An Empirical Investigation of Changes in Asset Ownership Patterns: Microeconomic Aspects and Macroeconomic Consequences

Sònia Muñoz

PhD Thesis, Department of Economics

London School of Economics and Political Science

University of London

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Abstract

This thesis provides an empirical investigation of the causes and consequences of shifting asset ownership patterns.

Chapter 1 analyses the dynamics of the ownership structure of risky asset portfolios. The results show that household portfolio behaviour is better explained by infrequent decisions on their portfolio, rather than continuous adjustments as standard theory predicts. The model shows that there is strong persistence in both risky and safe asset holding decisions since households develop a taste for the assets that they hold and do not change portfolios frequently.

Chapter 2 evaluates the increasing exposure of households to risky financial assets in Europe and the impact of holdings and revaluations of risky assets on consumption, particularly as these are becoming increasingly widely held. The analysis provides evidence of wealth effects in two countries that differ dramatically in their financial structure and capital markets, unlike high frequency studies which have found little such effect.

Chapter 3 considers another main household asset, real estate. The chapter looks in depth into the United States housing market and tests the importance of wealth effects resulting from house price movements. I find evidence of strong housing wealth effects that is robust over three different estimation methods that allow for heterogeneity among states.

To my Parents

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Introduction

Motivation

One of the more surprising characteristics of financial markets is the low proportion of households holding risky assets. In 2000, less than half of households in the United States (US) owned risky assets, with the percentage of risky asset owners in Europe even lower. For instance, only 21 percent of households owned risky assets in Italy in the same year (see Table below). This is at odds with the classical theory pioneered by Merton (1969) and Samuelson (1969) that implies that, when risk aversion is finite, it is always optimal to take on some risk via financial markets. To explain this puzzle, it is necessary to deviate from the standard theory of complete markets. A factor that may explain such a deviation, and that has received much attention, in addition to the specific characteristics of households, is the existence of transaction costs. Since households have to incur a fixed cost to own risky assets, it might be optimal for some of them (the poorest and least well informed) not to invest at all under decreasing absolute risk aversion. In this respect, once a household has actually purchased the asset, and thereby met the associated transaction cost, there is a higher likelihood that the household will hold the same asset in the next period. This is often referred to as structural state dependence. There are also interindividual variations in behaviour which cannot be explained by their observed experiences, but can have an effect on portfolio choices. These factors, however, do not fully explain the stockholding puzzle.

	1991	1995	2000
United States	31.8[1]	40.1	48.6[3]
United Kingdom	22.1[2]	27.5	26.1
Italy	8.5	12.3	21.0

Note: Percentage of households owning risky assets (risky bonds or/and equity).

The set of risky assets is defined on Table 2.2 and 2.3.

[1]1989.[2]1988. Only equity. Family Expenditure Survey. [3]1998.

Sources: Survey of Consumer Finances, British Household Panel Survey, and Bank of Italy Survey of Household Income and Wealth, respectively.

An interesting, but less studied, feature of household portfolio behaviour is the infrequency of portfolio allocation changes. Most households do not make frequent changes to their portfolio allocations. Instead, they appear to acquire a taste for certain assets and then retain them regardless of the optimal portfolio choice. This implies that incentives to switch to a different asset may not be sufficient to shift a household from its habitual asset mix, and the individual will keep the same portfolio for a long time. This persistence will fade away only slowly. Modelling dynamic choice (state dependence, habit persistence and unobserved heterogeneity) in a manageable framework is still a challenge for researchers. It is however essential for a better understanding of portfolio behaviour and to resolve the stockholding puzzle.

Large movements in risky asset prices in industrialized countries, coinciding with large swings in growth rates, have led to renewed interest in the question of why the speed and magnitude of a monetary impulse on economic activity differs from country to country. These differences seem to depend in part on dissimilarities in financial structure and on the portfolio composition of households and firms, as well as liquidity constraints affecting consumption directly. Capital markets in Europe, for example, are rather heterogeneous. Stock markets and privately issued debt markets are well developed in some European countries like the United Kingdom (UK), while in Italy and Germany these markets are still emerging. Developments in financial structure have differed over recent years, with a rapid growth of non-bank intermediaries in some countries, leading to changes in the composition of assets and liabilities of households and firms. Moreover, risky asset ownership has broadened in general, but at different rates across countries. While 27 percent of households in the UK held risky assets in 1995, only 12 percent did in Italy. These percentages, however, have been converging and in 2000 they were 26 and 21 respectively. These developments have led to renewed interest in the role of risky assets in helping to explain consumption behaviour. A growing body of research, both at the macro and micro level, supports the view that increases in wealth should boost consumption and investment. Yet our understanding of the empirical relationship between these variables still seems incomplete.

There has also been considerable attention in both the UK and US, on the role of housing prices and the effect of rising housing prices in sustaining consumption following the US stock market crash. The apparent strength of housing prices has been explained by the drop in mortgage interest rates and by a combination of a strong housing demand and the low elasticity of housing supply. Moreover, home equity remains the cornerstone of household wealth, even among the majority of homeowners who also hold risky assets. Around 50 percent of homeowners hold at least 50 percent of their wealth in home equity. Interestingly, property prices are much less volatile than share prices, leading to less uncertainty surrounding gains and losses in property wealth. It is, therefore, not surprising that shifts in housing prices cause strong reactions among the general public. It is still unclear, however, how far house price developments feed back into aggregate spending. Determining the relative magnitude of wealth effects is difficult, since different forces go in opposite directions. Downsizers are better off when housing prices increase relative to other prices and can therefore increase their consumption. At the same, first-time buyers and upsizers might respond to the increase of housing prices by reducing their consumption.

Related Literature

The stockholding puzzle has been well studied in the literature following King and Leape (1998). Two recent books, Guiso, Haliassos and Jappelli (2002, 2003), summarize theoretical and empirical knowledge on household portfolio behaviour. Guiso, Haliassos and Jappelli (2002) examine (1) the status of theoretical knowledge on the structure of household portfolios, (2) the main tools of analytical, numerical and econometric analysis, and (3) a comparative analysis of household portfolios in the United States, United Kingdom, Italy, Germany and the Netherlands. Building on this framework, Guiso, Haliassos and Jappelli (2003) compare stockholding in Europe, adding France to the list of European countries studied. The econometric framework used in that book is the binomial probit model, accounting for unobserved heterogeneity with panel data. Chapter 1 of this thesis builds upon this literature, adding two dimensions to this framework: (i) the household portfolio decision is treated as a multinomial problem, in keeping with its nature and (ii) state dependence, habit persistence and unobserved heterogeneity are all included in a manageable framework based on the Börsch-Supan and Hajivassiliou (1993) model[1].

Alongside this literature, an active area of research has studied the existence of wealth effects from risky assets. Poterba and Samwick (1995) and Ludvingson and

[1]Perraudin and Sorensen (2000) use a multinomial framework but do not allow any time-varying correlation.

Steindel (1999) are examples at the aggregate level, and Parker (1999), Attanasio, Banks and Tanner (2002) and Attanasio (1998) at a micro level. As an empirical matter, a consensus has emerged to use microdata in order to understand how risky assets affect consumption. Yet, this evidence has yielded mixed results and no comparative studies have been undertaken to draw strong conclusions about wealth effect similarities and differences among countries. Chapter 2, to my knowledge, is the only microeconomic comparison done for two different countries using relatively similar datasets and the same microeconometric methodology. The econometric model of this chapter also nests two puzzles, the excess sensitivity puzzle (see Zeldes (1989)) and the stockholding puzzle, that have been always studied separately. Partly as a result, I can show that there is evidence of wealth effects in both countries (Italy and the UK).

Chapter 3 borrows from the dynamic heterogeneous cointegrated panel data literature (Pesaran, Shin and Smith (1999), Im, Pesaran and Shin (2003), Mark, Ogaki and Sul (2003), and Pedroni (1999)) and focuses on the real effects of housing prices on consumption. Previous analyses of housing prices in the US have either focused on microdata (for instance, McFadden (1994a, 1994b)) or on specifications omitting long-run relationships (for instance, Case et. al. (2001)), leading to opposite results and leaving some ambiguity in the interpretation of their statistical results. The chapter uses three different estimation methods that allow for heterogeneity among states and calculates an elasticity of consumption to housing prices ranging from 0.15 to 0.23. Although this result is not surprising in itself, it is at least obtained using efficient ways of modelling state variables such as consumption and housing prices.

Overview and main results

This thesis provides an empirical investigation of some international changes in asset ownership patterns and focuses on their microeconomic aspects and macroeconomic consequences. Consumer attitudes towards saving, risk bearing and uncertainty are crucial to understanding the behaviour of financial markets and therefore the monetary transmission mechanism. In this fashion, I explore the dynamics of the ownership structure of risky asset portfolios in the last decade. I then ask whether holdings and revaluations of risky assets affect consumption, particularly as these are becoming increasingly widely held, and how such effects appear in two countries that differ dramatically in their financial structure and capital markets. Finally, I consider another asset, real estate, that seems to have played an important role in smoothing the recent downturns in countries such as the US and UK. I explore whether house price developments feed back into consumption and how important this effect is.

I address these questions in three chapters.

Chapter 1 addresses, and answers, a question that lies at the heart of the stockholding puzzle: the infrequency of portfolio allocation changes. The paper uses six waves of the Bank of Italy Survey of Household Income and Wealth (SHIW) panel data to analyse the decision to hold safe and risky assets and its dynamics in the last decade in Italy. The household portfolio decision whether to hold risky financial assets is treated as a multinomial problem by applying the method of maximum smoothly simulated likelihood for a multinomial probit with autocorrelated errors. The results can be summarized as follows:

1. There is strong persistence in both risky and safe asset holding decisions. The results show that household portfolio behaviour is better explained by infrequent decisions on their portfolio, rather than continuous adjustment as standard theory predicts. Households develop a taste for the assets that they

hold and do not change portfolios frequently.

2. The model mainly works through time-varying components rather than through time-invariant ones, suggesting that habit formation is driving the behaviour of households.

3. I find both "true" state dependence and taste persistence in the decision to hold risky and safe assets.

4. Ignoring intertemporal linkages biases some estimation coefficients, leading to an underestimate of the effects of education and to an overestimate of the true state dependence of holding no financial assets.

5. Education levels, labour income, age and wealth turn out to be more important for holding stocks than for risky bonds. The larger the family, the less diversified the portfolio is. Finally, a high unemployment rate strongly decreases the likelihood of holding risky bonds.

The contribution of the chapter is the inclusion of intertemporal correlations between unobserved determinants of the portfolio allocation decision in a multinomial model of household portfolio participation.

Chapter 2 evaluates the increasing exposure of households to risky financial assets in Europe and the impact of these assets on consumption. The paper employs an endogenous switching model with bivariate switching[2] -where the switch depends on two criterion functions controlling for the endogeneous process that is responsible for liquidity constraints and risky asset ownership - to estimate wealth effects in two

[2]An endogenous switching model with univariate switching was used by the author to analyse the effects of a banking crisis on bank credit to the private sector for a panel of developing, developed, and transition economies for the period 1970-1998. The model illustrates how the behaviour of the bank credit function changes during a banking crisis, reflecting a generalized disruption in the stability of behavioural parameters (Muñoz, S. (2000), "The Breakdown of Credit Relations under Conditions of a Banking Crisis: A Switching Regime Approach", *IMF Working Paper* No. 135.). This paper was prepared during the author's PhD at the London School of Economics, but it is not included in this thesis since the topic is not directly linked to the main theme of the thesis. The econometric methodology is in the same spirit as the one used in Chapter 2.

countries with a different financial structure, Italy and the UK. The basic model is divided into a discrete and a continuous part that characterizes consumption demand and corrects for selectivity bias.

The first part is modelled using bivariate probit estimation and shows that there is a negative relationship between the errors in the equations to explain holdings of risky assets and liquidity constraints. The model suggests that households exposed to liquidity constraints and facing uncertain liquidity needs will tend to hold relatively liquid and safe assets. There are some differences in consumer behaviour in these two countries: employment of the spouse seems to be a critical factor in avoiding liquidity constraints and holding risky assets in Italy, while homeownership (with or without a mortgage) plays a major role in the UK.

I then ask how consumption responds to holdings of risky assets in the second part of the model. I use the life-cycle model as a conceptual framework throughout the chapter, stressing the role played by wealth following Modigliani and Ando (1963). The analysis of consumption functions presents a variety of problems that range from the availability and reliability of consumption data, to some more subtle econometric problems. Consequently, I use household data for each country for the same period and, when studying wealth effects, follow two approaches: (1) Euler equations to estimate structural parameters and test the life-cycle model and (2) consumption functions to assess the importance of wealth effects. The chapter provides evidence of wealth effects in both countries, unlike high frequency studies which find little effect, with a marginal propensity to consume out of financial assets of 0.04. Results are mixed with respect to liquidity constraints. Findings from Euler equations do not show excess sensitivity to current labour income in any of the countries, but consumption function equations show evidence of liquidity constraints in Italy and habit formation in the UK.

Chapter 3 looks in depth at the US housing market and tests the importance of wealth effects resulting from house price movements. Increases in home prices have outpaced overall inflation for the last decade, so widespread home price inflation has lifted household net worth. Since housing prices are locally driven, I study the housing wealth effect using state level quarterly data for the 50 US states and the District of Columbia. Due to the considerable heterogeneity in state level behaviour, fixed effects estimators that constrain intercepts, short-run coefficients and error variances lead to misleading inferences. Consequently, I use a recently developed methodology for dynamic heterogeneous cointegrated models for panel data, to study housing wealth effects from the 1970s to the 1990s.

The results of this chapter are three-fold: First, the study supports the existence of unit roots in housing prices and a cointegrating relationship between consumption, income and housing wealth at the state level. Secondly, I find evidence of a strong housing wealth effect. More importantly, this finding is robust over three different estimation methods that allow for heterogeneity among states. Thirdly, I show that differences in the age of population and homeownership play a role in the link between consumption and housing prices, although they do not satisfactorily explain all, or even a large proportion, of the different responses of consumption to housing prices among states.

Chapter 1

Habit Formation and Persistence in Individual Asset Portfolio Holdings

This chapter uses six waves of the Bank of Italy Survey of Household Income and Wealth (SHIW) to explore the dynamics of asset portfolio ownership. The household asset portfolio decision is a choice among discrete alternatives, and I model the problem in a multinomial framework. I discuss the well-known stockholding puzzle and focus on a particularly important feature of household portfolio behaviour: the infrequency of portfolio allocation changes.

I find evidence of strong unobserved heterogeneity through time-varying error components, which I interpret as taste persistence in both the risky and safe asset participation decisions. I estimate the model using the method of maximum smoothly simulated likelihood.

1.1 Introduction

In most developed countries a large fraction of households do not own risky financial assets. This fraction is, however, decreasing slowly over time. In Italy for instance, 89 percent of households did not hold any risky financial asset in 1991 but this fraction had decreased to 73 percent in 2000. Since there was previously strong persistence in portfolio decisions, some analysts have even suggested that the shift from safe assets to risky assets could be destabilizing to the economy and financial markets.

The stockholding puzzle has been widely studied in the literature, although no study has focused on the role of habit formation on household portfolio decisions in a multinomial context. I believe that it is important to model the choice this way because households may stay inside or outside of the stock market even if it is not appropriate at that point in time. In addition, since households may get a taste for certain investments and keep them, habit formation introduces state dependence. The contribution of this chapter is to show that habit formation plays a role in the decision to shift from zero financial assets to safe financial assets (checking accounts, savings accounts, certificates of deposits, postal deposits, postal bonds, treasury bonds and treasury certificates) and to risky financial assets (long-term government bonds, corporate bonds, investment funds and equities). To estimate the model, I first aggregate assets into two categories: risky and safe. Since a high level of aggregation is problematic - important differences exist among assets - I also consider a more disaggregated model where I differentiate between risky bonds, stocks and safe assets. In doing so, I am able to investigate the dynamics of the interaction between these kind of assets.

To this end, maximum smoothly simulated likelihood estimation is used for a multinomial probit with autocorrelated errors, as developed by Börsch-Supan and Hajivassiliou (1993). The autocorrelated errors - unobserved heterogeneity through time-varying error components - allow for the habit formation or taste persistence that households exhibit when deciding whether to buy safe assets or risky assets. The model allows us to distinguish taste persistence from time-invariant unobserved heterogeneity.

In order to study this dynamic participation problem panel data is required. Because the existence of incomplete markets and heterogeneity of preferences affects portfolio choices directly, household data are necessary for this analysis of the dynamics of portfolio choice behaviour. The Bank of Italy Survey of Household Income and Wealth (SHIW) has complete information on portfolio decisions over time through six waves for the period 1989 to 2000. The panel is unbalanced with 22,591 observations and 7,588 households who participate in at least two waves. To the best of my knowledge, there is only one other panel dataset with detailed information on ownership of assets over time, the Dutch CenTER Savings Survey.[1]

The chapter is organized as follows: Section 2 reviews those papers that model household asset portfolio decisions, including the limited participation in financial markets. It also introduces the importance of habit formation in household financial decisions. Section 3 presents the estimation procedure and section 4 describes the data and reports the results. I start with a simple benchmark model before moving to the multiperiod multinomial probit model with heterogeneous and autoregressive unobservables. Section 5 presents conclusions.

1.2 Habit Formation in Household Portfolios

The financial asset allocation decision of households has been extensively studied in the last two decades. While some of the studies discuss the rapid increase in the

[1] Ameriks and Zeldes (2001) use the TIAA-CREF (Teachers Insurance and Annuity Association-College Retirement Equities Fund) panel dataset. This data has the drawback that the sample is endogenous and unrepresentative. In addition, it does not contain information on household characteristics, so it would not allow the current analysis to be undertaken.

fraction of households owning equities (US and UK), others analyse the stockholding puzzle (for example Mankiw and Zeldes (1991), Poterba and Samwick (1995), Haliassos and Bertaut (1995), Vissing-Joergersen (2002), and Bertaut and Starr-McCluer (2002)). However, these studies are based on cross sectional data, ruling out dynamic considerations.

An interesting feature of household portfolio choice is the infrequency of portfolio allocation changes. This trend is in contrast with the standard portfolio choice model (without transaction costs) inherited from Samuelson (1969) and Merton (1969, 1971), which implies that individuals rebalance their portfolios each period. This rebalancing can be done by changing the allocation of the asset holdings or by changing the allocation of the flow of new contributions. A recent study of the US by Ameriks and Zeldes (2001) finds that almost one half of their sample made no active changes to their portfolio allocations for a period of 10 years. They show that households make few changes in either the allocation of stocks or flows, which they interpret as owing to the presence of transactions costs or inertia. They consider different types of transactions costs: minimum balance requirements, per-trade fees and information costs (costs of purchasing assets and monitoring costs).

The reluctancy of households to switch from holding one basket of assets to another may be associated with household specific historical characteristics. For example, the probability that a household holds safe assets may depend on the probability that it had already held safe assets in the previous period, the current realization being a function of the past one. The same type of state dependence may apply to the holdings of risky assets. These intertemporal linkages can be of two types: True (observable) state dependence and (unobservable) taste persistence, which can be confused with spurious state dependence. The former can happen as a consequence of an event that has marked the behaviour of a specific household and makes it allocate holdings in a certain way. Another household in the same position but not having experienced such an event will behave differently. The latter is related to household tastes for certain assets, hence may be interpreted as habit formation or taste persistence.

In order to relate the above intertemporal linkages to the portfolio allocation decision it might be helpful to go back to the standard model of lifetime consumption and portfolio choice of Samuelson (1969) and Merton (1969, 1971). In this model agents live off income generated by their invested wealth, and thus non-participation in the stock market, or entry or exit into that market, over time is not observed. The optimal portfolio of risky assets, and the split between risky and riskless assets, will vary across agents with different preferences, wealth and investment horizon. Conditions on return distribution/utility functions were derived, under which differences in investment horizon and wealth across agents should not lead to differences in portfolio choice. As shown by Samuelson (1969) investment horizons are irrelevant if agents face a constant investment opportunity set (i.i.d returns). CRRA preferences are sufficient for wealth not to matter. While return unpredictability and deviations from CRRA utility could explain some of the heterogeneity in the share of financial wealth invested in stocks across households and time, it is unlikely that these features can explain all such differences. While return predictability can generate large changes in the optimal share of financial wealth invested in equities over time, such changes would affect all households, in contrast to the considerable idiosyncratic (household specific) movements in equity portfolio shares.

So differences in risk aversion and transactions costs can help explain the remaining heterogeneity in observed portfolio choices. It is well-known that the parameter α in the standard CRRA utility function: $u(c) = \frac{c^{1-\alpha}}{1-\alpha}$ controls both the relative risk aversion and the elasticity of intertemporal substitution (EIS), which are different aspects of individuals' tastes. Much evidence documents significant heterogeneity in the EIS across the population. It has been argued that the non-participation phenomenon, due to transaction cost, should be considered part of the solution to the equity premium puzzle because the consumption growth of nonstockholders covaries substantially less with the stock return than the consumption growth of stockholders (see Mankiw and Zeldes (1991), Vissing-Jorgensen (2002), Attanasio, Banks and Tanner (2002)). However, heterogeneity in relative risk aversion has been not studied. The number of households who choose to enter the stock market or to change the number of stocks held in response to a shock to nonfinancial income, will depend on how many households are close to the point where it becomes worthwhile to adjust according to their taste preferences.

Miniaci and Weber (2002) review the methodological issues surrounding estimation of portfolio choice models from survey data. They point out that a panel structure is necessary to estimate portfolio choice models, propose the use of binomial probit models, and state the different mechanisms that can lead to limited participation. These are state dependence, unobserved heterogeneity, serial correlation in shocks, and time-varying observable characteristics including demographics. They then illustrate the significance of the second, third and fourth reasons for limited participation by estimating a binomial probit/logit with random effects/fixed effects for three waves of the SHIW. Guiso and Jappelli (2002) also estimate a binary probit model with random effects to study participation in risky financial assets using three waves of the SHIW. However, they ignore any state dependence in their analysis.

Vissing-Joergense (2002) estimates the first type of state dependence, namely true state dependence. In this sense, Vissing-Joergense (2002) introduces four different costs of stock market participation in the model: an entry cost, a fixed transaction cost, a proportional transaction cost, and a per period participation cost. The first three costs lead to true state dependence in the stock market participation decision and in the proportion of financial wealth invested in stocks. In the empirical part she uses the two waves of the Panel Study of Income Dynamics (PSID) with portfolio data (1984, 1989), adds the lag of participation in 1984 in a simple probit regression for 1989 and finds a significant positive coefficient for true state dependence. In other words, she finds that the likelihood of participation in the stock market in one period is strongly correlated with participation in the previous one. When she accounts for unobserved individual effects, the covariance of the error term for participation in 1984 and 1989 is not significant. The problem with her estimation is that she imposes a binary choice model and uses only two points of observation. The panel structure is too short to allow for taste persistence, which is well known to suggest state dependence when it is in fact absent.

Alessie, Hochguertel and van Soest (2001) also estimate the first type of state dependence using the Dutch CentER Saving panel survey. They use dynamic binary choice panel data models to explain the dynamics of mutual fund and stock ownership. In their model, correlated random effects account for unobserved heterogeneity, and dummies for lagged ownership of each asset type capture genuine state dependence. Errors, however, are assumed to be independent over time (the authors point out that first order autocorrelation was allowed for in some specifications but turned out to be insignificant).

Miniaci and Ruberti (2001) estimate a model of random effects suggested by Arellano and Carrasco (2003) using Generalized Method of Moments (GMM), where the assumption of strict exogeneity of income is relaxed. They find very strong true state dependence.

One drawback of these studies is that they treat household portfolio choices as a binomial problem when they are by nature multinomial. In contrast, Perraudin and Sorensen (2000) implement a multinomial logit model in order to study the demand of risky assets. They assume that all households hold some quantity of money and that households choose to hold either money alone, money and bonds, or stocks, bonds and money. The logistic model does not allow for some portfolios to be closer substitutes than others; and this property is justified on the grounds of the computational complexity of the multinomial probits. Moreover, since US cross-sectional data are used, the existence of time-varying correlation is ruled out.

Consequently, none of these approaches include both time-invariant unobserved heterogeneity (household effects) and time-varying unobserved heterogeneity (habit formation). Both features can explain why ownership of assets in period t is correlated with ownership of assets in period $t + 1$ and a less restrictive model could suggest the extent to which this correlation is due to one or the other. In addition, the previous literature has imposed the assumption of irrelevant alternatives (IIA) -zero correlation among alternatives- when it often seems unlikely. Modelling these features is the purpose of what follows.

1.3 The model: Multiperiod Multinomial Probit with Autocorrelated Errors and Unobserved Heterogeneity

This section of the chapter starts with a benchmark model similar in spirit to Perraundin and Soerensen (2000) and uses cross-sectional data multinomial logit with three alternatives to estimate a model of asset holdings. I then proceed to relax key assumptions that have been made in the literature. One can think of the decision of holding assets as a discrete choice problem in which households see some choices as closer substitutes than others (see Börsh-Supan et al. (1992) for a similar discussion of elderly living arrangements). Hence correlation among unobserved determinants of financial asset holding at a point in time is likely. The existence of *intratemporal correlation between unobserved determinants* is a violation of the assumption of the independence of irrelevant alternatives (IIA).

Another assumption that has been imposed in papers on household portfolio choices is that of no *intertemporal correlation of unobserved determinants*. The decision of whether to hold assets or not is clearly an intertemporal choice. Because of transaction and information costs, households hold or do not hold assets even if it is not appropriate at that point of time. That is, households may be substantially out of long-run equilibrium if a survey interview occurs shortly before or after the switch between asset holdings. In addition, households may get a taste for certain investments and keep them. This kind of habit formation may introduce taste dependence.

Börsh-Supan et al. (1992) distinguish between two components of intertemporal linkages: First, linkages through unobserved person-specific attributes: that is, *unobserved heterogeneity through time-invariant error components*. Second, *unobserved heterogeneity through time-varying error components*, for example, an autoregressive error structure. The focus of this paper will be the second, since my interest is in habit formation or taste persistence.

To my knowledge, all studies of household portfolio allocation that use multinomial probit or logit models have assumed no intertemporal correlation between unobserved determinants of the portfolio allocation decision. In my first model, households face a choice of three alternatives: holding risky financial assets; safe financial assets; or no assets. In order to cope with aggregation problems, my second model features households choosing between five alternatives: stocks and risky bonds; stocks; risky bonds; safe assets; or no assets.

1.3.1 Cross-Sectional Multinomial Logit (MNL)

In order to describe the dynamic nature of the participation decision I start from a static multinomial model and build up to a multiperiod multinomial model.

The multinomial logit model can be derived from the theory of random utility maximization. We assume that consumers are rational, so that they make choices that maximize their perceived utility subject to constraints on expenditures. Let us suppose that the consumer faces M_i choices and define y^*_{jit} as the level of indirect utility associated with the jth choice. The underlying response variable y^*_{jit} is defined by the regression relationship:

$$y^*_{jit} = x'_{jit}\beta_j + \epsilon_{jit} \tag{1.1}$$

where x_{jit} is the vector of individual characteristics for individual i and ϵ_{jit} is a residual that captures unobserved variations in attributes of alternatives and errors in the optimization strategy of the consumer.

The maximization vector in this case is:

$$y_i = argmax_k\{y^*_{i1}, .., y^*_{ik}, ..., y^*_{iM_i}\}, \tag{1.2}$$

In other words, I observe the index of which ever alternative gives the highest utility for individual i.

For full efficiency maximum likelihood methods need to be used. The probability density function (PDF) for an individual i choosing alternative k is as follows:

$$f(y_i|x_i) = prob(y_i = k|x_i), \tag{1.3}$$

Since this means that the utility of the k'th option was the highest, I can express the probability of a choice sequence in terms of integrals over the differences between the unobserved utility components and the chosen alternative:

$$
\begin{aligned}
f(y_i|x_i) &= prob\left(\begin{array}{cc} y^*_{i1} - y^*_{ik} \leq 0 & \\ \dots & |\, x_i \\ y^*_{iM_i} - y^*_{ik} \leq 0 & \end{array}\right) = \qquad (1.4) \\
&= \int_{D(y_i)} f(y^*_i|x_i, \beta, \sigma) dy^*_i.
\end{aligned}
$$

where $D(y_i) \equiv \{y^*_i | y^*_{i1} - y^*_{ik} \leq 0, ..., y^*_{iM_i} - y^*_{ik} \leq 0\}$.

To overcome the problem of high-dimensional integrals in limited dependent variable (LDV) models, McFadden (1974) showed that under the assumption that ϵ_{jit} is distributed iid, "extreme-value of Type II" implies a closed form expression for equation 1.4:

$$
prob(y_i = k|x_i) = \frac{exp(x_i' \beta_k)}{\sum_{j=1}^{M_i} exp(x_i' \beta_j)}. \qquad (1.5)
$$

which is the probability that an individual with characteristics i will choose the k'th alternative with some normalization (such as $\beta_{M_i} = 0$).

The MNL model generalizes the McFadden (1974) logit model and allows agent-specific characteristics to determine the choice probabilities. To prevent terms that do not vary across alternatives from falling out of the choice probability, I will create a set of dummy variables for the choices and then allow the coefficients to vary across the choices rather than the characteristics.

The main shortcoming of the MNL model is that it possesses the IIA assumption (zero correlation among alternatives). It predicts "too high a joint probability of selection for two alternatives that are in fact perceived as similar rather than independent by the individual".[2] This is inappropriate for modelling the household

[2]Maddala (1983), p. 62.

portfolio allocation problem.

1.3.2 Allowing for alternatives across different branches to have different substitutabilities: Nested Multinomial Logit (NMNL) model

The nested multinomial logit (NMNL) model developed by McFadden (1981) partially solves the problem stated above since it allows for alternatives across different branches to have different substitutabilites by involving the sequential combination of the multinomial logit model. In order to clarify terms, Figure 1.1 shows the choice problem that households face in the model.[3] This tree has two branches, financial assets and no financial assets. The first branch has two elemental alternatives: risky assets and safe assets. The second branch has only one elemental alternative: no financial assets. Other trees were tried but this one gave the most consistent results. Therefore, the household may decide whether to hold financial assets or not, and then if he chooses to hold financial assets he may decide to buy only safe assets, or risky and safe assets.

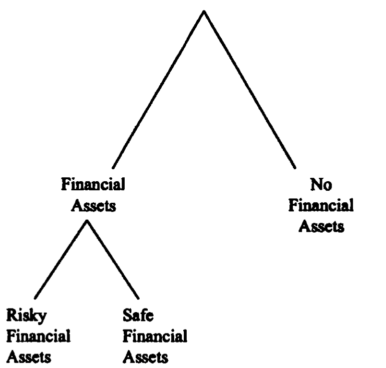

Figure 1.1: Choice Problem Tree

[3]Section 1.4.3. will analyse a more disaggregated model where a tree with five alternatives is modelled. The household faces the choice of holding stocks and risky bonds, stocks, risky bonds, safe financial assets and no financial assets.

Let us suppose a household faces a portfolio problem, with the choice of being a financial assetholder or not (i=1,...,C=2) and the possibility of holding risky assets or safe assets (j=1,...,N=2) in the first case and no financial assets in the second case. A consumer will therefore have a utility U_{ij} for alternative (i, j), which is a function of the consumer's characteristics (such as age, family size, and disposable income) and each consumer will choose the alternative that maximizes his utility.

The probability P_{ij} that the (i,j)'th alternative will be chosen is as follows:

$$P_{ij} = \frac{exp(x_{ij}'\beta)}{\sum_{m=1}^{c}\sum_{n=1}^{N_m} exp(x_{mn}'\beta)}, \tag{1.6}$$

I can write

$$P_{ij} = P_{j/i} \cdot P_i, \tag{1.7}$$

and define an *inclusive value* I_i as follows:

$$exp(I_i) = \sum_{j=1}^{N_i} exp\,(x_{ij}'\beta)\,. \tag{1.8}$$

The two terms of equation 1.7 can then be written as follows:

$$P_{j/i} = \frac{exp(x_{ij}'\beta)}{exp(I_i)}, \tag{1.9}$$

$$P_i = \frac{exp(I_i'\theta)}{\sum_{m=1}^{c} exp(I_i'\theta)}. \tag{1.10}$$

I will maximize P_{ij} with respect to the two parameters β and θ. The nested multinomial logit model is obtained by allowing the inclusive values to have a coefficient θ in the unit interval.

McFadden (1978) showed that the nested multinomial logit model is also consistent with stochastic utility maximization provided $0 < \theta \leq 1$, and that the coefficient of the inclusive value gives an estimate of the similarity of the observed choices at the lower level of the tree structure.

The main advantage of the NMNL is that while being computationally no more involved than the MNL model, it allows for alternatives across different branches to have different substitutabilities, that is, the IIA property holds only for alternatives on the same branch.

1.3.3 Allowing for differing substitutabilities between alternatives and adding intertemporal linkages: Multiperiod Multinomial Probit (MPMNP)

A natural alternative to the Nested Multinomial Logit is a Multinomial Probit (MNP) model. This allows differing substitutabilities between all asset holding alternatives faced by the household, rather than being constrained by hierarchical structures (like the NMNL model). It is computationally burdensome, however, both because of the difficulty of computing the multinomial integral and the difficulties involved in estimating the covariance matrix caused by the fact that the likelihood function is often found to be 'flat' in the region around the maximum likelihood estimates. In addition, extending the household portfolio choice problem to a multiperiod context requires the estimation of a multinomial choice model with unobserved determinants that are correlated across alternatives and over time. This leads to an even higher dimensional integration of the associated likelihood functions. A simulation estimation method is then necessary to tackle the problem.

I follow Börsch-Supan et al. (1992) and assume in this case that the space of possible outcomes is the set of N^T different choice sequences $\{i_t\}, t = 1, ..., T.$, and y_{it} is the maximal element over the utilities in $\{y_{jt} \mid j = 1, ..., t\}$. As above, what will be important for the household portfolio decision is the difference in utility levels between the best choice and any other choice, since the optimal choice delivers maximum utility. Let us define D error differences stacked in a vector z with joint cumulative distribution function F. Then:

$$z_{jt} = \epsilon_{jt} - \epsilon_{it} \text{ for } i = i, j \neq i_t. \tag{1.11}$$

where $D = (N-1) \times T$.

By comparing two indirect utilities (see equation 1.1), I obtain:

$$y_{it} > y_{jt} \longleftrightarrow x_{it}\beta + \epsilon_{it} > x_{jt}\beta + \epsilon_{jt},$$

$$x_{it}\beta - x_{jt}\beta > \epsilon_{jt} - \epsilon_{it} \longleftrightarrow x_{it}\beta - x_{jt}\beta > z_{jt}.$$

so that the maximum error differences can be as large as the difference in the deterministic utility components. The area of integration is

$$A_j(i) = \{z_{jt}| -\infty \leq z_{jt} \leq x_{it}\beta - x_{jt}\beta\} \; for \; j \neq i, \tag{1.12}$$

and the probability of choice sequence $\{i_t\}$ is

$$P(\{i_t\} \mid \{X_{it}\}; \beta, F) =$$

$$\int_{\{z_{j1} \in A_j(i_1)|j=1,\ldots,I,j\neq i_1\}} \times \ldots \times \int_{\{z_{jT} \in A_j(i_T)|j=1,\ldots,j\neq i_T\}} dF(z), \tag{1.13}$$

where the area of integration is $A_j = A_j(i_1) \times \ldots \times A_j(i_T)$, and where F is the cumulative distribution function that is assumed to be multivariate normal.

