.034)		0.064 (0.051)
individual faces at least one limitation to an activity of daily living			0.099§ (0.037)	
pre-defined high-cost and/or high-prevalence disease			0.005 (0.048)	
has public insurance (non Medicare)	-0.465§ (0.026)	-0.377§ (0.043)	-0.382§ (0.043)	-0.700§ (0.051)
changed insurance coverage this year		0.086§ (0.022)	0.086§ (0.022)	0.266§ (0.029)
self-employed	0.016§ (0.002)			
year is 1997	0.130§ (0.022)	-0.296§ (0.182)	0.152§ (0.030)	0.249§ (0.046)
year is 1998	0.169§ (0.026)	-0.074§ (0.152)	0.180§ (0.037)	0.304§ (0.053)
year is 1999	0.210§ (0.026)	-0.165§ (0.197)	0.178§ (0.037)	0.353§ (0.057)
year is 2000	0.289§ (0.026)	-0.033§ (0.206)	0.236§ (0.035)	0.395§ (0.053)
year is 2001	0.321§ (0.024)	0.194§ (0.190)	0.266§ (0.034)	0.434§ (0.051)
year is 2002	0.326§ (0.023)	0.045§ (0.187)	0.298§ (0.032)	0.416§ (0.047)
year is 2003	0.455§ (0.024)	0.199§ (0.184)	0.433§ (0.033)	0.573§ (0.049)
year is 2004	0.288§ (0.028)	0.375§ (0.197)	0.321§ (0.039)	0.271§ (0.056)

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Explanatory variable	Adult sample	Elderly sample	Elderly sample (revised)	Low-income sample
lambda	-0.229[§] (0.059)	0.071 (0.270)	-0.280* (0.157)	0.093 (0.108)
lambda 1997	-0.024 (0.042)	0.153 (0.038)	-0.094 (0.118)	-0.283[§] (0.097)
lambda 1998	0.002 (0.050)	0.201 (0.046)	-0.084 (0.153)	-0.209* (0.110)
lambda 1999	-0.054 (0.050)	0.200 (0.047)	0.079 (0.159)	-0.221* (0.114)
lambda 2000	-0.135 (0.049)	0.229 (0.044)	0.180 (0.152)	-0.360[§] (0.113)
lambda 2001	-0.062 (0.046)	0.289 (0.042)	0.212 (0.145)	-0.382[§] (0.107)
lambda 2002	-0.050 (0.045)	0.295 (0.041)	0.215 (0.143)	-0.315[§] (0.099)
lambda 2003	0.054 (0.046)	0.400* (0.043)	0.189 (0.147)	-0.190* (0.099)
lambda 2004	0.057 (0.053)	0.308 (0.049)	-0.021 (0.204)	-0.101 (0.113)
(mean) age 30 to 39	-0.060 (0.048)			0.103 (0.136)
(mean) age 40 to 49	-0.139[§] (0.060)			0.018 (0.173)
(mean) age 50 to 64	-0.137[§] (0.069)			0.169 (0.206)
(mean) age 65 to 74	0.029 (0.081)			0.470[§] (0.229)
(mean) age greater than 74	0.087 (0.093)	0.099[§] (0.048)		0.562[§] (0.258)
(mean) age above 79			0.124 (0.052)	
(mean) (log) income per person in family	0.006 (0.004)	0.010 (0.007)	0.009 (0.007)	0.003 (0.008)
(mean) retired			-0.002 (0.031)	
(mean) poor health	0.075[§] (0.018)	-0.056* (0.031)	-0.049 (0.030)	0.099[§] (0.037)
(mean) diagnosis of at least one of leading causes of death	-0.021 (0.020)	-0.025 (0.037)		-0.031 (0.054)
(mean) individual faces at least one limitation to an activity of daily living			-0.090* (0.049)	
(mean) pre-defined high-cost and/or high-prevalence disease			0.005 (0.044)	
(mean) has public insurance (non Medicare)	-0.378[§] (0.028)	-0.553[§] (0.048)	-0.554[§] (0.048)	-0.565[§] (0.054)
(mean) changed insurance coverage this year		0.355[§] (0.037)	0.349[§] (0.037)	0.226[§] (0.043)
(mean) self-employed	0.235[§] (0.083)			
constant	2.575[§] (0.047)	2.736[§] (0.066)	2.736[§] (0.073)	2.418[§] (0.087)
N	90,088	21,780	21,780	16,786
R^2	0.143	0.152	0.155	0.283

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 75, (age less than 79 for revised elderly regression), (individual is not retired for revised elderly regression), individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, (individual does not report at least one limitation to activity of daily living for revised elderly regression)

[§]significant at the 5% level, *significant at the 10% level

D.9. Estimates of the number of prescription drugs purchased

This section of the Appendix provides more detailed results for the analyses presented in Section 6.5.2. Specifically, all of the covariates included in the regressions, including time dummies and the Mills lambda, are listed in the tables below. The results are given for each of the three samples (general population, the elderly, and low-income group).

Appendix Table D.8. Estimates for the log of total number of prescription drugs obtained equation (adult sample)[a,b,c]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.058§	-0.284§	0.036§	-0.262§	-0.250§
	(0.004)	(0.014)	(0.004)	(0.037)	(0.039)
age between 30 and 39	0.207§	0.226§	-0.030	-0.039	-0.052
	(0.012)	(0.013)	(0.033)	(0.033)	(0.036)
age between 40 and 49	0.461§	0.503§	-0.010	0.007	-0.030
	(0.012)	(0.013)	(0.042)	(0.041)	(0.046)
age between 50 and 64	0.749§	0.812§	0.079	0.102§	0.039
	(0.012)	(0.013)	(0.049)	(0.048)	(0.053)
age between 65 and 74	0.878§	1.009§	0.113*	0.146§	0.051
	(0.014)	(0.016)	(0.056)	(0.056)	(0.061)
age above 74	0.948§	1.094§	0.075	0.099	-0.029
	(0.015)	(0.016)	(0.064)	(0.068)	(0.069)
(log) income per person in family	0.023§	0.028§	0.003	0.003	0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
individual reports poor health	0.558§	0.534§	0.060§	0.061§	0.060§
	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
individual diagnosed with at least one of leading causes of death	0.520§	0.534§	0.204§	0.218§	0.194§
	(0.009)	(0.009)	(0.012)	(0.014)	(0.017)
year is 1997	-0.016*	0.019*	-0.038§	0.006	0.087§
	(0.009)	(0.010)	(0.008)	(0.013)	(0.019)
year is 1998	0.018	0.071§	-0.067§	0.012	0.154§
	(0.014)	(0.015)	(0.014)	(0.019)	(0.029)
year is 1999	0.034*	0.100§	-0.065§	0.020	0.255§
	(0.014)	(0.015)	(0.018)	(0.022)	(0.029)
year is 2000	0.051§	0.133§	-0.066§	0.029	0.226§
	(0.014)	(0.015)	(0.021)	(0.027)	(0.030)
year is 2001	0.127§	0.230§	-0.036	0.081§	0.323§
	(0.013)	(0.014)	(0.024)	(0.031)	(0.029)
year is 2002	0.159§	0.255§	-0.038	0.079§	0.383§
	(0.012)	(0.014)	(0.025)	(0.033)	(0.028)
year is 2003	0.188§	0.335§	-0.064§	0.100§	0.445§
	(0.013)	(0.015)	(0.027)	(0.036)	(0.031)
year is 2004	0.181§	0.270§	-0.073§	0.038	0.430§
	(0.015)	(0.017)	(0.029)	(0.032)	(0.031)
lambda					0.162§
					(0.061)
lambda 1997					-0.136§
					(0.036)
lambda 1998					-0.175§
					(0.051)
lambda 1999					-0.214§
					(0.051)
lambda 2000					-0.196§
					(0.051)

