The London School of Economics and Political Science

# Essays on Economics of Aging

**Nilesh Shishupalji Raut**

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## Declaration of Authorship

I hereby certify that the thesis I am submitting to the PhD academy for examination for the PhD degree from the London School of Economics and Political Science is solely my own work other than where I have clearly specified that it is the work of others (in which case the extent to which any work carried out by me in collaboration with any other person is clearly identified in it).



I declare that this thesis consists of 58,264 words.

**Statement of co-authored work**

I confirm that I was the leading author of all the chapters of my thesis. Chapter 1 was co-authored with Prof. Joan Costa-Font (LSE) and Prof. Courtney van-Houtven (Duke University). We jointly conceived the research idea, while I produced all the estimates and wrote majority of sections of the chapter. Overall, I contributed 75% of the work. The Chapter 2 was co-authored with Prof. Joan Costa-Font and Dr. Chiara Orsini (LSE & University of Sheffield), who provided guidance on the structure of the chapter. I produced all the estimates and wrote considerable portion of this chapter. So, I contributed 70% of this work. Next, the Chapter 3 was co-authored with Prof. Joan Costa-Font, who helped me extend my conceived idea for this chapter. I investigated all the data sources, prepared the data for the analysis, carried out all the estimates, and wrote all the sections of the chapter. Overall, I contributed 70% of the work for Chapter 3. Lastly, the Chapter 4 was co-authored with Prof. Joan Costa-Font and Prof. Richard Frank (Harvard University and Brookings Institution, USA), who conceived the original idea that I extended further and carried out all the estimates for this chapter and wrote the relevant sections of this chapter. Overall, I contributed 65% of the work for this last chapter.

**Abstract**

Ageing and inequality – these are two major challenges the world has been facing for ages. Inequality is a condition of not being equal on various grounds, whereas ageing is inevitable process that affects individual's ability to participate fully in society and in economy, affecting the need of support to undertake activities of daily living (ADLs) or instrumental activities of daily living (IADLs). The process of ageing involves multiple factors such as the decline of physical and mental health and rise of demand for access to health and care services. The focus of my PhD dissertation is on the demand and supply of caregiving, and how best to finance such demand. The initial two chapters of my dissertation deal with informal caregiving supply available for elderly individuals and with caregivers' outcomes. The first chapter investigates the effect of the Affordable Care Act's Medicaid expansion on the mental wellbeing of spousal caregivers. The results indicate that availability of health insurance to adult spousal caregivers can significantly reduce the mental burden associated with informal caregiving. The findings from this chapter offer some answers to the demand of sustainable arrangements for informal caregiving. The second chapter of the dissertation examines the intergenerational transmission of caregiving duties and finds strong evidence suggesting the presence of intergenerational transmission of caregiving. The subsequent chapters of this dissertation study care-financing arrangements. The third chapter investigates the impact of Deficit Reduction Act's (2005) long-term care insurance partnership (LTCIP) on the uptake of public (Medicaid) and private-LTCI. The findings reveal that the rollout of LTCIP increased the uptake of LTCI coverage. LTCIP program has a direct impact on means testing component of the implicit tax on private-LTCI. The fourth chapter identifies the impact of housing and financial wealth on public and private insurance. It documents that the individuals view their housing assets as a form of self-insurance to be used in financing their future long-term care costs.

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This thesis is dedicated to the memories of my late grandmothers and my great friend, Dinesh.

**Contents**

## List of Abbreviations

| | |
|---|---|
| AARP | American Association of Retired Persons |
| ACA | Affordable Care Act |
| ACA-Medicaid | Affordable Care Act’s Medicaid Expansion |
| ADL | Activities of daily living |
| AHEAD | Asset and Health Dynamics among the Oldest Old |
| ATE | Average Treatment Effect |
| BBA | Balanced Budget Act |
| CESD Scale | The Centre for Epidemiologic Studies Depression Scale |
| CODA | The Children of the Depression Age |
| CWS | Constructed Stock-Market Wealth Shocks |
| DiD | Difference-in-Differences |
| DRA | Deficit Reduction Act |
| FHFA | The Federal Housing Finance Agency |
| FPL | Federal Poverty Level |
| HI | Health Insurance |
| HPI | House Price Indices |
| HRS | Health and Retirement Study/Survey |
| IADL | Instrumental Activities of Daily Living |
| IPS | Interim Payment System |
| IV | Instrumental Variable |
| KFF | Kaiser Family Foundation |
| LATE | Local Average Treatment Effect |
| LTC | Long-term Care |
| LTCI | Long-term Care Insurance |
| LTCIP | Long-term Care Insurance Partnerships |
| LTSS | Long-term Care Services and Supports |
| MPC | Marginal Propensity to Consume |
| MSA | Metropolitan Statistical Area |

| | |
|---|---|
| New-PS | New Partnership States |
| NIH | National Institute of Aging |
| OLS | Ordinary Least Squares |
| OOP | Out-of-Pocket |
| PCAFC | Program of Comprehensive Assistance for Family Caregivers |
| PP | Permanent partnership States |
| PPS | Prospective Payment System |
| PS | Partnership States |
| Q1 | First Quarter of the Year |
| RAND | Research and Development Corporation (USA) |
| RWJF | Robert Wood Johnson Foundation |
| SP500 | Standard and Poor's 500 |
| TWFE | Two-way Fixed Effects |
| TWM | Two-way Mundlak |
| US | The United States of America |
| WB | War Baby |

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# 1. Introduction

The population of the industrialised world is ageing quickly; in OECD countries, the proportion of older people is predicted to rise from 14% in 2010 to over 25% in 2050. (Colombo et al., 2011). The anticipated rise will have a greater impact on the availability and preferences for the traditional form of care for elderly individuals, namely informal care, as well as the supply and the demand for care. Aging impacts on morbidity (Breyer et al., 2010), the need for health and care services (Costa-Font and Vilaplana, 2020), and wealth effects of increased longevity on a larger scale (Wittenberg et al., 2006). In fact, longevity improvements are significantly shifting from young and working years to elderly ages (65+), according to Eggleston and Fuchs (2012). The financing of longevity and the long-term health and social policy dilemma of paying for caregiving in later life can both be seriously impacted by the recent shift in lifespan gains. The organisation of long-term care and health services, as well as retirement decisions, can be strongly impacted by the unequal sharing of longevity gains (Eggleston and Mukherjee, 2019).

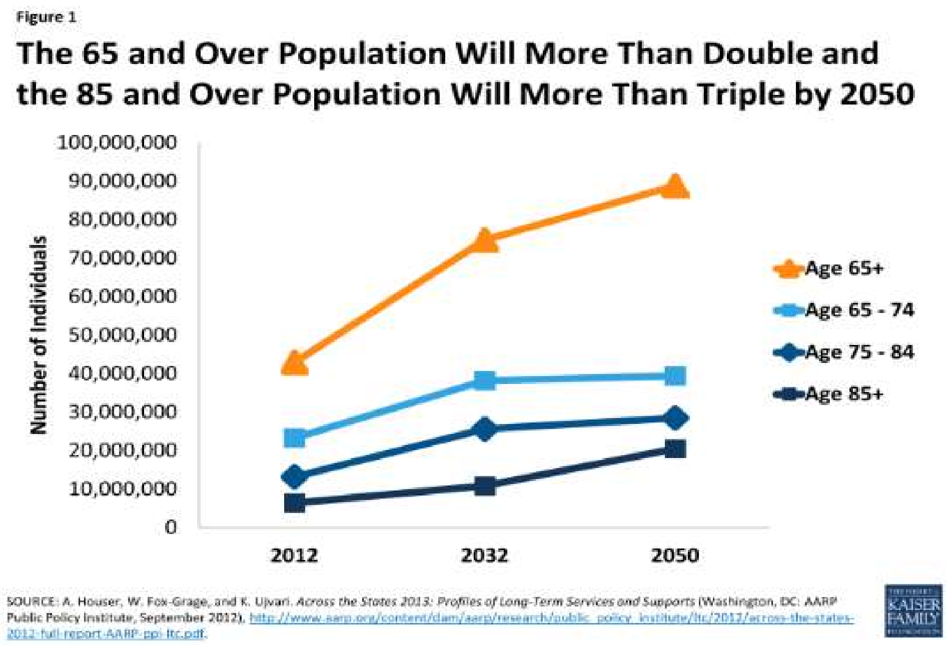



**Figure-(I): Elderly population estimates for USA (**Source:-Kaiser Family Foundation, USA**)**

The decline in physical and mental health, as well as the increase in demand for and access to health and care services, are all impacted by ageing (Costa-Font and Vilaplana, 2020). This is because chronic health conditions are more common as people get older (Steptoe et al., 2015), along with a number of other potential effects, such as the fact that older people value healthcare more than younger people (McGrail et al., 2000; Murphy and Topel, 2005; Bloom et al., 2015). The marginal value of healthcare consumption is biggest at older ages because older people require more health and medical care, according to additional data that supports these claims (Blanchflower and Oswald, 2008). This finding lends credence to the idea that healthcare use fluctuates over the course of a person's life and is higher as they get older. Most nations' healthcare systems are not built to withstand the significant changes in care needs brought on by an ageing population in the future. However, most nations are seeing a decline in the number of informal carers (Norton, 2016). The latter feeds the UK's so-called "social care crisis," or more broadly, the long-term care dilemma (Costa-Font et al, 2015).

The National Institutes of Ageing defines long-term care as "a variety of services (and supports) designed to meet a person's health or personal care needs during a short or long period of time (National Institute of Aging, 2017). When a person is unable to complete everyday tasks on their own, these services (and supports) enable them to live as freely and safely as possible (National Institute of Aging, 2017; Van Houtven et al., 2019). This phenomenon is attributed to population ageing (Alders and Schut, 2019; Colombo et al., 2011; Konetza, 2014; Rechel et al., 2013).

The increasing need of LTC services leads to a shift in the demand for care (Alders and Schut, 2019; Colombo et al., 2011; Rechel et al., 2013). This shift has impact on the two types of caregiving, formal caregiving, and informal caregiving. Informal caregiver is defined as "anyone, including children and adults who look after a family member, partner or friend who needs help because of their illness, frailty, disability" (Medical Directorate and Nursing

Directorate, 2014; Van Houtven et al., 2019). Informal care constitutes a major portion of long-term care provided (Kim and Lim, 2015). In contrast, formal care is typically paid care provided by professionals, either in the community (e.g. day-care, home help) or in a residential setting (e.g. nursing home or an assisted living facility).

Across the world, the number of informal caregivers is declining mostly due to the reduced family size, the reduced availability of caregiver at closer distance due to the migration of labour into cities (Grabowski, 2014; Narayana, 2010), as well as the increasing number of nuclear families, and rising participation of women in the labour force (Carmichael and Charles, 2003; Grabowski, 2014; Wimo et al., 2018). Both publicly and privately organized, several OECD countries are trying to tackle this shortage of informal caregivers by incentivising different types of public and private long term care schemes. In some countries, such as the United States private long-term care insurance (LTCI) has been developed for more than four decades, which covers the costs of LTC services availed by the insurance holder in the event of needing care. The introduction of LTCI in these countries has changed the way caregiving is financed and can potentially alter the economic activity in later life. One of the aims of this thesis is to study the effect of LTCI purchase on the uptake of public insurance, household finance and caregivers' wellbeing in the context of the USA – the country which gave birth to the idea of LTCI and was the first to implement it.

A growing body of research on the incentives and barriers to caregiving looks at how changes in the burden of caregiving affect a variety of outcomes, such as the physical and mental health, income, employment prospects, quality of life, and wellbeing of caregivers (Ajay et al., 2017; Alam et al., 2012; Brinda et al., 2014; Carmichael et al., 2010; Carmichael and Charles, 2003; Korfhage, 2017; Kumagai, 2017; Nizalova, 2012; Roth et al., 2015; Schulz et al., 2016; van den Berg et al., 2014). But our understanding of how to enhance caregivers' wellbeing is still limited. One of these methods is to offer financial support for caregivers

(Carmichael et al., 2010; Kim and Lim, 2015; Costa-Font et al, 2022), alternatively one can subsidise the access to health insurance (Finkelstein et al., 2012; Chirwa et al., 2020; Hampton and Lenhart, 2022), which can in turn impact the mental wellbeing of low-income caregivers. This thesis makes a contribution to this effort by looking at the evidence of the ACA Medicaid expansion in one of its chapters.

Another explanation for the expansion in the supply of care is the role of social incentives, and specifically the influence of changes in social norms that can be role modelled. Indeed, beliefs, and preferences are formed through role modelling and transmitting over generations, we do not know whether a caregiving activity that is heavily influenced by social norms can be transmitted from one generation to another and how informal and formal care are related to each other as a complement and a substitute (Grusec and Hastings, 2007; Bolin et al., 2008; Bonsang, 2009; Costa-Font et al., 2016; Norton, 2016; Van Houtven and Norton, 2004). This thesis also aids in that effort.

Next, although growing rapidly, the existing literature pertaining to financing caregiving at old age is in the early stage of development. The biggest predictor of demand for informal long-term care is lack of insurance or social insurance provisions in place. The remaining part of this thesis studies the financing of care in the US. Most of the studies have looked into financial risk protection against the need for caregiving through public insurance or Medicaid in the USA (Brown and Finkelstein, 2008; De Nardi et al., 2011; Frank, 2012; Goda, 2011; Reaves and Musumeci, 2015; Van Houtven and Norton, 2004), private LTCI (Barr, 2010; Brown and Finkelstein, 2009; Coe et al., 2015; Cohen et al., 2011; Cutler, 1996; Finkelstein et al., 2005; Finkelstein and McGarry, 2006; Johnson and Park, 2011; Norton and Sloan, 1997), and precautionary savings (De Nardi et al., 2010; Frank, 2012; Hubbard et al., 1994; Munnell et al., 2009; Palumbo, 1999; Scholz et al., 2004). In addition, Costa-Font and Vilaplana-Prieto (2017) and Ohinata and Picchio (2019) examine the relationship between public financing of caregiving and savings behaviour and find the reduction in savings post reform. Brown and Finkelstein (2008, 2011) investigate various reasons for public long-term care insurance such as Medicaid crowding out private-LTCI in the US. The problem of public insurance crowding out private-LTCI paves a way for introduction of state-tax subsidy and long-term care partnerships to stimulate the uptake of private-LTCI in the US. Goda (2011) studies the effect of LTCI state tax subsidies on Medicaid expenditure and LTCI coverage and finds that each dollar spent on State-tax subsidy reduces Medicaid expenditure by $0.84, while Coe et al. (2015) measured the spill-over effect of LTCI in reducing the likelihood of informal caregiving.

The slow growing of private-LTCI in the US is a major concern for old age Americans which also put fiscal burden on the role of the government expenditure via Medicaid when families find themselves with unmet needs they cannot finance. Thus, a lack of private-LTCI not only increases out of pocket expenses but also can increase Medicaid expenditure (Goda 2011). This poses three major social policy challenges: i) How to control the rise in Medicaid expenditure. ii) How to stimulate the demand of private-LTCI. iii) How to maintain the financial sustainability of public insurance via Medicaid. Various initiatives have been introduced so far to address the above challenges. One of the major initiatives adopted to stimulate the purchase of private-LTCI includes the Long-term Care Partnership (LTCIP) program (Meiners and Goss 1994). The LTCIP program is intended to reduce the Medicaid expenditure by incentivising the purchase of private-LTCI by offering the retention of assets equivalent to insurance coverage and at the same time getting qualified for Medicaid after meeting other eligibility requirements (Brown and Finkelstein 2008;2009; Norton 2000; Norton and Sloan 1997; Lin and Prince 2013; Rothstein, 2007; Bergquist et al., 2018). The third chapter of this thesis examines the effect of introduction of LTCIP program on the uptake of both private-LTCI and Medicaid. The staggered rollout of LTCIP in some states whilst remaining states not participating in the program creates a quasi-experiment, which can be exploited to identify the impact of LTCIP on private and public insurance.

One of the greater challenges in the aging societies is how to fund long-term care services and supports (LTSS), because almost 50% of elderly above 65 years of age need some form of LTSS (Favreault and Dey, 2015). For individuals who are not eligible for Medicaid and without private-LTCI, the only other funding option remains is self-funding by utilizing existing assets, more specifically housing and financial assets. Also, the major source of funding for LTSS at old age comes from housing and financial wealth. Finally, the fourth chapter of this thesis investigates the self-insuring care effects occurs through the interaction of wealth shocks and long-term care insurance in the US. The exogenous variations in housing and financial wealth come from house price indices and S&P 500 stock prices indices, respectively.

## 2. The Structure of the Thesis

The first part of this thesis attempts to bridge an existing gap in the caregiving literature by studying: i) whether an access to health insurance via Affordable Care Act's (ACA) Medicaid expansion can exert wellbeing effects on spousal caregivers. ii) the extent to which family level caregiving duties transmit role modelling effects from one generation to the next generation of informal caregivers by exploiting the exogenous variation in caregiving provisions brought about by Medicare Home Health Care Reform that reduced the public provision of home care services available for elderly individuals.

The second part of the thesis touches upon various aspects of care financing in the US and attempts to contribute to the growing literature of care financing by investigating: i) whether the introduction of LTCIP program stimulated the purchase of private-LTCI and in-turn reduced the uptake of Medicaid or public insurance. ii) the presence of self-insuring care effects, when housing as well as financial wealth of household increases, by exploiting the exogenous variation in housing and financial wealth occur due to house price indices and S&P500 stock market indices.

# 3. Chapter I: Medicaid Expansion and the Mental Health of Spousal Caregivers.

## 3.1.Abstract

Health insurance expansions can exert wellbeing effects on individuals who provide informal care to their loved ones, reducing their experience of depression. This study exploits evidence from the Affordable Care Act's (ACA) Medicaid expansion to *examine the effects on the mental wellbeing of informal caregivers*. Drawing on a Difference-in-Differences (DID) design we investigate the policy impact of ACA Medicaid expansion using longitudinal evidence (from the Health and Retirement Study, HRS) for low-income individuals aged 64 or below. We find that *ACA's Medicaid expansion reduced depressive symptoms among spousal caregivers*, and specifically we estimate that exposure to ACA Medicaid expansion gives rise to 8.2% points (on average, equivalent to 30% decrease) reduction in the feeling of depression and 8.7% points increase in the feeling of happiness (on average, 11% increase). We also find that *ACA Medicaid* causes a spill over effect at the household level, improving the well-being of the spouse care recipient. Our results are robust to various specifications, and we identify several potential driving mechanisms for the findings: reductions in out of -pocket expenses and labor supply and, as expected, increased Medicaid uptake. The evidence from falsification tests confirms that the estimated effects are likely due to ACA's Medicaid expansion.

### 3.2. Introduction

From January of 2014, several states expanded Medicaid eligibility criterion of qualifying for Medicaid, as a part of Affordable Care Act (ACA), to all adults under the age of 65 earning up to 138% of Federal Poverty Level (FPL). The ACA Medicaid significantly increased the number of individuals enrolled in Medicaid and reduced the number of those without insurance, affecting the health, access to care, and health and care utilization for those gained access to health coverage (Courtmanche et al., 2017; Kaestner et al., 2017, Miller and Wherry, 2017; Simon et al., 2017; Miller et al., 2020). In addition, Van Houtven et al. (2020) studies how ACA Medicaid was associated with the use of long-term care in the US. However, no study has explored the impact of ACA Medicaid on the mental health and wellbeing of spousal caregivers, despite the fact that spousal caregiving forms the major portion of informal care provided in the US.

Medicaid expansion may affect informal family caregivers who are the backbone of the long term supports and services infrastructure. 19% of Americans are providing unpaid care to an adult with health or functional needs and 61% of family caregivers are employed (AARP, 2020). Family caregivers provide substantial cost savings to Medicare and Medicaid, and very limited research has examined the effect of insurance expansions on spousal caregiver's wellbeing. Only one papers has examined an effect, but it relies on a proxy measures of caregivers' mental health and focuses on quality-of-life measures (Torres et al, 2020) rather than depressive symptoms.

In most western countries, care needs of old age individuals with disability are sustained by the duties performed by family caregivers. The informal supply of care by family caregivers reduces the potential of individuals going with unmet needs or being supported by government (Adelman et al, 2014). However, the reliance on an informal system of long-term care comes at the cost of significant wellbeing sacrifices by caregivers, more specifically spousal caregivers. Caregiving spouses exhibit a unique emotional and financial connection to disabled individuals, and for them providing care might results from a strong intergenerational social norm, and hence might not feel optional. The latter calls for potential government policies to protect such caregivers to continue with their caregiving duties. Informal caregiving is only sustainable if caregivers are supported, as caregiving limits the independence of caregivers, as well as their ability to maintain dual roles as caregivers and workers. Reductions in caregivers labor supply (Van Houtven et al 2013; Chairi et al 2015) such as temporary or permanent labor market exit (including early retirement) are common adjustments to cope with caregiving duties. Work reductions also can take place gradually through reducing hours or foregoing promotions, which also reduces caregiver income and financial wellbeing.

The wellbeing of caregivers can improve in countries where individuals with limited income generating sources are entitled to health insurance, as the United States (US). In the U.S., aside from low-income individuals who can qualify for public insurance throughout their working years (Medicaid), historically health insurance benefits have come from employment until citizens qualify for public governmental insurance (Medicare) at age 65. Given that health insurance typically is connected to employment decisions, limited employment opportunities can increase the prospect of not having any form of health insurance, thereby increasing exposure to the health and financial risks of ill health (including mental health). Limited health insurance can exert important detrimental consequences to caregiver wellbeing more generally, as it impacts the ability to engage in preventative activities (e.g., flu shots, preventive care, and screenings) and increases the stress associated with their daily duties. If uninsured caregivers delay or forgo needed health care, it may give rise to depressive episodes[1]. Thus, understanding

[1] Specifically, given that caregivers experience burden, stress and strain at higher rates compared to non-caregivers, lack of health insurance could prevent treatment of consequent mental health conditions such as anxiety and depression.

the experiences and mental health wellbeing of low-income caregiver spouses is critical, as there are not ready direct programs and tools to ameliorate consequent negative economic and health consequences of caregiving in the United States.