The likelihood function is

$$\pounds(\beta, M) = \prod_{n=1}^{N} P(\{i_{t,n}\} \mid \{X_{it,n}\}; \beta, M),$$

where n denotes an observation in a sample of N individuals and M is the covariance matrix.

The integral in 1.13 does not have a closed-form solution and its calculation will involve at least one D-dimensional integral for each observation and each iteration in the maximization process.

Moreover, I am assuming a multivariate normal distribution of the z_{jt} in equation 1.11 with a covariance matrix M that has up to $(D+1) \times D/2 - 1$ parameters to identify.[4] These covariance elements are the correlations among the z_{jt} and

[4]Much fewer in practice due to the modelling of M.

the variances.[5] Consequently, as noted above, I adopt the method of Smoothly Simulated Maximum Likelihood (SSML) estimation using the Geweke algorithm described in Börsch-Supan and Hajivassiliou (1993).[6]

The covariance matrix M can be specified in different ways:

1. $M = I$

This specification leads to a pooled cross-sectional probit model, ignoring intertemporal linkages and subject to IIA. The $D = (I-1) \times T$ dimensional integral of the choice probabilities factors into D one-dimensional integrals and there are no unknown parameters in M.

2. Interalternative correlation

M will be a block diagonal structure with $T \times (I-1)$ dimension blocks. In this case, $(I-2)$ variances and $(I-1) \times (I-2)/2$ covariances can be identified in M.

3. Intertemporal linkages: Random Effects

M will have a block-diagonal equicorrelation structure and $(I-1)$ variances of the random effects can be identified. This one factor structure leads to a one-dimensional-factorization of the integral in equation 1.13, which can be approximated accurately through Gaussian Hermite Quadrature.

4. Intertemporal linkages: Autorregressive Errors

M will be a block-diagonal structure where each block has the structure of an AR(1) process with $(I-1)$ parameters (ρ_i) to be identified.

The combination of (2), (3) and (4) leads to the following error structure:

$$\epsilon_{i,t} = \alpha_i + \eta_{i,t},\ \eta_{i,t} = \rho_i \cdot \eta_{i,\,t-1} + \nu_{i,t},\ \ i = 1, ..., I-1, \tag{1.14}$$

[5]With the exception of the restrictions due to the invariance of a discrete choice model to the scale of the indirect utilities (only differences of indirect utilities can be identified) and a single restriction due to the general non-identification of the scale of the vector β in discrete choice models.

[6]The Geweke algorithm is used to derive unbiased estimates of the choice probabilites.

with

$$corr\left(\nu_{i,t},\nu_{j,s}\right)=\begin{cases}0 & if \;\; t\neq s\\ \omega_{ij} & if \;\; t=s\end{cases}$$

and

$$cov\left(\alpha_i,\alpha_j\right)=\sigma_{ij},$$

which implies

$$cov\left(\epsilon_{i.t},\epsilon_{j,s}\right)=\sigma_{ij}+\rho_i^{(t-s)}\frac{\sqrt{\left(1-\rho_i^2\right)}\cdot\sqrt{\left(1-\rho_j^2\right)}}{1-\rho_i\rho_j}\omega_{ij}. \qquad (1.15)$$

All parameters in equation 1.15 are identified if $/\rho_i/<1$, $i=1,...,I-1$.

An interesting and important feature for my analysis are the two components of the covariance matrix. The first term is the random household effect component which reflects unobserved time-invariant individual heterogeneity or idiosyncracies. The second term can be interpreted as habit formation that slowly fades away.

1.4 Empirical Results

1.4.1 Data

In order to model the intertemporal linkages mentioned above panel data is needed. To this end, I use the SHIW dataset. This survey is run every 2 or 3 years and has complete information on household portfolios.

For the remainder of the paper, and following Guiso et al. (1996)'s classification, I define three categories of financial asset holdings:

1. Safe financial assets (SF): checking accounts, savings deposits, certificates of deposit, postal deposits, postal bonds, treasury bills up to one year maturity (BOTs), and floating-rate Treasury credit certificates (CCTs).

2. Risky financial assets (RK): long-term government bonds (BTPs and CTZs, the latter of which refers to zero-coupon bonds), corporate bonds, foreign bonds, investment fund units, domestic and foreign stocks, shareholdings in limited companies and in partnerships.[7]

3. No financial assets (NOA).

Few Italian households hold risky assets (see first two rows of Table 1.1), so I also show a broader definition of risky assets, following Guiso et al. (1996) by adding savings deposits, postal bonds, treasury bills to one year maturity (BOTs) and floating-rate treasury credit certificates (CCTs). For the econometric analysis that follows, however, I retain the narrow but more precise definition.

Tables 1.1 and 1.2 show the distribution of household portfolios of the unbalanced SHIW panel using the narrow (RISK0) and broad (RISK1) definition of risky assets respectively. Households are classified by their choice of assets: holdings of risky assets and safe assets (rksf), only risky assets (rknosf), only safe assets (sfnork) and no assets (noa).

Tables 1.3 and 1.4 show the total number of observations for the unbalanced and balanced panels. I have excluded from the following analysis the risky asset and no safe asset category (rknosf) from the narrow measure since it only represents 0.05 percent of the population (11 observations). The big difference between the balanced

[7]Long-term government bonds are included due to the risk of default in Italy since public debt is substantial.

risk0	1989	1991	1993	1995	1998	2000	Total
rksf	109	385	535	549	909	908	3395
rknosf	1	3	1	1	4	1	11
sfnork	1078	3279	3409	2925	3136	2422	16249
noa	158	489	591	543	613	542	2936
Total	1346	4156	4536	4018	4662	3873	22591

Note: Figures in the table give the count.

Table 1.1: Portfolio choice by year with a narrow measure of risky assets

risk1	1989	1991	1993	1995	1998	2000	Total
rksf	466	1563	1925	1773	2012	1539	9278
rknosf	200	615	579	447	370	162	2373
sfnork	522	1489	1441	1255	1667	1630	8004
noa	158	489	591	543	613	542	2936
Total	1346	4156	4536	4018	4662	3873	22591

Note: See Table 1.1.

Table 1.2: Portfolio choice by year with a broad measure of risky assets

and unbalanced panel is that the latter contains between two and six waves and the former contains only households that were followed for six waves.

1989/91/93/95/98/00	Unbalanced Panel			Balanced Panel		
Financial assets? (narrow def.)	freq	percent	cum	freq	percent	cum
rksf	3395	15.04	15.04	294	18.92	18.92
sfnork	16249	71.96	87.00	1130	72.72	91.63
noa	2936	13.00	100.00	130	8.37	100.00
Total	22580	100.00		1554	100.00	

Table 1.3: Portfolio choice with a narrow measure of risky assets

A notable feature of the data is that only 15 percent of households held risky assets in the narrow definition.

Tables 1.5, 1.6 and 1.7 illustrate the proportion of financial asset holders with different demographic characteristics: education, age and sex.

Table 1.5 classifies households depending on their degree of education in 2000. Forty-five percent of households that have a university degree held risky assets and only 1 percent did not hold any financial assets. By contrast, only 3 percent of

1989/91/93/95/98/00	Unbalanced Panel			Balanced Panel		
Financial assets? (broad def.)	freq	percent	cum	freq	percent	cum
rksf	9278	41.09	41.09	790	50.84	50.84
rknosf	2362	10.46	51.55	137	8.82	59.65
sfnork	8004	35.45	87.00	497	31.98	91.63
noa	2936	13.00	100.00	130	8.37	100.00
Total	22580	100.00		1554	100.00	

Table 1.4: Portfolio choice for a broad measure of risky assets

households with no schooling held risky assets and 44 percent held no assets. In general, the more years of education the larger the proportion of households holding risky assets. The majority of households held only safe assets.

risk0 2000	no schooling	elementary school	high school	university
rksf	2.73	11.33	28.75	45.45
sfnork	53.52	67.63	62.37	53.29
noa	43.75	21.03	8.84	1.25
total	100.00	100.00	100.00	100.00

Note: Figures in the table give percentages.

Table 1.5: Portfolio choice by education

In the same fashion, Table 1.6 shows that at any age, the majority of households held only safe assets in 2000. However, households between 35 and 55 years old were more likely to hold risky assets. The highest proportion of households that held no assets are either below 35 years old or above 65 years old.

risk0 2000	<35	35-45	45-55	55-65	65+
rksf	21.94	28.69	27.99	25.27	15.46
sfnork	64.56	62.95	59.94	61.97	64.38
noa	13.50	8.36	12.07	12.64	20.16
Total	100.00	100.00	100.00	100.00	100.00

Note: See Table 1.5.

Table 1.6: Portfolio choice by age

Table 1.7 presents the distribution of financial asset holdings by the sex of the household head in 1989 and 2000. The proportion of both male and female heads that held risky assets increased from 9 percent to 26 percent for male heads and from 6 percent to 17 percent for female heads, so the gender difference remains.

risk0	1989		2000	
	Male	Female	Male	Female
rksf	8.71	5.76	26.06	17.55
sfnork	80.71	77.70	62.08	63.56
noa	10.49	16.55	11.82	18.89
Total	100.00	100.00	100.00	100.00

Note: See Table 1.5.

Table 1.7: Portfolio choice by sex

In order to get a clearer picture of the determination of financial asset portfolios, the dynamics of participation in financial markets need to be analyzed. This is done in the next section.

1.4.2 Changes in Portfolio Allocations

This section aims to give a descriptive analysis of the transition frequencies between financial asset holding states. The SHIW panel contains portfolio choice observations for six years, which will allow us to analyze patterns of participation and changes in/out of the financial markets in the 1990s. Household portfolios exhibit dramatic variation. In 2000, 63 percent of household with safe assets did not hold stocks or risky bonds, 6 percent held stocks, risky bonds and safe assets, 18 percent held stocks and safe assets but no risky bonds, and 3 percent held risky bonds and safe assets but not stocks. Nobody is observed having no holdings of safe assets, and holding risky bonds, stocks or both. Finally, 10 percent held no safe assets, risky bonds or stocks (See Table 1.9). Similarly striking results were reported by Vissing-Joergense (2002) for the 1994 PSID dataset. She found that 42.4 percent of those with positive financial wealth held neither stocks nor bonds. An additional 29.1 percent held stocks but not bonds, whereas 13.5 percent held bonds but not stocks. Only 15 percent held both stocks and bonds.

Year	risk0			
	rksf	rknosf	sfnork	noa
1991	10.52	0.08	81.39	8.01
1993	13.75	0.00	77.35	8.90
1995	16.10	0.00	74.35	9.55
1998	24.92	0.00	65.94	9.14
2000	26.78	0.00	63.19	10.03

Note: Households are divided into those holding 4 categories of financial assets. Figures in the table give percentages per year.

Table 1.8: Portfolio choice per year using a balanced panel (1991-2000) for the narrow and broad measure of risky assets, respectively.

Table 1.8 illustrates the proportion of households in each of the four categories of the dependent variable "risk" for the narrow (risk0) definition of risky assets. Referring to the narrow definition of risky assets, during the 1990s the first category (people holding risky and safe assets) rose from 10 percent to 27 percent while the proportion of households that held safe assets but not risky assets - the majority - fell from 81 to 63 percent. Finally, the proportion of households that held no assets remained more or less constant.

Year	risk4							
	rbstsf	nrbstsf	rbnstsf	rbstnsf	rbnstnsf	nrbnstsf	nrbstnsf	nbnstnsf
1991	1.21	5.26	4.05	0.00	0.00	81.39	0.08	8.01
1993	3.48	7.36	2.91	0.00	0.00	77.35	0.00	8.90
1995	3.64	7.36	5.10	0.00	0.00	74.35	0.00	9.55
1998	6.07	14.32	4.53	0.00	0.00	65.94	0.00	9.14
2000	6.07	17.88	2.83	0.00	0.00	63.19	0.00	10.03

Note: Households are divided into those holding 8 categories of financial assets. Figures in the table give percentages per year.

Table 1.9: Portfolio choice per year using balanced panel (1991-2000), for narrow measure of risky assets

Table 1.9 gives additional insights into the portfolio structure by showing the behaviour of participation in risky bonds and stocks. RBSTSF refers to households holding risky bonds, stocks and safe assets simultaneously, NRBSTSF refers to households holding stocks and safe assets (but not risky bonds). RBNSTSF refers to households holding risky bonds, no stocks and safe assets. RBSTNSF refers to households holding risky bonds, stocks but no safe assets. RBNSTNSF refers to households holding risky bonds alone. NRBNSTSF refers to households holding safe assets alone. NRBSTNSF refers to households holding stocks alone. Finally, NBNSTNSF refers to households holding no financial assets.

In 1991, only 1 percent of households held risky bonds, stocks and safe assets. However, the percentage rose to 6 percent by 2000. Interestingly, the proportion of households that held stocks (and safe assets) but not risky bonds rose from 5 to 18 percent, but the proportion that held risky bonds and no stocks decreased slightly. The percentage of households holding only risky bonds fluctuated around 4 per cent, increasing in 1995 but declining since then. The highest proportion remains households holding only safe assets, but it has decreased over time.

Tables 1.10 and 1.16 describe the dynamics of ownership patterns using unrestricted empirical transition probabilities. They illustrate a measure of persistence by showing the proportion of households that switch from holding one basket of assets to another during the five years available. This approach does not illustrate changes in amounts held or changes within each category, but focuses instead on transitions for households that switch to, or stay with one category of financial assets.

I consider two different discretizations of the "risk" variable, focusing here on a 4-state model and leaving the 8-state model for the appendix. In 1991, 10 percent of households held risky assets, 81 percent held only safe assets, and 8 percent held no assets. Table 1.10 presents estimates of the unrestricted transition probabilities for risk0. Each matrix describes the changes in household portfolio choice from 1991 to 1993 ($T^{risk0}_{1991\to1993}$), from 1991 to 1995 ($T^{risk0}_{1991\to1995}$), from 1991 to 1998 ($T^{risk0}_{1991\to1998}$), and from 1991 to 2000 ($T^{risk0}_{1991\rightarrow 2000}$) respectively. For instance, looking at $T^{risk0}_{1991\rightarrow 1993}$, for the one year horizon, 7 percent of households that were holding safe assets in 1991 switched to risky assets in 1993. Overall, in both the 4-state and 8-state models, the one-year horizon transition behaviour shows a tendency for households to remain in their original states (the diagonals are uniformly the highest entries in each row), with households holding only safe assets showing the highest persistence. Table 1.10 effectively shows the existence of persistence. Households with no assets or risky assets show similar persistence. There is little mobility and the off-diagonal entries are very small. The largest move is from safe assets to risky assets, followed by a move from safe assets to no assets and from risky to safe assets, and finally the move from no assets to safe assets. Over the two- and three-year horizon, the persistence decreases for safe asset holders, but remains the same for risky asset holders.

$$T^{risk0}_{1991\to1993} = t\ \begin{array}{c|c} & \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{array}{c} rksf \\ rknosf \\ sfnork \\ noa \end{array} & \begin{pmatrix} 0.06 & 0.00 & 0.04 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.07 & 0.00 & 0.70 & 0.04 \\ 0.00 & 0.00 & 0.03 & 0.05 \end{pmatrix} \end{array}$$

$$T^{risk0}_{1991\to1995} = t\ \begin{array}{c|c} & \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{array}{c} rksf \\ rknosf \\ sfnork \\ noa \end{array} & \begin{pmatrix} 0.06 & 0.00 & 0.04 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.09 & 0.00 & 0.67 & 0.05 \\ 0.00 & 0.00 & 0.03 & 0.04 \end{pmatrix} \end{array}$$

$$T^{risk0}_{1991\to1998} = t\ \begin{array}{c|c} & \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{array}{c} rksf \\ rknosf \\ sfnork \\ noa \end{array} & \begin{pmatrix} 0.06 & 0.00 & 0.04 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.18 & 0.00 & 0.57 & 0.05 \\ 0.00 & 0.00 & 0.04 & 0.04 \end{pmatrix} \end{array}$$

$$T^{risk0}_{1991\to2000} = t\ \begin{array}{c|c} & \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{array}{c} rksf \\ rknosf \\ sfnork \\ noa \end{array} & \begin{pmatrix} 0.06 & 0.00 & 0.04 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.20 & 0.00 & 0.55 & 0.06 \\ 0.00 & 0.00 & 0.04 & 0.03 \end{pmatrix} \end{array}$$

Note : Entries may not add up to 1.00 due to rounding.

Table 1.10: Unrestricted Empirical Transition Probabilities in different horizons. Narrow definition

The above matrices describing households' transition from one financial asset state to another suggest long-run stability with interim short-run changes. To see the latter, Table 1.11 classifies the mobility histories from one wave to the next. There is an increasing tendency for households to switch from holding only safe assets to holding risky and safe assets simultaneously. At the same time, there is a smaller but growing tendency for households to move from holding risky and safe assets to focus only on safe assets. The diagonal elements show very high persistence in holdings of safe and risky assets.

I therefore conclude that there is persistence in household portfolio decisions.

$$T^{risk0}_{1991\to1993} = t \begin{array}{c} \\ rksf \\ rknosf \\ sfnork \\ noa \end{array} \begin{array}{c} \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{pmatrix} 0.06 & 0.00 & 0.04 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.07 & 0.00 & 0.70 & 0.04 \\ 0.00 & 0.00 & 0.03 & 0.05 \end{pmatrix} \end{array}$$

$$T^{risk0}_{1993\to1995} = t \begin{array}{c} \\ rksf \\ rknosf \\ sfnork \\ noa \end{array} \begin{array}{c} \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{pmatrix} 0.09 & 0.00 & 0.04 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.07 & 0.00 & 0.68 & 0.03 \\ 0.00 & 0.00 & 0.02 & 0.07 \end{pmatrix} \end{array}$$

$$T^{risk0}_{1995\to1998} = t \begin{array}{c} \\ rksf \\ rknosf \\ sfnork \\ noa \end{array} \begin{array}{c} \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{pmatrix} 0.11 & 0.00 & 0.05 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.14 & 0.00 & 0.57 & 0.04 \\ 0.00 & 0.00 & 0.04 & 0.06 \end{pmatrix} \end{array}$$

$$T^{risk0}_{1998\to2000} = t \begin{array}{c} \\ rksf \\ rknosf \\ sfnork \\ noa \end{array} \begin{array}{c} \overset{t+s}{\begin{array}{cccc} rksf & rknosf & sfnork & noa \end{array}} \\ \begin{pmatrix} 0.15 & 0.00 & 0.09 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 \\ 0.11 & 0.00 & 0.50 & 0.04 \\ 0.00 & 0.00 & 0.04 & 0.05 \end{pmatrix} \end{array}$$

Note : See Table 1.10.

Table 1.11: Unrestricted Empirical Transition Probabilities for one wave to the next. Narrow definition

Whether this persistence is due to taste persistence or some other heterogeneity is the issue that I analyse in the next section. The same exercise for the 8-state model is shown in the Appendix.

1.4.3 Estimation Results

The presentation of results is organized according to the progressive relaxation of assumptions.

Nested Multinomial Logit Results

Table 1.12 presents the results of estimating a NMNL model. Notice first that the coefficient on theta is highly significant and below 1, meaning that the model exhibits statistically significant nesting; that is, it violates the IIA property of the regular MNL model.

The R^2 of McFadden tests the model against the alternative of only a constant and no real explanatory variables on the right-hand-side. The relatively high value of 0.50 supports the joint significance of the explanatory variables. Hence when I apply a generalized approach to selectivity bias in a joint decision to hold risky and safe assets, I find a significant positive correlation. Ignoring the relationship between these two decisions would therefore lead to biased estimates.

I control for demographics (marital status: married (MS), gender (SEX), family size (FSIZE)) as proxies for observed heterogeneity; real labour income (WAGE) and real financial wealth (WEALTH) as measures of the initial endowment; and housing equity (HOUSEVALUE) as a measure of nontraded or illiquid asset. I also control for self-employment (SELF) and add the unemployment rate of the region in which the household lives (UNRT). EMPLH indicates the labour status of the head of the household, HOUSELOAN indicates whether the household is indebted, AGE is an indicator of planning horizon, and WEALTH and education (EDUC) are indicators of financial information.

The way to interpret the results is as follows. For each explanatory variable, (1) the relative influence on the likelihood of holding risky financial assets (and safe assets) relative to the likelihood of holding no assets (e.g. educ1), and (2) the relative influence on the likelihood of holding safe assets to the likelihood of holding no assets (e.g. educ2), are measured.

Table 1.12 illustrates that the parameter estimates for EDUC are positive and significant. Education can be interpreted as a measure of the ability to process

Dependent variable: i_{nt} :	1: rksf, 2:sfnork, 3:noa	
Variables[2]	Estimate[1]	t-Stat.
age1	0.000	0.00
age2	0.001	0.06
ms1	-0.217	-1.11
ms2	-0.094	-0.51
educ1	0.713***	7.20
educ2	0.391***	4.22
emplh1	0.437**	2.53
emplh2	0.162	0.98
fsize1	-0.258***	-4.42
fsize2	-0.213***	-3.89
sex1	-0.346**	-1.99
sex2	-0.322**	-1.98
housevalue1	0.287***	2.68
housevalue2	0.261*	1.76
wage1	0.628***	8.23
wage2	0.525***	6.81
wealth1	0.014**	2.22
wealth2	0.012**	1.95
houseloan1	-0.277	-1.02
houseloan2	-0.441*	-1.69
self1	-0.997***	-4.96
self2	-0.780***	-4.00
unrt1	-0.836***	-9.40
unrt2	-0.577***	-7.11
$i_{n,t-1}1$	-3.665***	-28.70
$i_{n,t-1}2$	-2.670***	-21.59
cte1	10.346***	12.477
cte2	10.140***	12.602
theta[3]	0.494***	15.52
McFadden R^2	0.50	
Log Likelihood	-714.9126	
No. of observations[4]	1295	

[1] *, **, and *** correspond to the 10 , 5 and 1 percent significance levels, respectively.
[2] Each explanatory variable is interacted with choice 1 (rksf) and choice 2 (sfnork), while choice 3 (noa) is the base category.
[3] Coefficient of the inclusive value.
[4] Balanced panel (1989/91/93/95/98/00)

Table 1.12: Nested Multinomial Logit

information about the market and investment opportunities. More highly educated household heads are more likely to be assetholders because the information is cheaper. The coefficient on EDUC1 is larger than the one on EDUC2, meaning that for risky asset holders the probability of entering the market increases more with higher education. This builds on the King and Leape (1998) hypothesis that information about more sophisticated financial assets plays a role in participation. It reflects financial knowledge or interest in financial issues. Lack of participation can sometimes be explained in terms of unawareness of the existence of particular assets among certain households.

EMPLH1 is highly significant, meaning that having a job in the survey year increases the probability of holding risky assets and is not essential for holding safe assets. FSIZE turn out to be highly significant and important, indicating that larger families hold fewer assets. SEX is significant and negative, indicating that male household heads are more likely to hold no assets (the same result is achieved by Perraundin et Soerensen (2000)). HOMEVALUE is particularly significant for risky asset holders, hinting that real estate could be used as collateral to invest in risky assets. The positive coefficient of WAGE (higher for WAGE1 than WAGE2) implies that the percentage of households that hold financial assets increases with the average of labour income because they are more willing to pay for the fixed information and transaction costs of risky assets. WEALTH gives the same result, implying that wealthier households will typically have more to invest, making the relatively large fixed costs of acquiring or holding individual stocks less important.

UNRT accounts for labour risk. When households are faced by unavoided risk such as unemployment, they are less willing to hold risky assets. UNRT is negative and highly significant even controlling for age, wealth, and demographics. Participation therefore depends on background risk.

Following Heckman (1981), I introduce $i_{n,t-1}$(lagged value of the dependent variable $i_{n,t}$)[8] to account for the effect of past experience on choices made in period t and to allow for the possibility of true state dependence. Since the three options on the choice variable are ordered in terms of risk, I decided to report only the results with the lagged ordered variable, though I experimented with entering separate dummy variables for each holding. Both versions for entering the lagged choice variable gave very similar results in terms of significance of lagged terms and the autocorrelation terms as well as the values of the other estimated coefficients and their t-statistics and standard errors.[9]

The assumption that I use concerning the initial conditions is that those are truly exogenous. In this case, the ML estimator is consistent if N (or N and T) goes to infinity. Since are not serially independent, I assume that a new process is observed (with respect to the past) when we start to sample the individuals; otherwise the initial state is determined by the process generating the panel. With respect to the decision to invest in risky assets, individuals started to hold more risky assets at the beginning of the 1990s due to privatization, etc. when the sampling period starts, so we can treat initial conditions as exogenous. In any case, the impact of the exact way the initial conditions are treated loses importance the larger T is. In our case T is 5 which implies the econometric treatment of the initial conditions may not be critical.

By looking at the coefficient of the lagged dependent variable, I can infer something about the existence of state dependence among financial asset holdings. The coefficient is large and significant. The sign is negative, meaning that a household holding no financial assets in the previous period (choice 3) is less likely to hold

[8] I define the lagged dependent variable as the lagged value of the dependent variable coded 1, 2, 3 where 1: risky assets and safe assets, 2: safe assets only, 3: no assets.

[9] Even when the dependent variable is completely ordered, it may be preferable to model the whole setup as an ordered probit as opposed to a multinomial probit one. However, when using an ordered probit (as opposed to MNP) one cannot simply condition on the lagged value directly in case of serial correlation. The joint probability of choice (i,t) and choice(i,t-1) must be taken into account in the likelihood function calculation. I leave this alternative modeling approach to future research.

risky financial assets in the current period (choice 1), while a household holding risky financial assets last period is more likely to hold them in the current period.

MS and SELF are insignificant as reported in other studies (See Perraudin and Soerensen (2000)). AGE turns out to be insignificant but, as is shown later, this is not necessarily the case. The initial idea was to test for non-linearity in age by including a squared term in age. Unfortunately the squared term in age was highly correlated with other variables and altered the specification. Therefore I chose to exclude it from the model. The same kind of problem is stated in Perraudin and Soerensen (2000). HOUSELOAN is only weakly significant for the case of holding safe assets.

Multiperiod Multinomial Probit Results (three alternative model)

Our estimated Multiperiod-Multinomial Probit (MPMNP) model is

$$i_{nt} = \arg\max_{j=1...I}(y_{jnt} = x_{nt}\beta_j + \epsilon_{jnt}) \tag{1.16}$$

where

i_{nt}: observed discrete choice by household n in time t, $i = 1...I, t = 1...T_i$

y_{jnt}: latent utility of alternative j as perceived by household n in time t

x_{nt}: agent-specific characteristics of household n in time t [10]

ϵ_{jnt}: multivariate normal error with covariance $\mathrm{cov}(\epsilon_n) = \Omega \ \left(\epsilon_n = (\epsilon_{jnt})_{j=1...I,\, t=1...T^i}\right)$

where Ω is $I \times T_i$, allowing interalternative and intertemporal correlation between ϵ_{jnt} and ϵ_{kns} for the same observation n.

I analyse the following covariance structures in the model:

[10] Note that there are not alternative specific attributes for each alternative (risky financial assets, safe financial assets and no financial assets). Hence the explanatory variables will be interacted with alternative dummy variables to achieve identification.

- Contemporaneous correlations and heteroscedasticity of $\epsilon_{nt} = (\epsilon_{jnt})_{j=1...I}$, therefore deviating from the i.i.d. assumption within a given period (see equation 1.14, ν_i in Table 1.13).
- Intertemporal correlations between $\epsilon_n = (\epsilon_{jnt})_{j=1...I,\ t=1...T^i}$
  - Random effects which account for *household effects (*see equation 1.14, α_i in Table 1.13).
  - First-order autoregressive errors which account for *habit formation or taste persistence (*see equation 1.14, ρ_i in Table 1.13)

An incorrect specification of the covariance matrix of the errors biases the structural coefficients β apart from the standard errors of the estimated coefficients. In what follows I explore combinations of these error processes. The parameters of the first model with three alternatives to be estimated are β_j and Ω and are shown in Table 1.13.

Dependent variable: i_{nt} :	(1)		(2)		(3)	
1: rksf, 2:sfnork, 3:noa	Estimate[1]	t-Stat.	Estimate[1]	t-Stat.	Estimate[1]	t-Stat.
	Household-specific variables[2]					
age1	0.626***	4.82	0.626***	4.82	0.663***	4.63
age2	0.111	1.07	0.111	1.07	0.129	1.10
ms1	-0.616	-1.30	-0.616	-1.30	-0.647	-1.30
ms2	-0.002	-0.01	-0.002	-0.01	-0.025	-0.06
educ1	0.941***	3.93	0.941***	3.93	1.112***	4.30
educ2	0.424***	2.61	0.424***	2.61	0.495***	2.85
emplh1	0.058	0.14	0.058	0.14	0.114	0.30
emplh2	-0.374	-1.13	-0.374	-1.13	-0.360	-1.10
fsize1	-0.253**	-1.98	-0.253**	-1.98	-0.275*	-1.88
fsize2	-0.206**	-1.96	-0.206**	-1.96	-0.234**	-2.00
sex1	-0.266	-0.70	-0.266	-0.70	-0.112	-0.29
sex2	-0.269	-0.85	-0.269	-0.85	-0.135	-0.40
homevalue1	0.010	0.05	0.010	0.05	-0.083	-0.44
homevalue2	-0.087	-0.47	-0.087	-0.47	-0.148	-0.82
wage1	0.288**	2.11	0.288**	2.10	0.309**	2.35
wage2	0.137	1.17	0.137	1.17	0.174	1.48
wealth1	0.053***	3.89	0.053***	3.89	0.055***	4.26
wealth2	0.053***	4.00	0.053***	4.00	0.055***	4.28
houseloan1	-0.337	-0.71	-0.337	-0.71	-0.509	-1.10
houseloan2	-0.482	-1.15	-0.482	-1.15	-0.530	-1.23
self1	-0.428	-1.15	-0.428	-1.15	-0.710**	-1.96
self2	0.095	0.32	0.095	0.32	-0.103	-0.34

(continued on next page)

unrt1	-1.274***	-5.62	-1.274***	-5.62	-1.374***	-6.07
unrt2	-0.722***	-4.80	0.722***	-4.80	-0.771***	-4.65
$i_{n,t-1}1$	-2.774***	-6.38	-2.774***	-6.38	-0.507*	-1.89
$i_{n,t-1}2$	-1.494***	-6.94	-1.494***	-6.94	-0.498**	-2.30
cte1	1.620	0.91	1.619	0.91	-2.487	-1.30
cte2	1.779	1.18	1.779	1.18	-0.042	-0.03
	Error structure[3]					
$SD\ (\nu_1)$ (Heteroskedasticity)	1.992***	4.09	1.992***	4.09	2.13***	7.72
$corr\ (\nu_1, \nu_2)$ (Interalternative corr)	0.738***	2.96	0.738***	2.96	0.98***	5.81
$SD\ (\alpha_1)$ (Household effects)	-	-	0.0001	0.99	0.00009	1.00
$SD\ (\alpha_2)$ (Household effects)	-	-	0.0001	0.97	0.0001	.998
$corr(\alpha_1, \alpha_2)$ (Household effects)	-	-	-0.00001	0.000	0.000	0.00
ρ_1 (Habit formation)	-	-	-	-	0.731***	13.66
ρ_2 (Habit formation)	-	-	-	-	0.909***	13.75
Log Likelihood[4]	-716.2914		-716.2914		-691.5662	
No. of observations[5]	1295		1295		1295	

[1] *, **, and *** correspond to the 10, 5 and 1 percent signficance levels, respectively.
[2] Each explanatory variable is interacted with choice 1 (rksf) and choice 2 (sfnork), while choice 3 (noa) is the base category.
[3] Three different specifications of correlations are employed: (1) $corr\ (\nu_i, \nu_j)$: unobserved time-specific utility components correlated, (2) $corr(\alpha_i, \alpha_j)$: random effects correlated, and (3) ρ_i: first-order autocorrelation.
[4] Significance is measured by the likelihood ratio statistic.
[5] Balanced panel (1989/91/93/95/98/00).

Table 1.13: Multiperiod Multinomial Probit with Autoregressive Errors

I present results of three specifications. Column (1) controls for contemporaneous correlations and heteroscedasticity. Column (2) also allows for random effects. Column (3) allows for autoregressive errors.

First, there are significant differences with respect to the NMNL model. AGE1 is now highly significant, increasing the probability of holding risky assets. EMPL1 is no longer significant while WAGE1 shows that high labour income is especially important for risky asset holders only. HOMEVALUE, HOUSELOAN2 and SEX lose their significance. Only SELF1 remains significant after controlling for the variability of the covariance matrix.

By looking at the components of the covariance matrix, the IIA assumption is clearly rejected since SD (ν_1) and *corr* (ν_1, ν_2) are highly significant. The introduction of random effects (household effects) does not affect the model since they are not significant - the log likelihood value remains unchanged. The introduction of the autoregressive error component however dramatically lowers the log likelihood value. The autocorrelation coefficients are highly significant, implying strong persistence in both decisions of holding risky and safe assets. This is consistent with the negative coefficient found for the lagged variable. However, as in the case of Borsch-Supan (1992), the panel is too short to separate the two error structures precisely.

By looking at the difference between the three columns of the MPMNP, it is clear that in general coefficients are underestimated when the panel structure is ignored, especially EDUC. WEALTH is remarkably stable across the different specifications of the covariance matrix. SELF1 turns out to be negatively significant, decreasing the likelihood of holding risky assets. Most interestingly, the coefficient on $i_{n,t-1}$ turns out to be overestimated by 1/7 when allowing for persistence, and is relatively less significant. This could be explained by the fact that the lagged financial holding variable was partially capturing the effect of the omitted $\rho_{i.}$

Final model: Multiperiod Multinomial Probit Results (five alternative model)

In order to shed light on the differences between holding risky bonds and stocks and to avoid aggregation problems, I consider a second discretization of the "risk" variable (risk2) as follows[11]:

1. Risky bonds, stocks and safe assets (rbstsf)

2. No risky bonds, stocks and safe assets (nrbstsf)

3. Risky bonds, no stocks and safe assets (rbnstsf)

[11]Categories rbstnsf, rbnstnsf, and nrbstnsf are excluded since there were no households with these holdings in Table 1.9.

4. No risky bonds, no stocks and safe assets (nrbnstsf)

5. No risky bonds, no stocks and no safe assets (nbnstnsf). This is the normalized category.

Table 1.14 provides the estimation results of the model. EDUC is more important for households who only hold stocks (EDUC2 has the highest coefficient). The same applies for WAGE and WEALTH. FSIZE is more a worry for households that hold a diversified portfolio with a combination of stocks, risky bonds and safe assets (FSIZE1 is highly significant). Highly indebted households tend to have fewer safe assets (HOUSELOAN4 is significant). AGE does not seem to matter as much for households holding risky bonds (AGE3 is insignificant). Interestingly, background risk (UNRT) strongly decreases the likelihood of holding risky bonds (UNRT3 has the highest coefficient).

Several alternative versions were run in terms of lagged terms. All versions produced high significance of lagged terms and autocorrelation terms and very similar parameter estimates and t-statistics for the other coefficients. I do not present the individual lagged dependent variable dummies themselves since the results would have been too cluttered and messy for the 5-way classification.