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
lambda 2001					-0.216[§] (0.048)
lambda 2002					-0.278[§] (0.046)
lambda 2003					-0.258[§] (0.047)
lambda 2004					-0.337[§] (0.053)
(mean) age 30 to 39					0.271[§] (0.040)
(mean) age 40 to 49					0.512[§] (0.050)
(mean) age 50 to 64					0.734[§] (0.058)
(mean) age 65 to 74					0.902[§] (0.067)
(mean) age greater than 74					1.056[§] (0.075)
(mean) (log) income per person in family					0.027[§] (0.003)
(mean) poor health					0.618[§] (0.018)
(mean) diagnosis of at least one of leading causes of death					0.334[§] (0.018)
(mean) has public insurance (non Medicare)					-0.017 (0.034)
(mean) self-employed					-0.179[§] (0.081)
constant	1.242[§] (0.016)	1.982[§] (0.034)	2.243[§] (0.041)	2.919[§] (0.102)	1.814[§] (0.000)
N	90,088	90,088	90,088	90,088	90,088
R^2	0.298	0.207	0.229	0.027	0.117

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, year is 1996

[§]significant at the 5% level, *significant at the 10% level

Appendix Table D.9. Estimates for the log of total number of prescription drugs obtained equation (elderly sample)[a,b]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.031§ (0.008)	-0.186§ (0.023)	0.022§ (0.008)	-0.129* (0.079)	-0.096 (0.080)
individual is above the age of 74	0.080§ (0.015)	0.090§ (0.016)	-0.064§ (0.029)	-0.068* (0.035)	-0.098§ (0.030)
(log) income per person in family	0.021§ (0.003)	0.023§ (0.003)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)
individual reports poor health	0.418§ (0.015)	0.389§ (0.016)	0.044§ (0.015)	0.047§ (0.017)	0.039§ (0.015)
individual diagnosed with at least one of leading causes of death	0.495§ (0.015)	0.497§ (0.016)	0.135§ (0.022)	0.139§ (0.023)	0.105§ (0.027)
year is 1997	-0.003 (0.018)	0.023 (0.019)	-0.004 (0.015)	0.023 (0.018)	0.001 (0.033)
year is 1998	0.050* (0.028)	0.084§ (0.029)	-0.015 (0.026)	0.029 (0.033)	0.056 (0.051)
year is 1999	0.072§ (0.028)	0.117§ (0.029)	-0.019 (0.034)	0.032 (0.042)	0.064 (0.052)
year is 2000	0.056§ (0.028)	0.117§ (0.029)	-0.057 (0.040)	0.001 (0.051)	0.083* (0.050)
year is 2001	0.175§ (0.026)	0.241§ (0.027)	0.003 (0.046)	0.059 (0.051)	0.206§ (0.050)
year is 2002	0.235§ (0.025)	0.298§* (0.027)	0.030 (0.048)	0.085* (0.049)	0.283§ (0.048)
year is 2003	0.281§ (0.026)	0.368§ (0.028)	0.043 (0.052)	0.104* (0.054)	0.366§ (0.053)
year is 2004	0.277§ (0.030)	0.336§ (0.032)	0.085 (0.055)	0.121§ (0.048)	0.334§ (0.055)
lambda					-0.253 (0.189)
lambda 1997					0.154 (0.124)
lambda 1998					0.136 (0.197)
lambda 1999					0.223 (0.208)
lambda 2000					0.142 (0.194)
lambda 2001					0.062 (0.191)
lambda 2002					-0.028 (0.188)
lambda 2003					-0.249 (0.202)
lambda 2004					-0.096 (0.249)
(mean) age greater than 74					0.174§ (0.035)
(mean) (log) income per person in family					0.018§ (0.006)
(mean) poor health					0.445§ (0.029)
(mean) diagnosis of at least one of leading causes of death					0.363§ (0.032)

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(mean) has public insurance (non Medicare)					0.059 (0.078)
(mean) changed insurance coverage this year					-0.096[§] (0.048)
constant	2.210[§] (0.035)	2.773[§] (0.066)	2.798[§] (0.046)	3.188[§] (0.213)	2.567[§] (0.231)
N	21,780	21,780	21,780	21,780	21,780
R^2	0.148	0.152	0.094	0.023	0.084

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 75, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, year is 1996

[§]significant at the 5% level, *significant at the 10% level

Appendix Table D.10. Revised estimates for the log of total number of prescription drugs obtained equation (elderly sample)[a,b]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.029[§] (0.008)	-0.150[§] (0.022)	0.021[§] (0.008)	-0.133* (0.079)	-0.108 (0.079)
age greater than 84	0.017 (0.017)	0.033* (0.018)	-0.038 (0.032)	-0.038 (0.036)	-0.066[§] (0.032)
(log) income per person in family	0.023[§] (0.003)	0.024[§] (0.003)	0.005 (0.005)	0.005 (0.004)	0.005 (0.005)
retired	-0.006 (0.015)	0.003 (0.015)	-0.027 (0.018)	-0.030* (0.016)	-0.034* (0.018)
poor health	0.407[§] (0.016)	0.386[§] (0.016)	0.041[§] (0.015)	0.044[§] (0.016)	0.037[§] (0.015)
limitation to an activity of daily living	0.342[§] (0.027)	0.321[§] (0.027)	0.082[§] (0.029)	0.098[§] (0.034)	0.089[§] (0.030)
pre-defined high-cost and/or high-prevalence disease	0.584[§] (0.017)	0.592[§] (0.017)	0.191[§] (0.026)	0.198[§] (0.026)	0.139[§] (0.041)
year is 1997	-0.014 (0.018)	0.008 (0.018)	-0.009 (0.015)	0.018 (0.018)	0.008 (0.027)
year is 1998	0.027 (0.028)	0.056* (0.028)	-0.025 (0.026)	0.018 (0.039)	0.037 (0.040)
year is 1999	0.064[§] (0.027)	0.101[§] (0.028)	-0.034 (0.034)	0.017 (0.048)	0.068* (0.040)
year is 2000	0.054[§] (0.027)	0.104[§] (0.029)	-0.074* (0.040)	-0.017 (0.050)	0.075* (0.041)
year is 2001	0.160[§] (0.025)	0.215[§] (0.027)	-0.021 (0.046)	0.034 (0.049)	0.191[§] (0.041)
year is 2002	0.215[§] (0.025)	0.267[§] (0.026)	0.002 (0.048)	0.054 (0.054)	0.257[§] (0.040)
year is 2003	0.253[§] (0.026)	0.325[§] (0.027)	0.008 (0.052)	0.067 (0.056)	0.319[§] (0.047)
year is 2004	0.261[§] (0.029)	0.311[§] (0.031)	0.048 (0.055)	0.079 (0.056)	0.318[§] (0.045)
lambda					-0.278* (0.159)
lambda 1997					0.104 (0.095)
lambda 1998					0.163 (0.151)
lambda 1999					0.205 (0.154)
lambda 2000					0.210 (0.146)
lambda 2001					0.138 (0.144)
lambda 2002					0.062 (0.141)
lambda 2003					-0.034 (0.149)
lambda 2004					-0.036 (0.182)
(mean) age greater than 84					0.084[§] (0.039)
(mean) (log) income per person in family					0.021[§] (0.006)

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(mean) retired					0.043* (0.025)
(mean) poor health					0.452§ (0.027)
(mean) limitation to an activity of daily living					0.251§ (0.046)
(mean) pre-defined high-cost and/or high-prevalence disease					0.408§ (0.037)
(mean) has public insurance (non Medicare)					0.012 (0.077)
(mean) changed insurance coverage this year					-0.095§ (0.047)
constant	2.035§ (0.037)	2.490§ (0.066)	2.731§ (0.050)	3.127§ (0.203)	2.416§ (0.231)
N	21,780	21,780	21,780	21,780	21,780
R^2	0.171	0.140	0.135	0.048	0.120

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 79, individual is not retired, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, individual does not report at least one limitation to activity of daily living, year is 1996