Health insurance reform in the United States, and more specifically associated Medicaid expansions in 2010 (hereafter called ACA-Medicaid) allows for testing the effect of Medicaid on caregiver's wellbeing. Medicaid is the historical public insurance program that serves low-income residents and ACA-Medicaid expansion occurred through increasing the income limits for eligibility, generally to 138% of the federal poverty level in states that expanded. In this way the Affordable Care Act (ACA) expanded health coverage for residents, yet the Supreme Court decision of 2012 made such expansion optional, allowing states to decide whether to continue with the Medicaid expansion. Hence, it is possible to exploit state variation in ACA-Medicaid expansion on the wellbeing of spousal caregivers.

This paper draws on longitudinal data from the Health and Retirement Survey (HRS) including state geographic identifiers to examine the effect of exposure to Medicaid expansion on caregiver's wellbeing, and especially the presence of depressive symptoms. We document evidence that suggests that Medicaid expansion reduces depressive symptoms, increases happiness, and that this effect primarily is the case among low wealth individuals who are most likely to gain insurance through the expansion.

The rest of the paper is organized as follows. The next section reports the related literature that overall summarizes the effects expanding caregiver's health insurance and other benefits on proxies for caregiver's wellbeing. Section three describes the data employed and the empirical strategy followed in this paper. Section four reports the results, fifth section extends the paper, and a final section concludes.

### 3.3. Related Literature

This paper contributes to two literatures debate, namely the wellbeing effects for caregiving and the effects of Medicaid expansion.

***3.3.1. Caregivers' mental health***. Coe and Van Houtven (2009) estimate that providing care for a sick mother increases the number of depressive symptoms reported by 47% (compared to caregivers whose mother died). Other studies suggest an association with an increased use of antidepressants, tranquilizers, painkillers, and gastrointestinal agents (Schmitz and Stroka, 2013). One paper that examined correlations found that the caregiver's number of prescription drugs increases (including SSRIs) among intensive caregivers compared to less intensive caregivers of persons with dementia (Van Houtven, et al, 2005). Thus, there may be differential effects on mental health based on intensity of caregiving provided. Smith et al. (2019) provide preliminary evidence that the PCAFC program reduced the perception of financial burden and controlled the depressive symptoms among treatment group participants. Finally, caregiver supports could spill over to care recipient wellbeing. Van Houtven et al. (2019) find that family caregiver enrolment in the Program of Comprehensive Assistance for Family Caregivers (PCAFC), a program for Veteran soldiers' families, increased Veteran use of mental health care.

Another way to improve the wellbeing of caregiver is by making sure that health care needs are met by providing health insurance to caregivers. Given that Medicaid expansion expanded health insurance among eligible individuals after the ACA, one could expect an effect on wellbeing. However, health insurance might be only one of the numerous barriers to caregiver access to health care, as caregivers are known to have trouble accessing care for themselves or delaying their own care compared to non-caregivers (Slaboda et al, 2021).

Hence, it is an empirical question whether insurance expansion did manage to improve wellbeing.

***3.3.2. Medicaid expansion***. Evidence so far has documented that Medicaid expansion reduces preventable hospitalizations (Wen et al., 2019), increases some indicators of quality care and outcomes (Sommers et al., 2017), lowers hospital readmission rates and improves financial wellbeing (Courtemanche et al., 2017; Han et al., 2015; Miller et al., 2020) including a reduction in eviction rates (Allen et al., 2019). Positive effects may result from several mechanisms such higher disposable income (e.g., by reducing out of pocket expenses), better access to health care (to address acute and chronic conditions that destabilize one's life in other domains such as work) and lower costs in the event of needing care (averting catastrophic costs). Similarly, Medicaid expansion improved the access to formal paid long-term care (Van Houtven et al, 2020). However, the effects of ACA-Medicaid expansion are specifically important among a population that otherwise has limited access to insurance because they perform caregiving duties – low-income caregiving spouses. Understanding the effects of ACA-Medicaid expansion on caregiver mental health among those most likely to gain insurance through the policy change, is the objective of this paper.

### 3.4. Data and Sample Selection

The ACA Medicaid expansion became a clean natural experiment after the Supreme court's ruling allowed states a freedom to decide whether or not to expand Medicaid. The most suitable dataset to explore our research question is the Health and Retirement Study (HRS), which includes extensive information on health, long-term care, and socio-demographic indicators[2].

[2] Although numerous annual health surveys provide several years of pre- and post- ACA data to carryout parallel trend test. (e.g, the National Health Interview Survey, the Behavioral Risk Factor Surveillance System,

We use HRS data for our analysis as it is the most appropriate data, compared to other available datasets including Panel Study of Income Dynamics (PSID) data, for answering the research question we ask. This is because of following reasons. The HRS contains longitudinal information on supply and demand of long-term care services and support, including both formal and informal care, provided to elderly individuals. It is a dataset with a relatively large sample size on the population we think is the most affected by the ACA Medicaid. In addition, as opposed to PSID data, the HRS has a user-friendly version available which is provided by researchers from RAND corporation, which systematically imputes some key variables for which some information is missing. This study draws on data from the HRS data from 2010 to 2018 to capture the effect of ACA Medicaid Expansion and avoid the data reflecting the effect of the Great Recession. The HRS is a nationally representative publicly available longitudinal data for people aged 50 years or older. It is a biennial survey that interviews respondents who were born in 1931-1941, 1942-1947 (War baby sample), and 1924-1930 (the children of the depression age-CODA) sample (National Institute on Aging and The Social Security Administration 2018). It collects the comprehensive information about the important aspects of elderly life. Given that our analysis is focused on Medicaid expansion for individuals up to the age 65, we restrict our sample to individuals aged 64 and below.

The HRS sampling is based on a multi-stage area probability design that includes geographical clustering, oversampling of specific demographic groups, and area stratification (Sonnega et al., 2014). Each sampled housing unit is subjected to a quick household screening interview to ascertain eligibility. The age and couple status of each adult living in the home (age 18+) are provided. A primary respondent is chosen at random from among all household members who are of legal age, and if they are married or cohabitating, their spouse or partner

and the American Community Survey), they do not contain information on caregivers and, hence are not suitable for our study.

is likewise drawn from the sample, regardless of age. Attempts to screen households have been made in 1992, 2004, and 2010. Subject to extra efforts taken by HRS staff for minimizing attrition rate, the HRS has quite high response rate. The response rate for core interviews ranges from 47.1% to 81.3%, whereas re-interview response rates range from 68.8% to 92.3% (Health and Retirement Study, 2017; Fisher and Ryan 2019).

In addition, to account for varied selection probability and differential non-response in each wave, sample weights are generated. Since the sample is not self-weighting by design, proper weighting is crucial for drawing conclusions about the population. Analysts should consider geographical clustering and stratification in the estimate of standard errors because the HRS has a complicated sample design (Sonnega et al., 2014). For the community-dwelling population, sampling weights are offered and post-stratified to the national totals (Current Population Survey through 2004; American Community Survey thereafter) (Sonnega et al., 2014).

*Sample Selection*. One of the limitations of the HRS is that it records full information on respondents and their spouses but not the other household members. The main reason of selecting only the sample of spousal caregivers is the un-availability of comprehensive information on the health and socio-demographic indicators of other caregivers, including children and friends, in the HRS. The sample of spousal caregivers, who provided care to their partners, is retrieved from “Functional Limitations and Helpers - Respondents” section of HRS Core file. These respondents are merged with the RAND HRS Longitudinal file to obtain the comprehensive information, including mental health, wellbeing, and health behaviours, for the selected respondents who cared for their partners. Further, we restrict our sample to low-income respondents only, using the income criterion followed by (Van Houtven et al., 2020). We restrict the income level such that the average income household should be the representative of households benefitting from the ACA Medicaid. The average income household comprised of 2 to 3 members in the family must have income below the eligibility threshold (FPL in 2014: $15,730 for 2 and $19,790 for 3 members households) to become eligible for ACA Medicaid. The representative household of our sample has an average income of $17,588, which falls in the range of FPL threshold of 2014. In addition, we have removed those respondents who are disabled and are already enrolled in the Medicare program, as they are not eligible for the ACA-Medicaid expansion. Finally, our data contains restricted geographical identifiers that include information about individuals' state of residence and combine our main sample with this restricted file. The geographical identification file maps an individual with her state of residence. The sample consists of at least one observation per caregiver, with overall 2489 observations for 1147 individuals.

The outcome variables are binary types indicating 1 if individual felt happy (depressed) but indicating 0 otherwise. These variables are part of the CESD[3] score scale, which is used to indicate individuals' mental health status. The CESD score of Mental Health is composed of eight different components that forms this score. The CESD stands for The Center for Epidemiologic Studies Depression (CESD) scale. The CESD score consists of both negative and positive components. The Negative Components of the CESD score include depression, everything is an effort, sleep is restless, felt alone, felt sad, and could not get going, whereas felt happy and enjoyed life fall under the positive category. The treatment variable ACA-Medicaid is defined as a binary variable equals 1 if states expanded Medicaid after January 2014 and equals 0 if state never participated in ACA Medicaid. In terms of selecting control variables, we follow the previous literature, such as Goda (2011). The included control

[3] The higher CESD score represents a worsening mental health. For our main analysis, we use one component (felt happy) from positive category and another (Depression) from negative category. The HRS RAND Longitudinal File states, "RwCESD is the sum of RwDEPRES, RwEFFORT, RwSLEEPR, (1-RwWHAPPY), RwFLONE, RwFSAD, RwGOING, and (1-RwENLIFE). Thus, the higher the score, the more negative the Respondent's feelings in the past week.
RwCESDM counts the number of missing values among the individual measures."

variables consist of health, education, age, ethnicity, retirement status, income, and children variables to be included in our main specification. Table A3.10. of the Appendix represents the detailed description of variables used in the analysis.

### 3.5. Empirical Strategy

Our empirical strategy relies on a generalized difference-in-differences (DID) estimation to identify the causal impact of ACA's Medicaid expansion on the mental wellbeing of spousal caregivers. The event study estimation strategy and its results are available in the appendix section.

***3.5.1. Difference-in-Differences***. To identify the impact of ACA Medicaid expansion on the mental wellbeing of spousal caregivers, we use a difference-in-differences (DiD) design, which is a quasi-experimental approach widely used for causal identification (Angrist and Krueger 1999; Athey and Imbens 2006; Bertrand, Duflo, and Mullainathan 2004; Ai and Norton 2003; Puhani 2012; Greene and Liu 2020; Lechner, Rodriguez-Planas, and Fernández Kranz 2016). The ACA's Medicaid expansion was brought in effect in the year 2014 when most states expanded their coverage in 2014 while a few of the remaining did so in 2016, making it a quasi-experiment with staggered rollout of treatment across time. The DiD approach is also extremely adaptable and includes a post-period control group for comparison, which the event study design does not. In the case of a staggered rollout and heterogeneous treatment effects over time periods, Wooldridge (2021) establishes the flexibility of the DiD technique, equivalency between the two-way fixed effects (TWFE) approach and the two-way Mundlak (TWM) regression approach.

We use the linear probability model (LPM/OLS) to obtain both event study and DID estimates. The advantage of LPM is that, unlike non-linear models such as logit and probit, the interpretation of interaction term coefficient is straightforward (Ai and Norton 2003; Athey and Imbens 2006; Puhani 2012). Because the treatment effect in non-linear difference-in-differences is the difference of two cross differences, which is a difference between the cross difference of conditional expectation of the observed outcome and of the potential outcome without treatment (Puhani 2012). However, unlike non-linear models, in linear models the cross-difference of the conditional expectation of the potential outcome without treatment is zero. Therefore, we prefer to use linear probability model for all our estimates. We divide the data into two groups, ACA Medicaid states and No-ACA Medicaid states, based on the Medicaid expansion reform took place in 2014 onward as a part of affordable care act. Our model for the generalized DiD is depicted in Equation 1.

$$\boldsymbol{Y_{ist} = \beta_0 + \rho X_{ist} + \sigma_s + \vartheta_t + \beta_1 * ACA\_ME + \beta_2 * Post + \beta_3 * ACA\_ME * Post + \theta_i + \epsilon_{ist}} \quad \textbf{(1)}$$

Where $Y_{ist}$ is any outcomes related to Mental health (Happiness and Depression) for individual (*i*) in state (*s)* at time (*t*). ACA_ME denotes the states that expanded Medicaid coverage as per the reform suggested under the Affordable Care Act, whereas Post refers to time-period when the reform began in 2014 onward. We are interested in the coefficient, $\beta 3$, as it estimates the causal impact of ACA's Medicaid expansion on the mental wellbeing of spousal caregivers living in states that expanded coverage post reform. The $\sigma_s$ is the state specific controls that eliminates time-invariant differences among various states, whereas $\vartheta_t$ accounts for variation in outcomes across time. The $X_{ist}$ incorporates the set of individual and household level controls into the model. Using a Fixed Effects Models, Equation 1 removes the person specific time-constant unobserved heterogeneity ($\boldsymbol{\theta_i}$) that can be a potential source of endogeneity.

## 3.6. Results

### *3.6.1. Descriptive Evidence*

The descriptive statistics is shown in Table 3.1 along with sample size. The mean CESD score of mental health is 2.48. The CESD score is a sum of eight components[4], which ranges from 0 to 8 and the lowest CESD score indicates the best mental health. Slightly more than three quarters of sample individuals felt happy, whereas 26% reported to feel depressed. The average individual has an annual family income of $17,588 and is 56 years old although the age range of the caregivers examines in the study range from 27 to 64. Approximately, 95% of individuals have at least one child. In addition, we show descriptive statistics for other individual level indicators such as health, retirement status, and other demographic variables.

The pre- and post-ACA Medicaid trends for Medicaid uptake, happiness, and depression are shown in the Figures 3.1 (a, b, & c). The trends for Medicaid uptake of individuals living in ACA Medicaid states compared to non-expansion states clearly indicate that ACA Medicaid increased the coverage among states who expanded Medicaid. The trend for happiness provides evidence of the existence of parallel trends before the adoption of ACA Medicaid. A table with the information on means and standard deviations for these variables (Happiness, Medicaid status, and CESD Score) is provided in the Appendix Section (Table A3.8).

**Table 3.1. Descriptive Statistics**

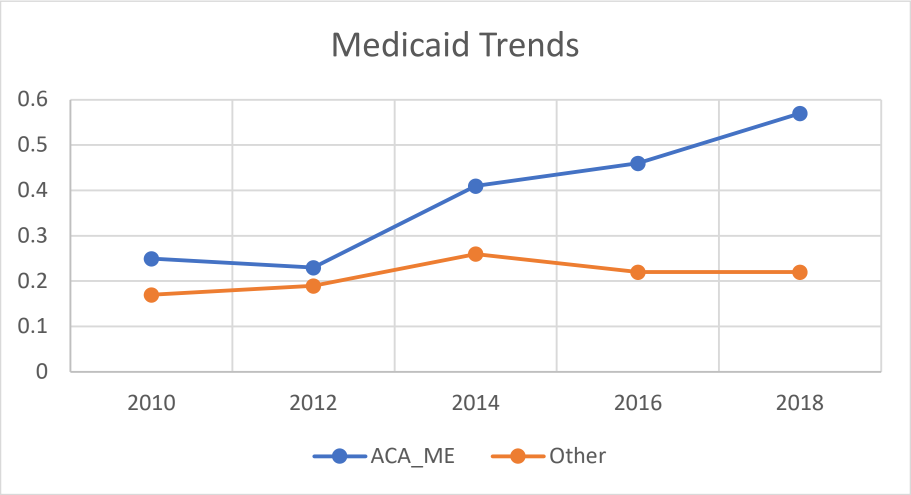
| | **Individual Level Characteristics of the Sample** | | | | |
|---|---|---|---|---|---|
| | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| ***CESD Score*** | 2,489 | 2.48 | 2.44 | 0 | 8 |
| ***Felt Happy*** | 2,484 | 0.77 | 0.423 | 0 | 1 |
| ***Felt Depressed*** | 2,487 | 0.26 | 0.44 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| ***ACA Medicaid*** | 2,489 | 0.29 | 0.45 | 0 | 1 |
| ***Age*** | 2,489 | 56.2 | 6.1 | 27 | 64 |
| ***Medicaid*** | 2,467 | 0.30 | 0.46 | 0 | 1 |
| ***Male*** | 2,489 | 0.42 | 0.49 | 0 | 1 |
| ***Family Income*** | 2,489 | 17588 | 9827 | 0 | 35200 |
| ***College/More*** | 2,489 | 0.28 | 0.45 | 0 | 1 |
| ***Have Children*** | 2,489 | 0.95 | 0.22 | 0 | 1 |
| ***White American*** | 2,489 | 0.512 | 0.5 | 0 | 1 |
| ***Retired*** | 2,489 | 0.49 | 0.5 | 0 | 1 |
| ***Fair/Poor Health*** | 2,489 | 0.51 | 0.5 | 0 | 1 |

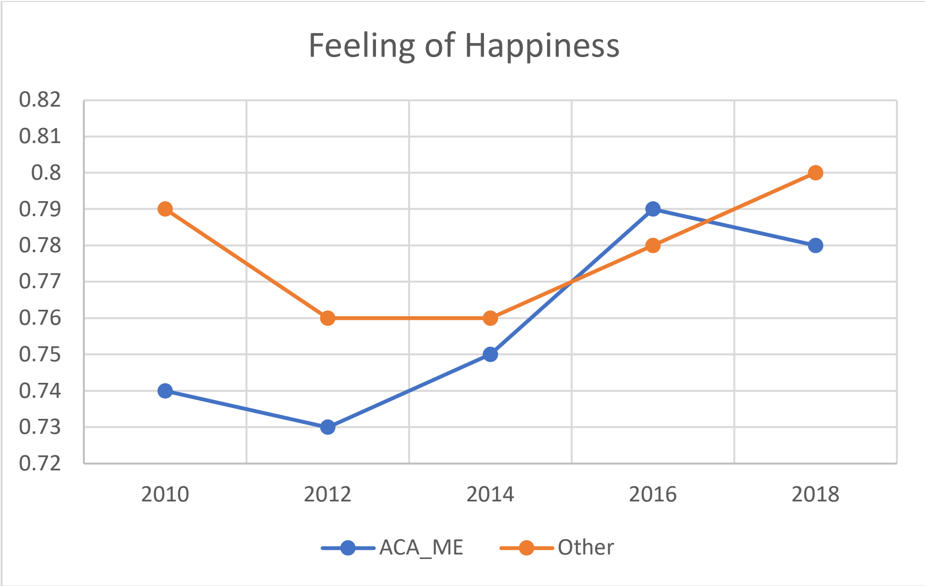
Note: this table provided the descriptive statistics of the main variables we employ in the analysis.

**Figure 3.1: Trends (2010-2018) for a) Medicaid uptake, b) Feeling of Happiness, and c) Feeling of Depression.**

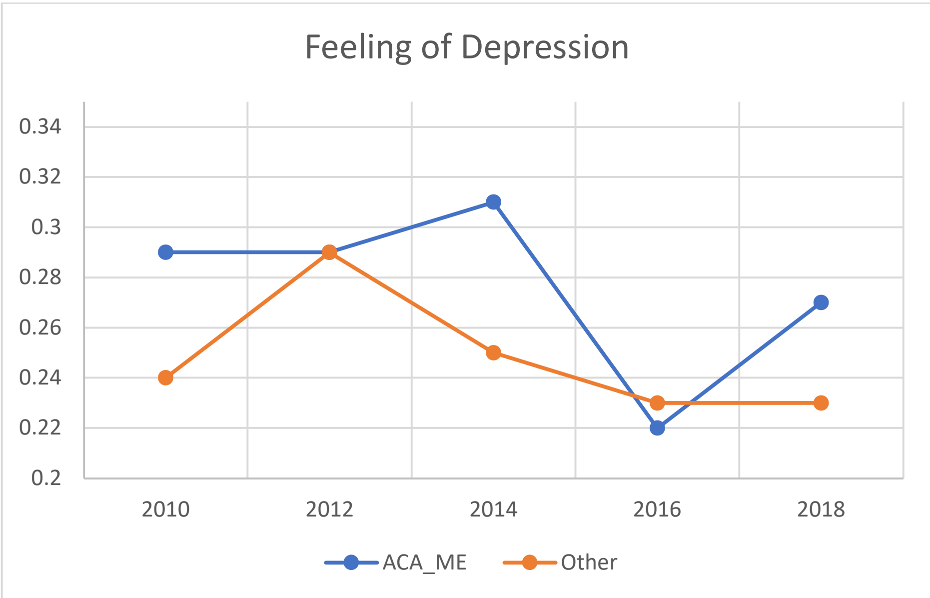
(a)




(b)




(c)




Note: The time trends of individuals exposed and not exposed to Medicaid expansion (2010-2018).

### *3.6.2. Baseline Estimates*

Next, Panel A and Panel B in Table 3.2 report the baseline results. Column 1 reports the baseline model without any controls, state, and year fixed effects, but incorporates the person level fixed effects into the model. All the models specified in Table 3.2 incorporate person level fixed effects into the model. Columns 2 & 3 indicate the estimates of the impact of Medicaid expansion on the feeling of happiness and of depression after the inclusion of year and state level fixed effects, respectively, into the models maintaining that ACA Medicaid expansion did improve the mental wellbeing of individuals living in Medicaid expansion states when compared with other states. Finally, we run the fully specified model and reports its results in Column 4 after the inclusion of set of controls into the model along with year and state fixed effects. We observe an approximately 9% points increase in the feeling of happiness among the states adopting Medicaid expansion, compared to the remaining states. Similarly, we estimate that the likelihood of feeling depressed decreases by more than 8% points after the ACA Medicaid reform. We find that these results are significant at 1% level and suggests that ACA Medicaid expansion is associated with improvement in mental wellbeing.

**Table 3.2. Baseline Linear Estimates of the effect of ACA-Medicaid on Mental Health**

| **PANEL A** | **Dependent Variable - Felt Happy** | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **ACA Medicaid** | 0.069*** | 0.076** | 0.09** | 0.087** |
| | (0.0245) | (0.034) | (0.036) | (0.036) |
| **Number of Observations** | 2,487 | 2,487 | 2,487 | 2,487 |
| | | | | |
| **PANEL B** | **Dependent Variable - Felt Depressed** | | | |
| | (1) | (2) | (3) | (4) |
| **ACA Medicaid** | -0.083*** | -0.077** | -0.085** | -0.082** |
| | (0.0254) | (0.035) | (0.038) | (0.0375) |
| **Number of Observations** | 2,487 | 2,487 | 2,487 | 2,487 |
| | | | | |
| **Year Fixed Effects** | NO | YES | YES | YES |
| **State Fixed Effects** | NO | NO | YES | YES |
| **Control Variables** | NO | NO | NO | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018), and Age<65. Each coefficient indicates OLS estimates of equation (2). The variable ACA_Medicaid is a treatment variable, which is a binary indicator for whether Medicaid expansion occurred in the state at a given year. We estimate the impact of ACA Med Exp on the feeling of happiness in Panel A and the feeling of depression in Panel B in which Column (1) includes no variables other than treatment or ACA Med Exp. Column (2) introduces years fixed effects into the model. Column (3) adds states fixed effects. Column (4) includes control variables namely age, gender, age^2, income, health status, retirement status, race, education, and children. All the models include individual fixed effects.