1.5 Conclusion

This chapter analyses the household portfolio decision of shifting from no financial assets to safe financial assets, risky financial assets or both. To this end, I use the SHIW panel dataset for Italian households. The novelty of this chapter is the inclusion and modelling of habit formation in a multinomial model of household portfolio participation. The estimation requires maximum smoothly simulated likelihood techniques for a multiperiod multinomial probit model.

The results show that household portfolio behaviour is better explained by infrequent decisions rather than the continuous adjustments that standard theory predicts. Moreover, the unobserved utilities determining the household portfolio choice clearly include significant time varying components. Since this model works mainly through time-varying components rather than time invariant ones, habit formation is driving the behaviour of households. In other words, households develop a taste for the assets that they hold and do not change portfolios very frequently. This result is essential for understanding the main reason for nonparticipation.

I also consider the existence of true state dependence in financial assets decisions and find true state dependence in the decision to hold risky and safe financial assets. More interestingly, holdings of risky and safe assets are also affected by persistence that fades away slowly. The finding of taste persistence in household portfolio choice is particularly relevant for policymakers, since household portfolios are an additional element to their social security systems.

In addition, it also appears that ignoring intertemporal linkages biases some estimation coefficients - for example, by underestimating the effects of education and overestimating true state dependence in holding no financial assets. Lastly, education levels, labour income, age and wealth turn out to be more important for holding stocks than risky bonds. The larger the family, the less diversified the portfolio is. A high unemployment rate strongly decreases the likelihood of holding risky bonds.

A caveat is that the panel is short, only six waves. However, the differences in goodness of fit (log likelihood values) indicate the importance of persistence in the model.

1.6 Appendix

1.6.1 Definition of variables

The following variables were constructed from questions from the Bank of Italy Survey of Household Income and Wealth.

AGE: Age of the head of the household.

MS: Marital status:

1=married

2=single, separated/divorced or widowed/widow

EDUC: Highest education earned:

1=none

2=elementary school

3=middle school or professional secondary school diploma (3 years of study) or high school or associate's degree or other course university degree

4=bachelor's degree or post-graduate qualification

EMPLH: Whether or not the head of the household was employed for the greater part of the year:

1=employed

2= non-employed

FSIZE: Number of persons living in the household.

SEX: Gender:

1=male

2=female

HOMEVALUE: The value of the household's dwelling.

WAGE: Real labour income in millions of 1989 lira.

WEALTH: Real financial wealth in millions of 1989 lira.

HOUSELOAN: Debts for real state purchasing or renewal at the end of the year:

1=yes

2=no

SELF: Self-employed head of household:

1=member of the arts or professions, sole proprietor, freelance worker, owner or member of a family business, active shareholder/partner, contingent worker not employed on any account or other.

2=employee or not employed

RISK: Participation variable. The empirical part of the paper uses two different discretizations of the dependent variable:

Risk0:

1=holdings of risky assets and safe assets (rksf)

2=only safe assets (sfnork)

3=no financial asset (noa). This is the normalized category.

Risk2:

1=Risky bonds, stocks and safe assets (rbstsf)

2=No risky bonds, stocks and safe assets (nrbstsf)

3=Risky bonds, no stocks and safe assets (rbnstsf)

4=No risky bonds, no stocks and safe assets (nrbnstsf)

5=No risky bonds, no stocks and no safe assets (nbnstnsf). This the normalized category.

The survey reports participation in 20 financial assets:

1. Current accounts.
2. Savings accounts.
3. Certificates of deposit.
4. Repurchase agreements.
5. Postal accounts.
6. Postal bonds.

7. Treasury bills up to one year maturity (BOTs)

8. Floating-rate treasury credit certificates (CCTs).

9. Long-term government bonds (BTPs).

10. Zero-coupon bonds (CTZs).

11. Other government bonds.

12. Corporate bonds.

13. Mutual Funds.

14. Listed stocks.

15. Unlisted stocks (three categories).

16. Managed investment accounts (three categories).

17. Foreign corporate and government bonds.

18. Foreign stocks.

19. Other foreign assets.

20. Loans to cooperatives securities.

In each wave from 1991 the survey asks the respondent to report the amount held at the end of the year of each asset according to the following intervals:

- Up to 2 million lire.
- Between 2 and 4 million lire.
- Between 4 and 8 million lire.
- Between 8 and 12 million lire.
- Between 12 and 16 million lire.
- Between 16 and 24 million lire.
- Between 24 and 36 million lire.
- Between 36 and 70 million lire.
- Between 70 and 140 million lire.
- Between 140 and 300 million lire.
- Between 300 and 600 million lire.

- Between 600 million and 1 billion lire.

- Between 1 and 2 billion lire.

- Above 2 billion lire.

In addition, the following external variable from REGIO (Eurostat's harmonized regional statistical database) was linked to the survey data:

UNRT: Italian regional unemployment rate: Unemployment at NUTS (Nomenclature of Statistical Territorial Units) Level 3 over working population at NUTS Level 3.

1.6.2 8-State transition probabilities

In the 8-state model using the narrow definition of risky financial assets for 1991, only 1 percent of all households held simultaneously risky bonds, stocks and safe assets, 5 percent held stocks (and safe assets) but no risky bonds, 4 percent held risky bonds (and safe assets) but no stocks. A large majority (81 percent) were households that held only safe assets. The 8 percent remaining held no financial assets. Table 1.10 shows that the highest persistence is observed in the behaviour of households holding only safe assets and then those holding only stocks and safe assets, or no financial assets. This persistence decreases slowly over time for households holding only safe assets. The very low persistence of the two extremes - holding risky bonds, stocks and safe assets and those holding no assets - do not change at all over time. The majority of the switchers from only safe assets went to stocks and safe assets (no risky bonds) and a smaller proportion to no financial assets. There was also an increase in the proportion of households switching from holding only safe assets to holding all financial assets. Table 1.15 confirms the above results.

Dependent variable: i_{nt} :	Estimate[1]	t-Stat.
1: rbstsf, 2:nrbstsf, 3:rbnstsf, 4:nrbnstsf, 5:nbnstnsf		
Household-specific variables[2]		
age1	0.141**	2.41
age2	0.120**	2.03
age3	0.031	0.41
age4	0.111**	2.39
ms1	-0.196	-1.08
ms2	-0.282	-1.55
ms3	0.020	0.09
ms4	-0.087	-0.61
educ1	0.816***	6.70
educ2	0.852***	7.52
educ3	0.773***	5.32
educ4	0.458***	6.15
emplh1	0.152	0.91
emplh2	0.150	0.93
emplh3	0.336	1.48
emplh4	-0.140	-1.07
fsize1	-0.142**	-2.38
fsize2	-0.112*	-1.87
fsize3	-0.117	-1.51
fsize4	-0.079*	-1.71
sex1	-0.221	-1.39
sex2	-0.132	-0.82
sex3	-0.269	-1.29
sex4	-0.181	-1.41
wage1	0.411***	7.14

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wage2	0.444***	7.55
wage3	0.418***	5.95
wage4	0.301***	5.73
wealth1	0.031***	2.90
wealth2	0.031***	2.87
wealth3	0.019	1.42
wealth4	0.030***	2.83
houseloan1	-0.145	-0.66
houseloan2	-0.247	-1.19
houseloan3	-0.084	-0.34
houseloan4	-0.388**	-2.09
unrt1	-0.754***	-7.05
unrt2	-0.815***	-8.43
unrt3	-0.825***	-5.84
unrt4	-0.506***	-8.02
lagged terms interacted with choice[3]	— [3]	—[3]
cte1	10.323***	11.25
cte2	10.504***	11.63
cte3	8.060***	5.97
cte4	10.498***	13.81
Error structure[4]		
SD (ν_1) (Heteroskedasticity)	0.886***	5.16
SD (ν_2) (Heteroskedasticity)	0.723***	3.37
SD (ν_3) (Heteroskedasticity)	1.570***	3.34
$corr$ (ν_1, ν_2) (Interalternative correlation)	-0.065	-0.18
$corr$ (ν_1, ν_3) (Interalternative correlation)	-0.090	-0.38
$corr$ (ν_1, ν_4) (Interalternative correlation)	0.564***	3.43
$corr$ (ν_2, ν_3) (Interalternative correlation)	-0.084	-0.35

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corr (ν_2, ν_5) (Interalternative correlation)	-0.087***	-2.03
corr (ν_3, ν_4) (Interalternative correlation)	0.308***	2.07
SD (α_1) (Household effects)	0.0001	1.00
SD (α_2) (Household effects)	0.0001	1.00
SD (α_3) (Household effects)	0.0001	1.00
SD (α_4) (Household effects)	0.0001	1.00
corr (Household effects)	-0.0002	0.00
corr (Household effects)	0.0001	0.00
corr (Household effects)	-0.000003	0.00
corr (Household effects)	-0.00001	0.00
corr (Household effects)	0.00001	0.00
corr (Household effects)	-0.0001	0.00
ρ_1 (Habit formation)	0.026	0.27
ρ_2 (Habit formation)	0.595***	5.30
ρ_3 (Habit formation)	0.543***	6.43
ρ_4 (Habit formation)	-0.191**	-2.40
Log Likelihood	-3655.5749	
No. of observations[5]	4940	

[1] *, **, and *** correspond to the 10, 5 and 1 percent significance levels.
[2] Each explanatory variable is interacted with choice 1 (rbstsf), choice 2 (nrbstsf), choice 3 (rbnstsf), choice 4 (nrbnstsf), while choice 5 (nbnstnsf) is the base category.
[3] Several alternative versions were run in terms of lagged terms. All versions produced high significance of lagged terms and very similar parameter estimates and t-statistics for the other coefficients. See page 57 for details.
[4] Three different specifications of correlations are employed: (1) *corr* (ν_i, ν_j): unobserved time-specific utility components correlated, (2) *corr*(α_i, α_j) : random effects correlated, and (3) ρ_i: first-order autocorrelation.
[5] Balanced panel (1991/93/95/98/00).

Table 1.14: Multiperiod Multinomial Probit with Autoregressive Errors

$$T^{risk4}_{1991\to1993} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.02 & 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.01 & 0.01 & 0.01 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.04 & 0.01 & 0.00 & 0.00 & 0.70 & 0.00 & 0.04 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.03 & 0.00 & 0.05 \end{pmatrix}}$$

$$T^{risk4}_{1993\to1995} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.02 & 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.03 & 0.01 & 0.00 & 0.00 & 0.03 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.01 & 0.00 & 0.00 & 0.01 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.03 & 0.03 & 0.00 & 0.00 & 0.68 & 0.00 & 0.03 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.07 \end{pmatrix}}$$

$$T^{risk4}_{1995\to1998} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.02 & 0.01 & 0.00 & 0.00 & 0.00 & 0.01 & 0.00 & 0.00 \\ 0.01 & 0.04 & 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.01 & 0.01 & 0.01 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.02 & 0.09 & 0.03 & 0.00 & 0.00 & 0.57 & 0.00 & 0.04 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.04 & 0.00 & 0.06 \end{pmatrix}}$$

$$T^{risk4}_{1998\to2000} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.02 & 0.03 & 0.00 & 0.00 & 0.00 & 0.01 & 0.00 & 0.00 \\ 0.02 & 0.07 & 0.00 & 0.00 & 0.00 & 0.05 & 0.00 & 0.00 \\ 0.01 & 0.01 & 0.01 & 0.00 & 0.00 & 0.03 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.02 & 0.07 & 0.02 & 0.00 & 0.00 & 0.50 & 0.00 & 0.04 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.04 & 0.00 & 0.05 \end{pmatrix}}$$

Note : See Figure 1.10.

Table 1.15: Unrestricted Empirical Transition Probabilities for one wave to the next. Narrow definition.

$$T^{risk4}_{1991\to1993} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.02 & 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.01 & 0.01 & 0.01 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.04 & 0.01 & 0.00 & 0.00 & 0.70 & 0.00 & 0.04 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.03 & 0.00 & 0.05 \end{pmatrix}}$$

$$T^{risk4}_{1991\to1995} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.02 & 0.01 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.01 & 0.00 & 0.01 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.02 & 0.04 & 0.03 & 0.00 & 0.00 & 0.67 & 0.00 & 0.05 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.03 & 0.00 & 0.04 \end{pmatrix}}$$

$$T^{risk4}_{1991\to1998} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.02 & 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.01 & 0.01 & 0.01 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.04 & 0.11 & 0.03 & 0.00 & 0.00 & 0.57 & 0.00 & 0.05 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.05 & 0.00 & 0.04 \end{pmatrix}}$$

$$T^{risk4}_{1991\to2000} = t \begin{array}{l} rbstsf \\ nrbstsf \\ rbnstsf \\ rbstnsf \\ rbnstnsf \\ nrbnstsf \\ nrbstnsf \\ nbnstnsf \end{array} \overset{t+s}{\begin{pmatrix} 0.00 & 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.01 & 0.02 & 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.01 & 0.01 & 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.04 & 0.13 & 0.02 & 0.00 & 0.00 & 0.55 & 0.00 & 0.06 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.04 & 0.00 & 0.04 \end{pmatrix}}$$

Note : See Figure 1.10.

Table 1.16: Unrestricted Empirical Transition Probabilities in different horizons. Narrow definition.

Chapter 2

Wealth Effects in Europe: A Tale of Two Countries

This chapter investigates the increasing exposure of European households to risky financial assets and the consequent impact on the real economy. I analyse household data for Italy and the UK, countries that differ dramatically in their financial structure and capital markets. I estimate an endogenous switching model with bivariate switching in order to overcome two important obstacles in this line of research, namely, the consumption Capital Asset Pricing Model puzzle and the excess sensitivity puzzle. By controlling for liquidity constraints, the results show that there are wealth effects in both countries. I find some evidence of liquidity constraints only in Italy and habit formation exclusively in the UK.

2.1 Introduction

A common monetary policy for Euroland may have different macroeconomic consequences from one country to another because of differences in the speed and magnitude of a monetary impulse into economic activity. These differences depend in part on dissimilarities in the financial structure and on households' and firms' portfolios' composition. Different liquidity constraints will also affect consumption directly. In this context, national transmission mechanisms can differ and the implementation of a common monetary policy by the European Central Bank (ECB) could lead to varying results among different countries.

The differences between capital markets and portfolio composition across European economies are marked. First, stock markets and privately issued debt are highly developed in some European countries (e.g., the UK), but not others (e.g., Italy and Germany). In addition, financial structures have evolved differently in recent years, with growth of non-bank intermediaries in some countries but not others, and different evolution of stock markets and changes in household and firm asset and liabilities composition. For instance, in households' portfolios there are relevant differences in the choice of fixed-income assets versus equity, which reflect differences in market capitalization. In particular, equity ownership has broadened in general, but to different degrees depending on the country. These trends have resulted in different ways of distributing liquidity among households and firms. Secondly, huge differences exist in the use of short term versus long term financing, in the share of fixed versus floating rates, and in the degree and composition of indebtedness of individuals.

At the same time, stock markets have experienced substantial fluctuations. These developments in the financial structure have increased the interest in the potential impact of major asset price movements on the real economy. In particular, the large swings in wealth induced by these movements might have effects on consumption. The logic goes as follows: an increase in the stock market makes households wealthier and that increases their spending. Concern about how to measure these wealth effects has increased following the changes in participation and volatility in securities.

Goodhart and Hofmann (2000) argue that due to the fact that some prices and wages are sticky, asset prices are likely to be the most flexible. Therefore, monetary policy shocks are likely to have their first effects via asset prices and the transmission mechanism will work through the effect of asset prices on output via wealth effects on consumption, exchange rates on net trade and Tobin's q on investment. In this chapter I examine the wealth effect.

There may be several, possibly related, channels: causation can go from monetary shocks to asset prices to output, or from asset price shocks to monetary and real variables (by raising the value of collateral and encouraging more borrowing from individuals, resulting in increased consumption). If part of the credit is used to buy more assets, a "financial accelerator"[1] effect is in place. In addition, in some cases expectations of capital gains appear to lead to increases in bank lending and expenditures.

Research on the transmission mechanism across countries using the same framework, the same monetary policy reaction function and constraining exchange rate movements for Europe is still lacking[2]. The existing literature only contains partial comparative studies, which are not adequate to draw strong conclusions about the dissimilarities among European countries. Consequently, as Guiso, Kashyap, Panetta and Terlizzesse (1999) point out, findings at the aggregate level should be supplemented by systematic comparisons at the micro level. There are various rationales for this: First, micro data offer a richer variety of information for each group of individuals in each country. This makes it easier to analyze the differences among

[1] See Kiyotaki and Moore (1997) and Bernanke, Gertler and Gilchrist (1999).

[2] See Guiso, Kashyap, Panetta and Terlizzese (1999) for a review.

them and to study differences among similar groups of agents in different countries. Second, they allow a better understanding of the causes and the persistence of those differences. Third, they eliminate the aggregation problems raised by the fact that similar households and firms in different countries can act differently but can be compensated at the aggregate level. And, finally, they might help to identify policy interventions that could help to modify micro-level behaviour in order to generate more uniform monetary policy effects. Nevertheless, although firm data has been used extensively to study the balance sheet channel, household data used for that purpose has been more limited.

The aim of this chapter is to evaluate whether structural differences in the financial system lead to differences in the transmission mechanism. Specifically, the role of wealth effects, liquidity constraints and habit formation in two countries, the UK and Italy, will be studied. The comparison is particularly interesting since these countries' household portfolios have a specific financial structure (i.e. high exposure of households to equities and bonds respectively). In the UK, 24 percent of households in 2000 held shares either directly or in mutual funds or pension plans, while in Italy only 18 percent did. The effect of a monetary shock in these two countries could be different and have a bigger impact here than in the rest of Europe. This disparity might result from agents being subject to greater wealth volatility, different liquidity constraints and habit formation.

The model in this chapter brings together two key elements so far analyzed separately by a number of studies. The contribution of the chapter is in dealing simultaneously with two sample selection biases. Using only households –which either do or do not hold assets, and either are liquidity constrained or not– results in biased estimates of the consumption elasticities of labour income and risky financial assets.

I present results of an application to the stochastic life-cycle consumption model under rational expectations as developed by Hall (1978). Since his seminal paper, the model has been extended by several contributions such as Zeldes (1989) for the US and Attanasio and Weber (1993) for the UK. The major innovation of this chapter is to account for endogeneity in the choice of financial wealth and liquidity constraints. The empirical study is carried out using a generalized approach to selectivity bias for a joint decision of households with data from the UK and Italy. For the former, the British Household Panel Survey (BHPS) is used, and for the latter, the Bank of Italy Survey of Household Income and Wealth (SHIW).

The rest of the chapter is organized as follows: Section 2 describes briefly the available micro datasets on asset holdings and consumption in Europe. Section 3 provides an overview on capital markets in Europe and in particular the financial structure of household portfolio compositions of risky assets for two countries of the European Union (UK and Italy). Section 4 develops the life-cycle model and illustrates its drawbacks. Section 5 outlines the basic model and describes the estimation procedure. Section 6 presents the results of the application of the stochastic life-cycle consumption model under rational expectations. Section 7 concludes and discusses the policy implications. Variable definitions and constructions are discussed in an Appendix.

2.2 Household Data on Wealth and Consumption

Household data are more appropriate than aggregate statistics to study wealth effects for various reasons.

First, due to the existence of incomplete markets, the standard separation theorems do not apply because individuals are heterogenous and this fact affects portfolio composition. Sources of heterogeneity are nonparticipation and lack of diversification. The former is clearly at odds with the simple two-asset portfolio model without transaction costs in which risky assets yield a higher expected return than the safe asset. The use of micro data avoids aggregation assumptions and representative agent frameworks.

Secondly, they allow us to study the distribution of wealth of the mass of the population, which has not been received much attention due to its small share in total wealth. Studies based on official statistics have little to say regarding the majority of the population, since they are concerned with those in the upper echelons of wealth distribution.

Finally, aggregate financial accounts do not allow us to disentangle whether the increase in asset shares in the data is due to a change in participation or in the amount invested. In addition, they cannot tell much about either portfolio mobility or how it is affected by wealth or demographic characteristics. European differences in household portfolios can be attributed to wealth, or to demographic characteristics such as age, education and family size, or to other differences.

An ideal dataset to study wealth effects, liquidity constraints and habit formation would include consumption, income, household characteristics and wealth disaggregated into different types of assets by type of individual. In what follows, major European household surveys are described.

Household surveys in the UK contain reliable information on consumption and income, but limited wealth data. On the one hand, the Financial Research Survey (FRS) is a dataset privately compiled by National Opinion Polls for about 8000 households per year. Unfortunately, the survey contains limited demographic data. In addition, it has not been collected on a comparable basis over a long period of time and lacks information on consumption. On the other hand, the Family Expenditure Survey (FES) is a cross-sectional dataset that has been mostly used in the UK to study consumption and savings behaviour. It contains information on demographic characteristics, income, and expenditure for 7000 households per year since 1968. However, wealth information in these datasets is limited.

One exception is the BHPS, where, in wave 5 (1995) and 10 (2000), detailed questions on wealth were asked in addition to detailed demographic characteristics, income and consumption information. The BHPS from 1991-2001 is an important source of data on the experiences of the same households over time, and panel members are followed wherever they move in the UK. Each wave consists of some 5,000 households drawn from 250 different areas of Great Britain. The only drawback of this dataset is that the consumption variables are not complete (for example, expenditure in clothes and shoes is not included).

The Italian SHIW is the only European panel which contains information on wealth, consumption, income and demographic characteristics in every wave. The SHIW is a biannual survey of about 8,000 households collected by the Bank of Italy. From 1989 it offers a rotating panel containing a set of portfolio data, demographic characteristics, expenditures and income information. The survey provides information on 20 financial assets but they are only available for heads of households.

The Spanish *Encuesta Continua de Presupuestos Familiares* (ECPF) is a rotating-sample survey of consumption patterns of 3,200 households from 1985. The same household is interviewed for eight consecutive quarters (two years). It contains information on consumption, income and demographic characteristics but lacks information on wealth.

The Dutch Socio Economic Panel (SEP) of 5,000 households and since 1993 the Dutch VSB-panel (VSBP) of 3000 households both contain wealth, income and demographic characteristics but lack information on consumption.

The Swedish National Survey of Living Conditions (ULF) began in 1979, and since 1986 a panel of 12,000 people has been followed as part of the ULF. The survey covers health, financial situation, education, working environment, and housing, but has no consumption information.

The German Income and Expenditure Survey (*Einkommens-und Verbrauchsstich-*

proben, EVS) for the period 1978-1998 has detailed information on consumption by type, wealth by portfolio category and income by source. However, the EVS is repeated cross-section data –not panel data– and is collected every five years. Another source is the German Socio-Economic Panel (SOEP), which has been collected since 1984. However, this panel does not have information on consumption and contains few questions on wealth. The same applies to the Panel Study on Belgian Households (PSBH) that started in 1990 and collects information from more than 4000 households.

The French *Budget des Familles* is a survey on household consumption collected every five years from 1979 but it is not a panel and the financial asset information is very poor. Detailed information on only financial assets can be found on *L'Enquête Patrimoine.* The situation in Portugal is similar with information on consumption and wealth found in two different surveys.

The European Community Household Panel (ECHP) survey is a longitudinal coordinated social panel for European countries. The survey started in 1994 with a sample of some 60,500 nationally representative households in 12 member states. Wave 2 also includes Austria and wave 3 included Finland. Unfortunately, questions on quantitative values of consumption and financial assets were not included.

The data sources that I use in this chapter are the BHPS and the SHIW. These are the most comparable sources of information across the two countries that include detailed wealth and consumption information (see Appendix for some comparative statistics based on this data). Since both are panels, they allow us to follow the same household over time.

2.3 Capital Markets in Europe and Household Portfolios

The expansion of capital markets in Europe has been encouraged by both transitory and permanent developments. On the one hand, the experience of high stock returns in the 1990s can be considered transitory. On the other hand, the last two decades have been characterized by several permanent changes in the financial systems stemming from deregulation, as well as capital liberalization, the introduction of the single market, and technological innovations. Deregulation has played a role both in the banking sector (abolition of interest-rate controls and abolition of direct controls on credit expansion) and in the capital markets (abolition of regulations on fees and commissions and on the establishment of foreign institutions). As a consequence, an "equity culture" among households has emerged as a response to the proliferation of mutual funds and the systematic education of employees regarding retirement accounts.

Despite these changes, European capital markets are still heterogeneous. This section presents some stylized facts emphasizing both the differences in the degree of development of capital markets and portfolio compositions in Europe, especially in the UK and Italy, by presenting some statistics on asset ownership. In what follows, I will focus on household portfolios since I am interested in wealth effects on consumption, particularly those operating with risky financial assets such as stocks, long-term government bonds and mutual funds. Efficiency of the financial industry might imply differences in the level of entry costs. Equally, differences in participation may be explained by differences in average household wealth and in the distribution of wealth even where entry costs are similar.

Individuals can opt for two types of financing: direct financing, where they invest directly in stocks or bonds issued by non financial institutions in the capital markets, or indirect financing, where savings are intermediated by financial institutions. The relative use of each of them characterizes the relationship between the private sector and the rest of the economy.

	France		Germany		Italy		UK		US	
	1980	2000	1980	2000	1980	2000	1980	2000	1980	2000
Deposits	59	26	59	36	58	25	43	22	33	14
Bonds	9	2	12	11	8	18	7	1	10	7
Equities	14	38	4	17	10	26	12	18	21	25
Institutional Investment	7	33	17	36	6	30	30	59	28	50

Note: Percentage share of total financial assets.
Source: Davis (2001, 2002)

Table 2.1: Financial Assets of Households

Table 2.1 shows that direct stockholdings have been growing in recent years, especially in France and Italy, where they have increased from 14 to 38 percent and from 10 to 26 percent respectively. This increase is mainly due to the privatization process. Transaction costs and bid-ask spreads still prevent households with low means from having direct stockholdings, because the cost of controlling the risk that a household would incur in order to diversify will not be compensated by the higher return. The evolution of assetholdings via institutions has been different: it has increased in all countries and significantly in France and the UK. Anglo-Saxon countries are the most developed in this respect. The UK has the highest percentage in institutional investment (59 percent), while that in Italy (30 percent) and France (33 percent) is much lower. This fact is in accordance with differences in market capitalization (in percent of GDP): in 2000 it was 180 percent in the UK, 68 percent in Germany, 78 percent in Italy and 110 percent in France (World Development Indicators, World Bank, 2003).

Institutional investors play an important role when securities entail fixed costs. They are able to combine and repackage a very large number of existing securities and make them available to individual investors that did not find it feasible to invest on their own. Institutional investors are "financial institutions that manage savings collectively on behalf of small investors, towards a specific objective in terms of acceptable risk, return-maximization and maturity of claims"[3]. Their fast growth in the last two decades is due to the decrease in institutional costs coming from improvements in price information, development of derivatives in risk control and improvements in capital markets with lower transaction costs. In addition, their success is a result of being able to match the increasing demand of long term savings at high return and low risk. Mutual funds differ from pension funds and life insurance companies by offering short-term liquidity at rates based on current market price. They can offer these rates via direct redemption of holdings (open-ended funds) or by trading shares in the funds on exchanges (closed-ended funds). Money market mutual funds can offer redemption of holdings at par and provide payment facilities by holding only liquid short term money market assets. Hedge funds are a type of closed-end fund that seeks to pursue high returns at the cost of taking high-risk leveraged positions. Guiso, Haliassos and Jappelli (2003) show, however, how available data on transaction costs and on characteristics of mutual funds suggest that Italy and France are likely to face higher production and distribution costs of investing in mutual funds notwithstanding the effects of less competition and fewer choices.

In addition, a general trend in Europe has been a decline in the share of deposits amongst assets, as Table 2.1 illustrates, although this trend differs among countries. The shares in Italy, the UK, the US and France dropped significantly, while in Germany the decrease has been lower. Bond holdings have remained relatively stable but in the case of Italy they increased from 8 to 18 percent and in the UK they dropped from 7 to 1 percent. The case of Italy shows that the high debt burden is highly financed by bonds, while in the UK households appear to be more

[3]Davis (2001).

keen to hold shares. Following the bank lending and balance sheet channels, one implication of the above facts is that small borrowers are more responsive to a monetary tightening than large borrowers, since small borrowers are bank dependent and face severe credit market imperfections.

This picture can be misleading, however, because it does not reveal whether the increasing proportion of share holdings comes from an increase in participation in capital markets or an increase in the value of assets. Aggregate data do not allow one to distinguish whether the change in asset shares comes from a change in participation or to the amounts invested. Micro data is therefore needed.

Specifically there are various factors that can lead to an increase in the share of risky assets: first, an increase in participation; secondly, an increase in the amount invested by the participants; and finally, an increase in assets accruing to risky asset holders because of a change in wealth distribution. The first factor seems to explain more than 60 percent of the increase in the share of risky assets in Italy, according to Guiso and Japelli (2002), while the latter is negligible.

In what follows, I will focus on two countries, the UK and Italy, and in particular on participation. In the former country, households directly hold more stocks and they do not put large amounts of savings into deposits. In the latter, bonds are the most widespread instrument. Italy is characterized as a country that is bank-dominated, with a large proportion of small firms, poor contract enforcement and rigid labour markets. In contrast, the UK is characterized by very developed capital markets, the existence of large firms, good contract enforcement and flexible labour markets. One might say that the rest of the European countries are somewhere in the middle[4]. France has more developed capital markets but borrowing is still not very high, while Germany has less developed capital markets and less flexible labour markets, but enjoys good contract enforcement and large firms.

[4]See Guiso, Kashyap, Panetta and Terlizzesse (1999) for more details.

Data from the BHPS and SHIW is used to analyze the case of the UK and Italy respectively. Table 2.2 shows the participation in capital markets of households in the UK[5]. British households saw dramatic changes during the 1980s in the distribution of wealth, having enormous increases in ownership of housing, private pensions[6] and stocks, but this trend has started to slow down.

Financial Assets	1978[1]	1988[1]	1995[2]	2000[2]
National Savings Certificates			5.16	2.69
Premium Bonds			24.16	17.07
Unit Trusts/Investment Trusts			6.28	8.05
Personal Equity Plan			9.04	4.46
Shares (UK or Foreign)			23.99	21.97
NS/NB Insurance Bond			11.98	2.09
Government or Corporate Bonds			3.24	3.93
Equity[3]	9.10	22.10	25.96	24.04
Risky Bonds[4]			3.24	3.93
Risky Assets[5]			27.47	26.14

Sources: [1]FES dataset from Banks and Tanner (2002). Table 6A.1.
[2]Author's calculations from BHPS dataset.
Notes: Percentage of households owning a specific asset.
[3]Shares, Unit Trusts/Investment Trusts or Personal Equity Plans.
[4]Government or Corporate Bonds.
[5]Risky Bonds or Equity.

Table 2.2: UK: Household Portfolio Ownership

The worry that employed people were not saving enough to provide for their consumption in old age led the Conservative Government to introduce tax incentives for various types of savings, such as TESSAs, PEPSs, PPPs, BESs between 1979 and 1984.[7] In addition, during the 1980s there was a much advertised privatization impulse, especially from 1985 to 1988 with the privatization of British Telecom and British Gas and the building society demutualisations (the so-called "share-owning democracy"). These changes altered the wealth holdings of the majority of the

[5]Following Banks et al. (2002) I use the original BHPS panel members (who were a representative sample of the population at large).
[6]There is no survey in the UK that collects information on defined-contribution pension funds.
[7]Tax Exempt Special Savings Schemes (TESSAs), tax favoured Personal Equity Plans (PEPs), Personal Pension Plans (PPPs), Business Expansion Schemes (BESs).

population with equity holdings moving down income and wealth distributions into segments of the population that were not typically holding other forms of risky financial assets.

Information on the first category of assets in Table 2.2 comes from the National Savings (NS) government agencies which provide savings and investment instruments in order to finance national borrowing. These assets include National Savings Certificates that are long-term savings deposits, NS Premium Bonds that are liquid assets offering returns from a monthly prize draw and NS Insurance Bonds that can be considered as government bonds bought at Post Offices directly by households. The main change over time has been within different types of financial assets.

There has been a decline in wealth held in cash and bank and building society accounts, and the same has occurred with short-term government bonds. The highest decline has been in premium bonds and insurance bonds.

The increase in awareness of investment opportunities brought by PEPs, privatization and mutual funds have helped spread the ownership of equities across the country. Nine percent of households held shares at the end of the 1970s while 26 percent of the sample held shares in 1995. In that year, 24 percent of the households held shares directly and 6 percent did so through unit trusts. In 2000, however, the percentage of share ownership declined slightly to 24 percent, breaking the increasing trend. While the number of households holding shares directly declined, the proportion holding unit trusts increased.

Not many households held a large number of assets but ownership rates of stocks, shares and bonds among middle-aged married couples was very high. Even in the 1990s, many households only owned shares in privatized companies. The advertisements at the time of the privatization resulted in an increase in asset owners among more young and less well educated people, but shareowners were still predominantly drawn from those at the top of the income distribution. Only recently was there an increase in share-ownership among poorer households due to the de-mutualization of building societies. Twenty-eight percent of households held risky financial assets in 1995 but this figure decreased to 26 percent in 2000.

There is a well-known trade-off between the accessibility (or liquidity) of wealth and the rate of return. Less wealthy households hold small amounts of risky assets due to the fact that transactions costs are too high to allow them to hold shares or other illiquid assets. Moreover, households that use their wealth as a buffer against uncertainty will tend to hold more liquid assets like bank and building society accounts. Therefore, low wealth households hold more interest-bearing assets (even though they are highly taxed[8]) and less non-liquid assets such as PEPs and TESSAs (which enjoy tax preferential treatment[9]). TESSAs aimed to eliminate double taxation for household savings held for 5 years; in fact, both PEPs and TESSAs were held more extensively by richer households. In this context, in 1999, the government launched ISAs (Individual Savings Accounts) aiming to be more widespread since the accounts do not require a minimum lock-in period. Then, PEPs and ISAs are tax-advantaged savings accounts that typically have a substantial component invested in stocks. Banks, Blundell and Smith (2003) show that higher house price volatility in the UK combined with much younger entry into home ownership explains the relatively small participation of young British households in the stock market.

The introduction of tax-incentive programs has been wide-spread. In France, the *Plan d'Épargue* was introduced in 1990, Germany has been using the *Vermögensbildungsgetz;* and the US has been using the Individual Retirement Account (IRA) and 401(k) plans in order to encourage retirement savings.

[8]The income paid into such an account is taxed at the marginal rate and also the nominal interest income is taxed at the 20% or at the 40% depending on the tax-payer. Stocks and shares contributions and returns are taxed but capital gains are only taxed on realisation and then only after a threshold.

[9]Payments into the accounts are taxed but returns and withdrawals are tax-free.

In comparison to other European countries, Italian portfolios are still poorly diversified and still focus on transactions accounts and government bonds with a very small proportion of shares in them. In addition, savings have very short-maturities and life insurance and pension funds are poorly developed. However, Italy is moving towards household portfolios more similar to other European countries, with higher proportions of riskier assets, especially in long-term bonds and mutual funds. This change has been due to an increase in participation. However, more than half of the population still have no risky assets. Guiso and Jappelli (2002) give some explanations for the lack of participation in risky assets. First, transaction costs are important for households with low wealth since brokerage fees and other transaction costs can amount to 4 percent of the investment. Secondly, background risk such as local unemployment can induce people to be more conservative at the time of investing. Third, information costs can prevent portfolio diversification. Fourth, the stock market has been very volatile due to its small size and illiquidity until very recently.