§significant at the 5% level, *significant at the 10% level

Appendix Table D.11. Estimates for the log of total number of prescription drugs obtained equation (low-income sample)[a,b,c]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.002 (0.007)	-0.261[§] (0.016)	-0.261[§] (0.012)	-0.239[§] (0.054)	-0.199[§] (0.046)
age between 30 and 39	0.256[§] (0.031)	0.304[§] (0.033)	0.304[§] (0.026)	-0.148* (0.081)	-0.151* (0.082)
age between 40 and 49	0.600[§] (0.034)	0.690[§] (0.036)	0.690[§] (0.027)	-0.168 (0.118)	-0.188* (0.112)
age between 50 and 64	0.903[§] (0.032)	1.016[§] (0.034)	1.016[§] (0.026)	-0.034 (0.136)	-0.087 (0.127)
age between 65 and 74	0.934[§] (0.034)	1.085[§] (0.037)	1.085[§] (0.028)	0.002 (0.146)	-0.078 (0.142)
age above 74	0.951[§] (0.033)	1.134[§] (0.036)	1.134[§] (0.028)	-0.073 (0.142)	-0.194 (0.157)
(log) income per person in family	0.047[§] (0.004)	0.046[§] (0.004)	0.046[§] (0.003)	0.003 (0.004)	0.003 (0.005)
individual reports poor health	0.525[§] (0.018)	0.494[§] (0.019)	0.494[§] (0.015)	0.070[§] (0.018)	0.069[§] (0.018)
individual diagnosed with at least one of leading causes of death	0.532[§] (0.019)	0.541[§] (0.020)	0.541[§] (0.015)	0.199[§] (0.027)	0.138[§] (0.035)
year is 1997	-0.053[§] (0.022)	-0.021 (0.024)	-0.021 (0.031)	-0.004 (0.025)	0.042 (0.037)
year is 1998	-0.047 (0.034)	0.008 (0.036)	0.008 (0.034)	-0.003 (0.042)	0.072 (0.055)
year is 1999	0.039 (0.034)	0.115[§] (0.037)	0.115[§] (0.035)	0.008 (0.054)	0.191[§] (0.058)
year is 2000	0.023 (0.034)	0.104[§] (0.036)	0.104[§] (0.034)	-0.010 (0.064)	0.150[§] (0.055)
year is 2001	0.111[§] (0.031)	0.197[§] (0.033)	0.197[§] (0.032)	0.022 (0.077)	0.295[§] (0.053)
year is 2002	0.179[§] (0.030)	0.247[§] (0.031)	0.247[§] (0.031)	0.039 (0.079)	0.387[§] (0.050)
year is 2003	0.214[§] (0.030)	0.323[§] (0.032)	0.323[§] (0.031)	0.034 (0.082)	0.429[§] (0.053)
year is 2004	0.237[§] (0.035)	0.272[§] (0.037)	0.272[§] (0.035)	-0.064 (0.081)	0.410[§] (0.055)
lambda					0.065 (0.106)
lambda 1997					-0.150[§] (0.074)
lambda 1998					-0.164 (0.101)
lambda 1999					-0.209[§] (0.105)
lambda 2000					-0.121 (0.104)
lambda 2001					-0.302[§] (0.100)
lambda 2002					-0.371[§] (0.093)
lambda 2003					-0.322[§] (0.092)
lambda 2004					-0.351[§] (0.104)

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(mean) age 30 to 39					0.423[§] (0.090)
(mean) age 40 to 49					0.800[§] (0.120)
(mean) age 50 to 64					0.969[§] (0.136)
(mean) age 65 to 74					1.021[§] (0.154)
(mean) age greater than 74					1.171[§] (0.170)
(mean) (log) income per person in family					0.044[§] (0.006)
(mean) poor health					0.535[§] (0.033)
(mean) diagnosis of at least one of leading causes of death					0.349[§] (0.039)
(mean) has public insurance (non Medicare)					0.014 (0.059)
(mean) changed insurance coverage this year					-0.108[§] (0.039)
constant	1.296[§] (0.034)	1.786[§] (0.046)	1.786[§] (0.039)	3.200[§] (0.163)	1.691[§] (0.125)
N	16,786	16,786	16,786	16,786	16,786
R^2	0.355	0.112	0.173	0.040	0.099

[a]standard errors in parentheses, [b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, year is 1996

[§]significant at the 5% level, *significant at the 10% level

Appendix E: Appendix to Chapter 7

In line with Appendix D, this appendix is meant to provide supplementary material to Chapter 7, although the focus of this appendix is on British Columbia. We include the STATA code used to run the empirical model, the full results from the empirical analysis, and information on an alternative econometric specification that we considered. The empirical model is based on Semykina and Wooldridge (2006), but the program code is slightly different as the model does not correct for endogeneity. The next section provides the STATA program code used to implement the model. Sections E.2 through E.4 then present the full results of the empirical analysis, including the specification tests, the first-stage probits, and the full econometric model. Because we also considered a dynamic specification but chose not to include this aspect in the final models from Chapter 7, Section E.5 develops the dynamic specification and includes the results.

E.1. STATA code to implement fixed effects model correcting for sample selection bias