**Table 3.3. The effect of ACA Medicaid Expansion on Other CESD Components**

| **CESD Components** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | CESD Score | Can't Get Going | Felt Sad | Felt Alone | Enjoy Life | Sleep Restricted | Everything Effort |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **ACA_Medicaid** | -0.38** | -0.0325 | -0.0754** | -0.07** | 0.056* | 0.0123 | 0.00324 |
| | (0.176) | (0.0427) | (0.038) | (0.0346) | (0.0294) | (0.0441) | (0.039) |
| | | | | | | | |
| **State + Year Fixed Effects** | YES | YES | YES | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES | YES | YES | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES | YES | YES | YES |
| **No. of Observations** | 2,489 | 2,481 | 2,488 | 2,489 | 2,486 | 2,488 | 2,481 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018) and Age<65. Each coefficient indicates OLS estimates of equation (2). The variable ACA_Medicaid is a treatment variable, which is a binary indicator for whether ACA Medicaid expansion occurred in the state at a given year. We estimate the impact of ACA Medicaid on CESD score and each of remaining components of CESD score of Mental Wellbeing, from Column (1)-(7). All models include state, year, and person level fixed effects, along with control variables namely age, gender, age^2, income, health status, retirement status, race, education, and children.

The CESD score of Mental Health is composed of eight different components that forms this score. We regress these remaining components along with overall CESD score on treatment variable, controls, state, and year dummies in a Fixed effects model. Table 3.3 represents the results corresponds to these remaining components. We observe that not all the components of CESD score are significant or affected by ACA Medicaid. We find that ACA Medicaid reduced the feelings of sadness and loneliness, and consistently *increased the enjoyment of life*. Other components' estimates found to be not significantly associated with the ACA's Medicaid. These decomposed results help us identify which aspects of mental health are affected due to Medicaid expansion. Most importantly, we report that the reform brought happiness in the lives of caregivers, who otherwise did not have covered access to Medicaid services and reduced the feeling of depression.

### *3.6.3. Placebo Tests*

Next, we run a set of falsification tests to confirm that an improvement in mental wellbeing of caregivers is likely caused only by ACA reform and that it affected spousal caregivers as well as a specific age group of such caregivers, i.e., not all spousal caregivers. In a first instance, we separate an HRS sample for individuals up to age 64, who became eligible for ACA Medicaid but were different than spousal caregivers. There is mixed evidence that ACA reform affected the mental wellbeing of eligible low-income adults. However, most studies find no significant impact of ACA Medicaid on mental health of eligible individuals (Cowen and Hao 2020; Mclnerney et al. 2020), whereas others find that access to Medicaid can improve self-reported mental health (Finkelstein et al. 2008) and fewer days spent in poorer mental health (Griffin and Bor 2020). Panel A of Table 3.4 reports that ACA Medicaid had no impact on the feeling of happiness and depression for non-caregivers or individuals other than spousal caregivers. Secondly, we assume that Medicaid expansion reform began in 2010 instead of 2014 and check whether we find our falsification test to be true. Estimates from Panel B of Table 3.4 indicate that Medicaid reform began in 2010 had no significant impact on the mental health of spousal caregivers. This finding confirms that the effect on mental health of caregivers occurred only after 2014, when the passage of law allowed states to expand Medicaid coverage. At last, we carry out analysis using our fully specified model on individuals aged 65 and above and check whether our main results are valid. Panel C of Table 3.4 estimates that ACA's Medicaid expansion had no significant impact on the mental wellbeing of people aged 65 and above as well as people living in states that adopted Medicaid expansion, relative to remaining states. This is an important finding and allows us to infer that the reform affected the lives of only those who were eligible for extended coverage of Medicaid but did not have spillovers such as through the woodwork effect.

**Table 3.4. Placebo Tests - The effect of ACA Medicaid Expansion on Mental Wellbeing**

| | Happy | Depressed |
|---|---|---|
| *Panel A - Non-caregivers Sample* | (1) | (2) |
| ACA Medicaid | 0.0016 | 0.0023 |
| | (0.016) | (0.016) |
| N | 13,245 | 13,266 |
| | | |
| *Panel B - Assuming ACA Medicaid in 2010* | (1) | (2) |
| ACA Medicaid | 0.13 | 0.035 |
| | (0.11) | (0.09) |
| N | 2,484 | 2,487 |
| | | |
| *Panel C - Age 65 and above* | (1) | (2) |
| ACA Medicaid | -0.01 | -0.017 |
| | (0.026) | (0.024) |
| N | 3,596 | 3,604 |
| | | |
| State + Year Fixed Effects | YES | YES |
| Control Variables | YES | YES |
| Individual FE | YES | YES |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018). Each coefficient indicates OLS estimates of equation (2). The variable ACA_Medicaid is a treatment variable, which is a binary indicator for whether ACA Medicaid expansion occurred in the state at a given year. We estimate the impact of ACA Medicaid on Mental Wellbeing (happiness and depression) as a part of falsification tests shown in Panel A, B, and C. All models include state, year, and person level fixed effects, along with control variables namely age, gender, age^2, income, health status, retirement status, race, education, and children.

### *3.6.4.Robustness-Checks*

We test the robustness of our main estimates to different alternative specifications, and more specifically we test whether or not our estimates are consistent when we restrict our sample to individuals with total wealth below $100k (more likely to qualify for Medicaid), restricting the level of education to non-degree holders, using the bigger sample that is inclusive of year 2008 through 2018, and analysing a sample of spousal caregivers who provided care in 2012 as well as in 2014. The Panel I of Table 3.5 shows a robust and consistent result when restricting wealth to $100k and below. As expected, the magnitude of estimated effect increases slightly compared to our baseline estimates, and the effect is significant indicating that the effect is mainly driven by the states expanding Medicaid coverage in 2014. Similarly, Panel II of Table 3.5 reports the estimated effect after restricting our sample to non-degree holders or less educated individuals using the main baseline specification. Panel II of Table 3.5 indicate that the estimated effects for less educated individuals are almost like that of the estimates obtained using the main sample. Next, we analyse the expanded sample that also includes the data from year 2008 consistently with the event study estimates. Panel III in Table 3.5 indicates that the inclusion of year 2008 in the main sample slightly lowers the precision of our estimates, although it barely changes the magnitude of effects sizes for happiness and depression. Again, we find that our main results are mostly robust to such a change in specification as the effect only varies slightly[5]. Finally, we restrict our sample mainly to long-run spousal caregivers who provided care to their partners both in 2012 as well as in 2014 to check whether the selection of our sample affects our main results[6]. We observe that putting such a restriction greatly reduces the size of our main sample. The Table A3.5 of Appendix shows that restricting our main sample barely changes the magnitude of our baseline effects, namely the effect as well as its direction persist. However, due to the loss of almost 90% of sample observations, we lose precision in our estimates and hence, the statistical significance.

**Table 3.5. Robustness Checks - Effect of ACA Medicaid Expansion on Mental Health**

| | **Happiness** | **Depression** |
|---|---|---|
| | (1) | (2) |
| ***Main Baseline Estimates*** | | |
| ACA_Medicaid | 0.087** | -0.082** |
| (SE) | (0.036) | (0.0375) |
| No. of Observations | 2,484 | 2,487 |
| ***Panel I - Restricting wealth to $100k and below*** | | |
| ACA_Medicaid | 0.1*** | -0.1** |
| (SE) | (0.04) | (0.042) |
| No. of Observations | 2,052 | 2,053 |
| ***Panel II - Restricting education level to non-degree holders*** | | |
| ACA_Medicaid | 0.085** | -0.075* |
| (SE) | (0.041) | (0.042) |
| No. of Observations | 1,786 | 1,789 |

[5] Refer to Appendix Table A4 for the detailed version of

[6] Our main sample consists of spousal caregivers who are main caregivers and provided care at any point in time.

| Panel III - Using a sample of individuals from 2008 to 2018 | | |
|---|---|---|
| ACA_Medicaid<br>(SE)<br>No. of Observations | 0.082*<br>(0.034)<br>2,829 | -0.08**<br>(0.035)<br>2,832 |
| | | |
| **State + Year FE** | YES | YES |
| **Control Variables** | YES | YES |
| **Individual/House FE** | YES | YES |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018), and Age<65. Each coefficient indicates OLS estimates of equation (2). The variable ACA_Medicaid is a treatment variable, which is a binary indicator for whether ACA Medicaid occurred in the state at a given year. We estimate the impact of ACA Medicaid on the feeling of happiness and of depression as a part of Robust-ness check for baseline estimates shown in Panel I, II, & III of Table 5. All models include state, year, and person level fixed effects, along with control variables namely age, gender, age^2, income, health status, retirement status, race, education, and children.

### *3.6.5. Heterogeneity*

The US population differs, across various socio-economic characteristics, in the level of Medicaid coverage. Therefore, the expansion of Medicaid differs for several state with some states immediately expanding their coverage compared to others. The use of health and retirement study allows us to assess responses across various groups of population. Thus, we estimate our fully specified baseline model using the interactions of our treatment variable with different observable so characteristics such as gender, education, retirement status, ethnicity, health status and the number of children. Table 3.6 reports the heterogenous effect of ACA's Medicaid on the mental wellbeing of spousal caregivers across different socioeconomic categories. We observe that Medicaid expansion significantly improves the mental wellbeing of caregivers with fair or poor health, whereas it doesn't significantly affect the healthy caregivers. The female caregivers see significant improvement in mental wellbeing after the reform, when compared with their counterparts in terms of the effect on the feeling of depression. In addition, the lesser educated caregivers are more likely to see improvement in their mental wellbeing when compared with highly educated individuals. It is also observed that individuals without children have shown lesser or no improvement in mental wellbeing post reform compared to individuals with children. One of the major reasons that explains this can be that almost 95% of individuals in the sample have at least one child.

Finally, we find that full-time workers show lower but statistically non-significant improvement in mental health than individuals with part time or no work. This indicates that individuals with full-time work have less or no-time for caregiving, whereas individuals with part-time work or no work are more likely to provide care to their spouses.

**Table 3.6. Heterogeneity of ACA Medicaid Expansion on Mental Wellbeing**

| | | Happiness | Depression |
|---|---|---|---|
| **State & Year FE + Controls** | | YES | YES |
| **Individual FE** | | YES | YES |
| | | (1) | (2) |
| **ALL** | | | |
| **Health** | **Good/Best/Excellent** | 0.04 | -0.037 |
| | **Fair/Poor** | 0.13*** | -0.12*** |
| | | | |
| **Gender** | **Female** | 0.084** | -0.081* |
| | **Male** | 0.092** | -0.083 |
| | | | |
| **Education** | **High School/Less** | 0.083** | -0.076** |
| | **Some/More College** | 0.1 | -0.1 |
| | | | |
| **Have Children** | **No** | -0.006 | -0.2* |
| | **Yes** | 0.09** | -0.078** |
| | | | |
| **Spouse Medicaid** | **No** | 0.08* | -0.095* |
| | **Yes** | 0.075* | -0.032 |
| | | | |
| **Ethnicity** | **Non-White** | 0.096** | -0.11** |
| | **White** | 0.076* | -0.045 |
| | | | |
| **Type of Work** | **Full-Time** | 0.05 | -0.044 |
| | **Part time or No-work** | 0.089** | -0.092 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018), and Age<65. Each coefficient indicates OLS estimates of equation (2). The variable ACA_Medicaid is a treatment variable, which is a binary indicator for whether ACA Medicaid expansion occurred in the state at a given year. Column (1) shows the estimates of the impact of ACA Medicaid on the feeling of happiness across different sub-populations. Column (2) represents the estimates for the feeling of depression for spousal caregivers across various sub-populations. All models include state, year, and person level fixed effects, along with control variables namely age, gender, age$^2$, income, health status, retirement status, race, education, and children.

### *3.6.6. Mechanisms*

Finally, we examine several potential mechanisms driving the effect of ACA Medicaid expansion on mental wellbeing of caregivers as reported in Table 3.7. First, we identify the impact of ACA Medicaid on the Medicaid uptake of individual as the reform is expected to increase the coverage for individual caregivers. The alternate provision of long-term care via Medicaid coverage can be relaxing and relieving for spousal caregivers. Thus, increase in Medicaid coverage due to ACA's Medicaid reform can have positive impact on the welfare of caregivers. Another potential channel occurs via Out-of-pocket expenses (OOP). We find a negative and significant effect of ACA Medicaid on the extensive margin of out-of-pocket expenses e.g., the likelihood of paying expenses out of pocket. We also find that ACA Medicaid expansion reduced the likelihood of purchasing private health insurance as well as employee sponsored health insurance. However, we observe that the results are not statistically significant at the conventional level of significance.

**Table 3.7. Potential Mechanisms**

| | Medicaid | OOP | Private HI | Employer HI | Working | Hr/Wk | P(Work) after 62 | P(Work) after 65 |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **ACA_Medicaid** | 0.15*** | -0.079* | -0.035 | -0.0123 | -0.062* | -2.62* | -4.83* | -4.86** |
| | (0.036) | (0.0439) | (0.035) | (0.023) | (0.035) | (1.44) | (2.84) | (2.26) |
| | | | | | | | | |
| **N** | 2,467 | 2,489 | 2,476 | 2,459 | 2,489 | 2,460 | 1,947 | 2,403 |
| **State & Year FE + Controls** | YES | YES | YES | YES | YES | YES | YES | YES |
| **Individual FE** | YES | YES | YES | YES | YES | YES | YES | YES |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018) , and Age<65. Each coefficient indicates OLS estimates of equation (2). The variable ACA_Medicaid is a treatment variable, which is a binary indicator for whether ACA Medicaid expansion occurred in the state at a given year. We estimate the impact of ACA Medicaid on CESD score of Mental Wellbeing on outcomes, which potentially drive the effect, as a part of mechanism. Column (2) represents proportion of sub-group relative to its counterpart across categories. All models include state, year, and person level fixed effects, along with control variables namely age, gender, age^2, income, health status, retirement status, race, education, and children.

Finally, the ACA Medicaid reform is estimated to have negative impact on the likelihood of working for wages (extensive margin) and on the number of hours worked per week (intensive margin). This is because low-income caregivers without insurance are usually constrained to work for funding their medical costs (or to be insured by their employers). In contrast, if they are on Medicaid then, they can reduce or adjust the number of hours on employment. This finding is suggestive of a potential causal link between caregiver's labor market participation and her mental health. We also find that ACA Medicaid reduces caregiver's probability of working after 62 as well as 65 years, respectively.

### *3.6.7. The Effect on the Mental Health of Spouses*

We also investigate whether ACA Medicaid resulted in household spill over due to improvement in wellbeing of caregivers. It is important to note that caregiver's mental health can have significantly larger impact on the wellbeing of their spouse due to respondents' unique role of caregiving. We especially find the impact of ACA Medicaid on the mental wellbeing of the spouse being care for. Column 1 of Table 3.8 indicates that ACA Medicaid significantly improves the feeling of happiness of spouse being cared for by 7.9% points, when compared with remaining states. However, we do not find statistically significant impact of ACA Medicaid on the feeling of depression for spouses being cared for.

**Table 3.8. The effect of ACA Medicaid Expansion on Mental Health of Caregiver's Spouses**

| | **Happiness** | **Depression** |
|---|---|---|
| | (1) | (2) |
| **ACA_Medicaid** | 0.079* | 0.0052 |
| | (0.042) | (0.05) |

| | | |
|---|---|---|
| | | |
| **State + Year Fixed Effects** | YES | YES |
| **Control Variables** | YES | YES |
| **Individual Fixed Effects** | YES | YES |
| **Number of Observations** | 2,028 | 2,035 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018) , and Age<65. Each coefficient indicates OLS estimates of equation (2). We estimate the impact of ACA Medicaid on happiness, depression, and CESD score for spouse being cared for, as a part of spillover effect of ACA Medicaid on household. Column 4 includes state, year, and person level fixed effects, along with control variables namely age, gender, age^2, income, health status, retirement status, race, education, and children.

### 3.7. Discussion

This paper has examined the effect of the expansion of public health insurance (Medicaid) resulting from the introduction of the Affordable Care Act (ACA) to caregivers who previously had limited access to private health insurance (due to low-income and low-benefit work activities and/or limited employment opportunities derived from their caregiving duties). Drawing on evidence from Affordable Care Act's Medicaid expansion; we document evidence of Medicaid expansion effects on the mental health of caregiving spouses. We exploit the quasi-experimental change that occurred due to the expansion of Medicaid coverage under ACA. We observe that ACA Medicaid improved the mental wellbeing of careers. We estimate 8.2% points (on average, equivalent to 30% decrease) reduction in the feeling of depression and 8.7% points increase in the feeling of happiness (on average, 11% increase). The effects are driven by specific components of the CESD score, mainly happiness, sadness, depression, and loneliness, which were affected due to ACA Medicaid.

These results indicate that availability of health insurance to adult spousal caregivers can significantly reduce the mental burden associated with informal caregiving. These findings offer some answers to the demand of sustainable arrangement for informal caregiving. The ACA Medicaid is observed to benefit spousal caregivers by significantly improving their otherwise deteriorating mental health. We also find that the ACA Medicaid results in spill-over at household level by significantly improving the well-being of spouses being cared for. No one has cast ACA Medicaid expansion as a caregiver support policy. However, combined, our results suggest that ACA-Medicaid expansion is in fact an indirect caregiver support policy, improving mental health of both caregivers and spousal care recipients. Therefore, indirect and direct programs supporting the modal providers of long-term care in the United States -- unpaid informal caregivers – could help minimize the negative mental health impacts of caregiving, while supporting the preference of disabled older adults to remain safely in their own homes.

## 3.8. Appendix

***3.8.1. Event Study Design***. Equation A1 represents our specification for a non-parametric event study. As ACA's Medicaid expansion was brought in effect in the year 2014, most states expanded their coverage in 2014 while a few of the remaining did so in 2016. We define the event (r=0) for the year 2014 that is when the expansion of Medicaid began. The biannual nature of HRS survey makes us assign events once in every two years. We define indicator variables representing events relative to the event of Medicaid expansion. The following model of non-parametric event study treats year 2012 (r = -1) as a baseline category.

$$\boldsymbol{Y_{it} = \beta X_{it} + \lambda_s + \varphi_{-2} + \sum_{r=0}^{2} \varphi_r + \left(\gamma_{-2} + \sum_{r=0}^{2} \gamma_r\right) * ACA\_ME + \mu_i + \epsilon_{it}} \quad \textbf{(A1)}$$

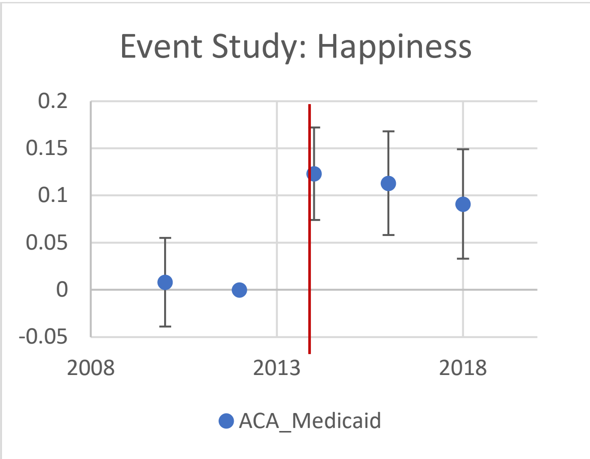
Where $Y_{it}$ corresponds to the outcome variables i.e., the feeling of happiness and of depression. The $\lambda_s$ and $\mu_i$ represent state as well as individual level fixed effects. The $\gamma_r$ indicates coefficients on leads and lags on Affordable Care Act Medicaid Expansion states (ACA_ME) relative to omitted baseline category, $\gamma_{-1}$. The $X_{it}$ represents the control variables included in the model, whereas $\varphi_r$ indicates coefficients on leads and lags for no-ACA Medicaid expansion states relative to the omitted category of $\varphi_{-1}$. One of the major advantages of the event study is that it allows us to identify the significant outcome pattern relative to the adoption of Medicaid reform of 2014. For the event study to be credible, we need to satisfy the parallel trend aka mean-independence of the timing of the reform and no-anticipation of treatment assumptions.

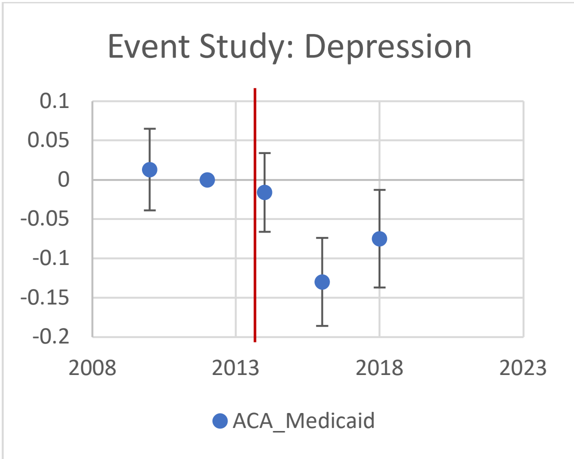
***3.8.2. Results (Event Study):*** After running the model specified in Equation A1, we then subsequently plot the estimated coefficients of the non-parametric event study regression as depicted in Figure A3.1. Figure A3.1 (a & b) displays the event study plots for happiness and depression. We observe that ACA Medicaid expansion increases the feeling of happiness and decreases the feeling of depression, when the event occurred at t=0, for spousal caregivers living in expansion states compared to their counterparts in non-expansion states, with respect to year 2012 (or t = -1). We observe that the parallel trends assumption satisfies for happiness and feeling depressed. Next, Figure A3.2 reports the event study estimates, as a part of robustness checks, examining the impact of ACA Medicaid expansion on the mental health. We draw on a larger sample starting from year 2008 through 2018. In contrast, our main sample removes the year 2008 to avoid picking up the effect of the Great Recession. Thus, we further check whether our estimates including the year 2008 affect our main event study estimates. Figure A3.2 (a & b) displays the event study trends after using a full sample from year 2008 to 2018. Consistently with our main results, we find that the post reform trends are unaffected for both the outcomes examined, and the pre-reform trends continue to satisfy parallel trends assumption in case of happiness and depression. At last, we also run the event study analysis for Mechanisms[7] and find that labor market outcomes are one of the reasons driving the effect which is quite evident in Figure A3.3 (a-c). We can also observe that the parallel trend assumption is not violated in Figure A3.3 (a-c). These findings strengthen our results from Figure A3.1 (a & b).