Table 2.3 illustrates how short-term government bonds are more widespread than long-term government bonds using data drawn from the SHIW[10]. Nevertheless, although the former remained stable until 1995, since then, they have declined dramatically. Long-term bonds -riskier bonds- issued by the government, and especially by private companies, have increased significantly. The spread between the long- and the short-term rate explains the shift. In addition, stocks and investment funds have increased during the 1990s as the return on equities and mutual funds increased dramatically during that period[11], particularly after 1995. In addition, financial in-

[10]Guiso and Jappelli (2002) point out that underreporting of financial assets in the SHIW causes particular understatement of risky assets when it is compared to official statistics. The reason is that the survey is not focused specifically on rich household wealth, which still hold the majority of risky financial assets.

[11]Italy has a very favourable tax treatment limiting the tax rate on capital gains to 1 percent. (Guiso, Haliassos and Jappelli (2003)).

Financial Assets	1991	1993	1995	1998	2000
Postal Interest Bearing Bonds	4.09	5.14	7.04	6.55	5.32
Short-term Treasury Bonds	21.56	20.31	21.65	9.67	10.26
Treasury Certificates	7.10	6.81	7.56	4.74	3.57
Long-term Treasury Bonds	2.69	2.84	4.46	2.70	2.04
Other Government Bonds, Zero Coupon and Foreign Bonds	0.95	0.89	1.49	1.53	1.16
Corporate Bonds	1.39	2.41	2.57	5.55	6.40
Shares of Stock Companies Held	2.85	4.19	5.16	8.33	10.32
Investment Fund Shares Held	2.31	4.29	4.50	10.86	12.12
Shareholding in Limited Companies	0.60	0.37	0.16	0.53	0.27
Shareholding in Partnership	0.67	0.53	0.07	0.15	0.17
Equity[1]	5.53	7.80	8.44	15.53	18.14
Risky Bonds[2]	4.25	5.25	6.82	7.88	8.44
Risky Assets[3]	8.49	10.83	12.29	18.60	21.06

Source: Author's calculations from SHIW dataset

Notes: Percentage of households owning a specific asset.

[1] Stocks, Investment Funds, or Shareholdings.

[2] Long-term Bonds, Zero Coupon Bonds, Foreign Bonds or Corporate Bonds.

[3] Equity or Risky Bonds.

Table 2.3: Italy: Household Portfolio Ownership

novation reduced minimum investment requirements and offered new diversification opportunities. Moreover, as in the UK, there has been a large privatization process of public utilities and state-owned companies with advertisement campaigns making households more aware of investment possibilities. Another factor that explains the different behaviour of young households in the 1990s from their predecessors is the removal of capital controls since 1989, which has led to an increase in foreign asset holdings, decreasing the home bias. Finally, the reform of the social security system (1992, 1996) and the lower expectations of pension benefits has led households to increase their own savings.

It seems plausible that a long-run wealth effect exists. It is not clear, however, if the relationship in the short-run between asset prices and consumption is merely a statistical correlation. Asset prices may simply lead to economic activity that eventually translates into an increase in consumption in the short-run and does not explain changes in consumption. Therefore, in order to analyze the implications of these changes in household portfolios, I look at the predictions of theoretical models in the following section.

2.4 The Life-Cycle Model of Consumption

Following Ludwig and Sloek (2002), Friedman (1957), Ando and Modigliani (1963) and Modigliani and Brumberg (1979) there are two transmission channels relating to stock market wealth:

1. Wealth effects: These can be realized or unrealized. When the value of consumers' stock holdings increases and households realize their gains then consumption would increase. This would be a direct effect as a consequence of higher current liquid assets. In addition, an increase in stock prices can also have an expectation effect where the value of stocks in pension accounts and other locked-in accounts increases. If these assets increase in value but are not realized, consumption would be higher today as expected future income and wealth would be higher.

2. Liquidity constraints effects: Increases in stock market prices raise the value of portfolios. Borrowing against the value of this portfolio in turn allows the household to increase consumption. Haliassos and Hassapis (2002) find that the "equity culture" creates incentives to increase loans that lead to an increase in current consumption. This is due to the fact that better prospects for future financial wealth accumulation (because of the equity premium) dominate the increase in riskiness of future income streams (that could discourage current consumption).

There are, however, some stylised facts from the literature that characterize life-cycle consumption and portfolio behaviour. First, the majority of households hold no equity - the participation puzzle. Second, levels of asset holdings in equity are very small. Third, the covariance of consumption growth and equity returns is low.

In what follows I would like to show evidence of wealth effects by controlling for liquidity constraint effects. Specifically, I will study the implications of changes in consumption that develop the equity culture, and how these changes are influenced by credit market conditions.

2.4.1 First Approach

Let us consider the conventional life-cycle consumption model under uncertainty with multiple periods. The consumer with additively separable utility wants to pick a sequence of consumption and asset stocks which maximize the expected value of his life-time utility subject to each period's budget constraint plus the boundary condition that requires that the consumer cannot die in debt, as follows:

$$Max_{\{C_s,A_s\}}E_t\left[\sum_{s=t}^{T}U(C_s)/(1+\delta)^{s-t}\right] \tag{2.1}$$

$$\begin{aligned} s.t.\ A_s &\leq (1+r_s)A_{s-1}+Y_s-C_s \\ A_T &\geq 0 \end{aligned} \tag{2.2}$$

where δ (0< δ ≤0) is the consumer rate of time preference, Y_s is a non-property income sequence (labour income and grants), r_s is the real rate of interest, T is the length of the economic life, A_s is the end of period assets (including the interest income on them) and U is the instantaneous felicity function which is a Van-Neumann Morgensten utility function.

The constraints will be equalities providing that this utility function is always increasing in consumption. Then I can write

$$Max_{\{A_s\}}E_t\left\{\sum_{s=t}^{T}U\left[(1+r_s)A_{s-1}+Y_s-A_s\right]/(1+\delta)^{s-t}\right\} \tag{2.3}$$

to get the Intertemporal Optimality Condition:

$$E_t\left[U'(C_s)/(1+\delta)^{s-t}\right]=E_t\left[(1+r_{s+1})U'(C_{s+1})/(1+\delta)^{s+1-t}\right] \tag{2.4}$$

with $s=t$:

$$U'(C_t)=E_t\left[(1+r_{t+1})U'(C_{t+1})/(1+\delta)\right] \tag{2.5}$$

that is, the relative consumption levels at different dates.

Under rational expectations with ε_{t+1} orthogonal to the information set available at time t, the fundamental first order condition or the observable equation is:

$$(1+r_{t+1})U'(C_{t+1})=(1+\delta)U'(C_t)+\varepsilon_{t+1} \tag{2.6}$$

I now impose some assumptions about the utility function in order to generate an expression that can be related to real data. Hall (1978) gives two possibilities: a quadratic and an isoelastic utility function. With the latter, also called Constant Relative Risk Aversion, $U(C)=(C^{1-\gamma}-1)/(1-\gamma)$, and equation 2.6 becomes,

$$C_{t+1}^{-\gamma}=[(1+\delta)/(1+r)]C_t^{-\gamma}+\varepsilon_{t+1}/(1+r) \tag{2.7}$$

where γ is the coefficient of risk aversion.

To sum up, Hall's paper shows that consumption is a random walk. That is, no variable apart from current consumption has any value in predicting future consumption, and time profile of income is irrelevant. The permanent income hypothesis/life-cycle hypothesis (PIH/LCH) under rational expectations implies that changes in consumption should be uncorrelated with anticipated changes in income and other variables that are in the consumers' information set. Hall's specification can be expressed in terms of the following log-normal approximation of the Euler equation with $\gamma = 1$:

$$\Delta lnC_{t+1} = \alpha + \varepsilon_{t+1} \tag{2.8}$$

where Δ is the first-difference operator taken with respect to time. Consequently, the permanent income/life-cycle model of consumption, under rational expectations, would predict that consumer expenditure should approximately follow a random walk with drift.

Extensions

Without denying the intuitive appeal of the PIH, some drawbacks have been pointed out in subsequent papers. These follow from the two major discrepancies that have been found between the model's predictions and empirical estimations.

Excess Sensitivity Puzzle One deficiency of the standard model is the failure to adequately capture the dynamic interaction of consumption, income and interest rates. This failure has much to do with the underlying assumption that capital markets are perfect so that agents can transfer their resources from one period to another. However, capital markets are far from perfect. Altonji and Siow (1987) point out the asymmetry of the response of consumption to predictable income growth. If predicted income increases, consumers want to borrow but are prevented from doing so, hence consumption responds to income (liquidity constraint binding). But if predicted income decreases, they will save and not borrow (liquidity constraint not binding).

One of the leading alternatives to the basic model is obtained by relaxing this assumption and allowing the existence of Keynesian-type consumers. In this case, consumption changes are no longer orthogonal to predictable, or lagged, income changes, since a correlation exists between consumption growth and lagged income growth. This is the excess sensitivity puzzle that has been investigated by Zeldes (1989) among others.

To allow for credit constraints, Zeldes (1989) modifies the second equation of the budget constraints 2.2 by $A_s \geq 0$. The Intertemporal Optimality Condition for $s = t$ then becomes:

$$U'(C_t) = E_t[(1 + r_{t+1})U'(C_{t+1})/(1 + \delta)] + \lambda_t \tag{2.9}$$

where λ_t is the Lagrange multiplier on the borrowing constraint.

By assuming iso-elastic preferences, joint log normality, $\gamma = 1$, and constant interest rates I get:

$$\Delta lnC_{t+1} = \alpha + \lambda_t' + \varepsilon_{t+1} \tag{2.10}$$

where λ_t' is a renormalisation of λ_t.

Zeldes divides the sample into consumers who are life-cycle optimizers and Keynesian-type consumers who are supposed to be consuming proportional to their existing income. Zeldes then finds that the *time profile of income is relevant*, not just the present value.

Borrowing restrictions –limited access to financial markets– have effects on consumption that are not clear cut. When restrictions are directly binding, they make households consume their disposable income. When restrictions are not binding, they also affect consumption through the individual's usual intertemporal optimisation concerns.

The evidence from microdata has yielded mixed results. Zeldes (1989) and Eberly (1994) find excess sensitivity to liquidity constraints - a significant relationship between changes in consumption and lagged income using the Panel Study of Income Dynamics (PSID) for US households. On the other hand, Altonji and Siow (1987) and Runkle (1991) find no evidence of liquidity constraints. Recently, studies have also tested for liquidity constraints. For the US, Hajivassiliou and Ioannides (1998) establish excess sensitivity for the low-asset income group while allowing for liquidity constraints to be endogenously determined. Garcia, Lusardi and Ng (1997) find excess sensitivity for the low wealth group as well as for the high wealth one, due to the fact that households do not have time-separable preferences as assumed by the classical theory. Instead, there is inertia in preferences, hence households adjust their behaviour slowly.

In the case of Italy, Japelli and Pistaferri (2000) find that consumption growth is uncorrelated with predicted income growth. Attanasio and Weber (1993, 1995) point out the possible biases created by aggregation and by omitting demographic variables which are important in models with nonseparable preferences, and find that consumption growth does not exhibit excess sensitivity to labour income for the UK. The excess sensitivity seems to disappear when changes in family composition and labour supply are controlled for.

These contradictory findings in the literature can be explained by the fact that some of these studies consider that λ_t does not vary over time. The fact that a consumer is liquidity-constrained does not mean that he will be a Keynesian type of consumer forever. λ_t can still vary over time because the consumer could save transitory increases in income. This is allowed, for example, by Hajivassiliou and Ionnides (1998).

In the following sections, I present further evidence on liquidity constraints and habit formation using data from the BHPS and the SHIW.

Risk Asset Puzzle or Participation Puzzle Another key prediction of the pure LCH model is that lagged wealth should have no predictive power for consumption because the previous value of consumption incorporates all information about the well-being of consumers at that time. To test this hypothesis, Hall (1978) uses stock prices lagged by a single quarter as a proxy for wealth and finds that changes in stock prices have a predictive value for consumption. He justifies the finding as being consistent with a modified random-walk hypothesis that allows for a brief lag between changes in permanent income and changes in consumption.

Poterba and Samwick (1995) find some effects of changes of stock prices on consumption for US aggregated data for the period 1947-1995. However, they justify the correlation between consumption and stock prices as the role of share prices as a leading indicator[12]. Ludvigson and Steindel (1999) analyse the short-run effects of wealth on aggregate consumption and find that changes in wealth are not correlated with the next quarter's consumption growth, because the response of consumption growth to an unanticipated change in wealth is largely contemporaneous. Attanasio and Banks (1998) claim that aggregate household savings data are inappropriate for the analysis of household savings and that only data relating to the life-time experiences of households will help to understand recent trends and patterns in saving rates. They question the fact that capital gains can explain the evolution of savings because people do not always cash capital gains and claim that it is not

[12]Stock prices may rise in anticipation of strong economic activity, including consumption.

clear if changes in asset prices are perceived as permanent.

Parker (1999) also estimates a Euler equation by adding the lag of wealth to test for wealth effects and controlling for stock ownership exogenously. He finds a negative but insignificant coefficient on wealth.

The puzzle that remains is why so few households hold risky assets. This is the micro analogue of the equity premium puzzle. Equilibrium portfolio theory predicts that individuals will diversify risks and maximise returns by holding a diversified portfolio containing a large number of different assets such as equity, government bonds, housing, etc. Despite this, the level of risky assets that are held is still low given the size of their returns.

Some studies have addressed the issue of limited participation in capital markets for risky assets. Haliassos and Bertaut (1995) point out that the excess returns to shares remains as a puzzle since 75 percent of American households do not hold shares despite the expected-utility model predictions.

Mankiw and Zeldes (1991) study the failure of the consumption-based Capital Asset Pricing Model (CAPM) based on a Euler equation estimated for the US. The equity premium puzzle is explained by the fact that aggregate consumption growth covaries too little with the return on equities to justify the large observed risk premium on stocks. The authors claim that this is because the CAPM relies on consumption data aggregated across stockholders and non-stockholders whose behaviour differs substantially. They find that aggregate consumption of stockholders is more highly correlated with the stock market than the aggregate consumption of non-stockholders. In addition, the consumption of stockholders is more volatile than the consumption of non-stockholders and the coefficient of relative risk aversion calculated from the PSID falls from 100 to 35 if only consumption of stockholders is considered. Even though 35 is still implausibly high, it moves in the right direction. Therefore, as the share of equity holdings in income increases, consumption should become more sensitive to asset price fluctuations.

Attanasio, Banks and Tanner (2002) find that the Consumption CAPM model works for the group of households who hold risky assets, once separated from the rest, thereby reaffirming the results of Mankiw and Zeldes (1991). They improve the Mankiw and Zeldes analysis by using a more complete measure of consumption and allowing shareownership to be endogenous. Mankiw and Zeldes used only food consumption and shareownership in the last period of the sample. In addition, they find that the largest increase in shareownership comes from households with high incomes but low levels of education. Therefore the fact that the Consumption CAPM model holds for risky assetholders raises the possibility that stock returns affect consumption through wealth effects.

Attanasio (1998) analyses the decline in aggregate personal saving in the US in the 1980s and concludes that households in their 40's and 50's during this period are responsible for the decline in savings. He is unable to say, however, why those households did not save enough. He controls for financial asset ownership and rejects the hypothesis that the decline in savings in the 1980s is explained by unmeasured capital gains on real estate and/or financial assets[13]. However, Maki and Palumbo (2001), using a cohort-level, times series data, show that aggregate trends in household consumption and savings over the 1990s can be explained by the existence of wealth effects on consumption.

Since the econometric techniques employed above ignore the two puzzles already stated, I think it makes sense to study both phenomena jointly. This is the approach taken in the next section.

A Euler equation is an equilibrium condition for a set of consumers that are unconstrained. To test it, variables are included that might be important in alternative settings, in particular expected income and expected wealth. The Euler

[13]He uses a very rough measure of capital gains by interacting the value of stocks of assets with year dummies.

equation, however, is not an equation which explains consumption or even consumption growth. For instance it does not tell us what consumption growth will be for an unexpected change in wealth, income, interest rate or any other variable. Therefore the possible rejection of the Euler equation gives valuable information but it is not clear how to interpret the coefficients on wealth. An alternative is to estimate consumption functions.

2.4.2 Second Approach

In this section I study consumer behaviour via the estimation of household consumption functions. The advantage of this approach is that the consumption function can be used to understand consumer behaviour rather than simply to estimate intertemporal substitution (as is the case with Euler equations). The old-style consumption function was derived by Friedman (1957) and Modigliani and Brumberg (1956) where each household (h) chooses at age (t) an amount of nondurable expenditures ($C_{h,t}$)[14] that provides utility through an intertemporally-separable, increasing, and concave utility function ($u(.)$). The function can be written as follows (See Parker (1999) for details):

$$Max_{\{C_{h,t}\}} E_S \left[\sum_{t=s}^{T} \beta^{t-s} \nu_a u\left(F_{h,t} C_{h,t}\right) + \beta^{T+1-s} V_{T+1}\left(F_{h,t} X_{h,T+1}\right) \right]$$

where E_S is the expectation operator conditional on all information available at time s; ν shifts utility as households age; β is the discount factor; F is a family-size adjustment that normalizes consumption to per-capita terms; X is household cash-on-hand and wealth; and $V(.)$ captures the possible value of cash on hand and wealth remaining at death. Households choices are constrained by an intertemporal

[14] Utility from nondurable consumption is assumed to be additively separable from utility from durable consumption or leasure.

budget constraint, and given their current levels of assets and income:

$$X_{h,t+1} = \tilde{R}_{h,T+1}\left(X_{h,t} - C_{h,t}\right) + Y_{h,t+1}$$

$$X_{h,t} \geq C_{h,t}$$

where $\tilde{R}_{h,T+1}$ is the gross after-tax rate of return on the household's optimal portfolio, and $Y_{h,t+1}$ is disposable non-asset income.

I follow Parker (1999) in assuming that in order to forecast future income, households only use as the basis of their forecast an estimate of the permanent component of its income $(P_{h,t})$. The latter is estimated as the forecast of the log of current income from two lags of income, education and age. Therefore, the consumption function of household h is a function of family size, wealth, income, age, the permanent component of income, and the aggregate state:

$$C_{h,t} = f\left(F_{h,t}, X_{h,t}, age_{h,t}, P_{h,t}, T_t\right) \tag{2.11}$$

Aggregate, planned consumption is explained above by labour income and wealth. However, actual consumption is not always equal to planned consumption due to several factors such as adjustment costs and liquidity constraints. Adjustment costs can prevent consumers from adjusting their housing services within each period. Capital restrictions prevent individuals from smoothing consumption by borrowing, therefore these liquidity-constrained consumers are more dependent on current consumption.

To sum up, the wealth effect reflected in the coefficient on lagged wealth in the Euler equation in the previous section is different in nature from the wealth effect reflected in the coefficient on current wealth in the consumption function in this section. The former is an excess sensitivity test of the underlying PIH model. The latter measures the (conditional) effect of additional financial wealth on the level of consumption, which is consistent with the PIH null, but close to the notion of wealth effects used to motivate this chapter.

2.5 The Basic Model

The existence of both households who invest in risky financial assets and households who do not invest at all suggests the use of selectivity models to address the issue of data censoring. If assetholders are prevented from investing in the capital markets, then the consumption of the households that are in the market should be higher than those that are outside the market. The key issue is that an increased participation in capital markets affects households already in the market and asset prices, while the expectation of entering the market affects those that are not. Furthermore, endogenous changes in capital stock have effects on all households.

The basic model is divided into a discrete and a continuous part that characterizes consumption demand and corrects for selectivity bias. The former part will be modelled using probit estimation. I will use a parametric model with censored endogenous variables to derive estimates to correct for the selection bias resulting from the unobserved endogeneity in the consumption function. Selectivity bias refers to the bias that arises due to the fact that the underlying discrete decision process is ignored. This bias occurs because the consumption that is observed for household participating in capital markets and being liquidity unconstrained depends on the underlying decision processes. I correct for that by estimating the consumption equations conditional on the asset or non-assetholding decision and the liquidity constrained probability.

In what follows I will introduce two variations on the life-cycle/permanent income hypothesis. First, I introduce a measure of wealth to analyse its possible effect on consumption in Italy and the UK in the 1990s, during which ownership increased. The variable has an obvious rationale, but is less closely related to competing theories of consumption. Theory and prevailing practice agree that contemporaneous wealth has a strong influence on consumption, particularly now that assets are held by a majority of the population. Secondly, the presence of liquidity constraints prevents consumers from smoothing consumption over transitory fluctuations in income.

2.5.1 Two-Step Switching Model with Endogenous Switching

To tackle the two puzzles in the literature, the inconsistency of the rational expectation-permanent income model of consumption and the consumption CAPM puzzle, I propose that:

1) λ_t is endogenous. That is, the degree to which liquidity constraints bind and the length of time over which they bind varies over time. Unfortunately, λ_t is unobservable, hence I follow Zeldes (1989) and Runkle (1991) in grouping households according to variables that determine whether or not households are liquidity constrained.

2) The decision to own risky assets in each period is likely to be endogenous with respect to consumption.

The econometric model extends the classic Heckman-Lee two stage estimation method that allows for double-selection (See Fishe et al. (1981), Maddala (1983) and Tunali (1986) for examples).

I would like to model two selection equations described by the following bivariate probit model:

$$L_{it} = 1\left(z_{it}^{L\prime}\gamma^{L} + u_{it}^{L} \geq 0\right) \tag{2.12}$$

$$R_{it} = 1\left(z_{it}^{R\prime}\gamma^{R} + u_{it}^{R} \geq 0\right) \tag{2.13}$$

where the indicator function $1(\cdot)$ is equal to 1 if the statement in the argument is true, and equal to 0 otherwise. That is, L_{it} and R_{it} are underlying utility indices that enable an individual to make one choice out of two alternatives. These two decision equations are likely to be correlated, so that $E\left[u_{it}^{L} \cdot u_{it}^{R}\right] = \rho_{u_{it}^{L}, u_{it}^{R}}$.

I next consider a choice model with four categories and one regression outcome in each category, following Dubin and McFadden (1984) and Fishe et al (1981):

$$C_{qit} = x_{qit}\beta_q + \varepsilon_{qit} \;\; (q = 1, 2, 3, 4)$$

$$L_{it}^{*} = z_{it}^{L}\gamma^{L} + u_{it}^{L} \;\; (i = 1, 2, ..., N) \tag{2.14}$$

$$R_{it}^{*} = z_{it}^{R}\gamma^{R} + u_{it}^{R} \;\; (i = 1, 2, ..., N)$$

where x_{qit} and z_{it}^{K}, with $K = L, R$, are exogenous variables, ε_{qit} are identically and independently distributed normal variables and u_{it}^{K} are assumed to be normally distributed with zero mean and variance normalized to unity.

When $L_{it}^* \geq 0$ the household is liquidity constrained. When $R_{it}^* \geq 0$ the household is a risky assetholder. This generates the following probability of the joint decision:

$$Prob\left(L_{it}^* \geq 0, R_{it}^* \geq 0\right) = Prob\left(u_{it}^L < z_{it}^L \gamma^L, u_{it}^R < z_{it}^R \gamma^R\right) = F\left(z_{it}^L \gamma^L, z_{it}^R \gamma^R, \rho\right) \tag{2.15}$$

To obtain the ML estimates of γ^L, γ^R and ρ, I maximize the following likelihood function:

$$L = \prod_{I=1} F\left(z_{it}^L \gamma^L, z_{it}^R \gamma^R, \rho\right) \cdot \prod_{I=0} \left[1 - F\left(z_{it}^L \gamma^L, z_{it}^R \gamma^R, \rho\right)\right] \tag{2.16}$$

under the assumption of normality of u_{it}^K. Since the Σ (variance-covariance matrix of the standardized error terms) is not a diagonal matrix, I will use a maximum likelihood bivariate probit to produce consistent estimates of γ^L, γ^R, and ρ.

In this model, I have four possible decision combinations:

$$\Delta \ln C_{1it} = x_{1it}\beta_1 + \varepsilon_{1it} \;\; iff \;\; i \in PC\,(1)$$

$$\Delta \ln C_{2it} = x_{2it}\beta_2 + \varepsilon_{2it} \;\; iff \;\; i \in PC\,(2)$$

$$\Delta \ln C_{3it} = x_{3it}\beta_3 + \varepsilon_{3it} \;\; iff \;\; i \in PC\,(3) \tag{2.17}$$

$$\Delta \ln C_{4it} = x_{4it}\beta_4 + \varepsilon_{4it} \;\; iff \;\; i \in PC\,(4)$$

where the combination sets are:

$$PC\,(1) = \{\, it \mid L^*_{it} \geq 0\,,\; R^*_{it} \geq 0\}$$

$$PC\,(2) = \{\, it \mid L^*_{it} < 0\,,\; R^*_{it} \geq 0\}$$

$$PC\,(3) = \{\, it \mid L^*_{it} \geq 0\,,\; R^*_{it} < 0\} \tag{2.18}$$

$$PC\,(4) = \{\, it \mid L^*_{it} < 0\,,\; R^*_{it} < 0\}$$

and ε_{qit} are jointly distributed with u^L_{it} and u^R_{it}, such that

$$E\left[\varepsilon_{qit}\, u^K_{it}\right] = \sigma_{qk}.$$

Since the disturbances in the decision equations are correlated ($Cov(u^L_{it}, u^R_{it}) = \rho$), equation 2.17 implies that

$$E[\Delta \ln C_{qit} \,|\, i \in PC(q)] = x_{qit}\beta_q - \sum_{q=1}^{Q} \sigma_{qk} \frac{\phi(z_{it}^K \gamma^K) \,.\, \Phi((2\,1\,(i \in PC(q)) - 1)(z_{it}^L \gamma^L, z_{it}^R \gamma^R, \rho))}{\Phi_2((2\,1\,(i \in PC(q)) - 1)(z_{it}^L \gamma^L, z_{it}^R \gamma^R, \rho))} \tag{2.19}$$

where $q = 1, 2, 3, 4$ and $K = L, R$.

The last term of equation 2.19, the Heckman correction term or Inverse Mills ratios, can be interpreted in terms of the endogeneity of the two selection equations, M_{it}^K hereafter. $\Phi_2(.)$ is the bivariate standard normal distribution, $\Phi(.)$ is the standard normal distribution function, and $\phi(.)$ is the density function. (see Appendix for details).

By looking at the BHPS and SHIW calculations stated in Table 2.4[15], I observe that the PC(1) combination of equation 2.18 -namely, L, R- contains a small proportion of households. As a result I will mostly be concerned with equations defining $\Delta \ln C_{2it}$, $\Delta \ln C_{3it}$ and $\Delta \ln C_{4it}$.

1995			
UK		IT	
NL,R:0.22	NL,NR:0.27	NL,R:0.12	NL,NR:0.43
L,R:0.05	L,NR:0.46	L,R:0.01	L,NR:0.44
2000			
UK		IT	
NL,R:0.18	NL,NR:0.20	NL,R:0.20	NL,NR:0.35
L,R:0.08	L,NR:0.54	L,R:0.01	L,NR:0.44

Source: Author's calculations from BHPS and SHIW.
Note: Percentage of households in each category.
L=Liquidity constrained, NL=no-L; R=Risky Assetholder, NR=non-R.

Table 2.4: Liquidity Constraints and Assetholdings

[15]The asset-based split is used to calculate the proportion of liquidity constrained households in Table 2.4. See section 2.6.1. for an explanation on the definition.

2.6 Empirical Results

The principal economic framework underlying the analysis is the life-cycle model, and my aim is to test the model and improve its empirical specification. Once the estimation equations have been obtained, I will discuss the implications for the theoretical model. For the sake of comparison I use the same time period for both countries. The BHPS has only financial information for 1995 and 2000 (while the SHIW has information for the whole period 1991-2000) hence I restrict the analysis to these two years.

2.6.1 Liquidity Constraints

Different forms of liquidity constraints have been examined in the literature, usually in the form of a price or quantity restriction on the holding of assets. I consider two measures of liquidity constraints: first, following Zeldes' paper I rely on an asset-based sample separation rule, that is, the ratio of total wealth in t to the average of disposable income in t and $t-1$. Based on the level of assets held, households are divided into liquidity constrained (low wealth) households and those with access to credit markets (high wealth). Second, following Jappelli, Pischke and Souleles (1998) I consider a more direct measure of liquidity constraints, namely, information on credit card holdings. The Appendix contains an explanation of the construction of the variables. In this way I can weaken the spurious problem arising from the correlation between consumption growth, lagged income, and assets when the Euler equation is estimated in a linearized way, omitting the second and higher order terms of the conditional distribution of consumption growth.

Tables 2.5 and 2.9 (the latter in the appendix) display the results of the liquidity-constrained equations for the UK and Italy using two measures of liquidity constraints, the asset-based and credit card splits. The explanatory variables in these probit equations include age of head of household, age squared, a dummy for the poorest region, house ownership (with mortgage and without), sex of household head, marital status (married), family size, number of children, employment status of household head, employment status of spouse, education of head, and year effects.

The coefficients on age for the asset split in both countries are negative and significant, implying that aging decreases the probability of being liquidity constrained. The positive sign on age squared suggests that after a certain age, aging increases the probability of being liquidity constrained. Education is highly significant and negative in both countries, implying that schooling is a predictor of future earnings and ability to repay loans.

Female headed households might have a lower level of expected future income and appear to suffer from additional credit rationing. This difference may be the result of discrimination. On the other hand, sex turns out to be insignificant when the credit card split is used.

The negative sign on the marital status dummy also accords with theory but is only significant in the case of the UK, thus supporting the idea that married couples are less constrained than singles. A big family is likely to be more constrained in the UK although the family size variable is insignificant in the case of Italy. A larger number of children increases the likelihood of being constrained for both countries using the asset split. I include a dummy for the poorest regions and this is significant in both countries; northern regions for the UK and southern regions for Italy.

In the UK, employment status of the household head plays an important role in determining the existence of liquidity constraints when either of the two splits is used. In Italy, however, it is only significant when the credit card split is used. Employment of the spouse is important in the case of Italy (according to both splits). For the UK, it is only significant for the credit card split. The year effect is significant in both countries. Interestingly, the data suggests that households that own a house are less liquidity constrained in the UK. In Italy, however, it is only

	Italy				UK			
	Dependent variable:							
	Asset Split		Risky Assets		Asset Split		Risky Assets	
Variables	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.
Constant	1.682	11.82	-5.151	-22.80	2.310	16.08	-3.614	-21.90
Age	-0.026	-5.52	0.038	5.65	-0.034	-6.33	0.054	8.71
Age^2	0.000	3.77	-0.000	-5.25	0.000	2.71	-0.000	-7.44
Region	0.600	26.08	-0.759	-21.73	0.063	5.02	-0.033	-2.73
Own1mort	0.010	0.16	-0.132	-0.25	-0.344	-8.64	0.764	16.17
Own0mort	-0.282	-11.84	-0.009	-0.20	-0.684	-17.04	0.877	18.25
Sex	-0.152	-5.24	0.163	4.45	-0.153	-4.14	0.161	3.89
MS	-0.048	-1.43	0.086	2.02	-0.126	-3.15	0.080	1.81
Fsize	0.001	0.05	-0.091	-5.67	0.054	2.42	-0.086	-5.12
Child	0.091	3.89	-	-	0.082	3.07	-	-
Adult	-	-	0.101	5.04	-	-	-0.028	-0.88
Emplh	-0.004	-0.14	-	-	-0.143	-3.56	-	-
Empls	-0.177	-6.93	0.127	3.77	0.042	1.11	-0.010	-0.21
Educ	-0.342	-20.05	0.545	22.53	-0.255	-16.45	0.294	18.06
Wage	-	-	0.013	3.59	-	-	0.031	4.78
Selfemp	-	-	0.015	0.37	-	-	-0.045	-0.90
FWealth	-	-	0.121	7.17	-	-	0.041	9.21
YearEffect	0.047	2.33	0.371	14.43	0.180	7.26	0.057	1.96
$\rho_{u^L_{it},u^R_{it}}$	-0.680 (-31.31)				-0.471(-22.27)			
Log likelihood	-15118.076				-10545.485			
No. Obs	16136				10195			

Notes: t-statistics calculated with robust standard errors clustered by household and corrected for heteroskedasticity. Sample: 1995, 2000.

$\rho_{u^L_{it},u^R_{it}}$ controls for common determinants of liquidity constrains and asset holding equations, not fully captured by the explanatory variables.

Table 2.5: Selection Equation. Asset Split

the case if the household does not have a mortgage.

To sum up, the fraction of constrained households is endogenous, and varies in response to changes in demographic characteristics and future income.

The difference in liquidity constraints results between the credit card measure and the asset ratio measure is due to the fact that the group without credit cards is observed to be different to one with a low asset ratio. The former can be characterized as unmarried, older and with lower education.

2.6.2 Assetholding Ownership

Empirical models of household portfolio choice in the literature are typically of a reduced form, not least because a structural empirical model will require more complete information than typically provided in the data. In this fashion, King and Leape (1998), Hochguertel, Alessie and van Soest (1997), Banks and Tanner (2002), and Guiso and Japelli (2002, 2003) analyse American, Dutch, British and Italian household portfolios respectively.

Among the variables that can affect assetholding ownership, I consider net worth, age, age squared, sex of head, poorest region, family size, number of adults, marital status, homeownership (with and without mortgage), education of head, employment of spouse, dummy for self-employment, labour income, financial wealth, and year effects.

Tables 2.5 and 2.9 present the asset ownership equations for the UK and Italy. They show that ownership of risky financial assets depends strongly on financial wealth in the positive direction predicted by portfolio theory. In addition, the percentage of households that hold risky financial assets increases with average labour income. This is because households have larger portfolios, hence they are more willing to pay for the fixed information cost.

Standard asset portfolio models without transaction costs, in which risky assets have a higher return than safe assets, do not address the issue of participation/ non-participation. Since some households do not hold assets because they are not aware of their existence, models should include transactions costs and incomplete financial information. Education is a good proxy for these variables since it can be interpreted as a measure of the ability to process information about the market and overcome the barriers to shareholding.

Older households are more likely to hold assets than younger ones. The positive sign on age and the negative sign on squared age implies that participation is hump shaped. Households invest a small proportion of their wealth in risky financial assets when they are young, but they increase this proportion as they accumulate more wealth to cover the fixed costs of investing in risky assets. After reaching a maximum at middle age, this proportion starts declining. Young and old people have greater income variability, and therefore they are the groups less likely to hold risky financial assets. In addition, liquidation costs and market imperfections make younger households less willing to invest in risky assets, especially when they are looking for a home purchase. On the other hand, health risk shortens the period of investment payoff and thus makes elder people more reluctant to invest in risky assets.

The significant positive sign of marital status indicates that married couples own more risky assets than single people. Single-parent households tend to have the lowest ownership rates and married couples without children tend to have the highest. Larger households own less risky assets but the larger the number the adults the higher the likelihood of having risky assets in Italy. Employment of the spouse is important for Italy. Homeownership is critical for households in the UK but not Italy. The self-employment dummy turns out to be insignificant. The dummy for poor regions has a negative influence on market participation. Finally, male heads of household are more likely to be risky asset holders in both countries.