This section of the Appendix provides the code that was used to run the Semykina and Wooldridge (2006) model (SS FE). In order to help the user better understand the program, there are comments on aspects of the code inside of the following symbols:

```
/*************************
*                                                    (a)
*************************/

//                                                   (b)
```

```
/*****************************************************************
* PROGRAM TO RUN THE 'SS FE' MODEL
*****************************************************************/

// generates the base variables used in the model
scalar time_lambdas = 1
scalar num_time_pers = 11
gen selection_indicator=0
replace selection_indicator=1 if rxtot>0

// # periods the person had positive drug spending
by studyid: egen keep_obs = sum(selection_indicator)
```

```
// defines the variable list
local varlist_main age_65to74 age_75to84 socio_dep2 socio_dep3 socio_dep4
                   socio_dep5 morb_us died_this_year socio_morb

// generates the time dummies
local i=1993
while `i'<2003 {
 quietly gen T_`i'=0
 quietly replace T_`i' = 1 if year==`i'
 local i = `i'+1
}

// generates the mean variables for the selection probit estimations
local j=1
foreach var of varlist `varlist_main' {
 quietly egen ms_`var' = mean(`var'), by(studyid)
 local j = `j'+1
}
scalar NUM_INSTR = `j'-1



/*****************************************************************
* PROCEDURE 1: RUN THE FIRST STAGE PROBITS
*****************************************************************/

// generates the inverse Mills ratio for each year
gen lambda = .
local i = 1992
while `i'<2003 {
 quietly probit selection_indicator `varlist_ins' ms_ if year==`i'
 quietly predict rhat, xb
 quietly replace lambda = normden(rhat)/norm(rhat) if selection_indicator==1 &
                          year == `i'
 drop rhat
 local i = `i'+1
}

// generates interaction terms for lambda
if time_lambdas == 1 {
 local i = 1993
 while `i'<2003 {
  quietly gen lambda_`i' = T_`i'*lambda
  local i = `i'+1
 }
}
```

```
/*****************************************************************
* PROCEDURE 2: RUN THE SECOND STAGE AND CORRECT THE
* STANDARD ERRORS
*****************************************************************/

// runs the regression without correcting for the Heckman standard errors
regress ln_rxtot ln_rxcopay `varlist_main' lambda* T_* ms_* if keep_obs>1 &
selection_indicator==1, robust cluster(studyid)

// obtain the coefficient on the Mills ratio
if time_lambdas==1 {
  scalar b_mills1992 = _b[lambda]
  local i = 1993
  while `i'<2003 {
    scalar b_mills`i' = _b[lambda_`i'] + b_mills1992
    local i=`i'+1
  }
}
if time_lambdas==0 {
  local i = 1992
  while `i'<2003 {
    scalar b_mills`i' = _b[lambda]
    local i=`i'+1
  }
}


*****************************************************************/
* Generates the diagonal matrix with Hessians
*****************************************************************/

// count the number of Heckman regressors
local c=0
foreach var of varlist `varlist_main' {
  local c = `c'+1
}
scalar stage_1 = `c'

gen cons = 1

// defines the list of regressors used in the first stage
local varlist_i1 `varlist_main' ms_* cons
local varlist_i3
local varlist_i4

// generates matrix H, a square matrix of dimension [# regressors in 1st stage
   probit --BY-- # time periods]
```

```
mat H = I((2*stage_1+1)*num_time_pers)

local i=1992
while `i'<2003 {
 quietly probit selection_indicator `varlist_main' ms_* if year == `i'
 predict rhat, xb
 mat H`i' = e(V)
 quietly generate tempvar1 = normden(rhat) / norm(rhat) if selection_indicator == 1
                             & year == `i'
 quietly generate tempvar2 = -normden(rhat) / (1 - norm(rhat)) if
                             selection_indicator == 0  & year == `i'
 assert lambda = tempvar1 if selection_indicator == 1 & year == `i'
 local j = `i' - 1992
 mat H[(2stage_1 + 1)`j' + 1,(2stage_1 + 1)`j' + 1] = H`i'

 foreach var of varlist `varlist_i1' {
  quietly generate g_`var'`j' = 0 if selection_indicator == 1
  quietly replace g_`var'`j' = -lambda  (lambda + rhat)b_mills`i'`var' if
                             selection_indicator == 1 & year == `i'

  quietly generate q_`var'`j' = .
  quietly replace q_`var'`j' = tempvar1`var' if selection_indicator == 1 &
                             year == `i'
  quietly replace q_`var'`j' = tempvar2`var' if selection_indicator == 0 & year == `i'

  sort pid year
  quietly by pid: replace q_`var'`j' = q_`var'`j'[`j'  + 1] if year ~= `i'
  local varlist_i3 `varlist_i3' g_`var'`j'
  local varlist_i4 `varlist_i4' q_`var'`j'
 }

 drop rhat tempvar1 tempvar2
 mat drop H`i'
 local i = `i' + 1
}

foreach var of varlist `varlist_i4' {
 quietly replace `var'=0 if `var' == .
}

keep if keep_obs>1 & selection_indicator == 1
```

```
*****************************************************************/
* Replicates the second stage equation using matrices
*****************************************************************/

/*****************************************************************
* matrix XX = X'X
* matrix Xy = X'y
*****************************************************************/

matrix accum XX = ln_rxcopay `varlist_main' lambda* T_* ms_* cons, nocons
matrix vecaccum yX = ln_rxtot ln_rxcopay `varlist_main' lambda* T_* ms_* cons,
                     nocons
matrix BETA = inv(XX)*yX'

quietly regress ln_rxtot ln_rxcopay `varlist_main' lambda* T_* ms_*
predict ehat, res

// checked and this is identical to when I run the regression!
matrix list BETA



*****************************************************************/
* Replicates the robust variance matrix using matrices

* Define a new varlist_1r, which is the list of main variables in the main equation
* varlist_2r is the list of interaction terms
*****************************************************************/

sort studyid year
by studyid: gen num=_n

// scalar g is the number of individuals in the selected sample
gen countid = (num==1)
sum countid
scalar g = r(sum)

// count the number of regressors that are in the main part of the regression
local c=0
foreach var of varlist `varlist_main' {
  local c = `c'+1
}
scalar MAIN = `c'
scalar M = 1 + MAIN + 1 + time_lambdas*(num_time_pers - 1) + (num_time_pers -
           1) + 1

local varlist_1r ln_rxcopay `varlist_main' lambda* T_* ms_* cons
```

```
local varlist_2r

local j=1
foreach var of varlist `varlist_1r' {
  quietly gen eh_`var' = `var'*ehat
  quietly egen ttt_`var' = sum(eh_`var'), by(studyid)
  local varlist_2r `varlist_2r' ttt_`var'
  local j = `j'+1
}
drop eh_*

matrix accum XEEX = `varlist_2r' if num==1, nocons

// obtain standard errors corrected for the first stage estimation
matrix TERM1 = XEEX



**********************************************************************/
* The number of variables in varlist_2r should be equal to the number of
* instruments at the second stage

* The number of variables in varlist_i4 should be equal to # 1st-stage regressors
* # time periods
**********************************************************************/

matrix accum TEMP = `varlist_2r' `varlist_i4' if num==1, nocons

// extract the upper right hand corner of the TEMP matrix
matrix ZEQ = TEMP[1..M + NUM_INSTR, M+NUM_INSTR+1...]
matrix drop TEMP

matrix accum TEMP = `varlist_1r' `varlist_i3', nocons

// extract the upper right hand corner of the TEMP matrix
matrix ZG = TEMP[1.. M + NUM_INSTR, M + NUM_INSTR + 1...]
di "Number of rows in ZG="rowsof(ZG)
di "Number of columns in ZG="colsof(ZG)
matrix drop TEMP

matrix TERM2 = ZEQ*H*ZG'
matrix accum QQ = `varlist_i4' if num==1, nocons
matrix TERM4 = ZG*H*QQ*H*ZG'

matrix V2 = inv(XX)*(TERM1 - TERM2 - TERM2' + TERM4)*inv(XX)*
            (e(N) -  1)*g/((g - 1)*(e(N) - M))
```

```
mata:
{
   mata_V2 = st_matrix("V2")
   mata_Beta = st_matrix("BETA")
}
end

drop q_* g_* ttt_*

if time_lambdas==1 {
 local out_varlist ln_rxcopay `varlist_main' `lambda_varlist' `T_varlist' `ms_varlist'
_cons
 local pred_varlist ln_rxcopay `varlist_main' `lambda_varlist' `T_varlist'
}
if time_lambdas==0 {
 local out_varlist ln_rxcopay `varlist_main' lambda `T_varlist' `ms_varlist' _cons
 local pred_varlist ln_rxcopay `varlist_main' lambda `T_varlist'
}

quietly ci ln_rxtot
mata: mata_se_y = st_numscalar("r(se)")
mata: mata_var_y = mata_se_y*mata_se_y

matrix beta_1 = BETA[1..M-1,.]
matrix beta_2 = BETA[M + NUM_INSTR .. M + NUM_INSTR, .]
mata: mata_beta_1 = st_matrix("beta_1")
mata: mata_beta_2 = st_matrix("beta_2")
mata: beta_new= mata_beta_1 \ mata_beta_2
mata: beta_new

mata: x_varlist_1 = st_local("pred_varlist")
mata: x_varlist_2 = st_data(.,tokens(x_varlist_1))
mata: rows_xs = rows(x_varlist_2)

mata: constant = J(rows_xs,1,1)
mata: x = (x_varlist_2,constant)

mata: y_pred = x*beta_new
mata: var_y_pred = ((1/rows_xs)*colsum(y_pred:*y_pred)) -
                   ((colsum(y_pred)/rows_xs)^2)

mata: y_pred_new = st_addvar("float","ln_y_pred")
mata: st_store(.,y_pred_new,y_pred)

correlate ln_y_pred ln_rxtot if keep_obs>1 & selection_indicator==1
mata: mata_corr = st_numscalar("r(rho)")
mata: mata_r2 = mata_corr*mata_corr
```

```
**********************************************************************/
* Outputs the results
**********************************************************************/

mata: v_a = st_local("out_varlist")
mata: varname = J(0,0,.)
mata: variable_vector(v_a, varname)


mata:
{
 st_err_adj = sqrt(diagonal(mata_V2))
 t_value_adj = mata_Beta:/ st_err_adj
 p_value_adj = get_pvalue(t_value_adj)

 printf("Heckman Fixed effects output with standard errors adjusted\n")
 printf("\n")
 printf("R2 = ")
 printf("%8.4g\n", mata_r2)
 printf("\n")
 printf("{hline 21}{c +}{hline 55}\n")
  printf("ln_rxtot          {c |}Coef.      Std. Err.      t-value
  p-value\n")
 printf("{hline 21}{c +}{hline 55}\n")
 i = 1

 while (i<=rows(t_value_adj)) {
     printf("%-20s {c |}%8.4g     %8.4g     %8.4g     %8.4g\n", varname[i],
     mata_Beta[i], st_err_adj[i], t_value_adj[i], p_value_adj[i])
  i++
 }
 printf("{hline 21}{c +}{hline 55}\n")

}
end
```

E.2. Results of specification tests

The results of the specification tests for the appropriateness of various assumptions related to the model are covered in this section of the Appendix. As we restricted our sample to those who were over the age of 65, it was important to determine whether this was a random sample. To do so we used a runs test, where the null hypothesis is that the number of runs is outside the expected range. More detail on this procedure is available in Section D.6 of Appendix D. The resulting value from the runs test was –1,354 (p=0.000), indicating that the sample was not non-random, and we could proceed with the estimation.

We also employed other tests for the specification of the model and the choice of the main variables and instruments (Appendix Table E.1).

Appendix Table E.1. Results from various specification tests

Test	Models compared	Results
Wald test for appropriateness of fixed effects	FE-OLS (with SS) and OLS (with SS)	$\chi^2(8) = 77{,}383$ (p=0.000)
Semykina -Wooldridge test (Wald test) for sample selection	FE-0LS (no SS) and SS FE (with SS)	$\chi^2(11) = 23{,}611$ (p=0.000)
Condition index to test for multicollinearity		CI = 8.88
Variance Inflation Factor to test for multicollinearity		VIF = 1.90

As we had the option of using panel data techniques, we tested for the validity of a fixed effects approach as opposed to a pooled OLS that did not account for the unobserved effects. The null hypothesis is that all of the time-means parameters are zero, and we find a Wald statistic that is sufficient to reject the null hypothesis and conclude that a fixed effects model is more appropriate than pooled OLS[1].