[7] Please refer to the Figure A1 of Appendix for the event study trends for another set of mechanisms i.e., Out-of-pocket expenses (extensive margins for OOP, $100 or More OOP, and $500 or more OOP).

**Figure A3.1.: Event study design of ACA Medicaid Expansion exposure on the feeling of Happiness and of Depression.**

a) (b)

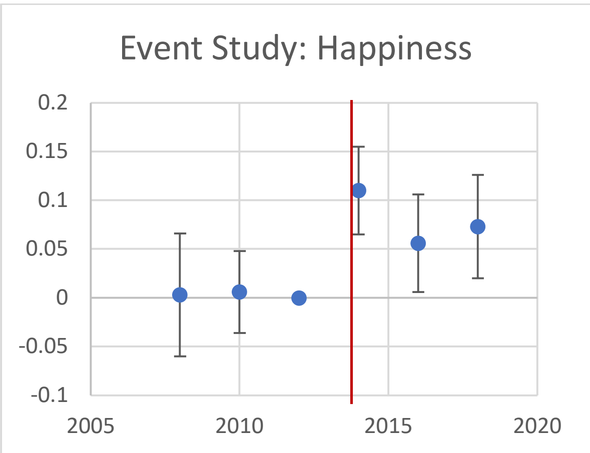


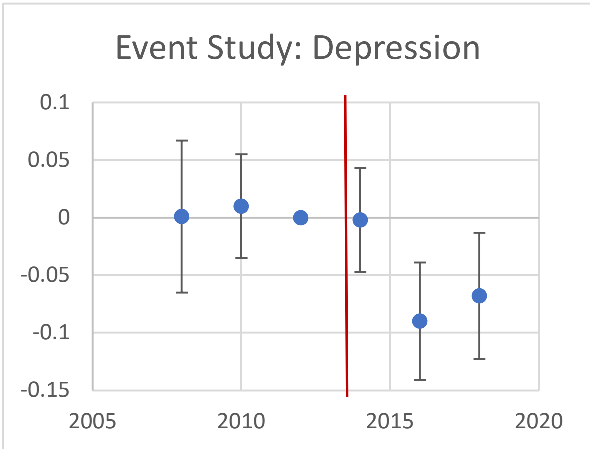




Note: This figure depicts the results of the events study design of the ACA Medicaid expansion on mental health (feeling of happiness and of depression) for the period 2010-2018. The red line indicates the ACA Medicaid reform began in the January of 2014. The estimates are obtained after estimating Equation A1.

**Figure A3.2.: Robustness Check for Event Study Trends Using a Sample from 2008 to 2018.**

a) (b)

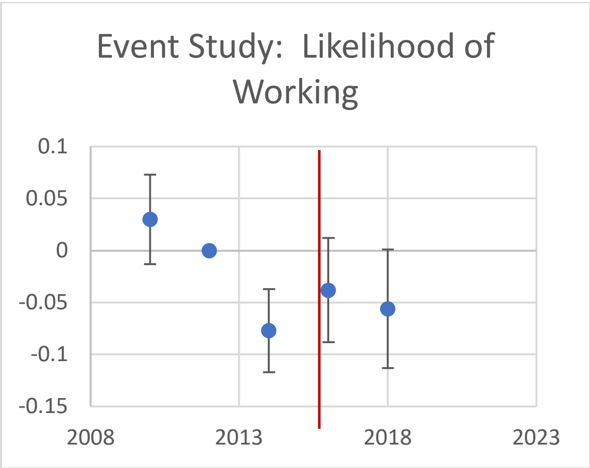


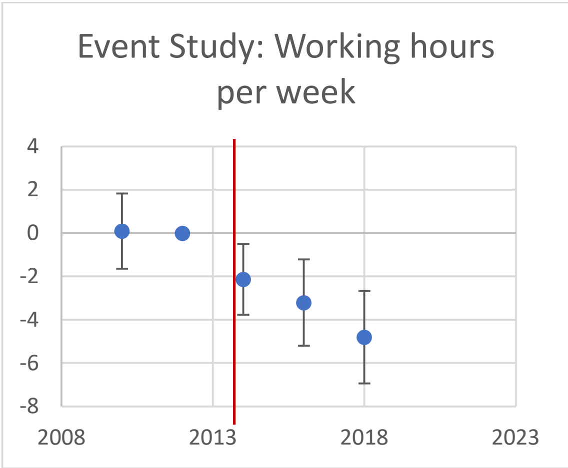

Note: This figure depicts the results of the events study design of the ACA Medicaid expansion, as a part of robustness check, on mental health (feeling of happiness and of depression) for the period 2008-2018. The red line indicates the ACA Medicaid reform began in the January of 2014. The estimates are obtained after estimating Equation A1.

**Figure A3.3.: Event study design of ACA Medicaid Expansion exposure on Potential Mechanisms (Labor participation).**

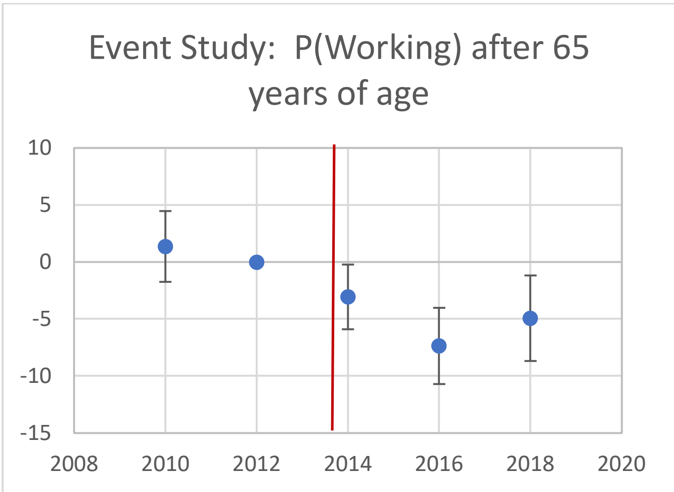
(a)




(b)




(c)




Note: This figure depicts the results of the events study design of the ACA Medicaid expansion on labour market outcomes of spousal caregivers for the period 2010-2018. The red line indicates the ACA Medicaid reform began in the January of 2014. The estimates are obtained after estimating Equation A1.

**Figure A3.4. Event study design of ACA Medicaid Expansion exposure on CESD score and the feeling of Sadness.**

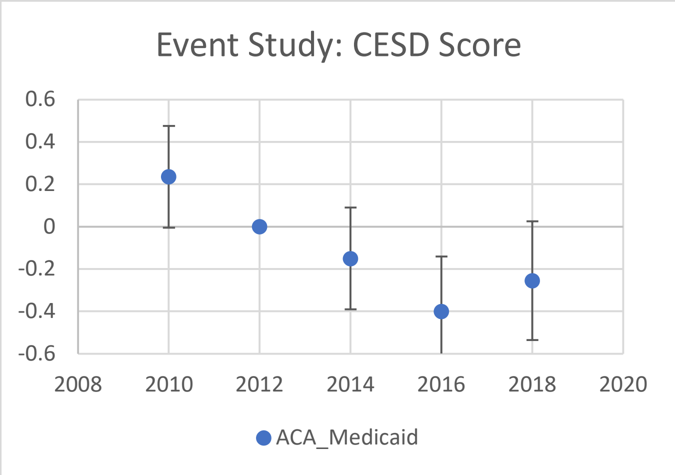
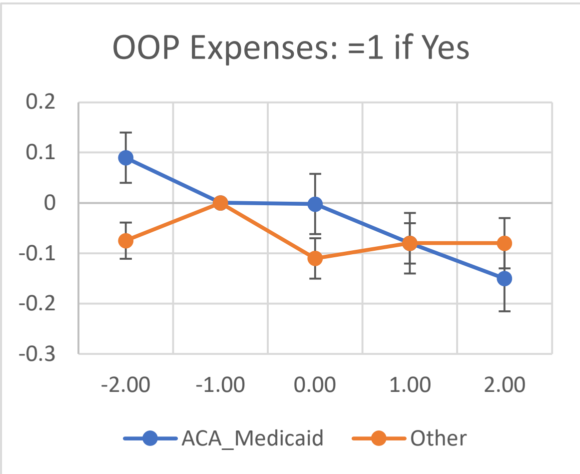
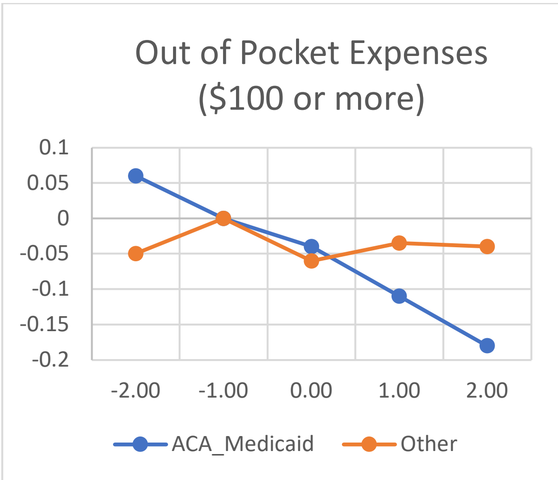



**Figure A3.5. Event study design of ACA Medicaid Expansion exposure on Out-of-Pocket Expenses.**

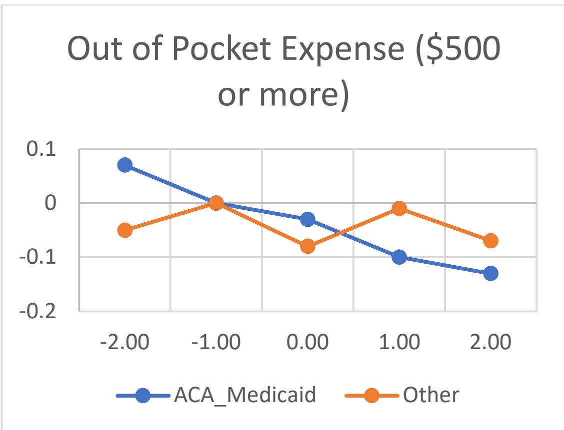
a)




(b)




(c)



### Table A3.1. Linear Estimates of the effect of ACA Medicaid Expansion on CESD Score

| | Dependent Variables | | | |
|---|---|---|---|---|
| | CESD Mental Health Score | | | |
| | (1) | (2) | (3) | (4) |
| **ACA_Medicaid** | -0.34*** | -0.337** | -0.372** | -0.376** |
| | (0.112) | (0.157) | (0.168) | (0.176) |
| **Age** | | | | 0.339 |
| | | | | (0.285) |
| **Age$^2$** | | | | -0.00164 |
| | | | | (0.00227) |
| **Married** | | | | -0.343 |
| | | | | (0.233) |
| **Non-Housing Wealth** | | | | -2.94e-07 |
| | | | | (8.86e-07) |
| **Income** | | | | 5.67e-06 |
| | | | | (6.01e-06) |
| **Fair/Poor Health** | | | | 1.014*** |
| | | | | (0.144) |
| **R_retire** | | | | |
| | | | | |
| **Year Fixed Effects** | NO | YES | YES | YES |
| **State Fixed Effects** | NO | NO | YES | YES |
| **Control Variables** | NO | NO | NO | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES |
| **N** | 2,822 | 2,822 | 2,822 | 2,489 |
| **R-squared** | 0.004 | 0.011 | 0.043 | 0.094 |
| **Number of respd_id** | 1,130 | 1,130 | 1,130 | 1,061 |

### Table A3.2. Linear Estimates of the effect of ACA Medicaid Expansion on CESD components of Non-caregivers

| **CESD Components (Non-caregivers Sample)** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | EnjoyLife | CantGetGoing | FeltSad | FeltAlone | Happy | SleepRestricted | EvrytngEffort | FeltDepresse |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **ACA_Medicaid** | -0.0137 | 0.0048 | 0.0036 | -0.0128 | 0.0016 | -0.029* | 0.0073 | 0.0023 |
| | (0.013) | (0.018) | (0.017) | (0.0163) | (0.016) | (0.018) | (0.017) | (0.016) |
| | | | | | | | | |
| **State + Year Fixed Effects** | YES | YES | YES | YES | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES | YES | YES | YES | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES | YES | YES | YES | YES |
| **N** | 13,253 | 13,228 | 13,259 | 13,265 | 13,245 | 13,256 | 13,259 | 13,266 |

**Table A3.3. Placebo test: The effect of ACA Medicaid Expansion on CESD score of**

| | **CESD - Mental Health Score** |
|---|---|
| | |
| ***I) Non-caregivers Sample*** | (1) |
| **ACA_Medicaid** | -0.01 |
| | (0.08) |
| **N** | 13,275 |
| | |
| ***II) Assuming ACA ME in 2010*** | (2) |
| **ACA_ Medicaid** | -0.362 |
| | (0.49) |
| **N** | 2,489 |
| | |
| ***III) Age 65 and Above*** | (3) |
| **ACA_ Medicaid** | 0.05 |
| | (0.114) |
| **N** | 3,605 |
| | |
| **State + Year Fixed Effects** | YES |
| **Control Variables** | YES |
| **Individual FE** | YES |
| | |

**Table A3.4. Robustness Checks – A Detailed Version**

| | **CESD Score** | **Happiness** | **Depression** | **Sadness** |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Main Baseline Estimates*** | | | | |
| ACA_Medicaid<br>(SE)<br>No. of Observations | -0.376**<br>(0.176)<br>2,489 | 0.087**<br>(0.036)<br>2,484 | -0.082**<br>(0.0375)<br>2,487 | -0.075**<br>(0.038)<br>2,488 |
| ***Panel I - Restricting wealth to $100k and below*** | | | | |
| ACA_Medicaid<br>(SE)<br>No. of Observations | -0.43**<br>(0.191)<br>2,055 | 0.1***<br>(0.04)<br>2,052 | -0.1**<br>(0.042)<br>2,053 | -0.068<br>(0.042)<br>2,054 |
| ***Panel II - Using Household level fixed effects*** | | | | |
| ACA_Medicaid<br>(SE)<br>No. of Observations | -0.37*<br>(0.191)<br>2,223 | 0.058<br>(0.04)<br>2,218 | -0.087**<br>(0.04)<br>2,222 | -0.08*<br>(0.053)<br>2,222 |
| ***Panel III - Using a sample of individuals from 2008 to 2018*** | | | | |
| ACA_Medicaid<br>(SE)<br>No. of Observations | -0.32*<br>(0.17)<br>2,834 | 0.082*<br>(0.034)<br>2,829 | -0.08**<br>(0.035)<br>2,832 | -0.053<br>(0.036)<br>2,834 |
| | | | | |
| **State + Year FE** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual/House FE** | YES | YES | YES | YES |

**Table A3.5. Robustness Check – Reducing sample to spousal caregivers who provided care both in 2012 as well as in 2014.**

| | Outcome variables | | | |
|---|---|---|---|---|
| | **CESD Score** | **Happiness** | **Depression** | **Sadness** |
| ACA_Medicaid | -0.31 | 0.105 | -0.07 | -0.012 |
| (SE) | (0.45) | (0.088) | (0.096) | (0.089) |
| No. of Observations | 296 | 296 | 294 | 296 |
| | | | | |
| **State + Year FE** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual/House FE** | YES | YES | YES | YES |

**Table A3.6. Effect of ACA Medicaid Expansion on Mental Health of Caregiver's Spouses: CESD Components**

| | **EnjoyLife** | **CantGetGoing** | **FeltSad** | **FeltAlone** | **Happy** | **SleepRestricted** | **EvrytngEffort** | **FeltDepressed** |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **ACA_Medicaid** | 0.01 | -0.053 | -0.094** | -0.084** | 0.12*** | -0.07 | -0.07* | -0.08* |
| | (0.031) | (0.047) | (0.041) | (0.04) | (0.039) | (0.044) | (0.039) | (0.043) |
| | | | | | | | | |
| **State + Year Fixed Effects** | YES | YES | YES | YES | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES | YES | YES | YES | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES | YES | YES | YES | YES |
| **N** | 2,412 | 2,407 | 2,413 | 2,416 | 2,407 | 2,413 | 2,413 | 2,414 |

**Table A3.7. Heterogeneity in effect of ACA Medicaid on Mental Health (CESD Score)**

| ALL | | CESD - Mental Health Score |
|---|---|---|
| ***Health*** | Good/Best/Excellent | -0.158 |
| | Fair/Poor | -0.551*** Ϯ |
| | | |
| ***Gender*** | Female | -0.453** |
| | Male | -0.27 |
| | | |
| ***Education*** | High School/Less | -0.42** |
| | Some/More College | -0.23 |

| | | |
|---|---|---|
| | | |
| ***Marketplace*** | Federal Exchange | -0.314 |
| | State Exchange | -0.405** |
| | | |
| ***Retirement Status*** | Not Retired | -0.554** |
| | Retired | -0.24 |
| | | |
| ***Have Children*** | NO | -1.14** |
| | YES | -0.35** |
| | | |
| ***Ethnicity*** | Non-White | -0.51** |
| | White | -0.20 |
| | | |
| ***Type of Work*** | Full Time | -0.24 |
| | Part-Time or No work | -0.36** |
| | | |
| State & Year FE + Controls | | Yes |
| Individual FE | | Yes |

**Table A3.8. Trends: ACA Medicaid States Vs Remaining States**

| **Happiness Trends** | | | | |
|---|---|---|---|---|
| **Wave** | **ACA_ME States** | **SE** | **Other States** | **SE** |
| 2010 | 0.74 | 0.44 | 0.8 | 0.41 |
| 2012 | 0.72 | 0.45 | 0.77 | 0.42 |
| 2014 | 0.75 | 0.43 | 0.75 | 0.433 |
| 2016 | 0.78 | 0.41 | 0.79 | 0.41 |
| 2018 | 0.78 | 0.41 | 0.80 | 0.40 |
| **Medicaid Trends** | | | | |
| **Wave** | **ACA_ME States** | **SE** | **Other States** | **SE** |
| 2010 | 0.25 | 0.43 | 0.17 | 0.38 |
| 2012 | 0.23 | 0.42 | 0.19 | 0.4 |
| 2014 | 0.41 | 0.49 | 0.26 | 0.44 |
| 2016 | 0.46 | 0.5 | 0.22 | 0.42 |
| 2018 | 0.57 | 0.5 | 0.22 | 0.42 |
| **CESD Score Trends** | | | | |
| **Wave** | **ACA_ME States** | **SE** | **Other States** | **SE** |
| 2010 | 2.7 | 2.53 | 2.15 | 2.21 |
| 2012 | 2.7 | 2.5 | 2.52 | 2.54 |
| 2014 | 2.8 | 2.5 | 2.4 | 2.44 |
| 2016 | 2.4 | 2.35 | 2.12 | 2.39 |
| 2018 | 2.67 | 2.67 | 2.3 | 2.35 |

### 3.8.3. An Extension – An Instrumental Variable Approach

We extend our analysis to instrumental variable (IV) approach and run the baseline models using Medicaid uptake as a treatment variable, which is one of the important mechanisms responsible for the effect on mental wellbeing. We use this approach to test alternatively the impact of ACA Medicaid expansion on the mental wellbeing of caregivers ($Y_{ist}$) who are mainly low-income adults in the US. Equation A2 & A3 represent the first and second stage regressions, respectively.

$$\boldsymbol{Medicaid_{ist} = \beta_0 + \rho X_{ist} + \sigma_s + \vartheta_t + \beta_1 * ACA\_ME_{st} + \theta_i + \epsilon_{ist}} \quad \textbf{(A2)}$$

$$\boldsymbol{Y_{ist} = \eta_0 + \lambda X_{ist} + \delta_s + \Psi_t + \eta_1 * \widehat{Medicaid}_{ist} + \theta_i + \vee_{ist}} \quad \textbf{(A3)}$$

Table A3.9 denotes the IV estimates in which we use ACA Medicaid expansion as an instrumental variable for Medicaid update. The exogeneity assumption requires that ACA Medicaid must affect Mental wellbeing only through Medicaid uptake. We think this assumption is satisfied because ACA Medicaid is designed solely for Medicaid expansion and states without ACA Medicaid do not expand Medicaid coverage. The F-statistics of the first stage is 18, which is well above the threshold of 10. Thus, our instrument satisfies the validity assumption. Column (1) indicates the OLS estimates of impact of Medicaid on CESD score of mental health, whereas column (2) represents IV estimates. We find that CESD score of mental health decreases for individuals with Medicaid by 3 points as compared to individuals without Medicaid. This is quite a strong effect and indicates the importance of Medicaid for improving the mental health of individual. Similarly, we repeat our models in equation A2 & A3 for other important components of CESD score, namely happiness, Sadness, and depression. We find that the uptake of Medicaid increases the happiness and decreases the feeling of sadness as well as depression. Overall, we infer that ACA Medicaid expansion improves the mental wellbeing of an individual living in the state that expanded Medicaid relative to other states.

**Table A3.9. Instrumental Variable Estimates of ACA Medicaid on Mental Wellbeing**

| | CESD Score | | Felt Happy | | Felt Sad | | Felt Depressed | |
|---|---|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Medicaid | 0.0181 | -3.001** | -0.0180 | 0.666** | -0.00886 | -0.59* | -0.0063 | -0.661** |
| | (0.153) | (1.453) | (0.0332) | (0.32) | (0.035) | (0.312) | (0.0342) | (0.31) |
| | | | | | | | | |
| First Stage F-Statistic | | 18 | | 18 | | 18 | | 18 |
| State + Year Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Control Variables | YES | YES | YES | YES | YES | YES | YES | YES |
| Individual Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |
| N | 2467 | 2108 | 2462 | 2103 | 2466 | 2107 | 2465 | 2106 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the panel level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018) , and Age<65. Each coefficient indicates OLS estimates of equation (4). The variable Medicaid is a treatment variable, which is a binary indicator for whether an individual is enrolled in Medicaid in the state at a given year. We estimate the impact of Medicaid on CESD score of Mental Wellbeing and on its components. Column (1,3,5,7) & (2,4,6,8) represent OLS and IV estimates, respectively. All models include state, year, and person level fixed effects, along with control variables namely age, gender, age^2, income, health status, retirement status, race, education, and children.