The correlation between the error terms of the two equations, $\rho^{u^L_{it},u^R_{it}}$, is negative and highly significant, showing a negative relationship between the errors of holding shares and liquidity constraints. The results are in line with Paxson (1990) who shows that households exposed to liquidity constraints and facing uncertain liquidity needs will tend to hold relatively liquid and safe assets. This result suggests that liquidity constraints and asset holdings may be determined by common variables omitted from both specifications.

2.6.3 Consumption Equations

Focusing on equation 2.10, I can test two orthogonality restrictions associated with the model. Specifically, under the null hypothesis of no borrowing constraints λ_{it} should equal zero for both constrained and unconstrained households, labour income (Y_{it}) should be insignificant, and parameters should be similar across both types of households. Under the alternative hypothesis of borrowing constraints λ_{it} will not equal zero for the constrained group and will be correlated with Y_{it}. Furthermore, I can test for wealth effects and see whether they can lead to another rejection of the Euler equation. A simple test of these hypotheses is to enter Y_{it} and financial wealth, W_{it}, as additional regressors and test their significance.

In order to fit the equation a number of modifications are necessary. The utility derived from consumption also depends on family composition. Therefore a simple correction is made by assuming that the utility is shifted by a number of demographic variables such as age, family size, number of children, and so forth. Moreover, following Attanasio and Weber (1995) I include a labour supply variable to take into account nonseparability between consumption and leisure.

Euler Equations of Consumption Growth

Estimates are based on the typical Euler equation derived from 2.10:

$$\Delta C^q_{it+5} = \alpha^q + \varphi^q A_{it} + \beta^q \Delta X_{it+5} + \varepsilon^q_{it+5} \quad (2.20)$$

where the dependent variable, $\Delta C^q_{it+5} = ln(C_{it+5}/C_{it})$, is real non-durable and services consumption, A_{it} represents age variables (controlling for changes in preferences) and $\Delta X_{it+5} = ln(X_{it+5}/X_{it})$ represents demographic characteristics.[16] The elasticity of intertemporal substitution is σ, q is the number of regimes ($q = 1, 2, 3, 4$) and ε^q_{it+5} is a residual uncorrelated with all the information available at time t or earlier for household i at time t in a regime q. The constant α^q depends on conditional second moments of consumption growth and the real interest rate.

I use five-year changes in consumption to maintain comparability with the financial data available from the BHPS. Notice that in these equations the only source of variation is cross-sectional.

According to theory, innovations in the Euler equation are not predictable by the variables on the right-hand-side. However, the existence of positive shocks to wealth could generate a correlation between innovations to wealth and predictable movements in the real interest rates. In other words, increases in consumption will remain unexplained after removing the substitution effect due to movements in real interest rates. In order to avoid possible sample bias on the remaining coefficients, I have allowed for different rates of consumption growth for assetholders and non-assetholders in the four regime model.

To recapitulate, the key hypothesis is that under a simple version of the life-cycle model, there should be no relation between consumption growth and expected income or wealth, since consumers with a concave utility function should smooth expected income and wealth fluctuations. I therefore include $ln\ Y_{it}$ to test for excess

[16]Following Japelli, Pischke and Souleles (1998), I include directly the change in number of adults and change in the number of children as opposed to using the measure of food needs.

sensitivity following Zeldes (1989), and I include the amount of financial assets held ($ln\, W_{it}$) in order to test for wealth effects. I modify equation 2.20 to make consumption expenditure a function of household wealth and labour income as follows:

$$\Delta\, C^q_{it+5} = \alpha^q + \varphi^q A_{it} + \beta^q \Delta X_{it+5} + \gamma^q \ln Y_{it} + \delta^q \ln W_{it} + \varepsilon^q_{it+5} \tag{2.21}$$

I therefore assume that households only require knowledge of demographic characteristics, current and expected future resources, income and wealth.

Since sections 6.1 and 6.2 have shown that both the probability of being liquidity constrained and of being an assetholder are endogenous, I cannot estimate Euler equations treating both characteristics as exogenous. Consequently, I modify equation 2.21 to account for selection by including M^K_{it}, the Heckman correction term for the endogenous selection as an additional regressor. The coefficients on the selection correction terms are identified in this analysis by excluding the dummy for the poorest region, house ownership (with mortgage and without), sex of household head, number of adults in the household, employment status of the household head, and education of head from the Euler equation. The analog of 2.17 will be as follows.

$$\Delta\, C^q_{it+5} = \alpha^q + \varphi^q A_{it} + \beta^q \Delta X_{it+5} + \gamma^q ln\, Y_{it} + \delta^q ln\, W_{it} + \psi^q M^K_{it} + \varepsilon^q_{it+5} \tag{2.22}$$

The specification of the equation is similar to that estimated by several authors, such as Zeldes (1989), Attanasio and Weber (1995), Shea (1995), Garcia et al. (1997) and Japelli et al. (1998). Following Japelli et al. (1998) and Garcia et al. (1997) I omit the interest rate from the Euler equation (I only have one cross section Euler equation for both samples).[17] As a consequence, I do not need to use instrumental

[17]Since I am asssuming a constant interest rate, I am not considering the channel of liquidity constrained households whose cost of borrowing is higher than the return to saving.

	Dependent Variable: $\Delta C^q_{it+5} = ln(C_{it+5}/C_{it})$					
Select. (K):	Asset Split, Risky Assets					
Regime (q):	UR		CNR		UNR	
Country:	Italy	UK	Italy	UK	Italy	UK
α	0.359	0.91	0.536***	0.995	0.248	2.592***
	(0.43)	(0.76)	(0.184)	(0.36)	(0.21)	(0.78)
Age_{it}	-0.006	-0.06**	-0.015**	-0.031***	-0.012*	-0.03*
	(0.013)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
Age^2_{it}	0.410	0.047**	1.194*	0.020	1.092	0.012
	(1.27)	(0.02)	(0.65)	(0.15)	(0.67)	(0.02)
$\Delta\text{Fsize}_{it+5}$	0.350**	0.263*	0.449***	0.349***	0.420***	0.463***
	(0.14)	(0.16)	(0.079)	(0.12)	(0.10)	(0.14)
$\Delta\text{Child}_{it+5}$	0.012	-0.015	-0.244***	-0.178*	-0.115*	-0.015
	(0.10)	(0.18)	(0.06)	(0.09)	(0.07)	(0.16)
$\ln \text{Y}_{it}$	-0.00008	0.009	-0.003	-0.006	-0.0003	-0.017
	(0.006)	(0.02)	(0.003)	(0.01)	(0.004)	(0.02)
$\ln \text{W}_{it}$	-0.034**	-0.012	-	-	-	-
	(0.017)	(0.02)	-	-	-	-
Married_{it}	-0.037	0.103	-0.004	-0.071	0.079**	0.172*
	(0.07)	(0.09)	(0.04)	(0.06)	(0.06)	(0.10)
Empls_{it}	0.065	0.010	0.040	-0.052	-0.023	-0.210*
	(0.05)	(0.11)	(0.03)	(0.07)	(0.03)	(0.11)
M^L_{it}	-0.030	0.582	-0.089	0.453*	-0.026	0.625**
	(0.49)	(0.47)	(0.065)	(0.24)	(0.09)	(0.30)
M^R_{it}	0.158**	0.580**	0.075	1.286***	-0.035	1.149***
	(0.07)	(0.26)	(0.38)	(0.34)	(0.09)	(0.24)

Notes: U=unconstrained, C=constrained; R=assetholder, NR=non-R.
Dependent variable is the five-year change in log of non-durable consumption. Standards errors in parenthesis. Standards errors obtained by bootstrapping (1000 replications) to adjust for the presence of M^K_{it}.
*, **, and *** denote significance at 10, 5 and 1 percent level respectively.

Table 2.6: Euler equation. Asset split

Dependent Variable: $\Delta C^q_{it+5} = ln(C_{it+5}/C_{it})$						
Select. (K):	Credit Card, Risky Assets					
Regime (q):	UR		CNR		UNR	
Country:	Italy	UK	Italy	UK	Italy	UK
α	-0.684	0.842	0.397**	.891**	0.484***	1.136**
	(0.87)	(0.73)	(0.20)	(0.38)	(0.21)	(0.50)
Age_{it}	0.004	-0.068**	-0.010*	-0.016	-0.019**	-0.054***
	(0.02)	(0.29)	(0.01)	(0.01)	(0.01)	(0.02)
Age^2_{it}	-0.562	0.064**	0.773	0.007	1.600**	0.044**
	(2.40)	(0.03)	(0.67)	(0.01)	(0.70)	(0.02)
$\Delta\text{Fsize}_{it+5}$	0.411	0.327**	0.285***	0.433***	0.579***	0.335**
	(0.26)	(0.16)	(0.09)	(0.12)	(0.08)	(0.13)
$\Delta\text{Child}_{it+5}$	-0.085	0.157	-0.091	-0.091	-0.300***	-0.166
	(0.18)	(0.17)	(0.06)	(0.11)	(0.08)	(0.10)
$\ln \text{Y}_{it}$	-0.011	0.018	-0.001	-0.012	-0.002	0.004
	(0.01)	(0.02)	(0.003)	(0.01)	(0.004)	(0.02)
$\ln \text{W}_{it}$	-0.012	-0.040*	-	-	-	-
	(0.03)	(0.02)	-	-	-	-
Married_{it}	0.198	0.090	0.056*	0.012	0.017	0.059
	(0.15)	(0.10)	(0.03)	(0.07)	(0.04)	(0.08)
Empls_{it}	0.097	0.035	0.028	-0.097	0.003	-0.100
	(0.10)	(0.10)	(0.03)	(0.10)	(0.04)	(0.08)
M^L_{it}	-0.144	-0.181	-0.135	-0.310**	-0.124	-0.272*
	(0.37)	(0.32)	(0.12)	(0.14)	(0.14)	(0.16)
M^R_{it}	0.409**	0.262*	0.146	0.382*	0.151	0.363**
	(0.16)	(0.16)	(0.12)	(0.21)	(0.13)	(0.16)

Notes: U=unconstrained, C=constrained; R=assetholder, NR=non-R.
Dependent variable is the five-year change in log of non-durable consumption. Standards errors in parenthesis. Standards errors obtained by bootstrapping (1000 replications) to adjust for the presence of M^K_{it} .
*, **, and *** denote significance at 10, 5 and 1 percent level respectively.

Table 2.7: Euler Equation. Credit Card split

variables in the estimation since all regressors are part of the household information set. Since the analysis is motivated by the existence of wealth effects coming from risky assets, the wealth term is not included in those cases where the household is not a risky asset holder. The inclusion of different components of wealth as separate regressors is ruled out since comparable disaggregated wealth for both countries is not available. Following Zeldes (1989) I assume that family composition (and the number of children) and the age of the head at $t + 5$ are known at time t. I include a large number of demographic characteristics (age, age squared, family size, number of children, a dummy that equals unity if the spouse works, and a dummy for married individuals) to address Attanasio and Weber (1995)'s point that excess sensitivity disappears when controlling for those variables. For obvious reasons, I do not include time effects since I do not have enough variability in the data. Moreover, given that the analysis uses only one cross-section observation, the inclusion of a constant prevents the estimation of separate time dummies. This is a strong assumption since there may be aggregate expectations errors.[18] Shea (1995), Japelli et al. (1998) and Garcia et al. (1997), however, only report the estimation without time effects after finding that results were qualitatively and quantitatively similar. In addition, for the same reason, I do not include fixed household effects in the estimation. Japelli et al. (1998) and Garcia et al. (1997) do not include fixed household effects either.

Tables 2.6 and 2.7 show the results. In general the negative coefficients on age and sometimes positive coefficients on age-squared are consistent with the hump-squared pattern of consumption over the life-cycle.

The first regime is the group of unconstrained and risky asset households. When the asset split is used in the selection equations, the coefficient of labour income

[18]The time average of individual forecast errors over T periods should converge to zero as $T \to \infty$ assuming forecast errors are unbiased; but an average of forecast errors at a given point in time across N individuals surely need not converge to zero as $N \to \infty$, there may be common components in those errors, due to the economy-wide innovations.

is insignificant, as predicted by the theory of liquidity constraints with both splits (asset and credit card). The coefficient on financial assets, however, is significant. This violates the PIH, and gives room for wealth effects. In the case of Italy, this occurs when the asset split is used, while in the UK this happens with the credit card split. The coefficient for Italy is 0.034 while the coefficient for the UK is a bit higher (0.04). The second column shows the case for constrained households where, contrary to expectations, the labour income coefficients are insignificant for both countries, although the sign is correct. The interpretation of the negative coefficient on the labour income in levels is that if disposable income at time t increases and nothing else in the model changes, consumption will rise today relative to tomorrow, lowering the expected growth in consumption. This interpretation suggests a negative partial correlation between λ_{it} and Y_{it}. In summary, I do not find excess sensitivity although PIH is violated by wealth effects on consumption.

Consumption functions

The log-linear approximation of equation 2.11 will be as follows:

$$\ln C = \delta_0 + \delta_1 fsize + \delta_2 child + \delta_3 \ln W + \delta_4 \ln Y + \delta_5 age + \delta_6 \ln Yp + \delta_7 T + \varepsilon$$

where $fsize$ is family size, $child$ is number of children, W is wealth, Y is current labour income, age is age of the household, Yp is the permanent component of labour income[19] that forecasts expected labour income and T is a year effect.

This equation is estimated based on 1995 and 2000 data for both countries. Results are similar if a two-stage least squares estimation is implemented and more

[19] Following Parker (1999), I construct the permanent component of labour income as the forecast of the log of current labour income from two lags of the log of labour income, education, and age-group dummy variables.

control variables are added.[20] The coefficients on the selection correction terms are identified in the estimation by excluding age squared, the dummy for the poorest region, house ownership (with mortgage and without), sex of household head, marital status, number of adults in the household, employment status of the household head, employment status of the spouse, and education of head from the consumption function.

Tables 2.8 and 2.10 show the results. The first thing to note is the significant coefficient of financial wealth in all specifications. The marginal propensity to consume out of risky financial assets is estimated to be around 4 percent in both countries. A common assumption is that the coefficient of stock market wealth is 0.05 for the US. For example, Ludvigson and Steindel (1999) find a marginal propensity to consume out of wealth of 0.04 for aggregate consumption. The fact that this coefficient on equity wealth is different from the coefficients on other kinds of wealth (such as housing, see Chapter 3) might be explained by the fact that consumers are heterogeneous and stock market owners may be systematically older or younger than other wealth owners, or may have other distinctive characteristics.

All specifications show, consistent with Parker (1999), a significant correlation between consumption and the permanent component of income. Another interesting result is that while current income is significant in all specifications for the UK, it is only significant for constrained households in Italy. In the presence of liquidity constraints, I expect to see a significant coefficient on current income for the constrained households. At the same time, however, habit formation applies to both constrained and unconstrained individuals, hence the current income coefficient is significant in both cases.[21] I might therefore interpret the results as owing to the

[20] Given the limited number of time periods available for the analysis, the use of Generalised Method of Moments estimators in the context of single equation, autoregressive-distributed lag models was not feasible. (See Bond (2002) for a review of dynamic panel data models).

[21] Habit formation assumes inertia in preferences. If this is the case, households will adjust their behaviour slowly, therefore omitting lags of consumption might explain the significant coefficient of income (See Garcia et. al (1997) for a discussion).

	Dependent Variable: $C^q_{it1} = ln(C_{it})$					
Select. (K):	Asset Split, Risky Assets					
Regime (q):	UR		CNR		UNR	
Country:	Italy	UK	Italy	UK	Italy	UK
α	11.611***	5.873***	10.907***	6.221***	11.550***	4.628***
	(0.15)	(0.43)	(0.07)	(0.16)	(0.08)	(0.46)
Age_{it}	0.007***	-0.007*	0.004***	0.005**	0.003***	0.005
	(0.001)	(0.004)	(0.001)	(0.002)	(0.0008)	(0.004)
$Fsize_{it}$	0.159***	0.168***	0.157***	0.153***	0.172***	0.177***
	(0.01)	(0.03)	(0.01)	(0.02)	(0.007)	(0.03)
$Child_{it}$	-0.037**	-0.063	-0.049***	-0.125***	-0.030***	-0.105**
	(0.02)	(0.04)	(0.010)	(0.02)	(0.010)	(0.04)
Y_{it}	0.001	0.032***	0.015***	0.063***	-0.001	0.066***
	(0.002)	(0.01)	(0.001)	(0.006)	(0.001)	(0.01)
Yp_{it}	0.017**	0.095***	0.021***	0.059***	0.013**	0.071***
	(0.008)	(0.02)	(0.005)	(0.01)	(0.005)	(0.02)
W_{it}	0.034***	0.037***	-	-	-	-
	(0.007)	(0.01)	-	-	-	-
T_{it}	-0.182***	-0.349***	-0.072***	-0.308***	-0.160***	-0.346***
	(0.02)	(0.05)	(0.009)	(0.03)	(0.01)	(0.051)
M^L_{it}	-0.343**	-0.958***	0.565***	-1.328***	0.163***	-0.938***
	(0.13)	(0.23)	(0.02)	(0.14)	(0.03)	(0.16)
M^R_{it}	-0.442***	-0.02	-1.968***	-2.353***	-0.803***	-0.370***
	(0.02)	(0.15)	(0.08)	(0.17)	(0.025)	(0.14)

Notes: U=unconstrained, C=constrained; R=assetholder, NR=non-R.
Standard errors clustered by household in parenthesis.
Standards errors obtained by bootstrapping (1000 replications) to adjust for the presence of W^K_{it} .
*, **, and *** denote significance at 10, 5 and 1 percent level respectively.

Table 2.8: Consumption Function Regression

presence of liquidity constraints in Italy and habit formation in the UK. Caution is needed when interpreting the coefficient on the income variables, since the time effects remove mean long-run correlations (see Parker (1999) for details).

2.7 Conclusion

I analysed the structure of financial household portfolios by looking at the determinants of risky assets for two European countries –the UK and Italy. Households have shifted towards riskier portfolios by substituting stocks and bonds for bank accounts in both countries. Differences remain, however. In 2000, while 24 percent of households held stocks in the UK, only 18 percent did in Italy (26 and 8 percent respectively in 1995).

I used a standard life-cycle model of consumption, augmented to include liquidity constrained consumers and risky financial assetholders who behave differently from other households. I estimated an endogenous switching model with the switch depending on two criterion functions to analyse the endogeneity process behind liquidity constraints and stocks and bond-ownership. My main argument was that if assetholders are prevented from investing in capital markets, then the consumption of the households that are in the market should be higher than those that are outside the market. An example of that is the case of households that are poor, which do not feel that the fixed costs of investment required to access capital markets are worth the potential payoff. The key issue is that increased participation in capital markets affects both households already in the market and asset prices, while the expectation of entering the market affects those that are not in the market. Furthermore, endogenous changes in capital stock have effects on all households.

I found that the value of financial assets had a significant impact on consumption in both countries, whilst high frequency studies find little relationship (a marginal propensity to consume out of financial assets of 0.04).

Results are not clear with respect to liquidity constraints. I found no evidence of excess sensitivity in the Euler equations. By analysing the standard consumption function equation, however, I found some evidence of liquidity constraints in Italy and of habit formation in the UK.

The task of finding empirical differences in the impact of monetary policy on output and prices is difficult. It is clear that there are cross-country differences in the financial structure, as we have seen in the third section of the chapter, but their direct translation to output and prices is not clear-cut due to different forces that can offset each other. In addition, using different models can bring different results for the same country as we saw in the case of liquidity constraints.

The financial structures are expected to converge in Europe and effects are expected to become more homogeneous. The convergence, however, can be slow and the asymmetry may have important consequences for the harmonized monetary policy of the ECB.

2.8 Appendix

2.8.1 Description of the Constructed Variables

Asset-based separable rule

I use an asset-income ratio split based on Zeldes (1989): specifically, I categorise a household as liquidity constrained if the ratio of wealth to the average disposable income in t and $t-1$ is less than 2/12.

More direct measures of constraints

Japelli, Pischke, and Souleles (1998) discuss some drawbacks of splitting the sample on the basis of wealth: 1) Since there is not a monotonic relationship between wealth and liquidity constraints, a household with zero or negative wealth has not necessarily reached the limit. 2) The fact that assets and income are poorly measured overstates the number of low-asset households. Therefore, they use direct indicators of credit constraints:

- Self-reported indicators of whether people were turned down for loans.
- Credit card ownership.
- Availability of a credit line

  Only the second measure is available for both datasets, therefore for comparability reasons I use only credit card ownership.

Real disposable income

The disposable income variable is income after taxes deflated by the Department of Social Security monthly price index before housing costs for the BHPS data and the Consumer Price Index for the SHIW data.

Consumption

The basic theory of consumption is applicable to the flow of consumption and so durable consumption is excluded from the definition used here. Durable consumption is not a service flow from the existing stock but replacements and additions to the asset stock.

The BHPS consumption measure does not include expenditures on shoes and clothing.

Asset values

The value of the different types of wealth were reported in intervals in both datasets (BHPS and SHIW) and for the purposes of this paper, I use mid-points of the bands to estimate asset holdings.

In the BHPS the calculation of single estimates of household wealth in each subcategory of financial wealth is not straightforward since it is not always clear whether assets are held solely by an individual or jointly with someone else (every individual is asked "Are your investments jointly held with someone else?"). I address this issue by using an upper bounding approach under the assumption that any jointly-held asset classes are actually held solely by the individual.[22]

Drawbacks also exist in using household survey data, such as measurement error, sample size and non-random non-response. In particular, BHPS data on net wealth is not fully comparable between 1995 and 2000 because debt in 2000 includes student loans and overdrafts whereas the 1995 survey did not include them. Moreover, the amount of investments seem to be overstated in 1995 (see Banks et al. (2002) for details).

2.8.2 Definition of variables

BHPS

Age: "Age at 1.12.XX".

Region: "Live in north?

1 if Inner London, Outer London, R. of South East, South West, East Anglia, East Midlands.

0 if West Midlands Conurb, R. of West Midlands, Greater Manchester, Merseyside, R. of North West, South Yorkshire, West Yorkshire, R. of Yorks & Humber, Tyne & Wear, R. of North, Wales and Scotland"

Ownhome: "Own home?

1 if Owned or on mortgage, Shared ownership

2 if Rented, Rent free, Other"

[22]Banks et al. (2003) compute two measures, an upper and lower bound. The latter is computed under the assumption that an individual only owns 1/Nth of the asset class in which joint ownership is reported. They show that the results appear not to be sensitive to the choice of measure.

Own0mort: "Own home without mortgage?

1 if Owned outright

2 if Buying mortgage/loan, Inapplicable"

Own1mort: "Own home with mortgage?

1 if Buying mortgage/loan

2 if Owned outright, Inapplicable"

Sex: "Sex

1 if Male

2 if Female"

Ms2: "Marital Status

1 if Married, Living as Couple

2 if Child under 16, Widowed, Divorced, Separated, Never married"

Fsize: "Number of persons in household"

Child: "Number of own children in household"

Adult: "Number of persons in employment in household"

Emplh: "Head employed?

1 if Self-employed, Employed

0 if Unemployed, Retired, Maternity Leave, Family Care, Full Time Student, Long Term Sick/disability, Government training scheme, Waiting the take up a job

Empls: "Spouse employed?

1 if Yes

0 if No"

Educ: "Highest academic qualification:

1 if None, CSE

2 if O Level

3 if HND, HNC, Teaching, A Level

4 if Higher Degree, 1st Degree"

Selfemp: "Self-employed?

1 if Self-Employed

2 if Employee

SHIW

Age: "No. of years"

Region: "Live in south?

1 if South

2 if North, Central Regions

Ownhome: "Own home?

1 if Property

2 if Rented, With Right of redemption, usufruct, free use

Housloan: "Debts for real estate purchase-renovation?"

1 if yes

2 if no

Own0loan: "Own home without debt?"

1 if own home and no debts for real estate purchase-renovation

2 otherwise

Own1loan: "Own home with debt?"

1 if own home and debts for real estate purchase-renovation

2 otherwise

Sex: "Sex

1 if Male

2 if Female

Ms: "Marital Status:

1 if Married, Cohabitant

2 if Single, Separated, Divorced, Widow

Fsize: "Nunber of household members"

Child: "Number of children"

Adult: "Number of income receivers"

Emplh: "Head employed?"

1 if Blue Collar, Apprentice, White Collar (low level), Teacher, White Collar (high level), Manager, Head Master, Magistrate, University Teacher, Professional Man, Entrepreneur, Self Employed, Owner, Assistant of a Family Firm, Partner in a company

2 if seeking first occupation, unemployed, housewife, independently wealthy, retired from work, retired not from work, student, pre-school age child, serving in the army, other not professional conditions, other.

Empls: "Spouse employed?

1 if Blue Collar, Apprentice, White Collar (low level), Teacher, White Collar (high level), Manager, Head Master, Magistrate, University Teacher, Professional Man, Entrepreneur, Self Employed, Owner, Assistant of a Family Firm, Partner in a company.

2 if Seeking first occupation, unemployed, housewife, independently wealthy, retired from work, retired not from work, student, pre-school age child, serving in the army, other not professional conditions, other.

Educ: "Education:

1 if No Schooling

2 if Elementary School (5 years)

3 if Junior High (8 years), High School Diploma (13 years)

4 if B.A./B.S. (17 years), Specialization

Self: "Self-employed?"

1 if self employed

2 otherwise

2.8.3 Comparison of Data between the SHIW and the BHPS

1995,2000	SHIW	BHPS
Variable	Mean	Mean
Age, years	54.60	50.95
Family Size	2.9	2.4
Male, fraction	0.70	0.66
Married, fraction	0.71	0.53
1st degree, fraction	0.08	0.43
A levels, fraction	0.31	0.22

SHIW(1991-2000)	BHPS (1995/2000)
1.Real estate value, firm's assets, valuables	1.Value of property, value of second property, value of car less amount outstanding
2.Bank current account, personal savings, certificates of deposit	2.Regular savings in banks, building societies and Post Office, non-regular savings (including TESSAs and ISAs)
3.Postal accounts and deposits, postal interest bearing bonds	3. Not available
4. Treasury bills, treasury certificates, long term treasury bonds	4. National Savings Certificates
5. Zero coupon bonds, other government bonds, non government bonds, foreign government bonds	5. Premium bonds; National Saving, Building Society, Insurance Bonds
6. Investment funds shares, stocks of listed companies, stocks of privatized companies, stocks of unlisted companies, shareholding (limited companies and partnership), foreign stocks	6. Unit Trusts, Personal Equity Plan, Shares (UK or Foreign), other investment, government or corporate securities
7. Debts for real estate purchase/renoval; valuable goods purchase; transport purchase; furniture, electric appliance purchase; nondurable goods purchase or other reasons	7. Total mortgage on all property; Debts for hire purchase, personal loan, credit card, mail order purchase, DSS Social Fund Loan, loan from individual overdraft, student loan, joint commitment or something else
Net Worth=1+2+3+4+5+6-7	Net Worth=1+2+4+5+6-7

SHIW (1989-2000)	BHPS (1991-2000)
1. Transportation expenditure	
2. Furnishing, electric appliance expenditure	2. Amount spent on consumer durables (TV, VCR, deep freeze, washer, tumble drier, dish washer, microwave, computer, CD player, satellite, cable TV, telephone), home improvements
3. Non durable consumption	3. Food and grocery bill, expenditure on gas/oil/electric, childcare, mortgage or rent costs
Durable Consumption: 1+2	Durable Consumption: 2
Non-durable Consumption: 3	Non-durable Consumption: 3
Consumption: 1+2+3	Consumption: 2+3

2.8.4 Correction terms for each sample selection regime

Following Tunali (1986), the correction terms for each sample selection regime are as follows:

For $PC\,(1) = \{\, it \mid L^*_{it} \geq 0\,,\ R^*_{it} \geq 0\}$:

$$W^L_{it} = \frac{\phi\left(z^L_{it}\gamma^L\right)\Phi\left(\frac{z^R_{it}\gamma^R - \rho z^L_{it}\gamma^L}{(1-\rho^2)^{1/2}}\right)}{\Phi_2\left(z^L_{it}\gamma^L, z^R_{it}\gamma^R, \rho\right)}$$

$$M^R_{it} = \frac{\phi\left(z^R_{it}\gamma^R\right)\Phi\left(\frac{z^L_{it}\gamma^L - \rho z^R_{it}\gamma^R}{(1-\rho^2)^{1/2}}\right)}{\Phi_2\left(z^L_{it}\gamma^L, z^R_{it}\gamma^R, \rho\right)}$$

For $PC\,(2) = \{\, it \mid L^*_{it} < 0\,,\ R^*_{it} \geq 0\}$:

$$M_{it}^{L} = -\frac{\phi\left(z_{it}^{L}\gamma^{L}\right)\Phi\left(\frac{z_{it}^{R}\gamma^{R}-\rho z_{it}^{L}\gamma^{L}}{(1-\rho^{2})^{1/2}}\right)}{\Phi_{2}\left(-z_{it}^{L}\gamma^{L}, z_{it}^{R}\gamma^{R}, -\rho\right)}$$

$$M_{it}^{R} = \frac{\phi\left(z_{it}^{R}\gamma^{R}\right)\Phi\left(-\frac{z_{it}^{L}\gamma^{L}-\rho z_{it}^{R}\gamma^{R}}{(1-\rho^{2})^{1/2}}\right)}{\Phi_{2}\left(-z_{it}^{L}\gamma^{L}, z_{it}^{R}\gamma^{R}, -\rho\right)}$$

For $PC\,(3) = \{\, it \mid L_{it}^{*} \geq 0\;,\; R_{it}^{*} < 0\}$:

$$M_{it}^{L} = \frac{\phi\left(z_{it}^{L}\gamma^{L}\right)\Phi\left(-\frac{z_{it}^{R}\gamma^{R}-\rho z_{it}^{L}\gamma^{L}}{(1-\rho^{2})^{1/2}}\right)}{\Phi_{2}\left(z_{it}^{L}\gamma^{L}, -z_{it}^{R}\gamma^{R}, -\rho\right)}$$

$$M_{it}^{R} = -\frac{\phi\left(z_{it}^{R}\gamma^{R}\right)\Phi\left(\frac{z_{it}^{L}\gamma^{L}-\rho z_{it}^{R}\gamma^{R}}{(1-\rho^{2})^{1/2}}\right)}{\Phi_{2}\left(z_{it}^{L}\gamma^{L}, -z_{it}^{R}\gamma^{R}, -\rho\right)}$$

For $PC\,(4) = \{\, it \mid L_{it}^{*} < 0\;,\; R_{it}^{*} < 0\}$:

$$M_{it}^{L} = -\frac{\phi\left(z_{it}^{L}\gamma^{L}\right)\Phi\left(-\frac{z_{it}^{R}\gamma^{R}-\rho z_{it}^{L}\gamma^{L}}{(1-\rho^{2})^{1/2}}\right)}{\Phi_{2}\left(-z_{it}^{L}\gamma^{L}, -z_{it}^{R}\gamma^{R}, \rho\right)}$$

$$M_{it}^{R} = -\frac{\phi\left(z_{it}^{R}\gamma^{R}\right)\Phi\left(-\frac{z_{it}^{L}\gamma^{L}-\rho z_{it}^{R}\gamma^{R}}{(1-\rho^{2})^{1/2}}\right)}{\Phi_{2}\left(-z_{it}^{L}\gamma^{L}, -z_{it}^{R}\gamma^{R}, \rho\right)}$$

	Italy				UK			
	Dependent variable:							
	Credit Card		Risky Assets		Credit Card		Risky Assets	
Variables	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.
Constant	0.453	3.24	-5.334	-21.97	2.665	18.57	-3.685	-22.07
Age	-0.014	-3.02	0.030	4.49	-0.053	-9.65	0.051	8.21
Age^2	0.000	2.58	-0.000	-4.35	0.000	9.53	-0.000	-7.28
Region	0.502	22.38	0.665	-18.57	0.031	3.25	-0.027	-2.41
Own1mort	-0.056	-1.52	-0.302	-5.20	-0.643	-16.05	0.867	18.57
Own0mort	-0.116	-5.01	-0.289	-5.71	-0.750	-16.99	0.777	16.01
Sex	-0.051	-1.76	0.150	3.95	0.024	0.62	0.145	3.49
MS	-0.058	-1.79	0.081	1.85	-0.221	-5.30	0.047	1.05
Fsize	0.028	1.37	-0.096	-5.87	0.039	1.75	-0.075	-4.48
Child	0.004	0.16	-	-	0.077	2.89	-	-
Adult	-	-	0.104	4.91	-	-	-0.047	-1.42
Emplh	-0.090	-3.17	-	-	-0.511	-12.68	-	-
Empls	-0.100	-3.93	0.076	2.15	-0.085	-2.15	0.012	0.25
Educ	-0.074	-4.49	0.463	18.41	-0.356	-21.61	0.272	16.62
Wage	-	-	0.013	3.17	-	-	0.035	5.11
Selfemp	-	-	0.003	0.06	-	-	0.050	-0.95
FWealth	-	-	0.199	9.80	-	-	0.084	20.27
Year Effect	-0.150	-7.60	0.374	14.23	-0.165	-6.72	0.151	5.13
$\rho_{u^L_{it},u^R_{it}}$	-0.171 (-10.26)				-0.272(-12.72)			
Log likelihood	-16267.563				-10176.477			
No. Obs	16136				10183			

Notes: t-statistics calculated with robust standard errors clustered by household and corrected for heteroskedasticity. Sample: 1995, 2000.
$\rho_{u^L_{it},u^R_{it}}$ controls for common determinants of liquidity constrains and asset holding equations, not fully captured by the explanatory variables.

Table 2.9: Selection Equations. Credit Card split

Dependent Variable: $C^q_{it1} = ln(C_{it})$						
Select. (K):	Credit Card, Risky Assets					
Regime (q):	UR		CNR		UNR	
Country:	Italy	UK	Italy	UK	Italy	UK
α	11.786***	7.495***	11.501***	6.290***	10.836***	7.640***
	(0.29)	(0.40)	(0.07)	(0.20)	(0.08)	(0.29)
Age_{it}	0.012***	-0.021***	0.003***	-0.006**	0.007***	-0.010***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)	(0.003)
$Fsize_{it}$	0.150***	0.168***	0.161***	0.197***	0.161***	0.103***
	(0.02)	(0.03)	(0.007)	(0.02)	(0.009)	(0.02)
$Child_{it}$	-0.027	-0.034	-0.042***	-0.117***	-0.066***	0.021
	(0.02)	(0.04)	(0.008)	(0.03)	(0.01)	(0.03)
Y_{it}	0.0005	0.024**	0.004***	0.063***	0.012***	0.054***
	(0.002)	(0.01)	(0.001)	(0.01)	(0.001)	(0.01)
Yp_{it}	0.033***	0.041*	0.009**	0.019	0.039***	0.046***
	(0.01)	(0.02)	(0.004)	(0.01)	(0.005)	(0.017)
W_{it}	0.036***	0.037***	-	-	-	-
	(0.01)	(0.007)	-	-	-	-
T_{it}	-0.161***	-0.315***	-0.170***	-0.244***	-0.138***	-0.268***
	(0.02)	(0.05)	(0.01)	(0.04)	(0.01)	(0.04)
M^L_{it}	0.214*	0.862***	0.061	0.562***	-0.089**	0.569***
	(0.11)	(0.19)	(0.04)	(0.08)	(0.04)	(0.10)
M^R_{it}	-0.448***	0.398***	-1.096***	0.407***	-1.196***	0.230**
	(0.06)	(0.10)	(0.03)	(0.13)	(0.04)	(0.09)

Notes: U=unconstrained, C=constrained; R=assetholder, NR=non-R.
Standard errors clustered by household in parenthesis.
Standards errors obtained by bootstrapping (1000 replications) to adjustfor the presence of W^K_{it} .
*, **, and *** denote significance at 10, 5 and 1 percent level respectively.