The next step in the construction of a model was to test whether sample selection was an issue, and we used a Wald test proposed by Semykina and Wooldridge (2006). The null hypothesis of the test is that the explanatory variables are not correlated with the error term in the main equation, i.e. $E(x_{it}, u_{it}) = 0$. The reported values in Appendix Table E.1 indicate that sample selection is an important aspect of the model.

Section D.1 of Appendix D discussed how the existence of multicollinearity can make the interpretation of the t-value on the inverse Mills ratio suspect. As it is important to test for this pitfall, we use a condition index, where a condition index of 20 or greater generally reveals that multicollinearity is a problem (Greene, 2003). For both dependent variables, we calculate a condition index of 8.88, indicating that according to this test multicollinearity is not an issue with the estimation. An additional tool to check for multicollinearity is the Variance Inflation Factor, where VIF values greater than 10 are suspect. As the mean VIF for each specification was 1.90, we were again able to conclude that multicollearity is not something we need to correct.

[1] We also tested for whether a fixed or random effects specification was more appropriate, although we only provide the results of the linear case (as opposed to the specification that accounts for sample selection). The results of the Hausman specification test yielded a p-value of 0.000, indicating that a fixed effects framework was more appropriate.

E.3. First-stage probit results for probability of any prescription drug use

This section provides the results for the individual year-probits (1992-2002). The probit results are used to predict a vector of Mills lambdas, which is then plugged into the second-stage equation that predicts the number of prescription drugs purchased.

Appendix Table E.2. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use [a,b,c]

Explanatory variable	1992	1993	1994	1995	1996	1997
age between 65 and 74	-0.023§	-0.021*	-0.033§	0.014	-0.056§	-0.099§
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
age between 75 and 84	-0.270§	-0.261§	-0.217§	-0.114§	-0.163§	-0.163§
	(0.022)	(0.022)	(0.022)	(0.020)	(0.019)	(0.018)
second socioeconomic quintile	0.036§	0.029§	-0.001	0.008	0.010	0.002
	(0.010)	(0.009)	(0.012)	(0.012)	(0.011)	(0.011)
third socioeconomic quintile	0.028§	0.028§	-0.016	-0.026§	-0.020	-0.006
	(0.011)	(0.010)	(0.013)	(0.013)	(0.013)	(0.012)
fourth socioeconomic quintile	0.062§	0.056§	-0.024*	-0.054§	-0.040§	-0.035§
	(0.011)	(0.011)	(0.015)	(0.014)	(0.014)	(0.013)
fifth socioeconomic quintile	0.082§	0.092§	-0.039§	-0.055§	-0.060§	-0.026*
	(0.013)	(0.012)	(0.017)	(0.016)	(0.015)	(0.015)
individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease	0.593§	0.591§	0.547§	0.379§	0.363§	0.382§
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
individual died this year	-0.697§	-0.395§	-0.324§	-0.267§	-0.230§	-0.257§
	(0.022)	(0.016)	(0.015)	(0.013)	(0.013)	(0.012)
(mean) age between 65 and 74	0.169§	0.181§	0.217§	0.008	0.010	0.022
	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)
(mean) age between 75 and 84	0.372§	0.389§	0.334§	0.256§	0.228§	0.155§
	(0.022)	(0.022)	(0.023)	(0.021)	(0.021)	(0.021)
(mean) second socioeconomic quintile	-0.042§	-0.044§	-0.038§	0.021	0.014	0.047§
	(0.013)	(0.013)	(0.017)	(0.016)	(0.016)	(0.015)
(mean) third socioeconomic quintile	-0.035§	-0.045§	0.005	0.073§	0.065§	0.076§
	(0.013)	(0.013)	(0.018)	(0.017)	(0.017)	(0.016)
(mean) fourth socioeconomic quintile	-0.074§	-0.072§	0.013	0.100§	0.075§	0.104§
	(0.014)	(0.014)	(0.019)	(0.018)	(0.017)	(0.016)
(mean) fifth socioeconomic quintile	-0.057§	-0.067§	0.079§	0.197§	0.205§	0.201§
	(0.015)	(0.015)	(0.019)	(0.019)	(0.018)	(0.017)
(mean) individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease	0.892§	1.001§	1.137§	0.891§	0.942§	0.967§
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)
(mean) individual died this year	0.355§	-0.081§	-0.246§	-0.542§	-0.664§	-0.758§*
	(0.023)	(0.028)	(0.031)	(0.032)	(0.034)	(0.034)
constant	0.335§	0.332§	0.299§	0.314§	0.326§	0.319§
	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
N	406,866	417,822	409,323	428,244	445,915	470,519
Log-likelihood	-152,906	-155,452	-152,539	-189,152	-198,577	-207,128
probability > χ^2	0.000	0.000	0.000	0.000	0.000	0.000

[a]standard errors in parentheses; [b]excluded dummy variables are age greater than 84, individual lives in a postcode that is in the lowest socioeconomic quintile in British Columbia, individual has not been diagnosed with at least one of the pre-defined high-cost and/or high-prevalence diseases; [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample
§significant at the 5% level, *significant at the 10% level

Appendix Table E.2. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use (continued) [a,b,c]

Explanatory variable	1998	1999	2000	2001	2002
age between 65 and 74	-0.149§ (0.010)	-0.155§ (0.010)	-0.091§ (0.010)	-0.028§ (0.009)	0.128§ (0.008)
age between 75 and 84	-0.164§ (0.018)	-0.124§ (0.018)	0.053§ (0.019)	0.147§ (0.018)	0.306§ (0.016)
second socioeconomic quintile	0.000 (0.010)	0.008 (0.010)	-0.009 (0.010)	-0.003 (0.011)	-0.012 (0.010)
third socioeconomic quintile	-0.004 (0.011)	0.016 (0.011)	-0.001 (0.011)	-0.002 (0.012)	-0.005 (0.011)
fourth socioeconomic quintile	-0.033§ (0.012)	0.029§ (0.012)	0.025§ (0.013)	0.014 (0.013)	0.021* (0.012)
fifth socioeconomic quintile	-0.015 (0.014)	0.001 (0.013)	-0.024* (0.014)	-0.009 (0.014)	-0.011 (0.013)
individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease	0.384§ (0.006)	0.450§ (0.006)	0.448§ (0.006)	0.508§ (0.006)	0.512§ (0.006)
individual died this year	-0.229§ (0.012)	-0.180§ (0.012)	-0.211§ (0.012)	-0.133§ (0.012)	0.093§ (0.013)
(mean) age between 65 and 74	0.068§ (0.014)	0.025* (0.014)	-0.095§ (0.014)	-0.232§ (0.014)	-0.248§ (0.013)
(mean) age between 75 and 84	0.074§ (0.022)	-0.082§ (0.022)	-0.367§ (0.023)	-0.566§ (0.023)	-0.534§ (0.021)
(mean) second socioeconomic quintile	0.046§ (0.014)	0.041§ (0.013)	0.064§ (0.014)	0.058§ (0.014)	0.018 (0.013)
(mean) third socioeconomic quintile	0.073§ (0.015)	0.059§ (0.014)	0.098§ (0.015)	0.092§ (0.015)	0.028§ (0.014)
(mean) fourth socioeconomic quintile	0.098§ (0.015)	0.040§ (0.015)	0.055§ (0.015)	0.073§ (0.015)	-0.036§ (0.014)
(mean) fifth socioeconomic quintile	0.186§ (0.016)	0.171§ (0.016)	0.205§ (0.016)	0.186§ (0.016)	0.017 (0.015)
(mean) individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease	1.023§ (0.009)	0.967§ (0.009)	0.977§ (0.010)	0.909§ (0.009)	0.950§ (0.008)
(mean) individual died this year	-0.966§ (0.036)	-1.368§ (0.035)	-1.320§ (0.041)	-1.645§ (0.046)	-2.125§ (0.052)
constant	0.342§ (0.007)	0.397§ (0.007)	0.425§ (0.006)	0.450§ (0.006)	0.108§ (0.006)
N	486,318	485,410	493,180	506,365	519,988
Log-likelihood	-208,750	-202,828	-199,653	-200,904	-249,206
probability > χ^2	0.000	0.000	0.000	0.000	0.000

[a]standard errors in parentheses; [b]excluded dummy variables are age greater than 84, individual lives in a postcode that is in the lowest socioeconomic quintile in British Columbia, individual has not been diagnosed with at least one of the pre-defined high-cost and/or high-prevalence diseases; [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample
§significant at the 5% level, *significant at the 10% level

E.4. Second-stage fixed effects regression results for log of prescription drug use

After estimation of the Mills lambda, the Semykina and Wooldridge (2006) estimation requires that the Mills lambda be inserted into the main equation (i.e. the equation which predicts the number of prescription drugs that the individual obtains in a given year). The Mills lambda can also be interacted with time. To account for

unobserved heterogeneity, the regression includes the time means of the first-stage independent variables. The abbreviated results of this regression are available in Section 6.7.2 of Chapter 6, but this section includes more detailed results that report the coefficients for the Mills lambda and the interactions of the Mills lambda with time, the time variables, and the time means.