**Table A3.10. Variable Description**

| Variables | Definition |
|---|---|
| **Dependent Variables** | |
| *Happiness* | Equals 1 if respondent felt happy, else 0. |
| *Depression* | Equals 1 if respondent felt depressed, else 0. |
| *CESD Score* | It is a sum of eight components, which ranges from 0 to 8; the lowest CESD score indicates the best mental health. |
| *Sadness* | Equals 1 if respondent felt sad, else 0. |
| **Treatment** | |
| *ACA-Medicaid* | Equals 1 if state adopted ACA Medicaid after 2014/2016, else 0. |
| **Demographic Controls** | |
| *Married* | Equals 1 if respondent is married, else 0. |
| *Income* | Total household income. |
| *Male* | Equals 1 if respondent is Male, else 0. |
| *Child* | Equals 1 if respondent has any children, else 0. |
| *Age* | Age of a respondent. |
| *College* | Equals 1 if respondent has college education or more, else 0. |
| *Retirement Status* | Equals 1 if respondent is retired, else 0. |
| *White* | Equals 1 if respondent is white American, else 0. |
| *Medicaid* | Equals 1 if respondent is covered under Medicaid, else 0. |
| *Private-Health Insurance* | Equals 1 if respondent has private health insurance, else 0. |
| *Fair/Poor Health* | Equals 1 if respondent has fair or poor health, else 0. |

# 4. Chapter II: Caring like Seen Cared? Intergenerational Transmission of Caregiving

## 4.1. Abstract

We examine the extent to which exposure to increased informal caregiving exerts effects on the supply of informal care across generations. We exploit a sharp reduction in the public financing of Medicare home health care in the United States, to investigate whether parental supply of adult care, subsequently exerted role model effects by increasing the children's supply of adult care a few decades later. We use data from the Health and Retirement Survey and exploit the exogenous variation in the supply of care brought about by a large decline in financing of Medicare Home health care between 1997 and 2000 with the Interim Payment System (IPS), which lead to a more pronounced reduction in the provision of Medicare home health care in some states relative to other control states. We find strong evidence supporting the presence of transmission of caregiving across generations, which is heterogeneous across groups, namely the effect is stronger among single, poor, and less educated individuals.

Keywords: caregiving, role modelling effects, Medicare home health reform, family toes, intergenerational transmission.

JEL: 113, Z1

### 4.2. Introduction

It is becoming increasingly apparent that the effect of public policies on beliefs and behaviours can be carried on across generations.[8] However, whether this is the case for adult care at old age is something we know little about despite the current and projected ageing of population in most countries (National Institute of Ageing, 2011). This paper studies the impact of cuts in public finding for home health care, which have been documented to encompass an exogeneous extension in the supply of informal care, on the provision of informal care *across the following generation*. Home health care consistent on health and care services provided in the patient's home to adults in need of care to live an independent life, which relief other family members from providing informal care.[9] The decline in the public funding for the provision of formal home health triggered an increase in informal care as in the United States (Golberstein et al, 2009), insofar as informal care by friends or family members may be a reasonable substitute for part of the services covered by home health care, in particular for those provided by home health aides.

We show that the decline in public funding for home health care not only immediately increases the provision of informal care to the elderly by their adult children (from now on we refer to people who were adults, but not elderly, when the cuts in public home health care happened as generation A), but after many years the policy change also impacts informal caregiving provided to Generation A by the next generation (from now on we refer to this next

[8]For instance, in the United States Hartley *et al* (2022) find that a mother's participation in the aid to families with dependent children (AFDC) and temporary assistance for needy families (TANF) programs increased her daughter's odds of adult participation in such programs down the line, and Dutch children whose parents eligibility for disability insurance (DI) was less likely to participate in DI themselves (Dhal and Gielen, 2021) Similarly, Jacobs (2020) documents that the introduction of the Earned Income Tax Credit (EICT) program in the United States led to higher approval of women labour market participation, and children whose fathers were eligible for paternity leave in Spain, exhibited more egalitarian attitudes towards gender roles and equally engagement in the labour market and in the home (Farre *et al*, 2022).

[9] For instance, recent data from a few developed countries suggest that home health care makes up more than a third of all long-term care spending in Lithuania and Austria and stands at around 20% in Ireland and Germany (OECD, 2020).

generation as generation B). Caregiving duties are a core part of social norms in many western societies, and informal care provided by the family is one of the main sources of care worldwide (Norton, 2016). Also, the economic value of unpaid caregiving exceeds that of the nursing homes and paid home care budgets (Arno et al, 1999). However, we still know little about what motivates individuals to supply care to their older age family members and financial incentives such as caregiving allowances can exert an influence alongside the availability of public funded home health care. For identification, we take advantage of a unique quasi-experiment, the Interim Payment System (IPS), in the United States in the late 90's – that caused a steep decline in the public funding of Medicare home healthcare. The IPS imposed a cap on the average reimbursement per patient that home care agencies were entitled to receive when treating elderly Medicare patients. The cap was based on a blend of each home health agency's average per patient cost in 1994 and the average per patient cost of home health agencies in the agency's census division. The cap had a regional component. Even states with similar pre-policy utilization potentially faced different restrictive reimbursement limits relative to the average utilization in their census division. Our estimates suggest that Generation A adults living in states where on average the decline in public funding for home health care to the elderly due to the IPS is larger, are more likely to supply informal care to the elderly directly affected by the decline in Medicare home health care as a consequence of the IPS. We also find that in later years, once Generation A ages and needs care, those of generation A who were living in states where on average the decline in public funding for home health care due to the IPS was larger are also more likely to receive informal care from their children (generation B), suggesting that the impact of the IPS altered informal care behaviour for the next generation as well. The plausible mechanism behind these findings rests on the state variation in the IPS: those of generation B, who were young children when the IPS happened and who were living in states that witnessed a relatively large decline if Medicare home health care, were also more likely to witness an increase in informal care provided by Generation A to the elderly compared to their peers living in states where the cuts in public home health care were less severe, and this higher exposure likely impacted their beliefs on the need to provide informal care to the elderly when needed. In other words, generation B living in states is more impacted by the IPS had role models from Generation A who were more likely to provide informal care to the elderly, and therefore, when Generation A aged and needed care, those of Generation B who were more exposed to role models who provided informal care to the elderly provided more informal care as well. The literature on the transmission of beliefs and behaviour across generation acknowledges that beliefs and behaviours across generations can be impacted not only by their families, but by peers' families as well. For instance, Dahl and Gielen (2021) find that children of parents whose disability insurance (DI) eligibility was reduced are 11 percent less likely to participate in DI themselves, do not alter their use of other government programs, and earn 2 percent more as adults, and Olivetti, Patacchini, and Zenou (2016) find that a woman's labour supply as a young adult is shaped by the work behaviour of her adolescent peers 'mothers. Our policy change does rests on geographic variation, so we can measure changes in behaviour across generation using state-based variation for identification so that generation B exposed to more informal caregiving to the elderly as children internalize the social norm of informal care provision and provided care to the elderly when reaching adulthood, and we acknowledge that generation B may have been exposed to informal care role modelling provided by their parents, or their extended family, or the families of their peers.

This paper adds to the literature along several dimensions. First, we add to the literature on the impact of public policy on behaviour across generations, as this is the first study that documents the causal impact of a change in public funding for long term care on informal care across generations. Indeed, the small literature on the transmission of caregiving (Charles et al, 2015) is mostly descriptive.

We also add to the literature on the effect of public funding on informal care (Golberstein et al, 2009) who document the contemporaneous effect of restrictive payment caps for Medicare home health care brought about by the IPS with increased informal care by the elderly who faced decreased public provision of Medicare home health care as a consequence of the IPS received an increase in informal care from their children, a response driven by lower income individuals.

Additionally, we contribute to the academic discussion on the incentives for the supply of informal care, and more specifically by highlighting the effect of social incentives such as social norms and expectations. This paper shows changes in the supply of care in the Generation A induced by public funding cuts, affect the social norms as well as the expectations to supply of care by the subsequent Generation B.

Finally, the paper adds to the literature on role modelling and intergenerational transmission, by examining whether role modelling effects are influenced by gender specific transmission. That is, traditionally, caregivers have been women, hence we specifically examine gender heterogeneities in the supply of care. In addition, we examine whether when those adult children age, they are more likely to receive care from their own children. Next, we examine the heterogeneous effect by groups that differ in family ties, namely Hispanics and Asians compared to Caucasian Americans.

The rest of the paper is organised as follows. The next Section provides the background of the paper. Section three describes the data and Section four provides the empirical strategy. Section five reports the main results. Section six proposed potential mechanisms for our results and a final Section concludes.

### 4.3. Related literature

This paper examines the intergenerational transmission of caregiving through social learning and role modelling effects, which contributes to a series of finding in the related literature, including the following:

#### *4.3.1. Intergenerational Transmission of Preferences, Attitudes, and Personality.*

The research examining the intergenerational transmission of preferences, attitudes, and personality gained popularity in the recent decade and the existing literature in this line is growing rapidly every passing year. Economics, compared to psychology- for instance- is relatively new to this topic (Zumbuehl et al., 2020) and it includes empirical as well as theoretical contributions. This body of literature suggests that both nature and nurture are involved in the transmission of preferences. Cesarini et al. (2009) demonstrate the genetic influence on preferences, while Dohmen et al. (2012) emphasise the significance of socialisation in the transmission of preferences across generations.

The intergenerational transmission of preferences, attitudes, and preferences arguably influences intergenerational correlation of traits, behavior, and outcomes. For example, the intergenerational transmission of risk and trust attitudes (Dohmen, 2012); cognitive and noncognitive abilities (Grönqvist et al., 2017); the role of parental involvement (Zumbuehl et al., 2020); the role of social environment in the formation of pro-sociality (Kosse et al, 2020); outcomes such as income, education, or health (Bjorklund and Salvanes, 2011; Black and Devereux, 2011; Holmlund et al., 2011; Lindahl et al., 2016); and intergenerational transmission of dependence (Hartley et al., 2022).

#### *4.3.2. Role modelling and gender assortative preferences.*

Parents play a central role in the child's socialization process (Collins et al, 2000), even though not necessarily in the same way. For instance, mothers might exhibit a stronger influence than parents in the transmission of trust (Dohmen et al., 2012), and this might be especially the case in the transmission of caregiving duties where one might find gender assortative preferences namely mother influence on daughters. The theoretical literature on cultural transmission makes different assumptions regarding the motivations of parents in influencing the transmission process, while it does presume that parents and the social environment have an impact on the transmission of culture, values, attitudes, and preferences. Bisin and Verdier (2012) make the assumption that parents have "imperfect empathy," i.e., that they are altruistic toward their children but believe that children's subjective evaluations of options are similar to their own subjective evaluations, which are based on their own utility functions. As a result, parents are unable to "completely empathise" with their kids and can only view their decisions through the prism of their own utility function. The outcome is a similarity in these personality qualities between parents and their children as a result of their propensity to instil their own values, attitudes, and preferences in kids. The model developed by Doepke and Zilibotti (2017) may presuppose that parent have paternalistic and altruistic motivations. To improve their children's welfare over the course of their lives, some parents make an effort to sway their kids' preferences. They are willing to bear expenses and make a trade-off between their children's childhood utility and better usefulness as adults. Instilling preferences and traits that promote success, such as those that encourage the accumulation of human capital, does not necessarily imply that parents want their children to possess those that are similar to their own, especially if those preferences do not themselves promote success in life. For instance, conscientiousness and an internal locus of control are examples of such attributes.

Gender assortative behaviour might give rise to additional intergenerational effects on caregiving when the offspring of the caregiver forms their preferences for caregiving after their parents. However, the evidence of such an effect is limited.

#### *4.3.3. Caregiving as occupation choice.*

Previous studies examining the supply of care study using evidence of the general social survey in the United States whether individuals whose parents provided care, either full-time at home or in the workforce, are more inclined to provide care (Charles et al, 2015). Interestingly, although they find an association, they attribute it to the fact that parents influence occupational choice as opposed to the supply of care. Care instead if conceptualised as a vocational activity resulting from a personal calling, which applied particularly among women and differ across ethnic groups. This involves some moral duty to provide care which in different countries takes the form of 'filial piety'.

#### *4.3.4. Supply of care as a proxy for pro-social and other behaviours.*

Children may be inspired to pursue care work if their parents' altruistic beliefs are more strongly transmitted to them. Wilhelm et al (2008) document that parents can influence their children's generosity. Similarly, Parental-child correlations in measures of risk and trust attitudes have been demonstrated by Dohmen et al. (2012). Some of those intergenerational correlation might well be influenced by other confounded such as parental cognitive abilities (Grusec and Hastings, 2007), this may underpin both pro-social preferences, alongside the probability of children to supply care.

#### *4.3.5. Incentives for the supply of care*

The effect of informal care supply on labour market participation suggests 'no causal effect' of labour market participation on the supply of care (Van Houtven et al., 2013). This can be in part the results of caregiving and employment being influenced by norms. However, we still know little about how such norms do attitudes change over time. For instance, Carmichael et al. (2010) find that future caregivers, are different from significantly from those who have never taken such a role. Hence, it is an empirical question whether changes in social expectation through role modelling exert an influence on the supply of care.

## 4.4. Medicare Home Health Care and the IPS

### *4.4.1. Medicare*

In order to address the health insurance needs of the elderly and the disabled, Medicare was established by Congress in the United States in 1965. During the time the Interim Payment System was in place, Medicare was divided into three parts: Part A covered hospital insurance, Part B covered supplemental medical insurance, and Part C provided beneficiaries with more options for enrolling in private health insurance policies. For those 65 and older who qualify for Social Security or Railroad Retirement Benefits, Medicare Part A is automatically supplied. Prior to 1997, Medicare Part A provided coverage for home health care, hospice care, short-term skilled nursing facility care, and inpatient hospital treatment. All home health care visits for people not enrolled in Part A of Medicare are now covered since 1997 by Part A. Medicare Part A covers the first 100 home health care visits that occur after an inpatient stay for people who are enrolled in Medicare Part B, and Part B covers visits that exceed the cap after the hospital stay and visits that are necessary without an earlier inpatient stay. Six medical services are covered by Medicare home care: skilled nursing, occupational therapy, speech therapy, physical therapy, occupational therapy, medical social work, and home health aide. Injections, intravenous nutrition therapy, monitoring serious disease and unstable health status, teaching about prescription medications, keeping track of medication adherence, and wound care for surgical or pressure sores are a few examples of competent care (Orsini, 2019). Home health nurses supervise, watch, and assess the patient's care requirements in addition to providing direct treatment and educating the patient and his or her caregivers about patient care. Medicare enrolees must be "home-bound" and in need of "intermittent" and "part-time" care in order to qualify for home health care coverage. Such treatment may be extensive. With rare exclusions in exceptional circumstances, Medicare defines part-time or "intermittent" care as the care required or provided on fewer than 7 days per week or for less than 8 hours per day. Furthermore, Medicare does not pay for home health aide services unless patients also receive professional care from the home health provider, such as nursing care, physical therapy, occupational therapy, or speech-language pathology services (Orsini, 2019).

#### *4.4.2. The IPS*

The Medicare home health care reimbursement programme was altered by the Balanced Budget Act (BBA) of 1997. The law's modification required two steps. First, an Interim Payment System (IPS) was established from 1997 to 2000, setting a cap on the amount that each home care agency may be reimbursed per patient annually (agencies were reimbursed on a cost basis before the IPS) (Kim and Norton, 2015; 2017). The cap had two components: 25% was based on the agency's census division's average per patient cost, and the remaining 25% was based on each agency's average per patient cost for 1994. (a cluster of neighbouring states). The cap was set at the national median per-patient cost for newer agencies. The transition from the IPS to the Prospective Payment System, which was the second step, began in October 2000. (PPS). The PPS regulations did not differ by state, hence they produced time series variance but not state variation like the IPS did (Orsini, 2019). As a result, similar to what other study has done for various outcomes (for example, See McKnight, 2006), we concentrate here on using the variation introduced by the IPS to study caregiving provision across generations.

The IPS cap suggested that even states with comparable pre-policy use would be subject to differing reimbursement restrictions based on how their utilisation compared to the average utilisation in their census division. Following the implementation of the IPS, the amount of Medicare home health care services provided decreased significantly: from 10.7% of beneficiaries in 1996 to 8.5 percent in 1999. Additionally, from 1996 to 1999, the typical number of visits per user decreased from 74 to 42.[10]

Previous research has relied quasi-random experiment represented by the IPS and the cross-state variation in reimbursement generosity it created.

### 4.5. Data and Summary Statistics

The data sample comes from Health and Retirement Study (HRS) Survey. The HRS is a nationally representative longitudinal survey data on individuals (both respondent and their spouses) who were 51-61 years old in 1992. We use HRS data for our analysis as it is the most appropriate data, compared to other available datasets including Panel Study of Income Dynamics (PSID) data, for answering the research question we ask. This is because of following reasons. The HRS contains longitudinal information on supply and demand of long-term care services and support, including both formal and informal care, provided to elderly individuals. It runs for a long enough period (30 years) that we can look at the intergenerational transmission of caregiving. It is a dataset with a relatively large sample size on the population we think is the most affected by the IPS reform. In addition, as opposed to PSID data, the HRS has a user-friendly version available which is provided by researchers from RAND corporation.

We analyse the HRS data in two different segments. First, we use data from 1994 through 2000 waves of the HRS to identify the impact of IPS on the care supplied by respondents to their parents. We restrict the first segment of our sample only till 2000, because IPS was replaced by the PPS in October 2000. The first segment of our sample contains 22,304 observations for 8573 individuals. Subsequently, we use the remaining segment of the sample that consists of waves from 2010 through 2018 of the HRS to investigate the intergenerational

[10] Data are from various years of the Medicaid and Medicare Statistical Supplement.

transmission of caregiving. We put the restriction on the second segment of our sample such that only those respondents with children and reported an IADL or ADL limitations are included in the sample. The respondents without any children are excluded from the analysis, because we want to focus only on intergenerational transmission of caregiving in the second segment. We carry forward individuals from the first segment of our sample, whose parents had ADL/IADL limitations in the past, to the second segment to identify individuals who provided care vs who did not provide care to parents. In addition, we create an outcome variable that takes the value 1 if children (son/son-in-law/daughter/daughter-in-law) or grandchildren; otherwise, it takes the value 0. We select the second segment of the sample to start in 2010 to balance the need of a large enough sample size to carry out the estimates of the impact of the IPS on receiving care later in life for people who were still young when the IPS happened, as well as the need to wait for people exposed to the IPS in their younger years (whose parents and elderly relative were more likely to be directly affected by the restrictions imposed by the IPS) to age "enough" and so be likely to be in need of care. Table 1 indicates summary statistics for the two different segments of the sample depicted in Panel A and Panel B, respectively. The average age of an individual during the IPS reform as represented in Panel A was 57 years old, whereas Panel B indicates that the average age of the older sample is 74 years. We also observe that females occupy a major share (64%) of respondents who provided care to their parents during the period of IPS reform. Also, the White Americans forms the majority in both the samples, however, their proportion decreased from 82% to 72% in the older sample. The Panel B also indicates that the average income of the older sample is close to $40k annually and forms a majority of low- and middle- income populations. The Panel B sample also has close to 23% enrolled in Medicaid insurance. Finally, close to 2/3$^{rd}$ of the sample in Panel B has poor or worst health outcomes and close to 90% of individuals suffer from Arthritis. At least 1 in 4 individuals from the older sample suffers from the chronic health conditions.

## Table 4.1: Summary Statistics (Panel A and B)

| ***PANEL A*: *HRS Sample, 1994 - 2000*** | | | | | |
|---|---|---|---|---|---|
| **Variable** | **Obs** | **Mean** | **SD** | **Min** | **Max** |
| Helped Parent with Care | 22,304 | 0.35 | 0.48 | 0 | 1 |
| Sib Helped Parent with Care | 19,401 | 0.18 | 0.38 | 0 | 1 |
| Sib Financially Helped Parent | 18,665 | 0.13 | 0.34 | 0 | 1 |
| Age | 22,304 | 56.8 | 6.9 | 23 | 88 |
| Male | 22,304 | 0.36 | 0.48 | 0 | 1 |
| Years of Education | 22,304 | 12.56 | 0.5 | 0 | 17 |
| Some College Education | 22,304 | 0.43 | 0.5 | 0 | 1 |
| Married | 22,304 | 0.76 | 0.43 | 0 | 1 |
| Income | 22,304 | 66205 | 86321 | 0 | 1836410 |
| White American | 22,297 | 0.82 | 0.39 | 0 | 1 |
| Fair/Poor Health | 22,304 | 0.21 | 0.41 | 0 | 1 |

| ***PANEL B*: *HRS Sample, 2010 - 2018*** | | | | | |
|---|---|---|---|---|---|
| **Variable** | **Obs** | **Mean** | **SD** | **Min** | **Max** |
| Received Care from Children | 1,726 | 0.53 | 0.5 | 0 | 1 |
| Hours of Care Received from Children | 1,726 | 3.44 | 6.35 | 0 | 48 |
| Average Days/Month Cared by Children | 1,726 | 7.8 | 15 | 0 | 94 |
| Age | 1,726 | 74.22 | 7.4 | 46 | 101 |
| Male | 1,726 | 0.31 | 0.46 | 0 | 1 |
| College Education | 1,726 | 0.3 | 0.46 | 0 | 1 |
| Married | 1,726 | 0.47 | 0.5 | 0 | 1 |
| Income | 1,726 | 39609 | 74055 | 0 | 1993984 |
| White American | 1,726 | 0.72 | 0.45 | 0 | 1 |
| Fair/Poor Health | 1,726 | 0.68 | 0.47 | 0 | 1 |
| Mental Health Score (CESD)[11] | 1,726 | 2.95 | 2.4 | 0 | 8 |
| Diabetes | 1,726 | 0.44 | 0.5 | 0 | 1 |
| Stroke | 1,726 | 0.23 | 0.42 | 0 | 1 |
| Lung Disease | 1,726 | 0.24 | 0.43 | 0 | 1 |
| Arthritis | 1,726 | 0.88 | 0.33 | 0 | 1 |
| Cancer | 1,726 | 0.26 | 0.44 | 0 | 1 |
| Psychological Problems | 1,726 | 0.38 | 0.49 | 0 | 1 |
| Heart Disease | 1,726 | 0.46 | 0.5 | 0 | 1 |
| Private-LTCI | 1,726 | 0.11 | 0.31 | 0 | 1 |
| Medicaid | 1,726 | 0.23 | 0.42 | 0 | 1 |

Note: The Panel A represents the sample of Health and Retirement Study (HRS) from 1994 to 2000, whereas the Panel B carry-forward the respondents from the Panel A and forms an older sample that includes observations from year 2010 through 2018. The Panel B sample includes only those respondents from the Panel A who need help with ADL and IADL activities between year 2010-2018.