Table 2.10: Consumption Function Equation. Credit Card split

Chapter 3

Real Effects of Regional House Prices: Dynamic Panel Estimation with Heterogeneity

This chapter uses recently developed methods for estimating dynamic heterogeneous cointegrated panel data models - which allow for heterogeneity in parameters and dynamics across agents - to study housing wealth effects in a dynamic model of the 50 US states and the District of Columbia from the 1970s to the 1990s. The results show that housing prices have a unit root and are cointegrated with consumption. Even though an aging population has some effect on consumption in some states, it cannot account for the heterogeneity in housing wealth elasticities. Finally, I find that when state heterogeneity is taken into account, housing capital gains translate into increased spending with an elasticity ranging from 0.15 to 0.23.

3.1 Introduction

Over the past few years, the US has experienced a housing boom, with prices continuing to rise at higher rates than in the 1980s. Figure 3.1 shows how real housing prices have risen steadily since 1994.

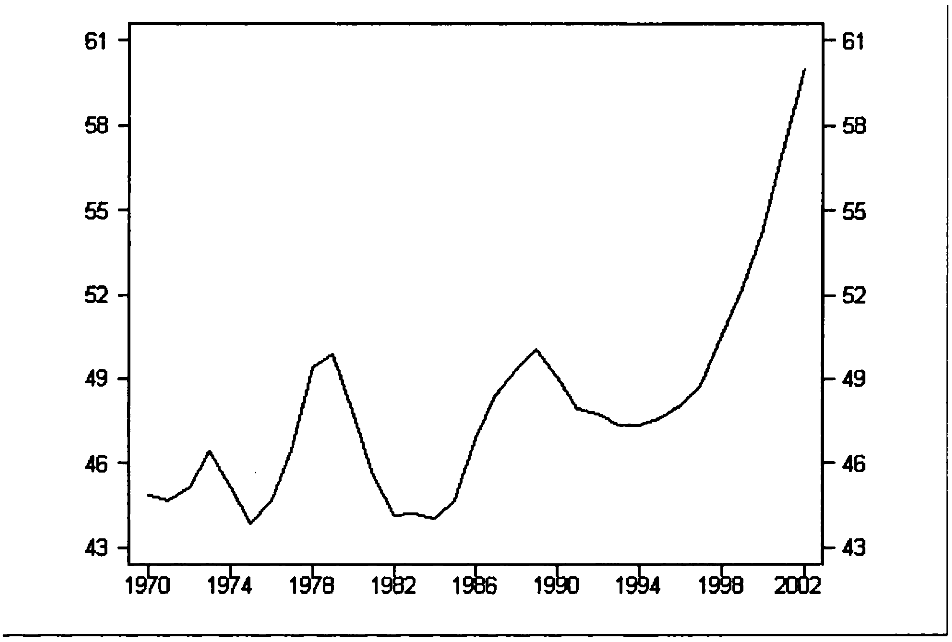

Figure 3.1: Real Housing Prices

In recent years, housing prices in most parts of the US have, rather surprisingly, stayed high despite the downturn in the economy. This has coincided with the decline in the stock market. The apparent firmness of housing prices has been explained by the drop in mortgage interest rates and by the combination of a strong housing demand and the stability of housing supply[1].

The importance of housing wealth and the mortgage debt available against this wealth has increased over the last 20 years in the US. In 1982 the ratio of debt to home equity was 0.43 while in 2002 it reached 0.80 (See Table 3.1). Of the increase

[1]See Krainer (2002) for a discussion.

	1972	1976	1982	1986	1992	1996	2002
Home equity	3234	3380	4497	5654	5461	5435	7587
Mortgage Debt	1498	1649	1933	2703	3666	4102	6054
Mortgage Debt/Home equity	.46	.49	.43	.48	.67	.75	.80

Note: All figures are in 2002 billions of dollars
Source: Federal Reserve Flow of Funds of Accounts (Table B.100)

Table 3.1: Home Equity and Mortgage Debt

in housing stock, the greater part has been due to changes in the relative value of houses. Figure 3.2 shows that inflation-adjusted home prices explain most of the changes in real home equity. Increases in home prices have outpaced overall inflation for the last decade, so widespread home price inflation has lifted household net worth. Despite huge gains in stocks during the 1990s, housing assets still account for much of the wealth of most Americans. Home equity remains the cornerstone of household wealth, even among the majority of homeowners who also have stock holdings. In 1998 around 50 percent of homeowners held at least 50 percent of their wealth in home equity. Less than one half of all households hold stocks and the top one percent own one-third of the total value. In addition, because property prices are much less volatile than share prices, there should be far less uncertainty surrounding gains and losses in property wealth.

This motivates the interesting question of whether housing prices have influenced the real economy significantly.

Over the 25 years from 1970 to 1995 house price inflation at the national level moved roughly in line with the consumer price index (CPI) inflation. (Figure 3.3 plots house price inflation and CPI inflation since 1976). Given this close comovement it was hard to identify the effect of housing wealth on consumption. In the last few years the movement of house price inflation and CPI inflation has been different. Figure 3.3 shows how since 1995, the series have grown apart. This suggests that the relative effect of housing and CPI prices and home equity on consumption may be identified with national aggregates. However, the close correlation between na-

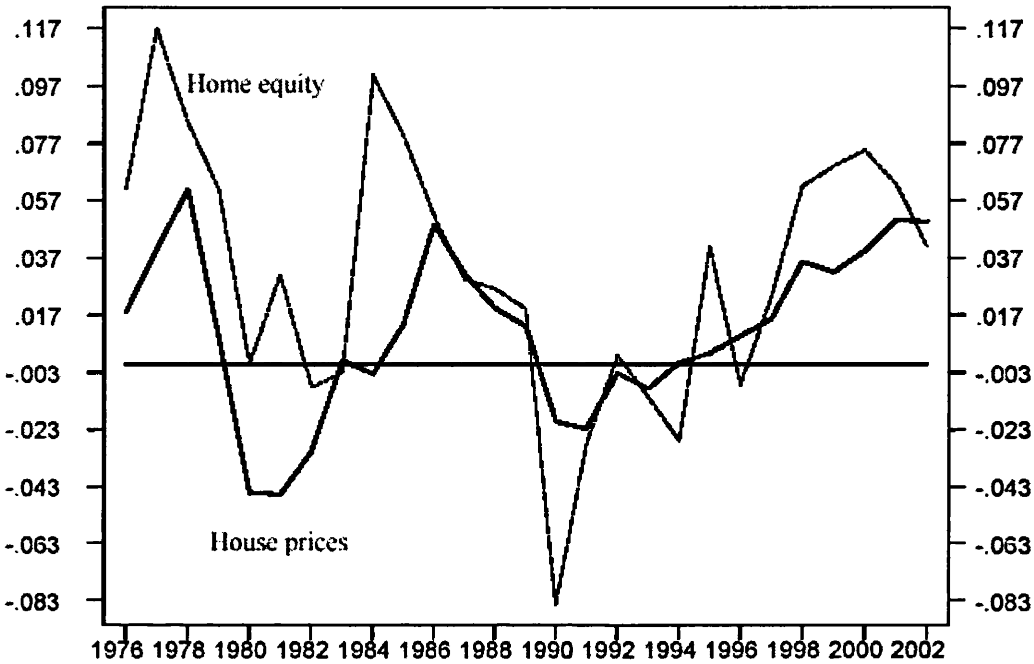

Figure 3.2: Real Home Equity and Real Housing Prices

tional housing prices and CPI has obscured the degree of heterogeneity and diversity between states. Looking at the state level allows us to examine the high degree of diversity and helps to identify the effects of housing prices on consumption.

Traditionally, empirical work on housing prices has focused on national level aggregate data, although micro-econometric studies have increased recently. I use state level data in order to exploit cross-sectional variation and at the same time reduce the measurement error included in micro-data. The same idea has been explored by Case et al. (2001) but this chapter improves the methodology used and comes to some different conclusions. In particular, this paper takes into account the long-term relationship between consumption, labour income and housing prices in order to estimate the effects of housing on consumption. As a consequence, the

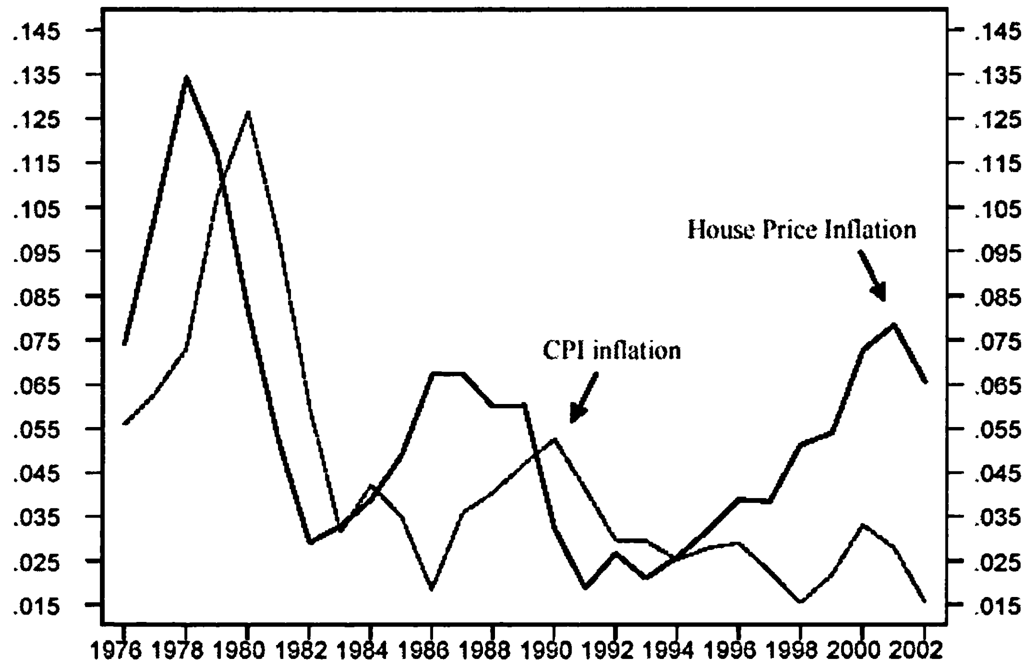

Figure 3.3: CPI Inflation and House Price Inflation

estimated effect of housing prices on consumption more than doubles that of Case et al. (2001). In addition, this chapter explores possible sources of heterogeneity among state estimates.

A national housing bubble has been denied by some economists, yet local inflations have appeared in New York and parts of California (*The Economist,* March 6, 2003). Figures 3.4, 3.5, 3.6 and 3.7 show the log level of housing prices in four regions: the Northeast, Midwest, South and West. There is an obvious change in behaviour from the end of the 1980s and the beginning of the 1990s. Before, housing prices were very volatile, whilst they have been relatively smooth since. Similar patterns of boom and bust were followed by new construction before the 1990s. National data masks heterogeneity across states and regions: the plots show that only in the Northeast is there coherence amongst states. In the other regions, particularly the West, there is more diversity within a region than between regions. Average annual housing prices have appreciated in the West and in the Northeast during the 1976-96 period, while real prices declined in the South and Midwest. The timing of the real price changes also differs between regions. In the 1970s, real prices more than doubled in the West, while homes in the Northeast gained only 17 percent. During the late 1980s, real prices declined in all regions except the Northeast. Despite reductions at the end of the decade, real prices in the Northeast climbed 39 percent between 1980 and 1990. Homes in the West declined in value by nearly 10 percent, and those in the South and Midwest lost more than 20 percent of their real value.

The contribution of this chapter is twofold: it describes the time series properties of state housing prices in the US and it shows how housing prices are related to consumption taking into account state heterogeneity, demography and homeownership rates.

Since there is a great diversity of state housing market activity in the US, it will be necessary to study state disaggregated consumer spending and housing prices in order to allow inter-state and regional differences and, then, achieve a tighter estimation. The model will seek to overcome the drawbacks of national level aggregate data in imposing equal slope parameters across states. In addition, since individuals in states can borrow from each other, each state in the panel is considered as an open economy where shocks can be transmitted through the housing and credit markets. To this end, I will use state cross-sectional and quarterly time-series data for the period 1975:1 to 1996:4. The choice of state data for this exercise is explained by the fact that wealth effects coming from housing prices are locally driven - while wealth effects coming from the stock market and capital inflows are nationally driven. The study will estimate dynamic heterogeneous panel models and will allow for spillover effects between states.

The chapter is organized as follows: section 2 assesses the links between housing wealth and consumption and reviews the empirical literature; section 3 describes the behaviour of state housing prices in the United States; section 4 shows efficient ways of modelling state variables such as consumption and housing prices; section 5 compares and contrast my results with Case et al. (2001); and section 6 concludes.

3.2 Theoretical Assessment of the Links between Housing Wealth and Consumption: An Empirical Literature Review

The fact that consumer spending has amounted to about 90 percent of income has led some earlier analysts to suppose that income alone could explain consumption. Yet different studies have shown that wealth can explain up to one fifth of total consumption. Income and wealth do not move tightly together over time, and their relationship is generally not stable. As a consequence, the behaviour of wealth represents an additional instrument in understanding consumption.

Housing prices can have an effect on consumption through both the easing of liquidity constraints and wealth effects. The easing of liquidity constraints is very intuitive. If households are liquidity constrained, access to credit against the value of the house would alleviate the constraint. Rising house prices increase house equity. Households can choose to sell the house or to refinance their mortgages (taking a loan on the increase of the house value) and take cash in the process. House appreciation is therefore a determinant of consumption. Households can trade up for better houses, purchase goods and services and accumulate resources for retirement. In addition, even for homeowners who do not refinance, the increase in home equity leads to a rise in consumer confidence.

Wealth effects are, however, more difficult to quantify, since different forces go in opposite directions. Some households choose to move to smaller houses when they get older. These downsizers are better off when housing prices increase relative to other prices and they can therefore increase their consumption. At the same time, house price appreciation undermines affordability, especially for first-buyers who are struggling to save for their downpayment and qualify for a mortgage. In addition, some households who own small houses want to move to larger houses, and these upsizers might respond to the increase of housing prices by reducing their consumption. Determining the relative magnitude of these effects is difficult. The Governor of the Federal Reserve Board, Edward M. Gramlich[2], suggested that downsizers generally have higher marginal propensities to consume out of housing wealth than upsizers since downsizers tend to be older and have more time to smooth consumption, whilst upsizers tend to be liquidity constrained. According to that hypothesis, housing prices might have a positive effect on consumption. In the end, the relative response of downsizers and upsizers is an empirical question.

In section 4, I will estimate the wealth effect of changes in housing prices. Before that, I summarize the previous literature dealing with housing effects on consumption that use different data than my own.

Some studies have tried to answer the question of whether housing wealth has an effect on the real economy. McFadden (1994a, 1994b) finds that the impact of house price changes on consumer welfare are quite small (and predicts that housing prices will be stable for generations to come). Lettau and Ludvigson (2001) argue that temporary movements in asset values are often not associated with aggregate consumption movements, and only permanent changes in wealth affect consumption. However, Skinner (1996) suggests that one of the reasons why housing wealth is

[2]Remarks by Governor Edward M. Gramlich: "Consumption and the Wealth Effect: The United States and the United Kingdom". Before the International Bond Congress, London, UK. February 20, 2002.

important for consumption is that there are regional fluctuations in housing prices even when national housing prices are flat.

Bosworth, Burtless and Sabelhaus (1991) argue that capital gains may have contributed to lower savings rates since savings rates of homeowners fell much more than those of nonhomeowners since the 1960s. They claim that the boom in housing prices may have contributed to reduced household savings. They also find that the decline for homeowners is pronounced in the middle age group. Summers and Carroll (1987) also argue that the growth in mortgage debt during the previous eight years has increased consumer spending and depressed private savings. Manchester and Poterba (1989) find that the incidence of second-mortgage borrowing rose from 1.5 percent of all mortgages in 1970 to 10.8 percent in 1987 and was concentrated in the middle age group. Their view is that increased access to second mortgages has reduced personal savings. Some second mortgages are incurred when a home is purchased, but post-acquisition second mortgages have grown faster. An alternative possibility is that households could have used second mortgages to invest in other assets or to repay other debts, although the majority of households used the second mortgages to make home improvements. They find that while net housing equity does not have a significant impact on second mortgage probabilities, accrued capital gains have a significant effect on second mortgage probabilities.

Aoki, Proudman and Vlieghe (2002) apply the financial accelerator mechanism[3] proposed by Bernanke, Gertler and Gilchrist (1999) to the household sector and show that fluctuations in housing prices significantly affect the value of houses as collateral and influence borrowing conditions for households in the UK. Their model is based on the macroeconomic effects of imperfections in credit markets that generate premia on the external cost of raising funds. They find that endogenous developments in

[3]The mechanism goes as follows: when house prices fall, households that are moving home have a smaller net worth available for the purchase of the new house. Therefore they will get less favourable mortgage interest rates when renegotiating their mortgage, and have less scope for extracting additional equity to finance consumption.

credit markets such as variations in collateral or net worth amplify shocks to the economy. Consequently, a positive shock to the economy causes a rise in housing demand that leads to a rise in housing prices and an increase in homeowners' net worth. This decreases the external finance premium that leads to a further rise in consumption demand. Muelbauer and Murphy (1993, 1995, 1997) also argue that changes in housing values can change the borrowing opportunities of constrained households via a collateral effect.

3.2.1 The Standard Model

The theory of consumer behaviour has been described by Friedman (1957), Ando and Modigliani (1963) and Galí (1990) among others. The latter develops a model for time-series analysis of aggregate consumption which dispenses with the assumption of an infinite-lived representative consumer[4]. Therefore the model preserves the main features of the explicitly aggregated life-cycle models (Ando and Modigliani, 1963) but gains the tractability of the infinite-horizon model in terms of its econometric implementation. The life-cycle models account for two factors: (a) finite horizons and (b) a life-cycle profile for individual labor income characterized by retirement in a late stage of the cycle. Therefore the models assume the existence of annuity markets whenever there is uncertainty about death.

Galí (1990) proposes a discrete-time, quadratic-utility, open economy version of the overlapping-generations framework in Blanchard (1985) where each consumer born at time s maximizes his expected present discounted value of utility as follows:

$$\max E_t \sum_{j=0}^{\infty} (1+\delta)^{-j} (1-p)^j U(c_{s,t+j}), \tag{3.1}$$

[4]The infinite-horizon model appears as a special case of the model by a specific configuration of values for those parameters.

subject to

$$W_{s,t+1+j} = W_{s,t+j}\,(1+z) + yl_{s,t+j} - c_{s,t+j}, \tag{3.2}$$

$$\lim_{j\to\infty}\,(1+z)^{-j}\,W_{s,t+j} = 0, \tag{3.3}$$

for j=0,1,2,..., and where c is consumption, W is nonhuman wealth, yl is labour income, and $x_{s,t}$ is the value of variable x at time t, for a consumer born in period s. δ is the discount rate. $E_t x_{s,t+j}$ denotes the expected value of $x_{s,t+j}$ conditional on the consumer being alive in period t+j, given the information available at time t. Equations 3.2 and 3.3 are the budget constraint and transversality condition, respectively. Individuals are born with zero financial wealth.

Galí (1990) derives from this model the aggregate consumption that is given by

$$c_t = \Omega + \beta yl_t + zW_t + u_t, \tag{3.4}$$

where

$$\beta \equiv \frac{z}{(z+\alpha)}, \quad \Omega \equiv \frac{\beta\mu\,(1-\alpha)}{(z+\alpha)},$$

$$u_t \equiv \beta\sum_{j=1}^{\infty}(1+z)^{-j}\,(1-\alpha)^j\,(E_t\,\Delta yl_{t+j} - \mu)\,.$$

and $(1+z) \equiv (1+r)(1+p)^{-1}$, with $(1+r)$ being the pure interest rate and $(1+p)^{-1}$ the annuity rate; α is the rate by which services supplied by an individual consumer is assumed to decline; and $\mu = E(\Delta yl)$is assumed.

Equation 3.4 establishes a linear relationship between aggregate consumption, labour income and nonhuman wealth in line with the life-cycle model of Ando and Modigliani (1963). Its aggregation properties generate a simple relationship between the coefficients of the consumption equation and the underlying structural parameters. The model is constructed based on the maintained hypothesis that the aggregate labour income is a unit-root process with drift and implies that W and c are also unit-root processes, and both u_t and ΔW are stationary. Therefore, the model implies a common trend in c, yl and W.

In this model, an unexpected increase in wealth will raise consumption over the lifetime. Agents will consume more today and save less. Aggregate, planned consumption is explained by labour income and wealth. However, actual consumption is not always equal to planned consumption due to several factors such as adjustment costs, habit formation in consumption and liquidity constraints. Adjustment costs can prevent consumers from adjusting their housing services within each period. If habit persistence is in place, households adjust their consumption towards the equilibrium level slowly. Capital restrictions prevent individuals from smoothing consumption by borrowing, hence these liquidity constrained consumers follow current consumption more closely. For these reasons I allow adjustment lags in the consumption function. In this sense, consumption will adjust to the planned level with an error correction dynamic specification.

3.2.2 The Consumption Function incorporating Housing Wealth

In what follows I will estimate aggregrated consumption functions at the state level and investigate the role of housing prices as a proxy for housing wealth. I will follow an Error Correction Model (ECM) for the estimation:

$$\Delta y_{it} = \alpha_1 \left(\theta_i + \sum_{j=1}^{k} \beta_j x_{jit-1} - y_{it-1} \right) + \sum_{s=1}^{m} \gamma_s \Delta y_{it-s} + \sum_{s=1}^{m} \sum_{j=1}^{k} \gamma_{js} \Delta x_{jit-s} \quad (3.5)$$

with $y_i = \theta_i + \sum_{j=1}^{k} \beta_j x_{ji}$ being the long-run relationship and where x_{jit} stands for labour income and housing prices and y_{it} for consumption.

By using an ECM I maintain the rationality implied by the Euler equation in the long-run, but I relax it in the short-run, where agents and households may be subject to various frictions. The ECM allows one to distinguish between the long-run relationship among the variables of interest and the short-run variation around the equilibrium. Even though the optimization is based on the long-run relationship, modelling the short-run dynamics is necessary for a proper description of the process. The idea is that outside forces drive the common stochastic trends in consumption, income and housing, whilst short-run shocks divert consumption, income and housing prices from their planned time paths. Adding the latter to the ECM improves the fit of the regression.

Unfortunately, there is no series of housing wealth by state available[5]. However, I will calculate a proxy in section 5 to facilitate comparison. Since the major variation in housing wealth comes from changes in housing prices, I estimate the consumption functions using housing prices instead of housing wealth in this section. Another series that is missing at a state level is consumption. I proxy it by Retail Sales (See the Appendix for detailed description of the data). I calculate real per capita retail sales by deflating by the calculated state CPI and using interpolated state population following Chow and Lin (1971). This is because population estimates by

[5] In addition, there are no series of stock wealth and high frequency demand deposits (non-equity financial wealth) by state either. A calculation of a proxy for them will imply too strong assumptions leading to misleading results.

state are only available on an annual basis.

Our long-run equilibrium consumption equation extends from 1975:1 to 1996:4 and uses real per capita retail sales (real per capita consumption, hereafter), real per capita labour income and real housing prices.

The decision of whether to pool the data will depend both on the degree of heterogeneity and on the purpose of the exercise. I want to estimate a dynamic consumption model from a panel set of data in which I have a number of economic units (states in the US) $i = 1, 2, ..., N$ (51 states) and a number of times series observations, $t = 1, 2, ..., T$ (T=88, from 1975q1 to 1996q4). Since both T and N are relatively large, two issues arise. First, time series are usually non-stationary and certain combinations of them are stationary (I deal with this issue in the next two subsections). Second, because of the large T, I can estimate a regression for each state, parameters can vary a lot among states, and so heterogeneous panels should be considered (This issue is addressed further below).

Ando and Modigliani's model does not imply that there is a cointegrating relationship among consumption, labour income and wealth. Rather, it says that consumption is linearly related to labour income and wealth. As seen above, Galí (1990) however, shows that consumption, income and wealth share a common trend. Therefore, if variables under study are unit root, estimates would be not consistent unless consumption is cointegrated with income and wealth variables.

3.3 Housing Prices in the United States

3.3.1 House Price Inflation versus CPI Inflation

One of the most interesting features of Figure 3.3 is that annual home price inflation is currently well above consumer price inflation. In addition, differentials in house price inflation tend to be persistent. One explanation for this is that house price changes are persistent themselves. Asset prices are expected to adjust automatically to the new information on the fundamental value, yet housing prices appear to adjust gradually. Krainer (2002) points to two possible reasons. First, housing markets might be inefficient because either the market does not clear automatically or housing price expectations are backward-looking. And second, housing prices themselves depend on persistent variables such as employment growth and changes in personal income.

Cecchetti et al. (2000) find that price level divergences across US cities are temporary although persistent. They show that the relative price levels among cities mean revert at an exceptionally slow rate due to a combination of transportation costs, differential speeds of adjustment to small and large shocks, and the inclusion of non-traded good prices in the overall price index.

Table 3.2 explores this idea for both real house price inflation and CPI inflation for the US state data and gives the highest and lowest 10 and 20-year rate of housing price real appreciation and CPI[6] inflation in each state. The table shows big fluctuations in real state housing prices and, most importantly, big differences among states in the same period. These localized price declines/increases affect household networth and contribute to the stress on financial institutions. For instance, while Massachusetts had the highest housing price inflation rate of 11.42, North Dakota had the lowest (4.23) during the period 1975-1985. At the same time, the highest CPI inflation rate was Ohio with 7.64 and the lowest New York with 6.35. The difference between the maximum and minimum is larger for the 1975-85 period than for the 1986-96 and, as expected, decreases as the sample increases. As Cecchetti et al. (2000) point out, inflation differences seem to reverse themselves since the high

[6]These are state consumer prices indexes. In the previous literature, national CPI has been used in order to deflate nominal variables. This is due to the fact that state CPI was not available. CPI is available at a national level for the four Census Regions and for 26 Metropolitan Statistical Areas (MSAs), Primary Metropolitan Statistical Areas (PMSAs) and Cities. This study, however, takes into account regional differences in CPI by matching each state with the closest MSA, PMSA or city CPIs. Appendix 1 lists the CPI used and the matching with each state.

inflation during the period 1986-96 period is preceded by a relatively low rate during the previous decade (as the New York case shows). House price changes, however, behave in a different way. While on average the difference between the state with the highest and the lowest inflation rate is 0.35 percentage points for the whole period, the same average for changes in housing prices is 4.09 percentage points. The speed of adjustment for CPI rates is slow, and it takes over 20 years for state CPI rates to converge. The speed of convergence of housing prices, however, is too slow, suggesting that real house price differentials can persist indefinitely, that is, housing prices in one state can deviate from that in another by an arbitrarily large amount. To this end, the next section will employ panel data procedures to study whether or not real housing prices between states are unit root processes. The econometric models used to deal with the problem of heterogeneity of housing price effects on consumption are presented in section 4.

Index	Sample	Maximum	State	Minimum	State	Differential
Real House Price	1975-1985	11.42	Massachusetts	4.23	North Dakota	7.19
Inflation	1986-1996	7.10	Oregon	.51	Alaska	6.59
	1975-1996	7.55	California	3.47	North Dakota	4.09
CPI	1975-1985	7.64	Ohio	6.35	New York	1.29
Inflation	1986-1996	3.90	New York	2.90	Texas	1.00
	1975-1996	5.31	Washington	4.96	Michigan	.35

Table 3.2: House Price Inflation and CPI Inflation Rates

3.3.2 Housing Price Properties

Econometric analysis of relationships between housing prices and other economic variables is sensitive to the possible existence of (common) trends (See Lettau and Ludvigson, 2003, 2001). Hence I begin this section by an exercise to test whether real housing prices are unit root processes, that is, whether they contain a unit root, or stochastic trend, and whether they diverge from one another. Figure 3.8 illustrates the log level behaviour of real housing prices. Looking at the plots, it seems the series are non-stationary.

Univariate unit-root tests like those of Dickey and Fuller have proven to have extremely low power and tend to be biased towards failing to reject the null of unit root in small samples, hence I will use the Im, Pesaran and Shin (2003) (IPS) test[7], which proceeds as follows:

1. First eliminate the common time effect θ_t by substracting the cross-sectional mean from the data $(q_{i,t})$ as follows:

$$\tilde{q}_{i,t} = q_{i,t} - (1/N)\sum_{i=1}^{N} q_{i,t} \tag{3.6}$$

θ_t stands for the common time effect, that is, macroeconomic shocks that induce cross-sectional dependence. The latter cannot be introduced in a univariate regression, but it can be fully taken into account by substracting the cross-sectional mean of the variable under study. In this way, it will take into account the cross-sectional dependence asymptotically[8].

2. Then calculate the Augmented Dickey-Fuller-GLS test[9] by Elliot, Rothenberg, and Stock (1996) of each state by regressing $\Delta\tilde{q}_{i,t}$ on $\tilde{q}_{i,t-1}$, a constant, a trend and lagged values of $\Delta\tilde{q}_{i,t}$.

$$\Delta\tilde{q}_{i,t} = \alpha_i + \beta_i\tilde{q}_{i,t-1} + \sum_{j=1}^{k_i} \gamma_{ij}\Delta\tilde{q}_{i,t-j} + \epsilon_{i,t} \tag{3.7}$$

where α_i accounts for the heterogeneity among states - reasons for such het-

[7] For cases where the number of individuals is large and the number of time periods is very small, see Bond et al. (2002) for a comparison of alternative unit root tests for micro panels.

[8] Cecchetti, Mark and Sonora (2000) also control for residual dependence across individuals and calculate the p-values of the IPS test from a parametric bootstrap consisting of 2000 replications using the estimated error-covariance matrix in the data-generating process.

[9] DF-GLS test is a modified augmented Dickey-Fuller test where the times series is transformed via a generalized least squares regression (GLS) prior to performing the test.

erogeneity being different tax rates and income levels. Note that these regressions implicitly allow for θ_t on the right-hand side since I have adjusted series $q_{i,t}$ by substracting the estimated common macro effect through $(1/N)\sum_{i=1}^{N} q_{i,t}$.

The null hypothesis is that each series has a unit root, $H_o : \beta_i = \beta = 0$ for all i. The interpretation is as follows: the closer the estimate of β is to zero, the closer to a stationary process $\Delta\tilde{q}_{i,t}$ is, implying that $\tilde{q}_{i,t}$ is a unit root non-stationary process. The alternative hypothesis is $H_a : \beta_i < 0$ for some i, allowing for heterogeneity across states.

ln hp	Levels	
State	$\bar{t}$	$lags$
Alabama	-1.752	11
Alaska	-2.261	8
Arizona	-3.873	9
Arkansas	-1.881	9
California	-2.007	8
Colorado	-2.654	8
Connecticut	-2.539	9
Delaware	-2.415	9
District of Columbia	-1.742	5
Florida	-3.703	10
Georgia	-2.283	10
Hawaii	-1.794	1
Idaho	-1.965	8
Illinois	-1.453	2
Indiana	-0.929	7
Iowa	-1.920	11
Kansas	-1.503	5
Kentucky	-0.875	3
Louisiana	-2.550	5
Maine	-1.560	6
Maryland	-2.051	4
Massachusetts	-2.157	10
Michigan	-0.990	6
Minnesota	-1.293	6
Mississippi	-1.399	8

(continued on next page)

Missouri	-3.185	9
Montana	-2.388	10
Nebraska	-2.373	11
Nevada	-1.129	1
New Hampshire	-2.415	8
New Jersey	-1.733	11
New Mexico	-2.683	10
New York	-2.593	7
North Carolina	-1.926	8
North Dakota	-0.903	5
Ohio	-2.487	11
Oklahoma	-2.348	5
Oregon	-2.435	7
Pennsylvania	-2.268	6
Rhode Island	-2.670	10
South Carolina	-1.438	11
South Dakota	-2.063	10
Tennessee	-1.874	5
Texas	-1.515	3
Utah	-2.868	9
Vermont	-1.535	11
Virginia	-1.596	8
Washington	-2.677	6
West Virginia	-1.408	9
Wisconsin	-1.624	1
Wyoming	-2.032	11
Average	-2.034	

Note: IPS test. 5% Critical Value:-2.36
from Im, Pesaran, and Shin (2003, table 2).
Sample Period: 1975:1-1996:4

Table 3.3: Panel Unit-Root Test for log Housing Prices

In order to determine the lag length (k_i) of equation 3.7 I follow Ng and Perron (1995), who suggest a sequential t-test algorithm for choosing k. For instance, let us suppose that I start with $k_i = 6$. If the absolute value of the t-ratio for γ_{i6} is less than 1.96, I reset $k_i = 5$ and reestimate the equation. The process stops when the estimated coefficient with the longest lag exceeds 1.96.

3. Calculate the IPS test statistic $\bar{t}$ by averaging the univariate ADF test t_i:

$$\bar{t} = (1/N)\sum_{i=1}^{N} t_i. \tag{3.8}$$

4. The null hypothesis is that each series has a unit root and there exists cross-sectional independence among them. Since the asymptotic distributions of the t-bar statistics are nonstandard and do not have analytic expressions, I will use the critical values tabulated by IPS using Monte Carlo simulations.

Table 3.3 shows the results of the IPS test for the whole period sample. The results provide evidence towards the existence of a stochastic trend in the series of interest. In most cases I cannot reject the null hypothesis of unit root. The IPS test $\bar{t}$ is -2.03 and the critical value -2.36, hence I cannot reject the null of a unit root in housing prices. Failing to reject the null hypothesis is interpreted as implying that housing prices are trended. As mentioned before I account for a common time effect (the cross-sectional mean) so that the results are invariant to the choice of a numeraire state . So the fact that the level of prices in most states relative to the cross-sectional mean contains a unit root means that relative prices would wander apart indefinitely and the housing prices could become arbitrarily high or low. Hence the issue of possible cointegration arises.

3.4 Methodology

The aim of this section is modelling the consumption-house prices linkage in order to shed light on how closely the two variables are actually correlated.

3.4.1 Integration

As a first step, I test the consumption series for integration as I did for the housing price series. Table 3.4 shows the IPS test results for real per capita consumption and real per capita labour income. These tests give unambiguous results; unit roots appear to be present for the log levels of the series in all three cases.

	Levels
Variable	$\bar{t}$
C	-2.157
Y	-2.068
HP[1]	-2.034

Note: IPS test. 5% Critical Value: -2.36 from Im, Pesaran and Shin (2003, table 2).
Sample Period: 1975:1-1996:4
[1]Later on I will show that housing wealth has a $\bar{t}$ of -2.118

Table 3.4: Panel Unit-Root Tests

Since both the independent and dependent variables are non-stationary, I now test whether a combination of them is stationary - a test of whether C, Y and HP are cointegrated.