Appendix Table E.3. Estimates for the log of total number of prescription drugs obtained equation[a,b,c]

Explanatory variable	Pooled OLS	Fixed Effects	SS Fixed Effects
(log) drug co-payment	-0.306[§] (0.002)	-0.167[§] (0.001)	-0.295[§] (0.002)
age between 65 and 74	0.188[§] (0.002)	-0.017[§] (0.001)	0.074[§] (0.002)
age between 75 and 84	0.358[§] (0.003)	0.010[§] (0.002)	0.141[§] (0.003)
second socioeconomic quintile	-0.041[§] (0.002)	0.002 (0.001)	-0.002 (0.002)
third socioeconomic quintile	-0.041[§] (0.002)	0.003[§] (0.001)	-0.002 (0.002)
fourth socioeconomic quintile	-0.053[§] (0.002)	0.001 (0.001)	-0.010[§] (0.002)
fifth socioeconomic quintile	-0.065[§] (0.003)	0.005[§] (0.002)	-0.007[§] (0.002)
individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease	0.458[§] (0.001)	0.165[§] (0.001)	0.188[§] (0.003)
individual died this year	-0.079[§] (0.003)	-0.418[§] (0.002)	-0.429[§] (0.003)
year is 1993	-0.018[§] (0.001)	0.027[§] (0.001)	0.060[§] (0.002)
year is 1994	-0.360[§] (0.002)	-0.122[§] (0.001)	-0.230[§] (0.003)
year is 1995	-0.556[§] (0.003)	-0.176[§] (0.002)	-0.411[§] (0.004)
year is 1996	-0.002 (0.002)	0.184[§] (0.001)	0.170[§] (0.003)
year is 1997	0.034[§] (0.002)	0.274[§] (0.001)	0.260[§] (0.003)
year is 1998	0.061[§] (0.002)	0.347[§] (0.001)	0.318[§] (0.003)
year is 1999	0.089[§] (0.002)	0.433[§] (0.001)	0.380[§] (0.003)
year is 2000	0.117[§] (0.002)	0.512[§] (0.001)	0.442[§] (0.003)
year is 2001	0.185[§] (0.002)	0.619[§] (0.002)	0.531[§] (0.004)
year is 2002	0.468[§] (0.002)	0.787[§] (0.002)	0.770[§] (0.004)
lambda			0.525[§] (0.019)
lambda 1993			-0.182[§] (0.008)
lambda 1994			-0.189[§] (0.009)
lambda 1995			-0.165[§] (0.010)

Explanatory variable	Pooled OLS	Fixed Effects	SS Fixed Effects
lambda 1996			-0.227[§] (0.010)
lambda 1997			-0.321[§] (0.010)
lambda 1998			-0.347[§] (0.011)
lambda 1999			-0.382[§] (0.011)
lambda 2000			-0.419[§] (0.011)
lambda 2001			-0.417[§] (0.011)
lambda 2002			-0.296[§] (0.011)
(mean) age between 65 and 74			0.149[§] (0.004)
(mean) age between 75 and 84			0.249[§] (0.005)
(mean) second socioeconomic quintile			-0.058[§] (0.004)
(mean) third socioeconomic quintile			-0.045[§] (0.004)
(mean) fourth socioeconomic quintile			-0.046[§] (0.004)
(mean) fifth socioeconomic quintile			-0.045[§] (0.004)
(mean) individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease			0.730[§] (0.006)
(mean) individual died this year			1.854[§] (0.012)
(mean) (log) drug co-payment			0.290[§] (0.002)
constant	2.696[§] (0.004)	2.427[§] (0.002)	2.095[§] (0.010)
N	4,071,186	4,071,186	4,071,186
R^2	0.122	0.043	0.060

[a]standard errors in parentheses, [b]excluded dummy variables are age greater than 84, individual reports being in good health, individual has not been diagnosed with at least one of the pre-defined high-cost and/or high-prevalence diseases, year is 1992, [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample
[§]significant at the 5% level, *significant at the 10% level

E.5. Explanation and results of the dynamic fixed effects model accounting for sample selection

E.5.1. Dynamic panel data models

As an alternative to the fixed effects sample selection model, we initially tried a dynamic model to account for repeated consumption over time. For example, as an individual becomes comfortable with a new prescription, he is more likely to continue consuming that drug in the next period and less likely to choose other non-

prescription alternatives to regain his health. This section provides an overview of the dynamic model and the results.

A dynamic panel data model is specified in the following manner:

$$y_{it} = g_i + x_{it}\beta + \alpha y_{i,t-1} + u_{it} \quad \text{(E.1)},$$

where $i = 1,...,N$ and $t = 1,...,T$. The dynamic element of the model is $y_{i,t-1}$, which is the y_{it} variable lagged one period. We assume that u_{it} is an independently and identically distributed random variable with a mean of zero and a variance of σ_u^2.

As there are biases associated with both OLS and fixed effects regressions on (E.1) (Bond, 2002)[2], instrumental variables estimators and generalized method of moments (GMM) estimators have been developed. Both methods involve taking the first differences to remove the individual effects[3]:

$$\Delta y_{it} = \Delta g_i + \Delta x_{it}\beta + \Delta y_{i,t-1}\alpha + \Delta u_{it} \quad \text{(E.2)}.$$

The first-differenced model still suffers from correlation between the lagged dependent variable and the error term. However, if the time series contains enough periods, the differences ($\Delta y_{i,t-2}$) or one or more of the lagged dependent variables ($y_{i,t-2}, y_{i,t-3}$, etc) can be used as instrumental variables for the first-differenced lag dependent variable ($\Delta y_{i,t-1}$) (Greene, 2003). But, when there are more than three time periods, the instrumental variables method is not asymptotically efficient (Bond, 2002). The 2SLS method also neglects information from the levels of y_{it} (Ahn and Schmidt, 1995).

Because of the problem with 2SLS when there are more than three time periods, the first-differenced GMM estimator has been used to obtain an asymptotically efficient estimator. Instead of using values of y_{it} lagged two or more periods, the GMM estimators take advantage of the moment condition:

$$E\left(Z_i'\Delta u_i\right) = 0 \text{ for } i = 1,2,\ldots,N \quad \text{(E.3)}.$$

The rows of Z_i each correspond to the first-differenced equations for periods t = 3,4,...,T. To estimate the coefficients, we use an estimator of the form (Bond, 2002):

[2] For a more detailed explanation of the biases associated with running OLS and fixed effects on a dynamic model, see Bond (2002).

[3] Whenever we use the convention Δa_{is}, the observation of a in period s - 1 is subtracted from the observation of a in period s so that $\Delta a_{is} = a_{is} - a_{i,s-1}$

$$B = \left(\frac{1}{N}\sum_{i=1}^{N}\Delta u_i' Z_i\right)\Omega\left(\frac{1}{N}\sum_{i=1}^{N}Z_i'\Delta u_i\right) \quad \text{(E.4)},$$

where Ω is the weighting matrix and is estimated by:

$$\Omega = \left[\frac{1}{N}\sum_{i=1}^{N}Z_i' H Z_i\right]^{-1} \quad \text{(E.5)}.$$

The H in the weighting matrix is a square matrix that is $(T-2)$ rows and columns and has twos on the main diagonal, ones on the first off-diagonals, and zeros elsewhere (Bond, 2002). The model is thus estimated in one step[4].