[11] Source: HRS RAND Longitudinal File, CESD stands for the Center for Epidemiologic Studies Depression (CESD) scale. The CESD score ranges from 0 to 8. Thus, the lower CESD score indicates better mental health outcome in the past week.

## 4.6. Empirical Strategy

### *4.6.1. Cross State Variation in the Policy Change*

The IPS implemented a ceiling based on a combination of the costs in the census division and each home health agency in 1994 (Kim and Norton, 2015; 2017). As a result, two agencies that had the same cost in 1994 but were located in separate states within various census divisions and had different usage levels may have experienced significantly different caps following the IPS. According to McKnight, (2004, 2006), we may develop a measure of restriction in Medicare home health care reimbursement at the state level by extrapolating the logic used to determine the average of agencies in a state from the reasons used to determine the average of agencies in that state. Therefore, states with aggregate home health agencies that have average per patient costs below the census division in 1994 face a reimbursement limit that is less onerous than the limit faced by states where, on average, the average per patient cost in 1994 is higher than the average per patient cost in their census division, given similar increasing trends between 1994 and 1997.

With the primary goal of determining the effect of the IPS, which the BBA implemented in 1997, on the number of Medicare home care visits received by beneficiaries of Medicare, McKnight (2004, 2006) designs a measure that captures a cross-state component of the variation implied by the IPS. Here, we examine whether the IPS has an impact on parental caregiving using the same metric.

We must utilize a measure of cost to construct the variable that McKnight (2004, 2006) used to represent the variance in reimbursement across states. The average number of visits per user is the best way to estimate cost in this case, as suggested by McKnight (2006). The following definition of the measure of constraint in reimbursement generosity is provided by McKnight (2004, 2006):

$$\text{Restrictiveness}_{sc} = \bar{A}_S - \bar{A}_C \tag{1}$$

where $\bar{A}_S$ is the average number of Medicare home care visits per user in state s in 1994 and $\bar{A}_C$ is the average number of Medicare home care visits per user in state s's census division in 1994. The measure of restrictiveness varies between -40.9 (Kentucky) and 34.7 (Utah).

### *4.6.2. Difference-in-Differences Specification: the impact of the IPS on caregiving for elderly parents*

Equation 2 below presents the difference-in-differences strategy that compares changes in care supply to parents in states that were more restricted by the IPS with changes in the supply of careto parents in states that were less restricted by the IPS:

$$H_{it} = \alpha_t + S_i + S_i t + Post_t \beta + Post_t * Restrictiveness_{st} \gamma + e_{it} \tag{2}$$

$H_{it}$ is the care supplied by respondents to their parents for the group in state i in year t ; $\alpha_t$ and $S_i$ are year and state fixed effects, and $S_j t$ are state trends. $Post_t$ is a dummy equal to 1 for years 1998-2000 in which the IPS was in place (McKnight, 2006). $Restrictiveness_{st}$ captures state variation in the policy change; $e_{it}$ is the error term. As per (Bertrand, Duflo, Mullainathan, 2004), we cluster the standard errors at the state level. We restrict our sample to the years 1994–2000 and interact year effects with the Restrictiveness measure, conditioning on state and year fixed effects, in order to test the plausibility of the identification strategy, which requires that, absent the IPS, trends in receiving care in rates would have been the same in more intensively treated states compared to less intensively treated states. We investigate the null hypothesis that the interactions between the year dummies and the restrictiveness measure are all zero. From this exercise, we cannot deny that the pre-policy period saw a similar trajectory in parental caring for jurisdictions with greater and less restrictions.

### *4.6.3. Intergenerational Transfer of Caregiving Specification*

Equation 3 presents the regression equation for the impact of caregiving to parents by respondents on the care provided to respondent by their children/grandchildren:

$$R_{ist} = \alpha_t + S_s + S_s t + \rho\, IPS\ Reform + \gamma\, Caregiver + \beta\, X_{ist} + e_{ist} \qquad (3)$$

$R_{it}$ is the care received by respondents from their children/grandchildren for individual i in state s in year t (R takes the value 1 if Yes, otherwise 0) ; $\alpha_t$ and $S_s$ are year and state fixed effects, and $S_s t$ are linear-trends. $\rho$ represents the ATE for the impact of IPS Reform, where IPS reform is a dummy equal to 1 when the respondent when the IPS was implemented was living in state where the cap imposed by the IPS was relatively more restrictive than in other states. More specifically, *IPS Reform* is a dummy equal to 1 if the Restrictiveness measure in the state is. $\gamma$ estimates the different intercept for those people who provided care to their parents when the IPS was enacted, as 'Caregiver' takes the value '1' if a respondent provided care to her parent during the IPS reform. X is a set of individual level controls, which includes demographic indicators, a set of chronic conditions, and a health status.

## 4.7. Results

### *4.7.1. Baseline Estimates*

We initially estimate the model focusing on the first segment of our sample that uses exogenous variation from the IPS Medicare reform to identify the impact of the IPS reform on the likelihood of respondents providing care to their parents. Table 4.2. Column 2 adds state as well as year level fixed effects along with linear trends into the model. The results from Column 2 are statistically significant and indicates that the IPS reform increased the likelihood of providing care to parents by almost 9%. Subsequently, we run a fully specified model that incorporate wide range of control variables into the model. Column 3 represents the estimates from a fully specified model indicating that the IPS reform was significantly associated with

4.6% increase in the likelihood of providing care to parents. We also run the model that adds individual level fixed effects in Column 4 and find that the effect magnitude increases to 7%, but it comes at the cost of reduction in the level of statistical significance to $p<0.1$ from $p<0.01$ in Column 3. Similarly, we also estimate the impact of IPS reform on the likelihood of sibling providing informal care and financial help to parents. Column 1 and 3 of Table 4.3 report the results from our fully specified diff-in-diff models indicating that the reform increased the probability of sibling providing informal care and financial help to parents by slightly greater than 3% points each, respectively.

Next, we use second segment of our sample that includes data from the year 2010 through 2018 to investigate whether there is evidence of intergenerational transmission of caregiving. We check whether Generation A needing long-term care and living in states where the IPS cap was relatively more restricted are relatively more likely to receive care from Generation B. We find that IPS reform is responsible for increase in the likelihood of receiving care from Generation B by 49 percentage points (Column 4 of Table 4.4), compared to their counterparts who need long-term care and reside in non-restricted states. We also attempt to identify if Generation A provided care to their parents during IPS reform, then check whether or not they receive care from Generation B should they need help to carry-out their day-to-day activities in the future, as evidence of the occurrence of intergeneration transmission of caregiving from one generation to another. Table 4.4 shows the baseline results for the intergenerational transmission of caregiving which consists of estimates obtained by incorporating various specifications into our baseline model. Column 1 of Table 4.4 represents the model without any added controls or fixed effects, and we find positive evidence of transmission of caregiving. Column 2 adds state and year fixed effects into our model which leads to change in the magnitude of the effect of Generation A cared for parents on the likelihood of receiving care from Generation B. Further, Column 3 adds various controls into the model along with state and year fixed effects. The estimates from Column 3 indicates that Generation A is 63 percentage points more likely to receive care form Generation B if they were living during the IPS years in states that were relatively more restricted by the IPS. The robust standard errors are obtained after clustering at the state level. Finally, we also test our specification after adding linear trends into our model as represented in Column 4 of Table 4.4 making it a fully specified model for analysis in which we find that the strong and statistically significant evidence of the presence of intergenerational transmission of caregiving. We find that IPS reform increases the likelihood of receiving care from Generation B. We also find that inclusion of linear trends does not greatly affect the magnitude of the effect of providing care in the past on receiving care from Generation B.

**Table 4.2: Impact of Medicare Interim Payment Reform on Caregiving to Parents**

| | **Dependent Variable: Caregiving to Parents** | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | | | | |
| **IPS (Medicare Restrictions)** | -0.0032 | 0.0916*** | 0.0462*** | 0.074* |
| | (0.00082) | (0) | (0.0586) | (0.0435) |
| | | | | |
| **State + Year FE & Lin Trends** | NO | YES | YES | YES |
| **Controls** | NO | NO | YES | YES |
| **Individual Fixed Effects** | NO | NO | NO | YES |
| | | | | |
| **N** | 22,402 | 22,402 | 22,322 | 22,322 |
| **Number of Persons** | | | | 8,573 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the state level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 2-5 (1994-2000). Each coefficient indicates OLS estimates of equation (2). The variable IPS is a treatment variable, which is a binary indicator for whether Medicare restrictions were enforced in the state after 1997. We estimate the impact of IPS (Medicare restrictions) on the likelihood of providing care to parents in which Column (1) includes no variables other than treatment or IPS. Column (2) introduces state as well as years fixed effects into the model. Column (3) adds control variables namely age, gender, age^2, income, health status, marital status, race, and education. Column (4) includes individual level fixed effects.

**Table 4.3: Impact of Medicare the IPS Reform on Caregiving to Parents & Fin Help by Sibling.**

| | **Caregiving to Parents (Sibling)** | | **Financial help to Parents (Sibling)** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | | | | |

| | | | | |
|---|---|---|---|---|
| **IPS (Medicare Restrictions)** | 0.0326*** | 0.112** | 0.0331*** | 0.0295 |
| | (0.0034) | (0.045) | (0.0056) | (0.0402) |
| | | | | |
| **State + Year FE & Lin Trends** | YES | YES | YES | YES |
| **Controls** | YES | YES | YES | YES |
| **Individual Fixed Effects** | NO | YES | NO | YES |
| | | | | |
| **N** | 21,716 | 21,716 | 20,966 | 20,966 |
| **Number of Persons** | | | | 7,791 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the state level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 2-5 (1994-2000). Each coefficient indicates OLS estimates of equation (1). The variable IPS is a treatment variable, which is a binary indicator for whether Medicare restrictions were enforced in the state after 1997. We estimate the impact of IPS (Medicare restrictions) on i) the likelihood of providing care to parents by siblings and ii) financial help given by siblings. All models include state, year, and person level fixed effects, along with control variables namely age, gender, age^2, income, health status, marital status, race, and education.

**Table 4.4: ITC: Likelihood for respondent receiving care from children/grandchildren (IADL)**

| | **Dependent Variable: Respondent receiving care from Children/Grandchildren** | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **IPS (Medicare Restrictions)** | 0.39*** | 0.44*** | 0.632*** | 0.492*** |
| | (0.04) | (0.024) | (0.147) | (0.166) |
| | | | | |
| **Caregiver** | 0.37*** | 0.0517 | 0.0454* | 0.0487* |
| | (0.076) | (0.032) | (0.0235) | (0.025) |
| | | | | |
| **State + Year FE** | NO | YES | YES | YES |
| **Controls** | NO | NO | YES | YES |
| **Linear Trends** | NO | NO | NO | YES |
| **N** | 1,726 | 1,726 | 1,726 | 1,726 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the state level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018). Each coefficient indicates OLS estimates of equation (2). The variable IPS is a treatment variable, which is a binary indicator for whether Medicare restrictions were enforced in the state after 1997. The variable Caregiver is a binary indicator for whether a respondent provided care to their parents between 1994 and 2000. We estimate the effect of IPS and for those who provided care to parents (between 1994 and 2000) on the likelihood of receiving care in the future (between 2010 and 2018) from their children as evidence of the presence of intergenerational transmission of caregiving. Column (1) includes no variables other than IPS reform and Caregiver variables. Column (2) introduces state as well as years fixed effects into the model. Column (3) adds control variables namely age, gender, income, health status, marital status, race, education, and existence of multiple chronic health conditions. Column (4) includes linear trends.

### *4.7.2. Intensive Margins*

We also obtain more evidence of intergenerational transmission of caregiving after running our fully specified model on the intensive margins of the care provided to respondents by their children. We mostly consider two variables namely hours of care received by Generation A per day and the number of days per month they receive such care from their children. Table 4.5 represents the results on the intensive margins. Both Column 1 and Column 2 uses our fully specified model that includes controls, state as well as year fixed effects, and linear trends. We find that association between IPS reform and the likelihood of receiving care from children is positive but statistically non-significant for both the outcomes. We also find that Generation A who provided care in the past to parents is likely to receive daily hours of care and the number of days of care per month they receive from Generation B. However, these estimates from Table 5 are not statistically significant. A possible reason for this finding is that these outcome variables, daily hours of care and the number of days per month received from Generation B, suffer from measurement errors problems.

**Table 4.5: Intergenerational Transmission of Caregiving to Parents (Intensive Margins)**

| | **Hours of Care by Ch/Gchild** | **Hours of Care by Ch/Gchild** |
|---|---|---|
| | (3) | (4) |
| **IPS (Medicare Restrictions)** | 0.0912 | 7.53 |
| | (2.424) | (4.88) |
| | | |
| **Caregiver** | 0.44 | 1.114 |
| | (0.5) | (0.871) |
| | | |
| **State + Year FE** | YES | YES |
| **Controls** | YES | YES |
| **Linear Trends** | YES | YES |
| **N** | 1,726 | 1,726 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the state level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018). Each coefficient indicates OLS estimates of equation (2). The variable IPS is a treatment variable, which is a binary indicator for whether Medicare restrictions were enforced in the state after 1997. The variable Caregiver is a binary indicator for whether a respondent provided care to their parents between 1994 and 2000. We estimate the effect for those who provided care to parents (between 1994 and 2000) on the intensive margins (Hours of care per day provided as well as days/month such care is provided) from their children as evidence of the presence of intergenerational transmission of caregiving. All models include state as well as year fixed effects, and linear trends, along with control variables age, gender, income, health status, marital status, race, education, and existence of multiple chronic health conditions.

### *4.7.3. Robustness Check*

Further to check the robustness of our main baseline estimates, we check whether the estimates after including person level fixed effects into our main specification can be compared. We estimate the impact on the extensive margin using fixed effects model and obtain the average treatment that is lower in magnitude but still precise, 39 percentage points as opposed to 49 percentage. The fixed effects estimate, obtained using probit model, shown in Table 4.6 shows that the IPS reform is responsible for 39 percentage points increase likelihood of receiving care from Generation B. Secondly, we check the robustness of our main specification looking at a sample with wealth below or equal to $100k. We find that the effect size increases slightly when the total wealth is restricted to below $100k for both IPS reform and Caregiver variables. Overall, we find that our main estimates are robust to some specification changes.

**Table 4.6: Robustness Check: Intergenerational Transmission of Caregiving**

| | **Respondent receiving care from Children/Grandchildren** |
|---|---|
| | (1) |
| ***I) Including Person Level Fixed Effects*** | |
| **IPS (Medicaid Restrictions)** | 0.395***<br>(0.154) |
| | |
| ***II) Restricting Total Wealth to $100k*** | (2) |
| **IPS (Medicaid Restrictions)** | 0.54***<br>(0.165) |
| | |
| **Caregiver** | 0.067*<br>(0.04) |
| | |
| **State + Year FE+ Controls** | YES |
| **Control Variables** | YES |
| **N** | (1) 1,710 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the state level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018). Each coefficient indicates OLS estimates of equation (2). The variable IPS is a treatment variable, which is a binary indicator for whether Medicare restrictions were enforced in the state after 1997. The variable Caregiver is a binary indicator for whether a respondent provided care to their parents between 1994 and 2000. We estimate the effect of IPS and for those who provided care to parents (between 1994 and 2000) on the likelihood of receiving care in the future (between 2010 and 2018) from their children as evidence of the presence of intergenerational transmission of caregiving. Column 1 uses fixed effects model as a part of robustness check that include state as well as year fixed effects, and linear trends, along with control variables age, gender, income, health status, marital status, race, education, and existence of multiple chronic health conditions.

### *4.7.4. Heterogeneity*

The US population differs across various socio-demographic characteristics. The level of urbanization in the east and the west coast areas of the US are different than the mid-west and southern regions and the populations vary across households and socio-economic characteristics in terms of caregiving at the family level. The data from the Health and Retirement Survey of the US includes extensive information on various socio-demographic characteristics. Therefore, we estimate our fully specified model after including the interaction of our treatment variable with various observable socio-demographic characteristics including gender, ethnicity, education, marital status, and health. Table 4.7 represents the heterogenous effect for the intergenerational transmission of caregiving from one generation to another across different socio-demographic groups. We find that Generation A males who cared for their parents between 1994 and 2000 are thrice as likely as their female counterparts to receive the care from Generation B. One of the reasons to explain this finding is that males relatively have lower life-expectancy at birth than females and are more likely to need help with ADL or IADL activities earlier than female caregivers. In terms of education, we find that the intergenerational transmission of caregiving is more dominant among less educated household compared to college degree holders. This explains that highly educated individuals as opposed to less educated ones are better at planning as well as funding their care requirements rather than relying on family members to take care of such requirements. However, these effects are not statistically significant at a conventional level of significance. The effect for intergenerational transmission of caregiving is slightly higher in white Americans as compared to other ethnic groups. Furthermore, we find that single individuals are approximately three times more likely to receive care from generation B than married individuals. This is because married individuals are mostly supported by their spouses given that the spouses are healthy. Thus, married individuals are more likely to rely on their partners than their children. Further, as expected, we find that Generation A individuals with poor health conditions are more likely to receive care from Generation B than their healthy counterparts. At last, we observe that people enrolled in Medicaid are more likely to witness intergenerational transmission of caregiving than others without Medicaid. Majority of our sample comprise of low- income individuals and almost a fourth of them have Medicaid insurance. However, we also find that the uptake of private-LTCI is negatively related to intergenerational transmission of caregiving, whereas individuals without private-LTCI witness positive intergenerational transmission.

In addition, the supply informal care is likely to be endogenous, because it is dependent upon several factors including generosity of care-receiver parent (Norton et al., 2013). The decision to provide care is an important one, because it comes at the cost of loss of income, leisure, and health outcomes for caregiver. The economics literature differs on existing relationship between inter-vivo transfers and informal care. Norton and Van Houtven (2006) and Norton et al. (2013) find evidence that a child who provide informal care to parents is more likely to receive larger inter-vivo transfers than other children, whereas Jimenez-Martin and Vilaplana Prieto (2015) reports that informal caregiver child receives less frequent and less generous inter-vivo transfer than non-caregivers. Additionally, Norton et al. (2013) put forward the theoretical framework which suggests that the strong sense of filial duty is another reason that might affect the provision of informal care. For example, a single child might provide more hours of care than average hours of care provided by children with siblings. Therefore, it is important to check if the effect differs by the number of children the respondent has. Thus, we do the sub-sample analysis to test if the effect differs for respondents with one child vs more than one child. Table 4.7 shows that the effect of IPS reform on average hours of care provided per children is much lower for individuals with more than one kids (2.2 hours) compared to those with single child (11.5 hours). However, these results are statistically non-significant.

**Table 4.7: Heterogeneity in Intergenerational Transmission of Caregiving**

| | | |
|---|---|---|
| | **Dependent Variable - Respondent receiving care from Child/Grandchild** | |
| **State & Year FE** | | YES |
| **Controls** | | YES |
| **ALL** | | |
| **(1)** | | (2) |
| **Gender** | **Female** | 0.028 |
| | **Male** | 0.095* |
| | | |
| **Education** | **High School/Less** | 0.055 |
| | **Some/More College** | 0.034 |
| | | |
| **Ethnicity** | **White** | 0.054* |
| | **Others** | 0.036 |
| | | |
| **Marital Status** | **Married** | 0.025 |
| | **Single** | 0.07* |
| | | |
| **Health** | **Good/Best/Excellent** | 0.008 |
| | **Fair/Poor** | 0.067* |
| | | |
| **Medicaid** | **NO** | 0.021 |
| | **YES** | 0.14** |
| | | |
| **Private-LTCI** | **NO** | 0.061** |
| | **YES** | -0.075 |
| | | |
| **Average Hours of care provided by Children** | **Single Child (N=134)** | 11.5 |
| | **Multiple Child (N=2,119)** | 2.2 |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the state level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018). Each coefficient indicates OLS estimates of equation (2). The variable Caregiver is a binary indicator for whether a respondent provided care to their parents between 1994 and 2000. The estimates in Table 4.7 are obtained after interacting Caregiver variable with variables representing various socio-economic characteristics. Column 1 shows different sub-populations across a specific socio-demographic characteristic. Column 2 represents the impacts across various subpopulations. All models include state as well as year fixed effects, and linear trends, along with control variables age, gender, income, health status, marital status, race, education, and existence of multiple chronic health conditions.

### 4.7.5. Potential Mechanisms

In this section, we attempt to identify potential mechanisms driving the intergenerational transmission of caregiving. We attempt to find if individuals engaged with any form of charitable activities (Such as helping friends, relatives, or charitable trusts) can make them influence Generation B to copy such behaviours as it is found to stimulate Generation B to follow similar behaviours. This variable is a representative of a behaviour that can induce the role modelling effect. Thus, it can lead to intergenerational transmission of such values that can lead to the transmission of caregiving from one generation to another. Column 1 of Table 5.8 reports the potential mechanisms in which we find that the IPS reform increases the likelihood of engaging with charitable activities by approximately 80% points in restricted states compared to non-restricted state for individuals who need care with ADL and IADL activities. We find that IPS reform was responsible for increasing the likelihood of bequest by 38% points for individuals needing help with ADL and IADL activities and residing in restricted states compared to their counterparts living in non-restricted states. We also find that the probability of Generation A leaving a considerable amount of bequest increases for those from Generation A who provided care to their parents between 1994 and 2000 than non-caregivers of that time are more likely to leave bequest for Generation B between 2010 and 2018.