3.4.2 Cointegration in Heterogeneous Panels

I follow Pedroni (1999) in testing the null of no cointegration in heterogeneous panels. The advantage of this test is that it allows for heterogeneity among individuals, both in the long-run cointegrating vector and the short-run dynamics from the cointegrating vectors. In addition it allows for multiple regressors.

I first compute the OLS residuals $e_{i,t}$ from each cointegration regression:

$$y_{i,t} = \alpha_i + \delta_i t + \sum_{j=1}^{k} \beta_{ji} x_{ji,t} + e_{i,t} \tag{3.9}$$

estimated from state i, with $t = 1, ..., T, T$ being the number of observations over time; $i = 1, ..., N$, N being the number of states; and $j = 1, ..., K$, K being the number of regressors. $y_{i,t}$ is real per capita consumption, $x_{ji,t}$ are real per capita labour income and real housing prices. The variables in the regression are not measured as deviations around a common component. When regressors coefficients are allowed to vary over individual members, as in equation 3.9, demeaning the data over the cross-section dimension can have the consequence of introducing data dependencies into the estimated residuals so that the asymptotic distributions are no longer nuisance parameter free (See Pedroni (1999) for details).

I then calculate the Panel Cointegration Statistic (Group t-Statistic) as the sum of the individual ADF t-statistic (τ_i) :

$$\tilde{Z}^*_{t_{N,T}} = N\bar{\tau} = \sum_{i=1}^{N} \tau_i \tag{3.10}$$

with a distribution expressed as

$$\frac{\frac{1}{\sqrt{N}}\tilde{Z}^*_{t_{N,T}} - \mu\sqrt{N}}{\sqrt{\nu}} = \frac{\sqrt{N}\bar{\tau} - \mu\sqrt{N}}{\sqrt{\nu}} \xrightarrow{D} N(0,1)$$

where μ and ν are functions of the moments of the underlying Brownian motion functionals that can be found in Table 3 (Pedroni, 1999).

Table 3.5 shows the results of the test. These are one-sided statistics with a critical value of -1.64, thus large negative values imply rejection of the null of no cointegration. The table shows that in all cases, with or without intercept and trend included, I can reject the null of no cointegration. Cointegration estimates are robust to the presence of measurement error and endogeneity of the regressors, hence the superconsistency result. Therefore there is evidence that C, W and Y are cointegrated and that they form a meaningful regression relationship.

Pedroni Group t-statistic	With housing prices		With housing wealth	
	t	p-value	t	p-value
Standard case	-12.452	0.000	-12.988	0.000
Heterogeneous Intercept Included	-8.444	0.000	-8.902	0.000
Heterogeneous Trends and Intercepts Included	-4.758	0.000	-4.935	0.000

Note: t-value calculated following Pedroni (1999)

One-tailed test at 5 percent level on the Normal distribution. Critical value: -1.64

Table 3.5: Cointegration IPS Test

3.4.3 Estimation and Results

In this section I deal with the estimation of a consumption function in which the regressors are non-stationary and there exists cointegration among variables. I consider three estimators: the Mean Group (MG) Estimator, the Pooled Mean Group (PMG) Estimator and the Dynamic Seemingly Unrelated Regression (DSUR) Estimator.

Mean Group Estimator

One way to estimate panel data models is to estimate the separate equations for each group of individuals and study the distribution of the mean of the estimated coefficients across groups. Since T is large (88 observations) I can estimate an Autoregressive Distributed Lag ($ARDL(p, q, q, ..., q)$) model for each group separately as follows:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{3.11}$$

where x_{it} is the vector of regressors for each equation i and μ_i is the constant for each equation. (I include seasonal dummies in one of the models). I allow for different lag order for each state and use the Schwarz Bayesian Criterion (SBC) to select the right lag order.

In what follows I work with the more convenient re-parameterization of the ARDL model of the form of an ECM as in equation 3.5 above. Pesaran and Smith (1995) show that this MG estimator gives consistent estimates of the average of the parameters. The drawback is that it does not take into account the fact that some parameters might be the same across groups.

Tables 3.13 and 3.14 present the MG estimated results (the first table does not include seasonal dummies whilst the second one does). The first column of each table shows the lag orders for each group selected by the SBC, and the second, third and fourth illustrate the labour income elasticity, housing price elasticity and the adjustment coefficient of equation 3.5, respectively. Table 3.13 illustrates how labour income and housing elasticities seem to differ among states. Housing prices are significant in half of the states, probably due in part to the fact that synergies among states are not taken into account (the DSUR below will correct for that). By synergies I mean special links between states: for instance, many people working in Washington DC live in Virginia or Maryland, where they can find better schools for their children and cheaper accommodations. Moreover, the coefficient of adjustment (α) is negative and significant, thus supporting the cointegration hypothesis and indicating the presence of lags in the response of consumption to income and wealth. Table 3.14 reestimates the long-run coefficients, including seasonal dummies.

Mean Group Estimate Summary	β_1	β_2	α
(without seasonal dummies)			
MG	.76 (13.51)	.20 (5.18)	-.72 (-12.03)
No. of states with correct sign	50	44	51
No. of states with correct sign and significant coefficients	38	22	35
(with seasonal dummies)			
MG	.87 (10.21)	.16 (3.0)	-.30 (11.59)
No. of states with correct sign	49	37	51
No. of states with correct sign and significant coefficients	37	19	48

Table 3.6: Mean Group Estimates

Table 3.6 summarizes the main findings of the MG estimation (Tables 3.13 and

3.14). β_1 is the coefficient of the log of real labour income, β_2 is the coefficient of real housing prices, and α is the adjustment coefficient.[10] The first row of the table shows the MG estimator. The housing price elasticity is 0.20 and is very significant. The value of all MG elasticities decreases when seasonal dummies are introduced, leading to a value of the housing price elasticity of 0.16. The table also shows how many states have coefficients with the correct sign and are significant. The coefficient on housing prices seems to be significantly less frequent, however at least more than half of the coefficients that have the correct sign are significant.

By looking at the short-run results, the significance of the estimates shows that consumption responds also to current period changes in labour income and wealth (available from the author under request).

Pooled Mean Group Estimator

The PMG developed by Pesaran, Shin and Smith (1999) is an intermediate estimator between the MG estimator described above and a pooled estimator (fixed or random effects estimator), where coefficients and error variances are constrained to be the same while the intercepts are allowed to differ across groups. It allows the intercepts, short-run coefficients and error variances to differ across groups, but the long-run coefficients are restricted to be identical among groups.

I use the MG estimates as initial estimates of the long-run parameters for the pooled maximum likelihood function and the Newton-Raphson algorithm since it considers the first and the second derivative of the log-likelihood function.

Table 3.7 illustrates the results. The housing price elasticities vary from 0.19 to 0.22 depending on the lag structure chosen when seasonal dummies are not included. If included, the elasticity ranges from 0.19 to 0.20.

[10] A value of -1.00 is sometimes imposed for in Tables 3.13 and 3.14 to maintain enough degrees of freedom.

ARDL	Seasonal Dummies	Pooled Mean Group	Restricted DSUR
SBC	no	.224(19.680)	
SBC	yes	.195(11.797)	
1,1,1	no	.213(16.711)	
1,1,1	yes	.191(10.829)	
0,3,3	no	.186(19.093)	
0,3,3	yes	.208(29.181)	
3lags3leads	no		.166(34.21)
3lags3leads	yes		.186(51.00)

Table 3.7: Pooled Estimates of the Long-Run Housing Price Elasticity

Dynamic Seemingly Unrelated Regression (DSUR) Estimator

Following Mark, Ogaki and Sul (2003) I consider N cointegrating regressions where N is fixed. Each equation has a triangular representation,

$$y_{it} = x_{it}'\beta_i + \bar{u}_{it} \tag{3.12}$$

$$\Delta x_{it} = e_{it} \tag{3.13}$$

A problem can arise in equation 3.12, since a correlation exists between the equilibrium error of equation i and leads and lags of first differences of the regressors of all other equations $j = 1, ..., N$. Therefore I need to adjust for possible spillover effects among states by including leads and lags not only of Δx_{1t} but also leads and lags of Δx_{2t} through Δx_{Nt} (z_t').

To purge endogeneity I project $\bar{u}_{it}$ on z_t:

$$\bar{u} = z_t'\delta + u_t \tag{3.14}$$

where $z_t' = (z_{1t}', ..., z_{Nt}')$, $i = 1, ..., N$ and $z_{it}' = \left(\Delta x_{it+p}', ..., \Delta x_{it-p}'\right)$.

Substituting the projection of $\bar{u}_{it}$ into equation 3.12 gives:

$$y_{it} = x_{it}'\beta_i + z_t'\delta_i + u_{it} \tag{3.15}$$

I then apply SUR to the above equation. This is the representation of the DSUR. This model can be used in small to moderate systems where the number of time periods, T, is substantially larger than the number of equations, N - as it is in this case. The model is estimated using the asymptotically efficient, feasible generalized least-squares algorithm.

The main attraction of the DSUR is that it takes into account the long-run cross-sectional dependence in the equilibrium errors in estimation and is asymptotically efficient. To test for cross-sectional dependence I estimate the innovation covariance matrix of the consumption function. The last row of Table 3.8 shows whether the off-diagonal elements in the innovation covariance matrix can be restricted to zero using the Breusch and Pagan test of independence of the residuals. Clearly the null is rejected.

Table 3.8 shows the elasticities of labour income and housing prices with or without seasonal dummies included. Most of the housing price elasticities are significantly different from zero and differ quite a lot among states. The average is 0.23 (0.17) when seasonal dummies are (are not) included.

In addition, I also calculate a restricted DSUR by assuming that $\beta_1 = \beta_2 = \beta$ and stack the equation together:

$$\tilde{y}_t = \tilde{x}_t\beta + u_t \tag{3.16}$$

The results are shown in last column of Table 3.7. The elasticity ranges between 0.17 and 0.19 depending on whether seasonal dummies are included.

State	(1) lags leads	(1) β_1	(1) β_2	(1) $\bar{R}^2$	(2) lags leads	(2) β_1	(2) β_2	(2) $\bar{R}^2$
Alabama	3,3	.777(19.37)	.477(11.97)	.63	3,3	.795(23.64)	.546(14.80)	.84
Alaska	3,3	.092(1.69)	.180(6.10)	.40	3,3	.100(2.55)	.178(8.17)	.69
Arizona	3,3	.248(2.99)	.352(5.90)	.37	3,3	.159(2.29)	.318(6.27)	.65
Arkansas	3,3	.545(10.46)	.034(.68)	.47	3,3	.615(15.04)	.130(3.35)	.77
California	3,3	.473(3.09)	-.245(-5.92)	.50	3,3	.423(3.62)	-.245(-8.05)	.74
Colorado	3,3	1.016(16.19)	-.197(-5.17)	.53	3,3	1.001(19.12)	-.160(-5.21)	.76
Connecticut	3,3	.663(12.55)	.437(16.33)	.81	3,3	.573(12.61)	.468(20.30)	.91
Delaware	3,3	.380(3.31)	.337(5.33)	.64	3,3	.213(2.42)	.460(9.68)	.77
DC	3,3	-.080(-1.65)	.037(1.18)	.46	3,3	-.089(-1.90)	.037(1.26)	.49
Florida	3,3	.694(14.97)	.709(5.07)	.70	3,3	.746(24.36)	.885(9.12)	.88
Georgia	3,3	.576(13.23)	.528(5.46)	.54	3,3	.541(13.98)	.585(6.87)	.77
Hawaii	3,3	.067(.66)	.583(15.74)	.75	3,3	.074(.90)	.550(18.26)	.89
Idaho	3,3	.759(8.22)	.443(8.10)	.43	3,3	.707(8.80)	.383(8.16)	.61
Illinois	3,3	.470(3.63)	.099(1.42)	.42	3,3	.306(3.39)	.218(4.41)	.77
Indiana	3,3	.401(6.04)	.412(7.71)	.57	3,3	.408(8.21)	.483(11.81)	.81
Iowa	3,3	.822(16.91)	.029(1.15)	.56	3,3	.834(22.50)	.062(3.34)	.83
Kansas	3,3	1.10(10.66)	.310(5.28)	.41	3,3	1.162(15.09)	.373(8.63)	.77
Kentucky	3,3	1.446(33.96)	-.173(-3.70)	.84	3,3	1.420(43.49)	-.095(-2.29)	.95
Louisiana	3,3	.604(8.75)	.293(8.90)	.50	3,3	.600(12.30)	.309(13.30)	.78
Maine	3,3	.992(11.37)	.036(.88)	.62	3,3	.922(12.51)	.042(1.30)	.84
Maryland	3,3	1.289(14.97)	-.989(-11.68)	.52	3,3	1.163(18.08)	-.813(-13.59)	.80
Massachusetts	3,3	.736(8.96)	.130(3.96)	.77	3,3	.704(13.94)	.142(7.14)	.92
Michigan	3,3	1.445(18.65)	-.276(-5.50)	.70	3,3	1.410(24.42)	-.274(-7.77)	.88
Minnesota	3,3	.551(12.59)	.490(6.38)	.43	3,3	.609(19.64)	.772(14.45)	.87
Mississippi	3,3	.648(16.93)	.522(16.04)	.54	3,3	.733(23.63)	.607(21.07)	.75

Missouri	3,3	.838(15.64)	.006(.11)	.57	3,3	.815(18.13)	.043(.90)	.81
Montana	3,3	.672(5.57)	.234(6.19)	.42	3,3	.624(5.52)	.282(8.07)	.58
Nebraska	3,3	.784(15.05)	.326(8.35)	.47	3,3	.858(21.36)	.462(14.79)	.80
Nevada	3,3	-.070(-.57)	.161(1.77)	.17	3,3	-.094(-.87)	.315(4.04)	.49
New Hampshire	3,3	1.046(17.64)	.202(6.01)	.76	3,3	.939(23.63)	.232(11.61)	.90
New Jersey	3,3	-.004(-.04)	.265(5.67)	.50	3,3	-.080(-1.11)	.308(9.83)	.78
New Mexico	3,3	.742(10.44)	.755(15.99)	.52	3,3	.757(12.89)	.804(20.28)	.79
New York	3,3	.475(4.60)	.076(1.71)	.48	3,3	.421(5.66)	.105(3.47)	.75
North Carolina	3,3	1.080(23.34)	-.041(-.44)	.76	3,3	1.055(29.60)	.055(.78)	.92
North Dakota	3,3	1.108(15.15)	.108(3.39)	.56	3,3	1.202(19.59)	.126(4.65)	.77
Ohio	3,3	1.053(11.59)	.060(1.30)	.58	3,3	.995(14.79)	.074(2.27)	.83
Oklahoma	3,3	-.044(-.52)	-.085(3.39)	.18	3,3	.032(.45)	.099(4.60)	.43
Oregon	3,3	1.580(12.18)	-.106(-2.23)	.37	3,3	1.467(13.19)	-.046(-1.13)	.68
Pennsylvania	3,3	.751(9.05)	.243(5.68)	.62	3,3	.587(8.98)	.330(10.67)	.82
Rhode Island	3,3	.104(1.31)	.313(10.94)	.59	3,3	.014(.19)	.335(12.11)	.81
South Carolina	3,3	.864(29.71)	.072(1.07)	.80	3,3	.872(42.77)	.148(3.01)	.94
South Dakota	3,3	.940(16.81)	-.143(-2.94)	.63	3,3	.933(20.30)	-.137(-3.58)	.83
Tennessee	3,3	1.278(46.76)	.171(3.58)	.86	3,3	1.265(68.64)	.211(6.18)	.97
Texas	3,3	.982(11.71)	.393(10.79)	.35	3,3	1.102(15.64)	.444(14.42)	.77
Utah	3,3	.232(3.29)	.213(7.82)	.49	3,3	.241(4.18)	.255(11.20)	.78
Vermont	3,3	.718(8.46)	.203(3.60)	.55	3,3	.670(8.39)	.182(3.37)	.76
Virginia	3,3	.492(9.56)	.198(3.18)	.58	3,3	.503(12.05)	.159(3.05)	.85
Washington	3,3	.971(10.62)	.068(1.36)	.68	3,3	.750(11.28)	.179(4.73)	.94
West Virginia	3,3	-.079(-1.24)	.000(.01)	.12	3,3	-.026(-.48)	.002(.09)	.26
Wisconsin	3,3	.373(4.44)	.092(2.09)	.27	3,3	.371(5.73)	.157(4.50)	.71
Wyoming	3,3	-.76(-4.83)	.483(9.63)	.59	3,3	-.791(-5.66)	.503(10.84)	.63
Seasonal Dummies			no				yes	
B-P test independence	chi2(1275) = 30733.553				chi2(1275) = 11066.492			
of residuals	p-value=0.000				p-value=0.000			
Average	3,3	0.644(10.67)	0.173(4.17)		3,3	0.620(13.72)	0.227(6.27)	

Table 3.8: Unrestricted DSUR Estimates

Aging of Population and Homeownership

The empirical evidence on the effects of an aging population on consumption and wealth is not clear cut. Venti and Wise (1991, 2001, 2002), McFadden (1994a, 1994b), Hoynes and McFadden (1997), Mankiw and Weil (1989), Hurd (1997), and Bosworth et al. (1991) studied the effect of changes in the housing equity of the aged on consumption and wealth and came to different conclusions. It is not clear whether demographic characteristics have a positive or negative effect on consumption. In the same vein, it is not clear whether increases (decreases) in elderly home equity arising from capital gains (losses) are translated into consumption. In the model used here the differences among housing price coefficients imply that different behaviour exists among states. There are two variables that can potentially explain these differences: different rates of aging of population and homeownership among states. The percentage of the population age 65 and older rose sharply after 1975 and will continue to rise for the next forty years. Table 3.15 illustrates the proportion of population aged 45 years or more (and 65 years or more). There appears to be a pattern: States with negative or insignificant housing coefficients are states with a relatively low proportion of households with heads aged 45 years or more. This is the case of California, Alaska, Colorado and Georgia (among others).

The second factor that could explain the difference in coefficients is homeownership rates in each state. The greater the proportion of households who are homeowners, the more the wealth effect dominates at the aggregate level[11]. Table 3.16 shows homeownership rates for 1986, 1990 and 1996. States with lower homeownership rates are the states with negative or insignificant housing price coefficients, including DC, Illinois, Massachusetts, and Nevada.

In what follows, I try to give further evidence on the changes in consumption after retirement and the possible effects on consumption of converting housing equity into liquid assets. To this end, I include the proportion of population aged 45 or older in the long-run relationship to control for aging population and the results are shown in Tables 3.17 and 3.18 using both Mean Group and DSUR estimations, respectively. β_3 is the coefficient of the aging variable that happens to be significant for at least half of the states. Housing coefficients, however, still differ widely among

[11]The homeownership rate at the US was 68 percent in the first quarter of 2003, an increase of 4 percentage points from 1993 due basically to the affluent baby boomers and the entrance in the market of minority middle class (immigrants). New finance alternatives have allowed low-wealth households to qualify for loans to become homeowners.

states. Consequently, I conclude that after controlling for different rates of aging populations, there are big disparities in the response of consumption to housing prices. Moreover, it is not possible to shed more light on the earlier discussions in the literature about the sign of the demographic impact on consumption via housing wealth. Around half of the significant coefficients of the aging population variable are positive and the other half are negative.

3.5 Compare and Contrast

As mentioned in the introduction, Case et al. (2001) follow a roughly similar procedure. They estimate regressions relating consumption to income, stock wealth and housing wealth for a panel of the 50 US states and the District of Columbia. They deflate all variables by the national GDP deflator and test for unit roots in the time series, rejecting the hypothesis of unit roots in the data for most of the series. They use three different specifications including fixed effects and adding a serial correlation correction and a lagged dependent variable and estimate the regression in differences[12]. The estimated effect of housing market wealth on consumption in their work ranges from 0.05 to 0.09.

Pesaran and Smith (1995) show that fixed effects, instrumental variables or Generalized Method of Moments estimators can be inconsistent and produce misleading estimates of the average values of the parameters in dynamic panel data models when T is large and the slope coefficients are not identical, as is usually the case. Therefore a more suitable estimator that imposes weaker homogeneity restrictions will be the PMG presented in an earlier section.

The use of constructed housing wealth and housing prices arise as competing proxies. As mentioned earlier, housing prices are used in this chapter because I

[12]The use of differences avoids the pitfall of spurious correlation due to common trending series, however it tends to lead to the omission of the long-run relationship that may exist among levels of these variables.

assume that the majority of the change in housing wealth is caused by housing price changes. However, it is worth checking whether the two variables are highly correlated. To this end, Table 3.9 shows a correlation matrix among housing wealth and its components - housing prices, number of households and homeownership rates. The correlation between changes of housing wealth and housing prices is 0.89. In addition, I estimate a linear regression corrected for first-order serially-correlated residuals using the Cochrane-Orcutt transformed regression estimator. A coefficient of unity is expected if housing prices are a good proxy of the evolution of housing wealth. The results are shown in Table 3.10. The housing prices coefficient is unity, hence I can conclude that I am justified in using housing prices as a proxy of housing wealth.

	dwealth	dhpm	dhh	dho
dwealth	1.0000			
dhpm	.8928	1.0000		
dhh	.3127	1.223	1.0000	
dho	.4133	0.0037	.0459	1.0000

Table 3.9: Wealth Structure

$\Delta \ln$ wealth	coefficient	t-student
$\Delta \ln$ hpm	1.015	98.89
constant	.002	9.75
DW-Statistic	1.97	
F-Statistic	9778.24	
$\bar{R}^2$	.79	

Table 3.10: Wealth Regression

Using net wealth takes into account both accumulated savings and capital gains. In contrast, using housing prices tests for capital gains only. A major part of variance in housing wealth is related to valuation changes that correlate with interest rates and income expectations. Capital gains due to real state wealth prices contain important forward-looking aspects. Net wealth is composed by financial savings, amortization of loans and/or capital gains. It is therefore interesting to see whether the results change when housing wealth is used instead of housing prices.

In order to make a comparison with Case at al. (2001) I reestimate my model using housing wealth instead of housing prices (although I do not include stock market wealth since stock market indexes are nationally driven). Following Case et al. (2001) I impute the aggregate value of owner-occupied housing to proxy for housing wealth as follows:

$$W_{it} = R_{it}N_{it}HP_{it}W_{io} \tag{3.17}$$

where

W_{it}=aggregate value of owner-occupied housing in state i in quarter t

R_{it}=homeownership rate in state i in quarter t

N_{it}=number of households in state i in quarter t

HP_{it}=quarterly conventional mortgage home price index for state i in quarter t

W_{io}=median house value for state i in the base year 1990

(See the Appendix for a detailed description of the data)

I test housing wealth for unit roots and cannot reject the null hypothesis of unit root (footnote of Table 3.4). I then test for cointegration between real retail sales, real labour income and real housing wealth and can reject the null of hypothesis of no cointegration (last two columns of Table 3.5). In this specification, housing wealth directly effects consumption through its market value, which provides a source of purchasing power to cope with fluctuations in income.

Table 3.11 shows the PMG housing wealth estimates of the cointegrating relation, the estimated elasticity ranges from 0.15 to 0.21 depending on whether seasonal dummies are included. These findings are very similar to the estimated effect of housing prices on consumption in the previous section.

ARDL	Seasonal Dummies	Pooled Mean Group
SBC	no	.200(24.03)
SBC	yes	.165(12.01)
1,1,1	no	.212(20.41)
1,1,1	yes	.185(12.52)
0,3,3	no	.202(17.226)
0,3,3	yes	.153(25.99)

Table 3.11: Pooled Estimates of the Long-Run Housing Wealth Elasticity

In sum, these results give support to my previous findings and imply that the estimated elasticity of housing wealth is more than twice the estimated elasticity in Case et al. (2001).

3.6 Conclusion

I have analysed the effect of housing prices on consumption using variables suggested by the life-cycle model. Since housing prices are locally driven I study the housing wealth effect using state level data for the 50 US states and the District of Columbia. I found unit roots in housing prices and a cointegrating relationship between consumption, income and housing wealth at the state level. Due to the considerable heterogeneity in state level behaviour, fixed effects estimators that constrain intercepts, short-run coefficients and error variances lead to misleading inferences. I therefore use three different estimation methods that allow for heterogeneity among states and calculate the elasticity of housing prices. I find that differences in the aging of populations and homeownership play a role in the link between consumption and housing prices, although they do not explain the different response of consumption to housing prices among states. I find evidence of a strong housing wealth effect with elasticities ranging from 0.15 to 0.23.

3.7 Appendix

3.7.1 US States and Regions

State	State Code	Census Regions	CPI Index
Alabama	AL	South	South:Urban:All Items, NSA
Alaska	AK	West	West: Urban: All Items, NSA
Arizona	AZ	West	West: Urban: All Items, NSA
Arkansas	AR	South	South:Urban:All Items, NSA
California	CA	West	Los Angeles-Riverside-Orange: All Items, NSA
Colorado	CO	West	West: Urban: All Items, NSA
Connecticut	CT	Northeast	NY-NJ,NY-CT-PA: All Items, NSA
Delaware	DE	South	Phila-Wilmington-Alt City: All Items, NSA
District of Columbia	DC	South	South:Urban:All Items, NSA
Florida	FL	South	South:Urban:All Items, NSA
Georgia	GA	South	Atlanta, GA: All Items, NSA
Hawaii	HI	West	West: Urban: All Items, NSA
Idaho	ID	West	West: Urban: All Items, NSA
Illinois	IL	Midwest	Chicago-Gary-Kenosha, IL-IN-WI:All Items, NSA
Indiana	IN	Midwest	Chicago-Gary-Kenosha, IL-IN-WI:All Items, NSA
Iowa	IA	Midwest	Midwest: Urban: All Items, NSA
Kansas	KS	Midwest	Midwest: Urban: All Items, NSA
Kentucky	KY	South	South:Urban:All Items, NSA
Louisiana	LA	South	South:Urban:All Items, NSA
Maine	ME	Northeast	Northeast: Urban: All Items, NSA
Maryland	MD	South	Phila-Wilmington-Alt City: All Items, NSA
Massachusetts	MA	Northeast	Boston-Brockton-Nashua: All Items, NSA

(continued)	State Code	Census Regions	CPI Index
Michigan	MI	Midwest	Detroit-Ann Arbor-Flint, MI: All Items, NSA
Minnesota	MN	Midwest	Midwest: Urban: All Items, NSA
Mississippi	MS	South	South:Urban:All Items, NSA
Missouri	MO	Midwest	Midwest: Urban: All Items, NSA
Montana	MT	West	West: Urban: All Items, NSA
Nebraska	NE	Midwest	Midwest: Urban: All Items, NSA
Nevada	NV	West	West: Urban: All Items, NSA
New Hampshire	NH	Northeast	Boston-Brockton-Nashua: All Items, NSA
New Jersey	NJ	Northeast	NY-NJ,NY-CT-PA: All Items, NSA
New Mexico	NM	West	West: Urban: All Items, NSA
New York	NY	Northeast	NY-NJ,NY-CT-PA: All Items, NSA
North Carolina	NC	South	South:Urban:All Items, NSA
North Dakota	ND	Midwest	Midwest: Urban: All Items, NSA
Ohio	OH	Midwest	Cleveland-Akron, OH: All Items, NSA
Oklahoma	OK	South	South:Urban:All Items, NSA
Oregon	OR	West	West: Urban: All Items, NSA
Pennsylvania	PA	Northeast	Phila-Wilmington-Alt City: All Items, NSA
Rhode Island	RI	Northeast	Northeast: Urban: All Items, NSA
South Carolina	SC	South	South:Urban:All Items, NSA
South Dakota	SD	Midwest	Midwest: Urban: All Items, NSA
Tennessee	TN	South	South:Urban:All Items, NSA
Texas	TX	South	Dallas-Fort Worth, TX: All Items, NSA
Utah	UT	West	West: Urban: All Items, NSA
Vermont	VT	Northeast	Northeast: Urban: All Items, NSA
Virginia	VA	South	South:Urban:All Items, NSA
Washington	WA	West	Seattle-Tacoma-Bremerton: All Items, NSA
West Virginia	WV	South	South:Urban:All Items, NSA
Wisconsin	WI	Midwest	Chicago-Gary-Kenosha, IL-IN-WI:All Items, NSA
Wyoming	WY	West	West: Urban: All Items, NSA

Table 3.12: State Consumer Prices' Sources

3.7.2 Data Sources

The panel data used is a balanced panel spanning from 1975:1 to 1996:4 for 50 US states and the District of Columbia.

Real per Capita Retail Sales

This is my proxy for Real per Capita Consumption. I construct the series from:

- Monthly Retail Sales for the period 1978:01-1996:12 for 20 states (CA, FL, GA, IL, IN, LA, MA, MD, MI, MN, MO, NC, NJ, NY, OH, PA, TN, TX, VA, WI) from the US Census Bureau (please note that the monthly retail sales series have been discontinued)

- Monthly Retail Sales for the period 1987:01-1996:12 for 7 states (AZ-CO-CT-DE-KS-KY-WA) from the US Census Bureau and partial interpolation using the Chow-Lin Method for the period 1975:1-1987:4.

- For the rest of the 23 states full interpolation was computed.

The series' used by the Chow-Lin Method in order to calculate the interpolations are the Monthly Retail Sales from 1978:01-1996:12 for 9 Census Divisions from the US Census Bureau and the Annual Retail Sales from 1963-1996 from the *Sales and Marketing Management magazine* for 50 states.

The series is deflated by the calculated state CPI described below and made per capita using the interpolated state population estimates.

Real Housing Prices

Real housing prices were calculated from the Quarterly Conventional Mortgage Home Price Index (CMHPI) by Freddie Mac. They were deflated by the calculated state CPI described below.

The CMHPI has been calculated since 1975 and uses a statistical method based entirely on "repeat transactions". Any time a house's value is observed twice over time (via either a sale or an appraisal), the change in the price contributes one observation of house price growth over that time period. The index is defined to be the statistically determined set of values that most closely fits many such repeated observations. Mathematically, the officially published index is a geometric repeat-sales index with a Goetzmann-like transformation.

The computation of the index is based on mortgages that were purchased or securitized by Freddie Mac or Fannie Mae since January 1975. These mortgages are "conventional" in their financing: they are not insured or guaranteed by any federal government agency such as the Federal Housing Administration or Veterans Administration. Although not specified in the name, the index is based on mortgages for single unit residential houses only; it does not reflect condominiums, multi-family or commercial properties. Finally, the mortgages are "conforming": at the time of purchase they met Freddie Mac or Fannie Mae underwriting standards, and they did not exceed the allowable loan limit set for the two companies. The conforming loan limit is revised each year based on a Federal Housing Finance Board survey.

A more technical description of the method can be found in Stephens et al. (1995) and Wang and Zorn (1997). Since none of the papers describe any change in methodology during the period, an increase in sample size could explain the reduction in high frequency fluctuations after the early 1980s that is observed in Figures 3.4-3.7.

Real per Capita Labour Income

Real per capita labour income was calculated from the quarterly labour income by the Bureau of Economic Analysis. The series is deflated by the calculated state CPI described below and made per capita using the interpolated state population estimates.

State Consumer Prices

State CPI was calculated by matching monthly CPIs of the 4 Census Regions by the Bureau of Labor Statistics and monthly or quarterly CPIs for 26 Metropolitan Statistical Areas (MSAs) and Primary Metropolitan Statistical Areas (PMSAs) and Cities, with the closest state. The CPIs used are listed in Table 3.12.

Population Estimates

State Population Estimates were interpolated from annual resident population estimates by the US Census Bureau. The Chow-Lin method used Monthly US Population Estimates by the US Census Bureau.

Real per Capita Housing Wealth

Real per capita housing wealth was calculated following Case et al. (2001). Apart from the housing prices describe above, I used:

Homeownership Rates State Quarterly Homeownership Rates were interpolated from Annual Homeownership Rates by the Housing Vacancies and Homeownership, Annual Statistics of the US Census Bureau, Table 13. The Chow-Lin method used the quarterly US Homeownership Rates by the US Census Bureau, Table 5.

Total Number of Households State Quarterly Estimates of Total Households were interpolated from the State Intercensal Estimates of Total Households by the US Census Bureau. The Chow-Lin method used the Quarterly Estimates of Total Households for the US by the US Census Bureau, Series H-111.

House Median Value Median house value from the 1990 Census of Population and Housing, US Bureau of the Census.

The series is deflated by the calculated state CPI described below and made per capita using the interpolated state population estimates.