There are a number of potential pitfalls related to a dynamic panel data model, including autocorrelation, endogenous variables, and persistent series. In a dynamic panel $E(u_{it}u_{i,t-1})$ does not need to be zero because Δu_{it} is mathematically related to $\Delta u_{i,t-1}$ through the shared $u_{i,t-1}$ term. However, the assumption that $E(u_{it}u_{i,t-2}) = 0$ is important and thus we need to determine whether there is correlation between the $u_{i,t-1}$ in Δu_{it} and the $u_{i,t-2}$ in $\Delta u_{i,t-2}$. Arellano and Bond (1991) have developed a test for second order serial correlation that is applied to the residuals in differences, where the null hypothesis is that $E(u_{it}u_{i,t-2}) = 0$. The result of this test is automatically given in STATA when we run the GMM estimator for a dynamic model.

Endogeneity is also a potential issue in the dynamic model. If the x_{it} are endogenous, computation of the GMM estimator involves the lagged values $x_{i,t-2}, x_{i,t-3}$ and longer lags. Alternatively, if we make a stronger assumption that the x_{it} are predetermined, then $x_{i,t-1}$ can be added as a valid instrument. Finally, if we assume that the x_{it} are strictly exogenous, then the complete time series $x_i' = (x_{i1}, x_{i2}, ..., x_{iT})$ can be used as instruments. Difference Sargan tests of overidentifying restrictions have been developed to test the validity of each of these assumptions. If we let S be the Sargan statistic under the stronger assumption and S^* be the Sargan statistic obtained under the weaker assumption, the value of:

$$D_S = S - S^* \quad \text{(E.6)},$$

---

[4] A two-step GMM estimator has also been developed where $\Omega = \left[\frac{1}{N}\sum_{i=1}^{N}\left(Z_i'\hat{\Delta}u_i\hat{\Delta}u_i'Z_i\right)\right]^{-1}$ and $\hat{\Delta}u_i$ are estimates of the first-differenced residuals from a preliminary consistent estimator (Bond, 2002). Because this weighting matrix is dependent on the estimated residuals, the asymptotic distribution approximations are less reliable than for the one-step GMM estimator (Bond, 2002).

is asymptotically χ^2 and tests the null hypothesis that the additional moment conditions of the stronger assumption hold.

Another potential problem is that of persistent series, specifically that $\alpha = 1$ (also called a near unit root property). Ignoring the independent variables x_{it}, an alternative specification is:

$$y_{it} = (1-\alpha)g_i + \alpha y_{i,t-1} + u_{it} \qquad \text{(E.7)},$$

where $i = 1,...,N$ and $t = 1,...,T$. As $\alpha \to 1$ the process becomes nonstationary and is known as a random walk. In this situation the instrumental variables for the equations in first differences are likely to be weak, biasing the estimator (Bond, 2002). We can test for unit roots by running an OLS regression on:

$$y_{it} = (1-\alpha)g_i + x_{it}\beta + \alpha y_{i,t-1} + u_{it} \qquad \text{(E.8)},$$

and using a t-test to determine if $\hat{\alpha}$ is significantly different from one (Bond et al., 2002). However, the OLS estimator is biased upwards unless $\alpha = 1$ (in which case the fixed effect drops out). To account for this, Breitung and Meyer (1994) have proposed a modified Dickey-Fuller statistic. This requires subtracting the first observation (y_{i1}) from both sides of equation (E.8), which yields:

$$y_{it} - y_{i1} = -(1-\alpha)(y_{i1} - g_i) + x_{it}\beta + \alpha(y_{i,t-1} - y_{i1}) + u_{it} \qquad \text{(E.9)}.$$

Although the OLS estimate from (E.9), denoted $\tilde{\alpha}$, is also biased, the asymptotic bias is given by:

$$\text{plim}_{N\to\infty}\tilde{\alpha}_{BM} = \frac{\alpha+1}{2} \qquad \text{(E.10)}.$$

Thus, $\tilde{\alpha}$ can be used to test for $\alpha = 1$. Monte Carlo results from Bond et al. (2002) indicate that the t-test from the OLS estimation performs well when the variance of the unobserved heterogeneity (g_i) is relatively small. The Breitung and Meyer (1994) test does not suffer from this problem when the variance is larger, although the power of this test is low (Bond et al., 2002).

If nonstationarity is a problem with the series, then the system-GMM estimator is preferred (Arellano and Bover, 1995; Blundell and Bond, 1998). This method involves transforming the instruments to make them exogenous to the fixed effects rather than transforming the regressors to difference out the fixed effects (Roodman, 2006). If we assume that the instrumenting variables (z_{it}) are endogenous, then $\Delta z_{i,t-1}$ can be used as an instrument, and earlier realizations of Δz_{it} can also be used. If we assume that the z_{it} are predetermined, then Δz_{it} and earlier realizations of Δz_{it} can be used as instruments. The system-GMM estimator thus involves building a

stacked dataset with the differenced individual-level observations on top and the untransformed (levels) observations below. The additional moment conditions for this estimator are:

$$E\left[u_{it}\Delta y_{i,t-1}\right]=0 \text{ for } t=3,\ldots,T \qquad \text{(E.11)},$$

and

$$E\left[u_{it}\Delta X_{i,t-1}\right]=0 \text{ for } t=3,\ldots,T \qquad \text{(E.12)}.$$

Because we determine that nonstationarity is not a problem with the dataset, we do not provide any further information on the system-GMM in this section.

E.5.2. Combining sample selection and dynamic panel data techniques

As outlined in the previous sections, there are a number of considerations relevant to the type of data being used and the outcome being tested. To account for a lagged dependent variable along with unobserved heterogeneity and sample selection, another similar specification developed by Ramón García et al. (2006)[5] is needed for this situation. The specification considers the following dynamic model:

$$y_{it}=g_i+x_{it}\beta+y_{i,t-1}\alpha+u_{it} \qquad y_{it}=y_{it}^{*} \text{ for } s_{it}=1$$
$$y_{it} \text{ is not observed for } s_{it}=0 \qquad \text{(E.13)},$$

$$s_{it}=1[\eta_i+z_{it}\gamma+\varepsilon_{it}>0] \qquad \text{for } t=1,\ldots,T \qquad \text{(E.14)}.$$

The variables from (E.13) and (E.14) represent the following: y_{it} is the number of prescription drugs obtained, x_{it} are the explanatory variables that determine y_{it}, β are the coefficients on x_{it}, $y_{i,t-1}$ is the lagged variable with a coefficient of α, g_i is the individual-specific term, and u_{it} is the error term. In the second equation which determines whether prescription drug consumption is positive, z_{it} are the instruments, which are assumed to be strictly exogenous conditional on g_i, η_i is the individual-specific term, and ε_{it} is the error term.

When $\text{cov}(\varepsilon_{it}u_{it})\neq 0$ OLS (or fixed effects) estimates are inconsistent, and a correction is needed that essentially accounts for an omitted variable. This involves calculating the inverse Mills ratio:

$$\lambda_{it}=\frac{f(v_{it})}{F(v_{it})} \qquad \text{(E.15)},$$

[5] We have explicit permission from the author to quote this work even though it is a work in progress.

and estimating:

$$y_{it} = g_i + x_{it}\beta + y_{i,t-1}\alpha + \lambda_{it}\rho + u_{it} \qquad \text{for } s_{it} = 1 \qquad \text{(E.16)}$$

to correct for sample selection bias. Equation (E.16) can either be estimated by difference-GMM or system-GMM. The sample selection correction method typically requires that the standard errors in the main estimation equation be corrected. However, correction of the standard errors in a dynamic panel data model is difficult, and the difference in standard errors between the adjusted and unadjusted output is likely to be small. Additionally, as can be seen below, two of the estimators suggested account for heteroskedasticity in the error term, and robust standard errors can be reported in STATA[6].

Ramón García et al. (2006) detail four different methods for calculating λ_{it}, depending on the assumptions regarding the exogeneity of the regressors, heteroskedasticity, and autocorrelation. Under the assumption of strictly exogenous regressors, no heteroskedasticity, and no autocorrelation, we can estimate lambda via:
(1) A year by year probit with contemporaneous regressors, or
(2) A random effects probit.