**Table 4.8: Potential Mechanisms for the Intergenerational Transmission of Caregiving**

| | Provide Charitable Help | P(Bequest_10k) |
|---|---|---|
| | (1) | (2) |
| **IPS (Medicare Restrictions)** | 0.79*** | 38.38** |
| | (0.136) | (17.7) |
| | | |
| **Caregiver** | 0.0315 | 6.294** |
| | (0.024) | (2.463) |
| **N** | 1,723 | 1,596 |
| **State & Year FE** | YES | YES |

| | | |
|---|---|---|
| **Controls** | YES | YES |
| **Linear Trends** | YES | YES |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at the state level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 10-14 (2010-2018). Each coefficient indicates OLS estimates of equation (2). The variable IPS is a treatment variable, which is a binary indicator for whether Medicare restrictions were enforced in the state after 1997. The variable Caregiver is a binary indicator for whether a respondent provided care to their parents between 1994 and 2000. Column 1 represents the impact of IPS reform on the likelihood of spending time providing unpaid help to friends, relatives, and other entities. Column 2 shows the impact of IPS reform on the likelihood of leaving a bequest of at least $10K for their children between 2010 and 2018. All models include state as well as year fixed effects, and linear trends, along with control variables age, gender, income, health status, marital status, race, education, and existence of multiple chronic health conditions.

### 4.8. Discussion

This paper studies the intergenerational transmission of caregiving. We examine how Interim Payment System (IPS) Medicare restriction reform impacted Generation A's likelihood of providing care to parents which in-turn exerts an intergenerational caregiving effect by estimating the effect on the likelihood of receiving care in the future Generation B. We use panel study from the Health and Retirement Survey to analyse both the initial and the last segments of the sample to identify two different impacts. Using the first segment of HRS sample, we document that the IPS Medicare restriction reform, which reduced the access to publicly subsidised home care, led to an increase in the likelihood of providing care to parents. In the first segment of our sample, the effect of IPS reform is approximately 5% and statistically significant. Further, we track Generation A from the initial segment of the sample (1994-2000) to later years (2010-2018) to identify the presence of intergeneration transmission of caregiving in the family. We observe that the effect of IPS reform is also reflected in the second segment of our sample and find that IPS reform increases the likelihood of receiving care from Generation B for Generation A needing help with ADL and IADL activities and living in restricted state when compared with their counterparts in non-restricted states. We also find that Generation A's caregiving behaviour in the past influences Generation B to provide care, in the present, should respondents need help with ADL or IADL activities as they age. The magnitude of the effect is slightly lower than 5% and the estimates are statistically significant. We also estimate that the intergenerational transmission of caregiving effect is driven by multiple factors including the level of helping or charitable involvement in the society, bequest motives in the family, and the level of interpersonal bonding in the family. These results provide us with richer evidence on how individuals plan on funding their care requirements in the absence of adequate public support, and how individual caregiving decision can exert signalling or role modelling effects on behaviours in the next generations. Our study suggests evidence of inter-generational spill overs of caregiving decisions, which if unaccounted underestimates the effects of policy interventions (both positive and negative) influencing care across generations.

# 5. Chapter III: Long-Term Care Partnership Effects on Medicaid and Private Insurance

## 5.1. Abstract

Can the expansion of Medicaid, a means-tested health and long-term care insurance, be slowed down by incentivising the purchase of private long-term care insurance (LTCI)? We study the implementation of the long-term care insurance partnership (LTCIP) program, a joint federal and state-level program that intended to promote LTCI coverage. Drawing on recent developments in a difference-in-differences (DD) design we study the effect of the rollout of the LTCIP program between 2005 and 2016 on both LTCI uptake and Medicaid eligibility, and we estimate the effect on Medicaid savings. We find that, unlike previous estimates, the introduction of the LTCIP *does significantly increase LTCI coverage (i.e., one standard deviation change in LTCIP is associated with an increase of 2.5% of standard deviation in private-LTCI which is equivalent to 86% of the effect of income on private-LTCI) and reduce the uptake of Medicaid*. The effects are driven by the introduction of LTCIP in states after 2010. We estimate that the adoption of LTCIP has given rise to an *average Medicaid saving of $36 for every 65-year-old*. This suggests scope for LTCI arrangements to reduce Medicaid spending.

*Keywords*: long-term care partnerships, long-term care insurance, Medicaid, United States, difference-in-differences.

JEL: I18, H11, H24.

## 5.2. Introduction

The design of insurance for long-term care services and supports (LTCSS) can have significant financial consequences for both households as well as the financial balance of public insurance programs such as Medicaid. Estimates suggest that two-thirds of Americans aged 65 and above are expected to use LTCSS at some point in their life (Congressional Budget Office 2013; Eggleston and Fuchs 2012; Eggleston and Mukherjee 2019; Kemper, Komisar, and Alecxih 2005). However, it is unclear how such access to LTCSS will be funded.

To date, public insurance programs fund 72% of LTCSS spending, and Medicaid, a public insurance program jointly financed by both states and the federal governments and administered for low-income families, alone makes up around 53% of the overall expenditure on LTCSS (AARP 2019; Kaiser Family Foundation 2019; Reaves and Musumeci 2015; Thach and Wiener 2018). The remaining 28% of LTCSS spending consists of private insurance or LTCI (11%) and out-of-pocket expenses (17%) (Thach and Wiener 2018; Reaves and Musumeci 2015). Even though private-LTCI is expensive and has high loading, the small share of private-LTCI is one of the most worrying concerns of old age Americans given their low savings. This slim coverage of private-LTCI, in addition to limited public insurance coverage, means that in the absence of any public intervention most Americans will go without insurance coverage. Thus, in the event of needed long-term care, a lack of LTCI increases not only the individual's out-of-pocket expenses but also the public expenditure via Medicaid for long-term care (Goda, 2011).

The uptake of a private-LTCI can impact the expected Medicaid spending as Medicaid act as a secondary payer, hence any private insurance benefit must be exhausted before availing the Medicaid-financed care (Pauly 1990; Brown and Finkelstein 2008). Also, it is mandatary by law that a private policy pays first even-though an individual satisfies both Medicaid income and assets entitlement means-testing criterion. However, the secondary payer status of Medicaid imposes an implicit tax on private-LTCI leading to a reduction in the net benefits obtained from private policy (Brown and Finkelstein 2008; 2011). Owing to these reasons, private-LTCI has exhibited very moderate growth over time, and barely 11% of individuals in the Health and Retirement Survey have contracted such an insurance policy.

The market for private-LTCI faces demand and supply side challenges. The demand side challenges include lack of awareness about LTSS as well as LTCI, Medicaid crowding out private-LTCI (Brown and Finkelstein 2008; 2011), a continuous increase in LTC policy premiums as well as decrease in the amount of coverage[12], and the availability of informal care arrangements at home. However, the supply side challenges consist of problem of adverse selection, moral hazards, strict insurance underwriting, indemnity policies, high administrative loads, and expensive premiums (Cutler, 1993; Konetzka, 2014). In addition, it was historically challenging to design popular and financially stable long-term care insurance products (Norton, 2016). The stand-alone LTCI product introduced in 2010 remained stable for more than 5 years with no change in daily benefit amount and policy deductible period, but its average annual premium increased by almost 20% at the same time (Ameriko et al., 2016). As the Baby boomers start to retire due to aging, the demand for public insurance is likely to rise as individuals cannot fully afford the costs of LTSS (Bergquist et al 2015). This presents three major social policy challenges: 1) a rise in Medicaid expenditures, 2) insufficient LTSS coverage, and 3) as a result a growth of the fiscal deficit, which compromises the public

[12] An insurance purchaser aged 55-64 in 2005 could buy LTC policy with average annual premium of $1900 with average coverage of $270,000 in benefits, whereas she had to spend $2,600 in 2015 to get a coverage of $235,000 in benefits (Ameriks et al., 2016).

sustainability of the current Medicaid design, and calls for strategic policy interventions to reduce spending to qualify for Medicaid (Pauly 1990).

One of the chief initiatives taken by some US states to stimulate the market for private-LTCI includes the design of an LTCIP program (Meiners and Goss 1994; Bergquist, Costa-Font, and Swartz 2018). The main advantage for individuals purchasing qualifying insurance is that those individuals may retain some assets equivalent to the amount specified in the policy and still qualify for Medicaid, provided they meet other eligibility requirements[13]. This paper examines the effects of LTCIP on both private-LTCI and Medicaid uptake.

Earlier studies focused on the introduction of the LTCIP before 2010, and did not find any evidence of an *immediate short-term effect* on the uptake of LTCI (Robert Wood Johnson Foundation (RWJF) 2007; Lin and Prince 2013). However, LTCIP might take some time to produce effects, and previous studies do not consider the significant expansion of LTCIP program after 2008 when a long list of states joined the program (see Figure 1 below). Earlier studies do not examine the effect on Medicaid spending, although the introduction of LTCIP in several U.S. states allows for the examination of long-term effects on both insurance uptake as well as spending. Finally, it is important to mention that LTCIP adds to other state-level fiscal incentives, many of which are not to be cost-effective (Goda 2011), to encourage the uptake of LTCI.

This paper examines whether the states' adoption of a LTCIP program led to an increase in the uptake of public (Medicaid) and private insurance (LTCI). Firstly, we use a Difference-in-Differences (DiD) design to identify the effect of the LTCIP in the uptake of LTCI (intensive and extensive margin) and Medicaid entitlement. We draw on a comprehensive longitudinal

[13] The LTCIP program is administered through the combined effort of public and private insurance providers in the form of a new insurance product known as LTCIP (Robert Wood Johnson Foundation (RWJF) 2007; Lin and Prince 2013).

dataset that follows individuals for 22 years (1996-2016) from the Health and Retirement Study, and we exploit the rollout of the LTCIP program in different states to evaluate whether the LTCIP program successfully stimulated the purchase of private LTCI and subsequent changes in the trends in Medicaid entitlement. Secondly, we examine the heterogeneous effects across household composition, alongside robustness checks including a placebo test and a confirmation of the short-term effects using earlier studies (Lin and Prince 2013). Finally, the paper provides a simple welfare evaluation of the impact of the LTCIP program compared to a state-specific tax incentive.

We contribute to the literature in several ways. First, we examine whether the introduction of the LTCIP design (where individuals manage to protect their assets equivalent to the value of their insurance coverage and still qualify for Medicaid) reduced Medicaid uptake (Brown and Finkelstein 2009; 2008; Norton 2000; Norton and Sloan 1997)[14]. Second, unlike previous studies which either focused on short-term effects on individual data (Lin and Prince 2013) or, aggregate-level data Bergquist et al. (2018), we examine the long-term effects of LTCIP. Furthermore, Lin and Prince (2013) overlook the differences between the Permanent Partnership states (RWJF states[1]) and the New Partnership states (DRA-2005 states). In contrast, we focus on the long-term effects of LTCIP, distinguishing between *the new and the so-called 'permanent' partnership states*. In addition, the use of individual-level surveys allows for the inclusion of a rich set of controls and individual-specific fixed effects that control for several unobservables (e.g., Medicaid stigma, risk aversion) and allows us to carry out heterogeneity analysis. Finally, this paper contributes to the literature by developing a welfare evaluation of the LTCIP effect on both LTCI (private insurance) and Medicaid (public

[14] One study examines aggregate changes in Medicaid spending after the introduction of the early partnerships (Bergquist et al., 2018), but it is restricted to the period 1999-2008 and significant number of states (20 states) adopted LTCIP program only after 2008. Hence, Bergquist et al. (2018) only observe three years of data after the implementation of the Deficit reduction Act (DRA).

insurance) adoption, and we compare it to the alternative stimulus available at the state level, namely the effect of a state-level tax incentive (Goda, 2011).

The rest of the paper is organised as follows. The next section describes the relevant institutional background on how long-term care is funded in the U.S. and the effects of the LTCIP. Next, we describe the data and empirical strategy. Section four reports the results, section five provides robustness checks, and a final section concludes the paper.

### 5.3. Institutional Background

***5.3.1. Funding long-term care.*** The funding of LTCSS is based on a combination of public and private insurance schemes. However, close to three quarters of spending on LTCSS is financed by public sources, whereas more than half of LTCSS is funded by Medicaid, a means-tested program that is jointly financed by state and federal governments (Reaves and Musumeci, 2015, AARP, 2019; Kaiser Family Foundation, 2019; Thach and Wiener, 2018)[15]. Although very popular among elderly people in the U.S., Medicare is a public health insurance program that only provides short-term stay coverage in a skilled nursing home (AARP, 2019). The bulk of LTCSS is financed by Medicaid. Nevertheless, due to the means-testing provision, Medicaid is an inefficient long-term care consumption smoothing mechanism for majority of the elderly population in the US (Brown and Finkelstein 2008). The means-testing limit not only restricts an individual's ability to choose optimal consumption of care but substantially reduces her household expenditure for non-care consumption. Most importantly, it exposes all but the poorest individuals to a risk of bearing considerable amount of out-of-pocket expenses (Brown and Finkelstein 2008). Limited Medicaid coverage exerts unintended consequences by lowering the demand of private-LTCI by imposing implicit tax on private-LTCI, leading to a significant welfare loss for an individual (Brown and Finkelstein 2008; 2011).

[15] As of January 2019, the income eligibility criteria to qualify for Medicaid is 138% of the federal poverty line

***5.3.2. Private Long-Term Care Insurance (LTCI)***. About 28% of spending on LTCSS is privately funded, which breaks down into LTCI coverage premiums (11%) and out-of-pocket expenses (18%) (Reaves and Musumeci 2015; Thach and Wiener 2018). Private LTCI covers the considerable costs of long-term care services for those who need help in performing day-to-day tasks such as dressing, bathing, and toilet activities (AALTCI 2019; National Institute of Aging 2017). In 2017, the average monthly costs of long-term care in a nursing home stood at $8,385 (AALTCI 2019; CMS 2018). The policy holders of private LTCI can receive long-term care services in-house, in a nursing care centre, in an adult day-care centre, or in an assisted living facility, and get the reimbursement for the money spent on buying such services. Approximately 11% of old age Americans hold an LTC insurance policy.

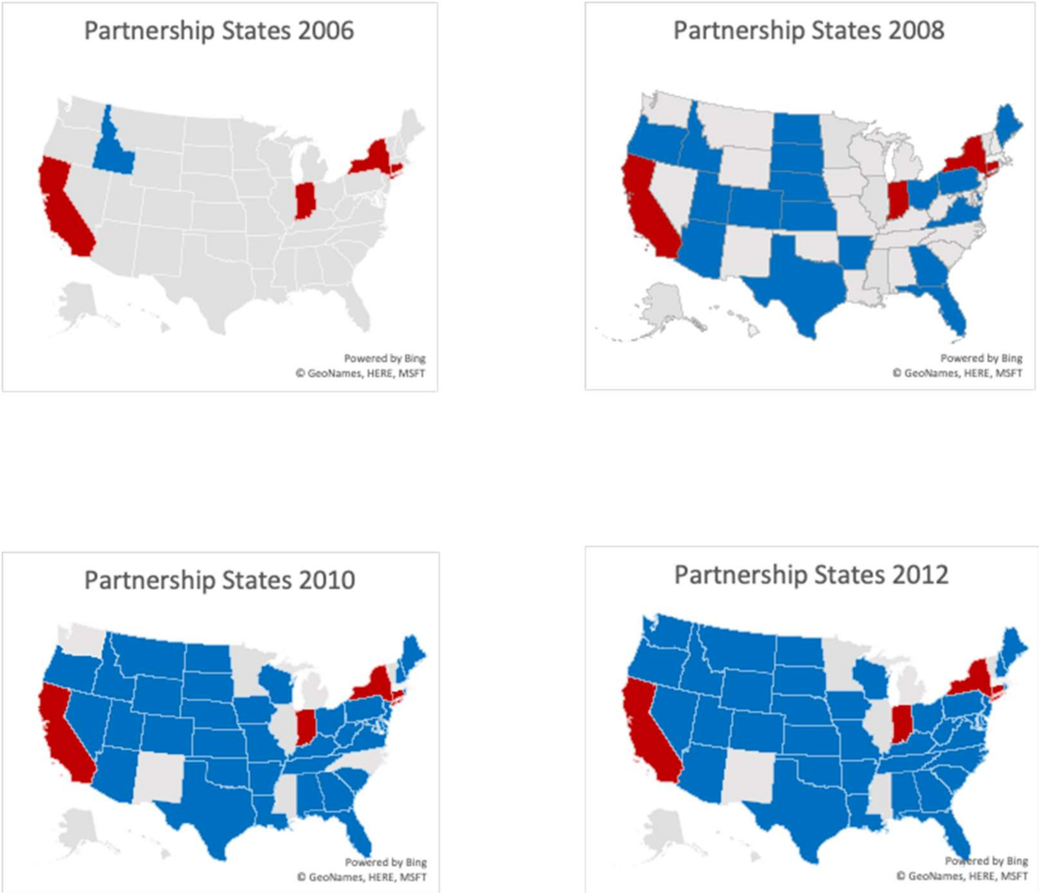
***5.3.3. The Long-Term Care Insurance Partnership (LTCIP) Program***. The LTCIP program is an intervention designed to incentivise LTCI coverage through an insurance design that entails a collaboration between state and private insurers (Robert Wood Johnson Foundation (RWJF) 2007), and it targets middle income individuals who fail to purchase LTCI as well as do not qualify for Medicaid. The LTCIP program was first promoted by the Robert Wood Johnson Foundation (RWJF) in 1987. Initially, only four states—commonly known as RWJF states—adopted the partnership program: California (1994), Connecticut (1992), Indiana (1993), and New York (1993) (Alper 2006; "The Federal Long-Term Care Insurance Program" 2018), given the constraints (moratorium) in federal legislation. In this paper, we call these four states 'permanent partnership states' and include them separately in our analysis.

We exploit the effect of the lifting of the moratorium in 2006, as part of the federal Deficit Reduction Act of 2005 (DRA 2005). The LTCIP program allows policyholders not to account for their long-term care expenses—usually equivalent to individual LTCIP coverage amount—in the Medicaid eligibility criteria (the model is also known as the 'dollar-for-dollar')[16]. For example, an insurance policy for a 65-year-old individual, with a median wealth of $144,000, provides a daily benefit of $100 per day for two years, thus an individual can protect an asset worth of $73,000 (= 365 x 100 x 2) (Brown and Finkelstein 2011). Therefore, she needs to spend down remaining assets worth of $69,000 (= $144,000 - $73,000 - $2000) to become eligible for Medicaid financed care. The LTCIP nevertheless offers an incentive to protect individuals' assets as well as reduce future Medicaid spending by stimulating the purchase of private LTCI (Rothstein 2007; Bergquist et al 2018). It is important to note that a resident of a state, who already holds a LTCI-policy when state adopts LTCIP program, can exchange existing LTCI-policy for LTCIP-policy under the guidelines suggested by DRA 2005[17]. Given the advantage of securing wealth under the LTCIP, this provision of DRA2005 makes it more likely for a policyholder to hold LTCI policy that she may not have had prior to LTCIP being implemented. Figure 5.1 depicts the adoption of LTCIP across U.S. states in a given year. Since 2006, there has been a proliferation of states that have progressively adopted the same LTCIP design that is standardised in its terms, and hence can be compared across different states.

**Figure 5.1 – The US states map representing the adoption of LTCIP in states over time. (Colour Codes: RED – Permanent partnership or RWJF states, BLUE – LTCIP states or new partnership states, GRAY-Remaining states).**

[16] Although the 'dollar-for-dollar' model was initiated by California, Connecticut, and Indiana and later embraced by New York in 2006 (Meiners, McKay, and Mahoney 2002; NYSPLTC 2011; Bergquist, Costa-Font, and Swartz 2018), all new partnerships developed after 2006 follow the 'dollar-for-dollar' model by default.

[17] DRA2005: "In the case of a long-term care insurance policy which is exchanged for another such policy, subclause (I) shall be applied based on the coverage of the first such policy that was exchanged." Subclause I - "The policy covers an insured who was a resident of such State when coverage first became effective under the policy." https://www.govinfo.gov/content/pkg/PLAW-109publ171/pdf/PLAW-109publ171.pdf




Note: State-wise information on the adoption of LTCIP is obtained from American Association of Long-Term Care Insurance website, which comes under U.S. Government Accountability Office's Consumer Information Center. Refer Appendix for more details.

***5.3.4. Interaction of LTCIP Program and Medicaid****:* An important feature of Long-term care partnership (LTCIP) is the dollar-for-dollar asset protection it offers to the insurance purchasers. In the absence of the LTCIP, the typical individual would either have to spend down their assets to become eligible for the Medicaid or purchase private-LTCI to fund their long-term care needs. Meiners (2009) refers such individuals in the middle of the income and assets range as Middle-Middle (MM) resource group – individuals with considerable savings and monthly income that can ensure a comfortable life in the absence of long-term care needs. This MM group can further be divided into two subgroups, MM group with fewer resources and MM group with greater resources (Meiners 2009). Thus, targeting such groups, especially the MM-group with fewer resources, can be cost-effective for LTCIP program and can result in Medicaid savings.

As per the Government Accountability Office report, the MM group constitutes of individuals with monthly income in the range of $1000 - $5000 and total assets between $100,000 and $350,000 (GAO 2007). Medicaid savings can be generated if individuals over-over-insure their assets using LTCIP compared to when individuals self-insure themselves[18]. The middle income (MM) group with greater resources can over-insure the average risk but under insure assets because they will buy more care through insurance than required as they will be willing to sacrifice little now to cover high care costs in the future. But it is difficult for the MM group with fewer resources to buy enough coverage, due to unaffordability, to insure the average risk and in the event of needing LTC they are more likely to spend down their assets to become eligible for Medicaid. However, in the presence of dollar-for-dollar asset protection under LTCIP, the MM group with fewer resources are most likely to fund their care through insurance instead of using their assets. While it insures the average risk, it becomes more likely for them to purchase a coverage amount greater than required to protect their assets (Meiners 2009). This additional coverage perhaps has a direct impact on the Medicaid costs; it leads to savings in Medicaid and reduce the fiscal burden on the government. Let 'X' be the additional coverage purchased by an individual, then Equation (1) indicates the marginal value of public funds (MVPF) (Hendren 2013; Finkelstein and Hendren 2020; Hendren and Sprung-Keyser 2020) when MM group individual with fewer resources over insuring the assets. Where A, C, & P indicate the protected assets, insurance coverage, and premium in $ respectively; for denominator, let M and t indicate Medicaid costs and tax on earnings, in $ amount.