	MG Estimator				
State	*ARDL*	β_1	β_2	α	$\bar{R}^2$
Alabama	2,0,0	.820(12.01)	.475(4.43)	-1.00(NA)	.43
Alaska	0,0,0	.076(.35)	.247(1.91)	-.462(-4.58)	.39
Arizona	0,0,2	.014(.047)	.051(.204)	-.440(-3.70)	.42
Arkansas	0,0,0	.831(5.18)	.358(1.88)	-.622(-4.57)	.50
California	2,0,0	1.259(1.71)	-.248(-1.40)	-.378(-3.90)	.48
Colorado	2,0,1	1.030(9.72)	-.107(-1.38)	-1.00(NA)	.34
Connecticut	2,1,0	.633(4.436)	.421(4.501)	-.663(-4.718)	.51
Delaware	2,1,0	.595(1.28)	.266(.91)	-.406(-3.26)	.56
DC	2,1,0	.056(.22)	-.184(-.92)	-.161(-3.45)	.38
Florida	2,1,0	.732(7.03)	.499(1.39)	-.549(-4.58)	.55
Georgia	0,0,0	.662(4.78)	.394(.94)	-.488(-3.77)	.55
Hawaii	3,2,0	.122(.48)	.546(6.06)	-1.00(NA)	.39
Idaho	2,0,0	1.022(3.02)	.612(2.68)	-.354(-3.58)	.30
Illinois	0,0,0	.286(1.00)	.247(1.26)	-.648(-4.50)	.70
Indiana	2,0,0	.618(6.14)	.511(4.89)	-1.00(NA)	.49
Iowa	0,0,0	.987(5.39)	.093(.76)	-.489(-4.15)	.47
Kansas	0,0,0	1.096(7.57)	.300(3.16)	-1.00(NA)	.52
Kentucky	2,0,0	1.419(20.34)	-.026(-.22)	-1.00(NA)	.50
Louisiana	0,0,0	.600(6.07)	.306(6.23)	-1.00(NA)	.47
Maine	2,2,1	1.049(6.87)	.069(.78)	-1.00(NA)	.45
Maryland	2,0,0	1.232(3.90)	-.821(-2.51)	-.497(-4.00)	.58
Massachusetts	2,1,0	.864(5.56)	.107(1.57)	-1.00(NA)	.58
Michigan	3,1,0	1.486(13.58)	-.239(-2.37)	-1.105(-6.51)	.63

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Minnesota	2,0,0	.689(8.55)	.690(3.77)	-1.00(NA)	.56
Mississippi	2,1,0	.766(6.34)	.651(5.38)	-.625(-4.96)	.44
Missouri	2,0,0	.875(6.16)	.023(.11)	-.568(-4.24)	.49
Montana	0,0,0	.963(2.93)	.247(2.13)	-.447(-5.08)	.22
Nebraska	3,0,0	.903(9.20)	.352(3.45)	-1.00(NA)	.45
Nevada	0,0,0	.440(.74)	.697(1.49)	-.329(-3.26)	.32
New Hampshire	3,0,0	1.053(10.66)	.219(3.20)	-1.00(NA)	.55
New Jersey	0,0,0	.213(.72)	.278(1.82)	-.571(-4.09)	.58
New Mexico	0,0,0	.695(2.71)	.444(2.22)	-.503(-3.68)	.30
New York	2,0,1	.438(1.16)	.109(.59)	-.425(-3.47)	.58
North Carolina	3,2,0	1.100(13.77)	.029(.14)	-1.00(NA)	.50
North Dakota	2,0,0	1.447(5.97)	.261(1.91)	-.493(-4.60)	.48
Ohio	0,0,0	1.326(7.203)	.044(.36)	-.726(-5.31)	.57
Oklahoma	2,0,0	-.180(-.39)	.083(.67)	-.305(-3.02)	.34
Oregon	3,0,1	.888(1.70)	.229(.951)	-.303(-3.19)	.40
Pennsylvania	2,1,0	1.078(2.83)	.048(.20)	-.495(-3.56)	.60
Rhode Island	0,0,0	.512(.72)	.008(.022)	-.246(-2.12)	.35
South Carolina	2,0,0	.913(20.14)	.158(1.11)	-.105(-6.16)	.69
South Dakota	1,0,0	1.142(3.98)	.026(.08)	-.319(-3.34)	.41
Tennessee	2,0,0	1.325(51.80)	.201(3.26)	-1.944(-9.39)	.70
Texas	2,0,0	1.019(7.91)	.418(7.43)	-1.109(-6.91)	.63
Utah	0,1,0	.486(4.74)	.315(5.52)	-1.00(NA)	.36
Vermont	1,0,0	1.153(2.27)	-.337(-.78)	-.322(-2.99)	.41
Virginia	2,0,0	.531(4.88)	.215(1.46)	-1.00(NA)	.54
Washington	2,0,1	.710(11.90)	.235(7.20)	-2.43(-11.86)	.76
West Virginia	0,0,1	.284(.77)	.093(.57)	-.175(-2.35)	.45
Wisconsin	2,0,0	.468(3.56)	.246(2.49)	-1.00(NA)	.54
Wyoming	3,0,0	.240(.18)	.530(1.58)	-.13(-2.48)	.06
Seasonal Dummies			no		
Average (MG)		.764(13.506)	.204(5.183)	-.721(-12.03)	

Table 3.13: Mean Group Estimation without Seasonal Dummies

	MG Estimator				
State	$ARDL$	β_1	β_2	α	$\bar{R}^2$
Alabama	3,0,0	.870(7.89)	.538(3.07)	-.298(-4.07)	.87
Alaska	1,0,3	.062(.24)	.270(1.91)	-.217(-3.64)	.84
Arizona	2,0,2	-.027(-.08)	-.002(-.01)	-.257(-3.33)	.74
Arkansas	3,0,0	.856(5.06)	.380(1.94)	-.302(-3.99)	.88
California	2,1,0	3.682(1.02)	-.898(-1.03)	-.051(-1.05)	.89
Colorado	1,1,0	1.099(5.97)	-.098(-.74)	-.314(-3.86)	.81
Connecticut	2,1,0	.669(4.57)	.408(4.31)	-.351(-4.033)	.86
Delaware	2,1,0	.812(1.56)	.108(.33)	-.250(-2.91)	.84
DC	2,0,3	.077(.36)	-.159(-.95)	-.128(-3.99)	.72
Florida	2,0,1	.637(5.94)	.073(.19)	-.345(-4.62)	.84
Georgia	1,0,1	.619(2.61)	-.132(-.16)	-.167(-2.00)	.85
Hawaii	3,0,0	.729(1.03)	.307(1.24)	-.179(-2.32)	.85
Idaho	2,0,2	1.242(2.73)	.830(2.52)	-.142(-2.60)	.81
Illinois	2,0,0	.340(.92)	.116(.45)	-.271(-3.02)	.91
Indiana	2,0,0	.618(4.34)	.501(3.50)	-.386(-4.47)	.86
Iowa	3,0,0	1.129(5.19)	.201(1.39)	-.202(-3.45)	.89
Kansas	3,0,0	.988(6.24)	.251(2.56)	-.496(-4.88)	.88
Kentucky	2,0,0	1.481(14.87)	-.058(-.37)	-.347(-4.53)	.89
Louisiana	2,0,2	.681(4.57)	.344(4.88)	-.373(-3.67)	.87
Maine	3,0,0	1.124(4.25)	-.058(-.38)	-.343(-4.28)	.86
Maryland	2,0,0	1.009(1.91)	-.581(-1.04)	-.157(-2.22)	.89
Massachusetts	3,0,0	.956(4.26)	.039(.37)	-.381(-3.76)	.89
Michigan	3,0,0	1.483(9.52)	-.213(-1.54)	-.416(-5.41)	.89

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Minnesota	1,0,2	.647(9.60)	.695(4.70)	-.589(-5.35)	.91
Mississippi	2,1,0	.611(3.93)	.495(3.24)	-.232(-3.25)	.87
Missouri	2,2,0	.818(4.31)	-.238(-.80)	-.235(-2.93)	.85
Montana	2,0,3	1.369(3.84)	.256(2.55)	-.267(-4.81)	.80
Nebraska	3,0,0	.740(3.29)	.253(1.13)	-.222(-2.92)	.89
Nevada	1,0,0	1.014(1.10)	1.135(1.56)	-.114(-2.22)	.84
New Hampshire	3,0,0	1.068(12.62)	.229(4.12)	-.621(-6.58)	.89
New Jersey	1,0,1	.062(.16)	.321(1.63)	-.268(-2.84)	.85
New Mexico	2,0,0	.687(1.87)	.320(1.06)	-.175(-2.42)	.82
New York	3,1,0	.280(.41)	.070(.21)	-.121(-1.77)	.89
North Carolina	1,0,0	.987(6.94)	-.159(-.42)	-.257(-3.24)	.91
North Dakota	3,0,0	1.263(4.60)	.303(1.84)	-.201(-4.04)	.89
Ohio	3,1,0	1.122(3.43)	.084(.44)	-.240(-2.67)	.89
Oklahoma	3,1,2	.077(.23)	.130(1.46)	-.202(-3.83)	.86
Oregon	1,1,1	1.333(1.92)	.251(.87)	-.124(-2.53)	.85
Pennsylvania	1,0,0	1.261(3.46)	-.105(-.45)	-.247(-3.79)	.93
Rhode Island	1,0,0	1.773(.49)	-1.008(-.42)	-.041(-.63)	.84
South Carolina	1,1,0	.925(17.71)	.123(.76)	-.494(-4.93)	.91
South Dakota	3,0,3	1.366(3.90)	.600(1.35)	-.135(-2.84)	.87
Tennessee	2,0,0	1.338(35.31)	.240(2.60)	-.736(-8.19)	.90
Texas	1,0,0	1.162(8.15)	.488(7.24)	-.506(-6.00)	.89
Utah	1,1,0	.555(2.61)	.271(2.30)	-.235(-3.29)	.85
Vermont	3,0,0	1.065(1.85)	-.228(-.47)	-.146(-2.48)	.83
Virginia	3,0,0	.572(4.97)	.165(1.06)	-.548(-5.60)	.85
Washington	2,2,0	.866(9.85)	.139(2.95)	-1.00(NA)	.91
West Virginia	2,0,0	.105(.37)	.038(.28)	-.127(-2.88)	.81
Wisconsin	2,0,0	.498(2.67)	.277(2.01)	-.411(-3.86)	.85
Wyoming	0,0,0	-.441(-.46)	.596(2.36)	-.106(-3.14)	.66
Seasonal Dummies			yes		
Average (MG)		.868(10.21)	.155(2.97)	-.294(11.589)	

Table 3.14: Mean Group Estimation with Seasonal Dummies

State	45+			65+		
	1975	1986	1996	1975	1986	1996
Alabama	30.15	31.28	34.27	10.44	12.29	13.09
Alaska	16.51	17.53	25.28	2.34	3.21	5.12
Arizona	29.20	30.16	32.75	9.99	12.40	13.38
Arkansas	32.93	33.41	35.53	12.76	14.46	14.47
California	29.75	27.96	29.32	9.72	10.54	11.07
Colorado	26.30	26.33	31.78	8.30	9.06	10.14
Connecticut	32.66	32.97	35.33	10.49	13.01	14.36
Delaware	29.02	30.66	33.10	8.63	11.46	12.86
District of Columbia	30.86	30.37	34.60	10.26	12.01	13.90
Florida	37.70	38.02	39.08	15.88	17.86	18.55
Georgia	27.30	27.49	29.95	8.67	9.87	9.98
Hawaii	25.58	27.66	33.48	6.63	9.92	12.96
Idaho	28.32	28.09	31.53	9.57	11.22	11.43
Illinois	31.08	30.68	32.65	10.36	12.06	12.55
Indiana	29.78	30.81	33.41	9.98	11.98	12.67
Iowa	32.74	33.44	36.03	12.71	14.82	15.23
Kansas	32.64	31.63	33.46	12.57	13.53	13.70
Kentucky	30.28	30.68	34.10	10.76	12.04	12.64
Louisiana	27.48	27.57	31.53	9.20	10.13	11.48
Maine	31.96	31.87	35.39	11.89	13.21	13.97
Maryland	28.80	29.61	32.14	8.35	10.50	11.44
Massachusetts	32.86	32.01	34.29	11.77	13.36	14.14
Michigan	28.89	29.95	32.92	9.02	11.33	12.47
Minnesota	29.97	29.86	32.24	11.23	12.44	12.45
Mississippi	29.11	29.37	31.99	10.79	11.94	12.35

Missouri	32.99	32.74	34.39	12.57	13.70	13.89
Montana	29.80	30.36	35.69	10.07	12.16	13.22
Nebraska	31.96	31.65	33.83	12.59	13.77	13.92
Nevada	27.98	29.64	33.00	7.27	10.03	11.51
New Hampshire	30.24	29.26	31.80	10.87	11.43	12.08
New Jersey	33.22	33.28	34.93	10.53	12.76	13.73
New Mexico	25.70	27.25	31.24	7.96	9.78	11.13
New York	33.31	32.64	34.30	11.43	12.78	13.35
North Carolina	28.90	30.57	33.49	9.07	11.45	12.60
North Dakota	30.54	30.18	34.22	11.50	13.10	14.54
Ohio	30.75	31.66	34.23	9.99	12.24	13.43
Oklahoma	32.29	31.32	34.62	12.23	12.44	13.57
Oregon	31.35	31.32	35.22	11.21	13.31	13.45
Pennsylvania	34.81	35.05	37.33	11.66	14.62	15.91
Rhode Island	34.77	33.58	35.06	12.18	14.55	15.78
South Carolina	26.87	28.67	33.03	8.14	10.53	12.10
South Dakota	32.19	31.76	33.79	12.56	14.10	14.47
Tennessee	30.49	31.52	34.27	10.52	12.24	12.59
Texas	27.93	26.58	29.40	9.41	9.44	10.19
Utah	23.28	22.00	24.81	7.44	8.03	8.80
Vermont	29.57	29.25	33.56	11.03	11.80	12.23
Virginia	28.38	28.94	32.09	8.59	10.33	11.23
Washington	29.80	29.29	32.18	10.18	11.62	11.63
West Virginia	33.29	33.88	38.37	11.70	13.66	15.23
Wisconsin	30.79	31.11	33.56	11.22	13.05	13.30
Wyoming	27.24	26.45	32.81	8.83	8.56	11.23
Mean	30.01	30.18	33.28	10.26	11.88	12.77
Variance	10.77	9.98	6.50	4.30	4.79	4.07
Highest	37.7	38.02	39.08	15.88	17.86	18.55
Lowest	16.51	17.53	24.81	2.34	3.21	5.12

Table 3.15: Aging Population

State	1986	1990	1996
Alabama	70.3	68.4	71
Alaska	61.5	58.4	62.9
Arizona	62.5	64.5	62
Arkansas	67.5	67.8	66.6
California	53.8	53.8	55
Colorado	63.7	59	64.5
Connecticut	68.1	67.9	69
Delaware	71	67.7	71.5
District of Columbia	34.6	36.4	40.4
Florida	66.5	65.1	67.1
Georgia	62.4	64.3	69.3
Hawaii	50.9	55.5	50.6
Idaho	69.8	69.4	71.4
Illinois	60.9	63	68.2
Indiana	67.6	67	74.2
Iowa	69.2	70.7	72.8
Kansas	66.4	69	67.5
Kentucky	68.1	65.8	73.2
Louisiana	70.4	67.8	64.9
Maine	74	74.2	76.5
Maryland	62.8	64.9	66.9
Massachusetts	60.3	58.6	61.7
Michigan	70.9	72.3	73.3
Minnesota	68	68	75.4
Mississippi	70.4	69.4	73
Missouri	67.8	64	70.2

(continued)	1986	1990	1996
Montana	64.4	69.1	68.6
Nebraska	68.3	67.3	66.8
Nevada	54.5	55.8	61.1
New Hampshire	64.8	65	65
New Jersey	63.3	65	64.6
New Mexico	67.8	68.6	67.1
New York	51.3	53.3	52.7
North Carolina	68.2	69	70.4
North Dakota	69.2	67.2	68.2
Ohio	68.2	68.7	69.2
Oklahoma	69.7	70.3	68.4
Oregon	63.9	64.4	63.1
Pennsylvania	72.3	73.8	71.7
Rhode Island	62.2	58.5	56.6
South Carolina	70.3	71.4	72.9
South Dakota	65.9	66.2	67.8
Tennessee	67.4	68.3	68.8
Texas	61	59.7	61.8
Utah	68	70.1	72.7
Vermont	69.8	72.6	70.3
Virginia	68.2	69.8	68.5
Washington	65.1	61.8	63.1
West Virginia	76.4	72	74.3
Wisconsin	66.5	68.3	68.2
Wyoming	72	68.9	68
Mean	65.5	65.5	66.8
Variance	47.1	42.9	44.7
Highest	76.4	74.2	76.5
Lowest	34.6	36.4	40.4

Table 3.16: Homeownership Rates

	MG Estimator					
State	*ARDL*	β_1	β_2	β_3	α	$\bar{R}^2$
Alabama	2,0,0,3	0.129(0.33)	0.465(1.06)	1.722(1.45)	-0.530(-3.62)	0.72
Alaska	3,0,0,2	-0.508(-2.30)	0.422(4.66)	0.749(4.73)	-0.703(-5.67)	0.70
Arizona	0,0,0,0	0.726(3.29)	0.289(1.93)	-0.330(-0.65)	-	0.44
Arkansas	2,0,1,3	-0.591(-1.23)	0.550(1.96)	6.497(3.36)	-0.604(-3.57)	0.76
California	1,0,2,2	0.813(3.27)	-0.038(-0.62)	0.314(0.79)	-1.258(-11.08)	0.66
Colorado	0,0,1,3	2.617(4.84)	-0.064(-0.81)	-0.768(-1.84)	-	0.74
Connecticut	3,0,0,3	1.612(2.82)	0.021(0.09)	-3.538(-1.84)	-0.698(-4.49)	0.73
Delaware	3,0,0,3	3.223(3.30)	-0.548(-1.40)	-5.215(-3.17)	-0.537(-2.82)	0.77
DC	3,0,0,3	0.185(0.86)	-0.193(-1.39)	-1.611(-3.29)	-0.341(-3.58)	0.61
Florida	1,0,0,2	1.049(13.55)	0.873(3.50)	1.175(2.46)	-1.263(-10.70)	0.63
Georgia	2,3,0,3	-0.164(-0.21)	0.749(0.76)	2.495(1.48)	-0.356(-1.96)	0.73
Hawaii	2,0,0,3	1.687(2.91)	-0.106(-0.62)	-0.173(-0.36)	-0.596(-3.48)	0.73
Idaho	3,0,1,3	-1.358(-1.79)	1.488(9.28)	3.607(2.68)	-0.754(-5.12)	0.69
Illinois	3,0,0,3	1.246(8.02)	0.066(0.64)	-3.135(-11.62)	-1.902(-6.02)	0.88
Indiana	2,0,0,3	0.362(0.72)	0.391(1.09)	0.416(0.30)	-0.663(-3.31)	0.70
Iowa	3,0,1,3	0.365(1.57)	0.648(7.69)	0.979(1.24)	-1.269(-5.58)	0.82
Kansas	0,0,0,3	1.102(3.26)	0.287(1.20)	-1.106(-1.27)	-	0.63
Kentucky	2,0,0,3	0.735(1.44)	0.440(0.97)	1.009(0.75)	-0.577(-3.74)	0.78
Louisiana	3,0,0,3	0.589(1.51)	0.350(3.43)	0.178(0.23)	-0.741(-3.95)	0.76
Maine	3,0,0,3	1.320(1.77)	-0.113(-0.43)	-1.525(-1.71)	-0.831(-4.16)	0.75
Maryland	3,0,0,3	1.694(6.78)	-0.770(-4.07)	-1.670(-2.66)	-0.823(-3.93)	0.81
Massachusetts	3,0,3,2	1.099(5.35)	0.010(0.12)	-0.446(-0.91)	-1.817(-7.39)	0.85

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Michigan	3,2,0,2	1.473(26.60)	0.021(0.44)	-0.427(-2.58)	-2.464(-11.69)	0.89
Minnesota	3,0,0,3	0.360(2.73)	0.208(0.62)	0.819(1.31)	-1.069(-4.45)	0.79
Mississippi	2,0,1,3	1.347(2.10)	0.813(3.12)	-2.777(-1.26)	-0.513(-4.22)	0.69
Missouri	0,0,0,3	0.823(4.07)	-0.001(-0.05)	-1.156(-1.27)	-	0.68
Montana	3,0,0,3	1.391(1.79)	0.390(2.80)	-0.591(-0.77)	-0.516(-3.44)	0.63
Nebraska	2,0,0,3	-0.196(-0.37)	0.435(1.13)	1.488(0.73)	-0.640(-4.09)	0.77
Nevada	2,0,0,3	-5.005(-1.57)	0.803(0.74)	6.852(1.62)	-0.222(-2.17)	0.65
New Hampshire	3,1,0,3	0.947(3.49)	0.160(1.29)	-0.844(-1.22)	-1.383(-6.65)	0.81
New Jersey	3,2,1,2	-0.144(-0.68)	0.403(5.32)	0.707(1.10)	-1.954(-7.40)	0.82
New Mexico	2,0,0,3	1.293(0.96)	0.782(3.87)	-0.523(-0.35)	-0.458(-2.74)	0.70
New York	3,0,0,2	0.279(1.02)	0.292(2.78)	0.943(1.11)	-1.641(-6.13)	0.72
North Carolina	2,0,0,3	0.594(1.02)	0.736(1.22)	0.135(0.10)	-0.551(-2.89)	0.73
North Dakota	2,2,0,3	1.980(1.59)	0.535(2.84)	-2.116(-0.93)	-0.489(-3.80)	0.74
Ohio	2,0,0,3	0.582(1.44)	-0.120(-0.37)	1.800(1.61)	-0.609(-3.18)	0.80
Oklahoma	3,0,0,3	-1.750(-1.28)	0.822(2.55)	3.209(1.55)	-0.297(-3.28)	0.65
Oregon	3,0,0,3	-0.019(-0.06)	0.318(6.62)	0.978(1.52)	-1434(-5.20)	0.81
Pennsylvania	2,0,0,3	-0.760(-0.13)	0.009(0.00)	-1.465(-0.12)	-0.141(-0.71)	0.74
Rhode Island	2,0,0,0	0.795(1.05)	-0.276(-0.78)	-4.895(-1.73)	-0.387(-2.47)	0.38
South Carolina	3,0,0,3	0.716(4.57)	0.449(1.50)	0.391(1.62)	-1.015(-4.49)	0.83
South Dakota	3,0,2,3	0.395(2.78)	0.521(4.06)	1.020(1.02)	-1.445(-5.77)	0.81
Tennessee	3,1,0,2	1.002(17.93)	0.423(8.15)	1.321(6.14)	-2.627(-13.05)	0.89
Texas	3,0,1,3	-0.026(-0.10)	0.099(1.53)	1.087(3.04)	-1.512(-5.66)	0.82
Utah	0,0,0,3	0.132(0.28)	.248(3.80)	0.751(1.03)	-	0.71
Vermont	2,0,3,3	1.391(1.71)	-0.521(-1.55)	-1.958(-1.97)	-0.449(-2.87)	0.76
Virginia	3,0,0,2	0.934(4.99)	0.054(0.38)	0.179(0.59)	-1.362(-6.84)	0.78
Washington	3,0,0,3	0.721(9.33)	0.248(5.20)	-0.234(-1.42)	-2.289(-8.05)	0.86
West Virginia	3,0,0,3	-1.338(-1.42)	0.457(2.14)	1.998(1.30)	-0.223(-2.90)	0.69
Wisconsin	3,0,0,2	0.734(2.87)	-0.078(-0.38)	1.200(1.07)	-1.283(-5.27)	0.74
Wyoming	3,0,0,3	-1.293(-1.47)	1.202(4.08)	0.649(1.15)	-0.207(-3.74)	0.50
Seasonal Dummies				no		

Table 3.17: Mean Group Estimation controlling for Aging Population

State	lags leads	β_1	β_2	β_3	$\bar{R}^2$
Alabama	3,3	0.318(2.12)	0.236(1.55)	2.010(3.97)	0.78
Alaska	3,3	-0.685(-3.92)	0.391(6.33)	0.896(8.54)	0.73
Arizona	3,3	0.888(7.62)	-0.025(-0.22)	-1.411(-3.70)	0.51
Arkansas	3,3	0.038(0.20)	-0.146(-1.57)	2.900(3.47)	0.68
California	3,3	1.091(5.29)	0.094(1.55)	-0.012(-0.03)	0.75
Colorado	3,3	2.882(8.88)	-0.239(-4.34)	-0.860(-2.91)	0.77
Connecticut	3,3	1.781(7.34)	0.034(0.34)	-3.727(-4.50)	0.84
Delaware	3,3	2.849(7.21)	-0.266(-2.03)	-3.375(-4.40)	0.84
DC	3,3	-0.059(-0.69)	-0.008(-0.18)	-1.382(-5.60)	0.56
Florida	3,3	0.985(11.33)	1.265(6.10)	0.858(1.78)	0.75
Georgia	3,3	0.865(7.76)	0.721(4.20)	1.549(3.97)	0.82
Hawaii	3,3	2.314(6.28)	-0.201(-1.79)	0.285(0.92)	0.86
Idaho	3,3	-3.893(-7.43)	1.757(18.07)	7.625(8.26)	0.81
Illinois	3,3	1.801(5.04)	-0.262(-1.37)	-3.962(-7.14)	0.82
Indiana	3,3	0.183(0.88)	0.505(2.98)	1.000(1.66)	0.68
Iowa	3,3	1.080(7.05)	0.914(10.67)	-1.780(-3.16)	0.76
Kansas	3,3	1.585(8.18)	0.118(0.83)	-1.123(-1.81)	0.66
Kentucky	3,3	1.220(5.93)	0.611(3.58)	0.508(0.88)	0.89
Louisiana	3,3	-0.070(-0.21)	0.507(5.05)	1.320(2.30)	0.57
Maine	3,3	0.328(0.80)	0.238(1.66)	-1.000(-1.95)	0.66
Maryland	3,3	1.699(12.79)	-0.854(-9.71)	-1.293(-3.22)	0.68
Massachusetts	3,3	1.190(5.97)	0.019(0.22)	-0.762(-1.29)	0.78
Michigan	3,3	1.095(11.19)	0.449(6.29)	-0.164(-0.55)	0.86
Minnesota	3,3	0.399(5.04)	-0.078(-0.41)	1.037(2.26)	0.67

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Mississippi	3,3	2.273(8.63)	0.733(7.27)	-6.235(-6.71)	0.72
Missouri	3,3	1.181(11.68)	0.036(0.35)	-1.156(-2.10)	0.75
Montana	3,3	-0.437(-1.35)	0.755(13.03)	0.760(2.28)	0.75
Nebraska	3,3	0.799(5.97)	1.012(9.76)	-1.322(-2.37)	0.75
Nevada	3,3	-3.331(-6.34)	0.421(1.73)	4.138(5.90)	0.45
New Hampshire	3,3	1.154(5.79)	0.006(0.06)	-2.017(-3.61)	0.80
New Jersey	3,3	-0.110(-0.45)	0.365(4.20)	-0.245(-0.30)	0.69
New Mexico	3,3	2.894(9.68)	0.452(7.72)	-1.964(-5.38)	0.76
New York	3,3	0.845(3.71)	0.169(2.17)	0.310(0.45)	0.69
North Carolina	3,3	1.420(8.04)	0.123(0.73)	-0.829(-1.65)	0.83
North Dakota	3,3	1.319(2.78)	0.441(5.29)	-0.990(-1.09)	0.69
Ohio	3,3	-0.172(-0.81)	0.707(3.91)	1.977(4.26)	0.79
Oklahoma	3,3	-2.283(-5.05)	0.292(3.98)	4.084(6.10)	0.49
Oregon	3,3	0.288(1.08)	0.473(10.92)	-0.634(-1.13)	0.70
Pennsylvania	3,3	1.025(3.44)	0.335(3.49)	0.200(0.26)	0.76
Rhode Island	3,3	0.953(6.54)	-0.161(-3.31)	-4.852(-8.91)	0.81
South Carolina	3,3	0.746(7.13)	0.393(2.11)	0.593(2.96)	0.89
South Dakota	3,3	0.426(3.63)	0.612(6.86)	1.008(1.26)	0.76
Tennessee	3,3	1.064(10.42)	0.388(5.26)	1.449(3.05)	0.92
Texas	3,3	0.408(1.86)	0.047(0.74)	0.503(1.57)	0.43
Utah	3,3	1.219(4.36)	0.052(1.27)	-0.513(-1.19)	0.71
Vermont	3,3	1.948(6.59)	-0.336(-2.50)	-2.547(-5.97)	0.78
Virginia	3,3	0.837(5.95)	-0.003(-0.03)	0.537(1.60)	0.73
Washington	3,3	1.161(7.13)	0.184(2.66)	-0.882(-2.90)	0.82
West Virginia	3,3	-1.413(-5.88)	0.469(5.69)	1.879(4.38)	0.41
Wisconsin	3,3	0.627(2.99)	-0.706(-2.32)	3.852(2.96)	0.58
Wyoming	3,3	-1.764(-5.00)	1.042(8.31)	0.529(2.22)	0.70
Seasonal Dummies			no		
B-P test independence of residuals			chi2(1275) = 23897.822 p-value=0.000		

Table 3.18: Unrestricted DSUR Estimates controlling for Aging Population

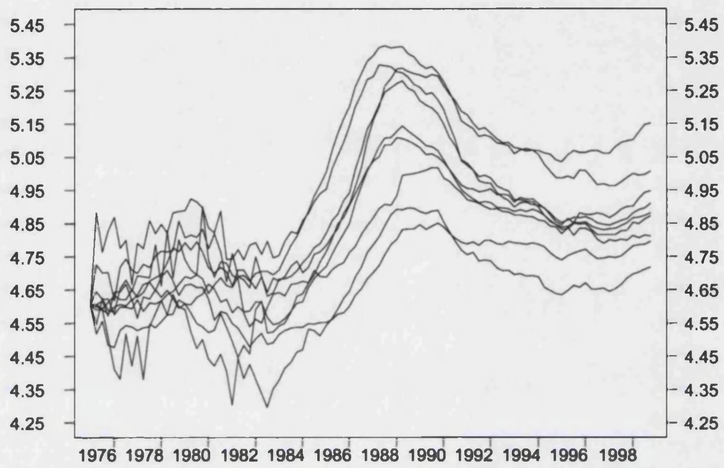

Figure 3.4: Log of State Real Housing Prices in the Northeast Region

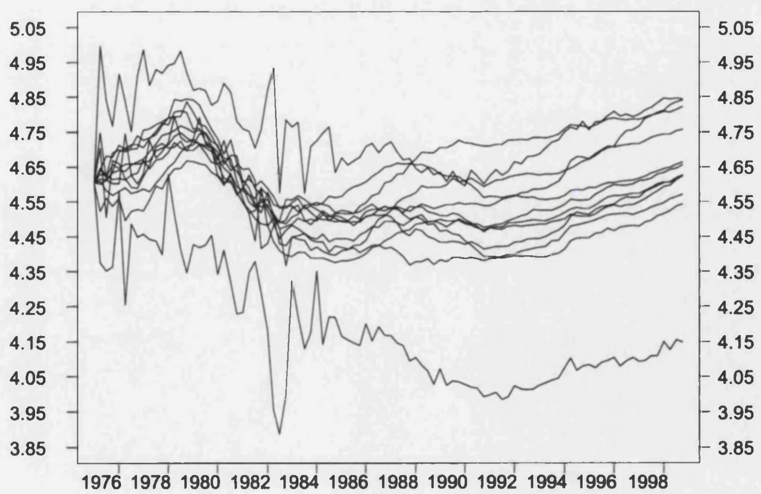

Figure 3.5: Log of State Real Housing Prices in the Midwest Region

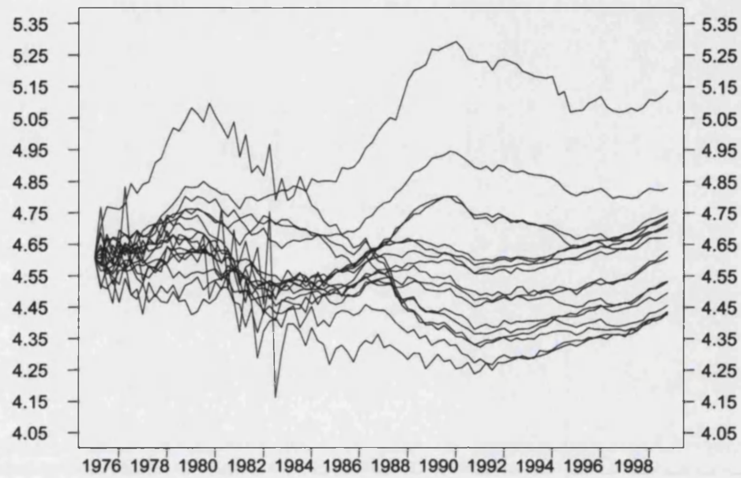

Figure 3.6: Log of State Real Housing Prices in the South Region

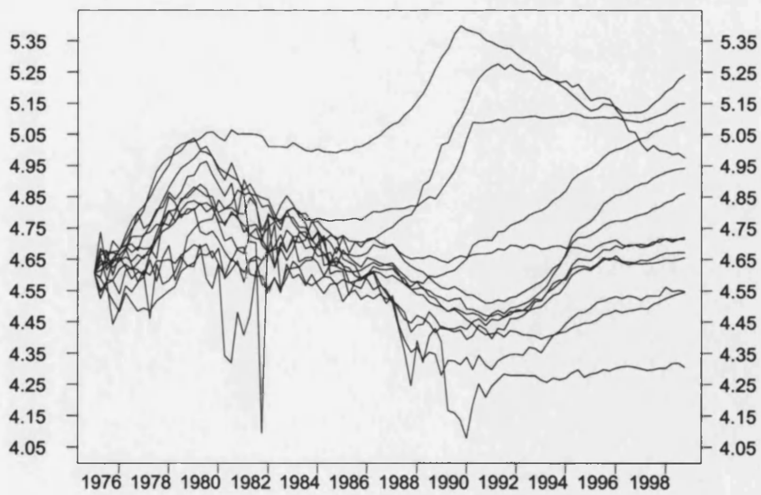

Figure 3.7: Log of State Real Housing Prices in the West Region

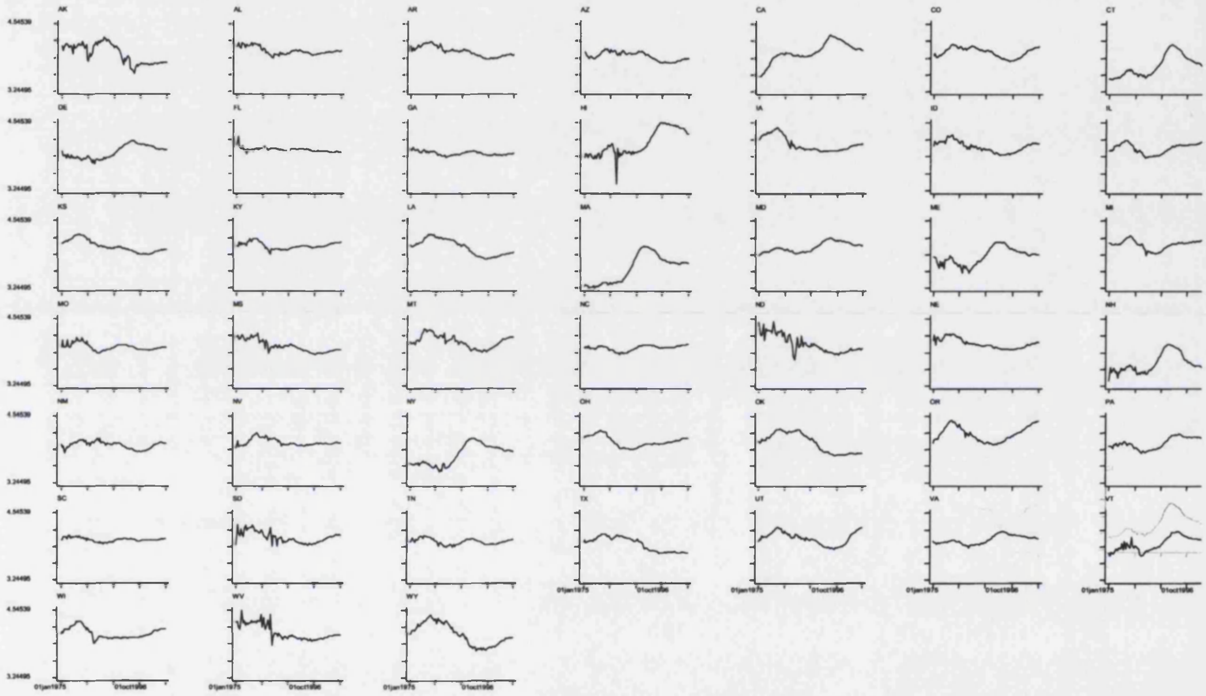

Figure 3.8: Log of Real Housing Prices in all States

Extensions

From the evidence of Chapter 1 and 2, three extensions of this thesis would be of interest:

1. Further microeconometric work on endogenous switching models could be undertaken. In particular, a natural extension would be to use the same framework of chapter 1 (Multiperiod Mutinomial Probit (MPMNP) models with Autocorrelated Errors and Unobserved Heterogeneity) to estimate the discrete part of the endogenous switching model and calculate suitable Mills ratios for the continuous part of the model of Chapter 2. To the best of my knowledge, the Mills ratios for the MPMNP model have not been figured out. Since they do not have a closed form solution, the way to proceed in this case would be to use computer simulation techniques to evaluate these formulae. This is the objective of a companion paper, joint with Vassilis Hajivassiliou, which is currently in process.

2. Given the results in Chapter 2, where some differences emerged between the results using the asset-based and credit card splits to measure liquidity constrained households, it might be a good idea to use the Multiple Indicators and Multiple Causes (MIMIC) model of Jöreskog and Goldberger (1975) in order to obtain a unique indicator for liquidity constraints.

3. One missing element in this thesis is an explicit test for the importance of

taxation in asset portfolio decisions. I had to abstract taxes from the model because the SHIW does not have such information. If this information should become available for a number of waves of the dataset, it would be a very valuable input for advancing the proposed asset participation model.

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