For a more general model the authors indicate that the selection equation can be estimated by:
(3) a reduced-form year by year probit, which includes all available lags of either the exogenous or predetermined variables
(4) a year-by-year probit in the spirit of Wooldridge's (2002) correction strategy

As autocorrelation is present in our estimation, we use procedure (4) to estimate the first stage probits. The reason for this choice is to maintain some consistency between the dynamic estimations from this section and the static estimations from Chapter 7. The Wooldridge (2002) estimation involves a separate probit for each year of the sample, and the regressors in the probit are the first stage independent variables along with their time means.

To determine whether a sample selection correction is needed, we follow a test developed by Wooldridge (1995). This involves calculating the Mills lambda and then including this correction term in the difference-GMM equation or system-GMM equation (if $\alpha \to 1$). If the coefficient on the Mills lambda is significant, then sample selection is an issue, and steps to correct for the problem need to be taken.

E.5.3. Results

This section of the Appendix provides the results of the dynamic fixed effects model that corrects for sample selection. The first-stage probit calculations were identical to

[6] These conclusions regarding the correction of standard errors in the main equation are from a personal communication with Sergi Jiménez-Martin, one of the authors in the Ramón García et al. (2006) paper.

the probits used in the Semykina and Wooldridge (2006) estimation in Section E.3 and thus are not provided here. The user-written command [*xtabond2*] (Roodman, 2003) was used to obtain the difference-GMM estimates for the restricted sample, i.e. the sample restricted to individuals with positive drug consumption.

As discussed above it is important to test for nonstationarity. We used the simple OLS test and the Breitung and Meyer (1994) modified Dickey Fuller test for the null hypothesis that the coefficient on the lagged dependent variable equals one. We reject the null hypothesis for both tests[7], indicating that we can proceed with difference-GMM estimation.

We also tested whether a sample selection correction was needed using the Wooldridge (1995) test. The results of the Wooldridge (1995) test were that the coefficient on the Mills lambda was significant (t=-4.90, p=0.000), indicating that sample selection is an issue.

There was also a possibility that some of the independent variables were endogenous or predetermined. We hypothesized that the socioeconomic status of the individual and morbidity were potentially correlated with the number of prescriptions she purchased. Using the difference Sargan test, we tested for the endogeneity of both of these variables separately and jointly, and in all cases we rejected the additional moment restrictions imposed by the endogeneity assumption[8].

Appendix Table E.4 lists the results of three different specifications based on the dynamic fixed effects model accounting for sample selection[9]. As highlighted in the table, Models 1 and 2 suffer from autocorrelation and identification problems. We tried a number of model changes to reduce these problems, including further lagging the dynamic variable, including lags of the other independent variables, restricting the number of lags of the dynamic variable, and restricting the instrument set. Model 2 is an example of the output when we lag the dependent variable up to seven periods. For Model 3 we attempted to correct for autocorrelation and identification problems through (i) restricting the number of lags of the dynamic variable to five periods and deeper[10] and (ii) including only the co-payment variable, the time variables, and the

[7] Using the simple OLS test, t=-1161 (p=0.000). Using the Breitung and Meyer (1994) test, t=-1100 (p=0.000).

[8] The result of the difference Sargan test for the exogeneity of socioeconomic position was 4,249 (p=0.000), the result of the difference Sargan test for the exogeneity of morbidity was 6,688 (p=0.000), and result of the difference Sargan test for the exogeneity of both socioeconomic position and morbidity was 10,633 (p=0.000). Because the assumption that a variable is endogenous is weaker than the assumption that a variable is predetermined, after rejecting the endogeneity of any variables, there was no need to test whether any variables were predetermined.

[9] We attempted to use the Windmeijer (2005) finite-sample correction for the variance of the two-step GMM estimator; however, the computation used up more memory than was available in the 64-bit Stata platform. Instead, we use the one-step estimator, which should provide similar results given that the efficiency gains from using the two-step estimator seem to be small (Bond, 2002).

[10] We also tried restricting the lags even further, but this still did not correct for the identification problems. Three is the minimum number of lags needed to reduce autocorrelation problems.

constant as instruments[11]. In the end, we were only able to eliminate the second-order autocorrelation problem, but identification still remained an issue with Model 3.

Appendix Table E.4. Dynamic estimates for the log of total number of prescription drugs obtained equation[a,b,c]

Explanatory variable	SS FE-Dynamic (Model 1)	SS FE-Dynamic (Model 2)	SS FE-Dynamic (Model 3)
lag of (log) number of drugs consumed, 1 period	0.268§ (0.001)	0.388§ (0.004)	0.362§ (0.121)
lag of (log) number of drugs consumed, 2 periods		0.048§ (0.002)	
lag of (log) number of drugs consumed, 3 periods		0.018§ (0.002)	
lag of (log) number of drugs consumed, 4 periods		0.005§ (0.002)	
lag of (log) number of drugs consumed, 5 periods		0.007§ (0.002)	
lag of (log) number of drugs consumed, 6 periods		0.008§ (0.002)	
lag of (log) number of drugs consumed, 7 periods		0.004§ (0.002)	
(log) drug co-payment	-0.074§ (0.001)	-0.177§ (0.003)	-0.069§ (0.021)
age between 65 and 74	0.000 (0.002)	0.009§ (0.003)	0.009 (0.021)
age between 75 and 84	0.009§ (0.003)	-0.009 (0.006)	0.310 (0.965)
second socioeconomic quintile	0.004§ (0.002)	0.004 (0.010)	4.455 (3.157)
third socioeconomic quintile	0.006§ (0.002)	0.009 (0.010)	1.883 (3.285)
fourth socioeconomic quintile	0.002 (0.002)	0.010 (0.011)	2.699 (1.658)
fifth socioeconomic quintile	-0.001 (0.002)	0.012 (0.012)	6.857 (4.670)
individual diagnosed with at least one of pre-defined high-cost and/or high-prevalence disease	0.107§ (0.002)	0.071§ (0.005)	-0.273 (0.914)
individual died this year	-0.082§ (0.002)	0.014§ (0.002)	-0.926 (1.014)
lambda	-0.574§ (0.003)	-0.660§ (0.006)	-0.118 (0.166)
year is 1995	-0.153§ (0.012)		-0.080 (0.073)
year is 1996	0.057§ (0.002)		0.011 (0.144)
year is 1997	0.298§ (0.005)		0.015 (0.213)
year is 1998	0.438§ (0.007)		-0.019 (0.287)
year is 1999	0.549§ (0.008)		0.056 (0.330)
year is 2000	0.682§ (0.010)		0.034 (0.402)

[11] We also tried restricting the instrument set to other variables, but this did not lead to any improvements in the model.

Explanatory variable	SS FE-Dynamic (Model 1)	SS FE-Dynamic (Model 2)	SS FE-Dynamic (Model 3)
year is 2001	0.798[§] (0.011)	-0.324[§] (0.026)	0.040 (0.475)
year is 2002	0.944[§] (0.013)	0.034[§] (0.002)	0.015 (0.547)
constant	1.072[§] (0.016)	0.130[§] (0.005)	0.061 (0.086)
Arellano- Bond autocorrelation test, AR(2) in first differences	16.84 (p-value = 0.000)	-6.86 (p-value = 0.000)	1.01 (p-value = 0.311)
Hansen test of overidentifying restrictions	1,734 (p-value = 0.000)	362.0 (p-value = 0.000)	48.33 (p-value = 0.000)
N	2,731,118	2,731,118	2,731,118
F-statistic	6,182	1,544	571.6
Prob > F	0.000	0.000	0.000

[a]standard errors in parentheses, [b]excluded dummy variables are age greater than 84, individual reports being in good health, individual has not been diagnosed with at least one of the pre-defined high-cost and/or high-prevalence diseases, year is 1992, [c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample
[§]significant at the 5% level, *significant at the 10% level

The results are not stable over different specifications, and because of this, we will not offer an explanation of the results. It is important to note that when more lags are added to the model (Model 2), the variables change significantly and even switch signs in some cases (age and income, for example). In particular, the coefficients on variables that are not included in the instrument set in Model 3 vary significantly between Models 1 and 3. For instance, while age has a negative effect in Model 1, it has a much larger positive effect in Model 3. The same is also true for morbidity and the variable indicating whether the individual died in the given year.

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