[18] Assuming that a rational individual insures against the average risk of needing long-term care, then, in the presence of LTCIP, MM-group individuals with fewer resources are more likely to under-insure their average risk but over insure their assets. However, MM-group individuals with greater resources are more likely to over insure their risks but under insure their assets (Meiners 2009). We also perform welfare analysis using MVPF approach suggested by Hendren and Sprung-Keyser (2020) that can be found in the Appendix: Section III.

$$MVPF = \frac{A + C - P}{(M \pm t - X)} \qquad (1)$$

These negative costs to the government (or Medicaid savings) also signify that the government spending pays for itself and MVPF is defined as infinite (Hendren and Sprung-Keyser 2020). Overall, the LTCIP can positively impact the welfare of an MM groups and at the same time can potentially reduce the costs to the government for providing Medicaid.

***5.3.5. Data***. We use a large-scale longitudinal dataset from the Health and Retirement Study (HRS). The HRS is a panel study sponsored by the National Institute of Aging (NIH). It is a biennial survey that began interviewing respondents and their spouses from 1992 onward. The first wave of HRS collected information from individuals aged 50 and above (mainly aged 51-61 and born between 1931-1941) when the sample was first collected in 1992 (National Institute on Aging and The Social Security Administration 2018). The HRS contains the oldest cohort, i.e. people born before 1923, named as Asset and Health Dynamics among the Oldest Old (AHEAD). Starting in 1993, the AHEAD sample was collected every alternate year until 1998 when it was merged with other samples. Subsequently, two additional sample cohorts were added, namely the War Baby (WB - Individuals born between 1942 and 1947) and the Children of Depression Age (CODA - Individuals born between 1924 and 1930) cohorts.

The HRS provides extensive information on various components of the elderly life, including information on household characteristics, income including pension income, employment and retirement records, education attainment, financial wealth, insurance coverage, alongside several health and disability records. We draw on restricted HRS data from 1992 through 2016, which allow to identify state information to locate the state residence for all sampled individuals. However, we remove the first two waves (1992 and 1994) from our main sample due to the vagueness in the questions' wording. Thus, the final sample consists of data from 1996 through 2016 which has 148,972 observations and 32,182 sample individuals.

Next, we have matched the final sample with the policy data referring to the LTCIP implementation for each of the states at time t. That is, information about a specific state's adoption of a LTCIP in a given time t. Hence, the policy variable equals 1 if an individual resides in a state that implemented a LTCIP program, otherwise it equals 0. This allows comparing the bulk of LTCIP to other states, locating the counterfactual, and identifying the shift in the purchase of private LTCI. However, all the reported estimates are calculated after including both North Carolina and Washington into the group of new-partnership states[19].

### 5.4. Empirical Strategy

***5.4.1. Difference-in-Differences***. Next, we use the generalized Difference-in-Differences (DiD) design to compare the changes in the average likelihood of LTCI uptake in New-Partnership states to that of non-Partnership states. Equation 2 represents our fully specified model for difference-in-differences, which is also a two-way fixed effects estimator. The recent literature in this regard observe that we know relatively less about the two-way fixed effect when treatment varies across different time periods for various groups (Borusyak and Jaravel 2017; Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfoeuille 2019; Abraham and Sun 2020; Goodman-Bacon 2021). As per Goodman-Bacon (2021), the two-way fixed effects method is a weighted average of all the existing 2x2DD estimators. Subsequently, we estimate the techniques suggested by Goodman-Bacon (2021) as well as (Callaway and Sant'Anna 2021) and report the estimates in the result section. However, the approach suggested by (Goodman-Bacon 2021) has few limitations when it comes to our data sample. Firstly, Goodman-Bacon (2021) DD decomposition approach needs a strongly balanced panel. Our sample consists of information on LTCI and Medicaid uptake over the period from 1996

[19] We include the state of North Carolina and Washington into the non-partnership member states only for the purpose of plotting graphs, because both introduced LTCIP only after 2011.

through 2016. It is an unbalanced panel data. We attempt to obtain a strongly balanced panel for stated approach but lose significant number (about 85%) of observations. Approximately, 11-12% of the sample respondents hold each of LTCI or Medicaid. Thus, obtaining a strongly balanced panel comes at a cost of scarce information and statistical power. Secondly, the bulk of our treatment (appx 34/37 of LTCIP) occurs in the year 2008 and 2010, only a wave apart. As the treatment timings almost coincide, therefore, we only obtain a proper comparison for '*Early Group (2008) vs. Late Group (2012)'* as suggested by Goodman-Bacon (2021). Hence, we continue to use two-way fixed effects DiD model for several group-time combinations as suggested by (Callaway and Sant'Anna 2021; Goodman-Bacon 2021). We also compare changes in the average uptake of Medicaid in New-Partnership states to comparable changes in average uptake of Medicaid in Non-Partnership states. The DiD estimation approach is one of the most widely used identification strategies in empirical economics (Angrist and Krueger 1999; Athey and Imbens 2006; Bertrand, Duflo, and Mullainathan 2004; Ai and Norton 2003; Puhani 2012). The DiD approach is also quite flexible and has a control group in the post period to compare which event study design does not have. Wooldridge (2021) establishes the flexibility of DiD approach, equivalence between the two-way fixed effects (TWFE) approach and two-way Mundlak (TWM) regression approach, when the treatment is a staggered rollout and has heterogenous treatment effects across time periods.

We disentangle the effect of partnership states from that of non-partnership states. However, among partnership states, we further form two groups, namely the Permanent Partnership states (or RWJF states) and New Partnership states (or DRA 2005 states), in order to spell out the effect of new partnerships. The data consists of information on LTCI and Medicaid uptake over the period from 1996 through 2016. New-Partnership states began participating only after 2005. We employ a linear probability model, and non -liner models in the robustness checks. An advantage of this approach is that the interpretation of the interaction terms is straightforward (Ai and Norton 2003; Athey and Imbens 2006; Puhani 2012). Our generalized difference-in-differences specification is as follows:

$$Y_{ist} = \beta_0 + \beta_1 LTCIP_{ist} + \beta_2 PP_{ist} + \rho X_{ist} + \theta_s + \sigma_t + \eta_i + \epsilon_{ist} \qquad (2)$$

Where $Y_{ist}$ is either private LTCI or Medicaid for an individual ($i$) in state ($s$) at time ($t$). Based on a year in which a state adopts a LTCIP program, we categorize states into New-Partnership states, Permanent-Partnership (PP) states, and non-Partnership states. In the above model, coefficients $\beta_1$ estimate the effect of New Partnerships in addition to the effect ($\beta_2$) of Permanent-Partnership (PP), and the effects of set of controls (X), respectively. The regression estimates control for additional state specific fixed effects ($\theta_s$) which eliminate time-invariant differences among various states and wave-year fixed effects ($\sigma_t$) to flexibly account for variation across time. This allows us to compare people living in different states as they differ in terms of socio-politico-economic characteristics. In addition, the regression model includes time-invariant individual specific characteristics ($\eta_i$) which can potentially be correlated with the error term ($\epsilon_{ist}$) and therefore a source of endogeneity. Such time-invariant individual heterogeneity can be removed using a Fixed Effects Model.

### 5.5. Results

***5.5.1. Descriptive Evidence***. Figure 5.2.a depicts the trends in the proportion of individuals that have private LTCI in New-Partnerships states, non-Partnership states and the states that participated in the Robert Wood Johnson initiative. Importantly, the figure displays evidence suggesting that the introduction and subsequent rollout of LTCIP programs increased the uptake of private LTCI compared with other states, given that the trends were comparable between the two groups in the pre-partnership period. In contrast, Permanent-Partnership and

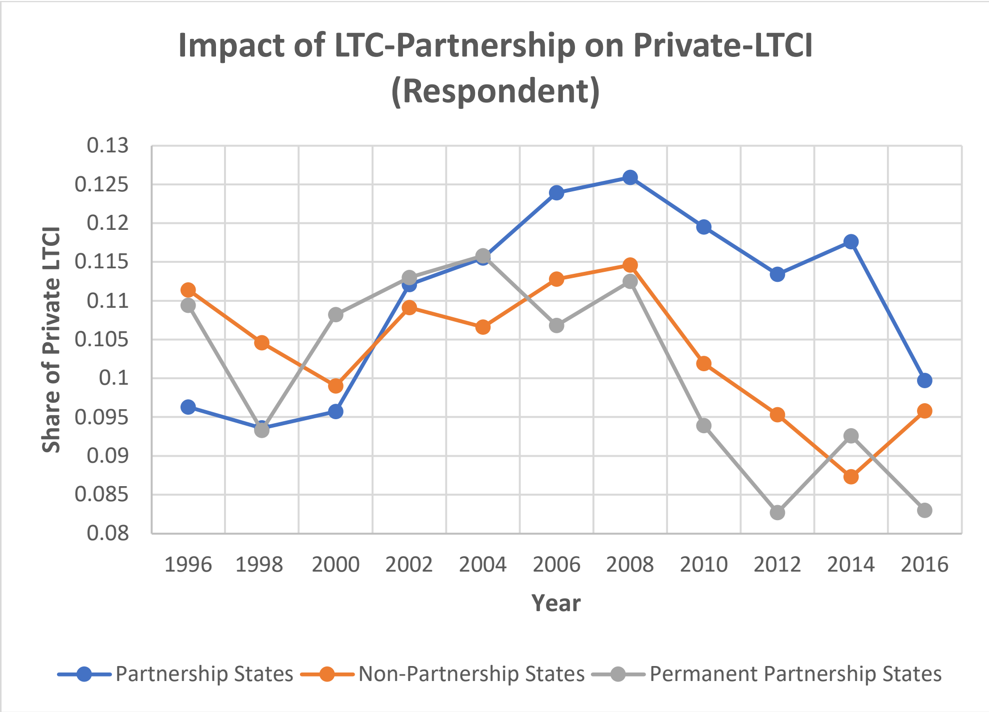
Non-Partnership states exhibit lower trends of insurance uptake share, suggesting an average insurance uptake gap of 1 to 2%.

Figure 5.2.a reports the trends in having private-LTCI over time for new-partnership states, permanent partnership states (PP), and non-partnership states. We observe steep decline in the coverage of private-LTCI after 2008 in case of permanent partnership and non-partnership states, whereas lower decline was observed in case of new-partnership states. The decrease in the coverage of private-LTCI observed after 2008 was resulted because of several factors including massive drop in individual market sales of policies after 2002. Figure A5.11 of the Appendix shows that the sales of insurance policies continued to decline after 2002 through 2014. Ameriks et al. (2016) reports that there was a rapid decline in the number of insurance providers in the market between 2002 and 2014 with many providers exiting market due to lack of sale of such policies. The introduction of LTCIP came at the time, when sales of such policies were declining, to encourage potential purchasers to buy insurance. As can be seen from the trends (Figure 5.2.a) that the decline was comparatively lower for new-partnership states. Therefore, it becomes important to investigate if the LTCIP policy had impact on the purchase of private-LTCIP. The difference-in-differences (DiD) approach is the most feasible approach to quantify the effect of LTCIP policy to understand whether the LTCIP was instrumental in subsiding the decline that was occurring during the time when the entire market was facing declining of sales in private-LTCI policies. The DiD allows us to have a control group which was similar to treatment group, in terms of declining insurance sales, in the absence of LTCIP. Thus, DiD approach allows us to compare treatment and control groups both before after the LTCIP reform.

Figure 5.2.b reports the trends of Medicaid uptake over time among what we define as the new-Partnership, the so-called permanent-Partnerships (PP), and the non-Partnership states. The figure suggests gradual shift in Medicaid uptake trend, though Medicaid uptake is

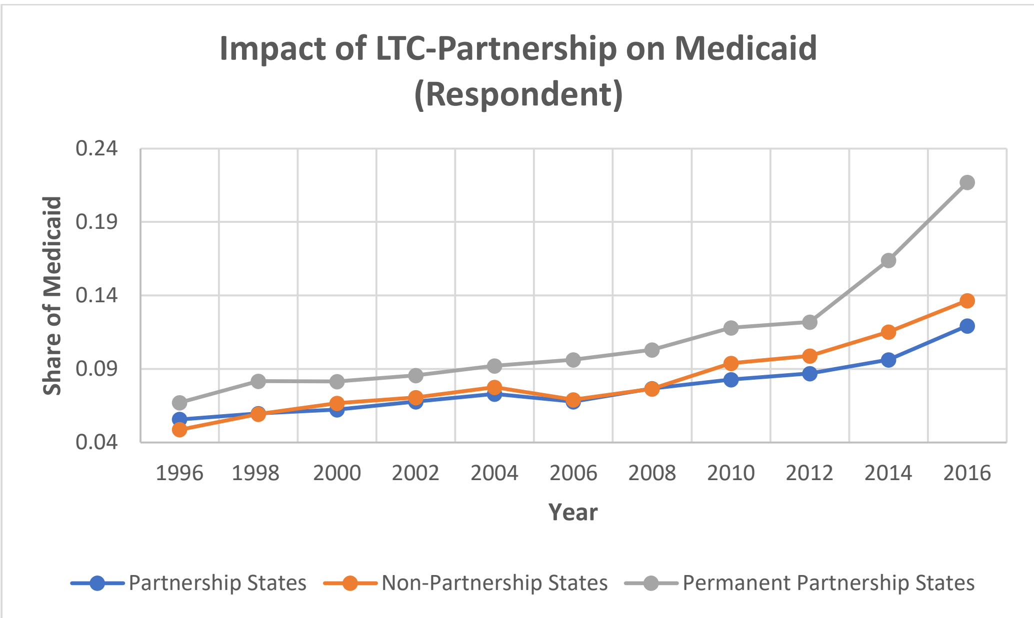
generally lower after the implementation of a LTCIP. In contrast, permanent-Partnership states exhibit a steeper rise in Medicaid expenditure throughout the entire sample period.

**Figure 5.2.(a). Effect of LTCIP on private LTCI**




Note : Trends in the percentage of long-term care insurance coverage of new-partnerships (NewPP_states), permanent partnerships, and non-partnership (NP_states) using Health and Retirement Study, Wave 3-13, 1996-2016. Each point indicates the average of private-LTCI coverage across three categories of states.

**Figure 5.2.(b). Impact of LTCIP on Medicaid Uptake**



Note: Trends in the percentage of Medicaid coverage of new-partnerships states, permanent partnerships states, and non-partnership states using Health and Retirement Study, Wave 3-13, 1996-2016. Each point indicates the average of Medicaid uptake across three categories of states.

Table 5.1 displays the descriptive statistics (means and standard deviations) of individuals that have private LTCI and Medicaid, respectively. LTCI purchasers have higher income and wealth, on an average, compared to the sample population, whereas LTCI purchasers from partnership states are slightly poor when compared with LTCI-purchasers in general. We report that LTCI coverage holders are healthy compared to the average population indicating the insurance underwriting in the market for private-LTCI. However, exactly opposite can be observed in case of Medicaid uptake, which is obvious given that it is meant for the poorest of the individuals.[20]

In Table 5.2, we compare the characteristics of the sample for private-LTCI uptake and Medicaid entitlements across the state categories viz. New-partnerships, Permanent-partnerships, and non-partnerships states. On average, the proportion of people having private-LTCI coverage is greater for New-partnership states, across all the socio-economic characteristics, compared to the remaining states. Similarly, we report that the proportion of people enrolled in Medicaid program is lower for New-partnership states across majority of socio-economic characteristics.

**Table 5.1: Summary Statistics of Individual Level Characteristics**

| | **Private-LTCI** | | | | **Medicaid (or Public-LTCI)** | | | |
|---|---|---|---|---|---|---|---|---|
| | **NO** | | **YES** | | **NO** | | **YES** | |
| | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** |
| **New-Partnerships** | 0.2795 | 0.449 | 0.3 | 0.46 | 0.278 | 0.448 | 0.308 | 0.462 |
| **RWJF-Partnerships** | 0.195 | 0.4 | 0.18 | 0.384 | 0.187 | 0.391 | 0.26 | 0.439 |
| **Income** | 64793 | 197352 | 96147 | 200502 | 73144 | 227184 | 17438 | 25701 |
| **Wealth** | 377746 | 1E+06 | 736146 | 2E+06 | 431003 | 1335141 | 45526 | 287864 |

[20] Appendix-Table I: It compares the sample means to that of insurance takers' means.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Age** | 62.68 | 6.9216 | 64.28 | 6.88 | 62.8 | 6.93 | 63.11 | 7 |
| **Male** | 0.433 | 0.4955 | 0.416 | 0.493 | 0.44 | 0.496 | 0.34 | 0.474 |
| **Married** | 0.649 | 0.477 | 0.728 | 0.445 | 0.691 | 0.462 | 0.315 | 0.46 |
| **College/More** | 0.428 | 0.495 | 0.61 | 0.49 | 0.471 | 0.5 | 0.203 | 0.403 |
| **Children** | 0.93 | 0.253 | 0.92 | 0.272 | 0.933 | 0.25 | 0.903 | 0.3 |
| **White** | 0.745 | 0.436 | 0.83 | 0.38 | 0.78 | 0.415 | 0.496 | 0.5 |
| **Retired** | 0.543 | 0.498 | 0.62 | 0.485 | 0.532 | 0.5 | 0.777 | 0.416 |
| **Fair/Poor Health** | 0.286 | 0.45 | 0.167 | 0.3733 | 0.238 | 0.426 | 0.638 | 0.48 |

Note: This table provides description of important variables using Health and Retirement Study, Waves 3-13, year 1996-2016. All observations are weighted using survey weights at person level. The present sample is restricted to age 50-75. 'Partnership' variable equals 1 if an individual living in a state that had LTCIP available at a given time t post DRA-2005, else equals 0. RWJF States mean Permanent Partnership states, equals 1 if New York, California, Indiana, Connecticut.

## Table 5.2: Coverage of Private Long-Term Care Insurance and Medicaid

| | | **LTCI Coverage** | | | | **Medicaid Coverage** | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Partnership States** | **RWJF States** | **Non-Partnership States** | **N** | **Partnership States** | **RWJF States** | **Non-Partnership States** | **No. of obs** |
| All | | **11.09** | **9.96** | **9.73** | **148972** | **7.81** | **11.56** | 8.29 | 148423 |
| Gender | Female | 11.43 | 10.18 | 10.03 | 84552 | 9.09 | 13.26 | 9.52 | 84232 |
| | Male | 10.64 | 9.8 | 9.33 | 64420 | 6.12 | 9.155 | 6.67 | 65687 |
| Age | 50-62 | 8.91 | 8.4 | 8.04 | 74919 | 7.26 | 11.62 | 8.58 | 74710 |
| | 63-75 | 13.2 | 11.87 | 11.48 | 74053 | 8.36 | 11.14 | 8.00 | 73713 |
| | | | | | | | | | |
| Education | HS or less | 7.73 | 6.94 | 7.25 | 81815 | 11.42 | 16.68 | 11.35 | 81392 |
| | Some/More degree | 15.27 | 13.35 | 12.83 | 67157 | 3.3 | 5.58 | 4.45 | 67031 |
| | | | | | | | | | |
| Marital Status | Unmarried | 8.57 | 8.23 | 8.24 | 51063 | 16.07 | 21.00 | 17.05 | 50733 |
| | Married | 12.39 | 10.97 | 10.49 | 97909 | 3.57 | 6.2 | 3.8 | 97690 |
| | | | | | | | | | |
| Retirement Status | Working | 9.63 | 9 | 8.95 | 59004 | 2.67 | 6.9 | 3.75 | 59961 |
| | Retired | 13.11 | 11.64 | 11 | 70827 | 9.92 | 13.68 | 10.31 | 71580 |
| | | | | | | | | | |
| Children | No | 12.69 | 11.8 | 12.43 | 10208 | 10.6 | 15.36 | 13.44 | 10144 |
| | YES | 11.03 | 9.85 | 9.54 | 136552 | 7.54 | 11.2 | 7.76 | 136083 |
| | | | | | | | | | |
| Race | Other | 7.33 | 7.41 | 7.94 | 36866 | 15.9 | 22.17 | 17.6 | 36587 |
| | White | 12.23 | 11.03 | 10.4 | 112106 | 5.36 | 7.15 | 4.84 | 111836 |
| | | | | | | | | | |
| Income | Low | 5.97 | 5.49 | 5.72 | 55047 | 18.4 | 27.6 | 20.21 | 54623 |
| | Medium | 11.83 | 9.36 | 10.55 | 40978 | 2.4 | 4.31 | 2.53 | 41820 |
| | High | 16.01 | 14.69 | 13.16 | 52947 | 0.78 | 1.14 | 1.23 | 52893 |
| | | | | | | | | | |
| Wealth | Low (<$144k) | 5.98 | 5.64 | 6.38 | 74036 | 14.2 | 22.32 | 16.00 | 73600 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Medium($144k-$523k) | 13.28 | 10.16 | 9.6 | 44708 | 1.41 | 3.09 | 1.71 | 44625 |
| | High (>$523k) | 21.42 | 18.15 | 17.88 | 30228 | 0.49 | 1.14 | 0.45 | 30198 |

Note: This table provides comparison of averages across types of states for both the outcomes using Health and Retirement Study, Waves 3-13, year 1996-2016. All observations are weighted using survey weights at person level.

***5.5.2. Baseline Estimates**.* The reported trends do not control for time varying state-level characteristics, alongside individual compositional differences. Next, we estimate equation (2), namely a Difference-in-Differences (DiD) design used to identify the effect of LTCIP on private coverage and Medicaid uptake. Table 5.3 reports the estimates of the impact of LTCIP on LTCI with no controls and no state and year fixed effects. Column (2) includes state and year fixed effects, whereas Column (3) indicates the fully specified regression model with full controls and year and state fixed effects. Column (3) reports an effect of 1.64 percentage points, which on average entails a 18% increase in the likelihood of LTCI coverage. The standardised estimates suggest that one standard deviation change in LTCIP is associated with increase of 2.5% in standard deviation of LTCI, *ceteris paribus* (Ref. Appendix Table A5.4). Column (4) displays a fully specified model with individual fixed effects, which account for time unvarying individuals' unobservables. Individual fixed effects models suggest the effect of within-individual uptake of LTCI varies after the implementation of the LTCIP and, estimates indicate a 1 percentage point (11% increase w r t mean) increase in the likelihood of LTCI coverage. Although a DiD specification should not provide a significantly different result when individual fixed effects are included, we prefer the Fixed Effects Model when the decision is made on a yearly basis. That is, Column (3) and Column (7) estimates when the decision is not affected by the year of its occurrence.

Similarly, Column (5) from Table 5.3 reports the impact of LTCIP on the uptake of Medicaid in the absence of any controls, state & year effects, and person specific fixed effects. Column (6) includes state and year fixed effects, whereas Column (7) from Table 5.3 is the fully specified model for Medicaid and reveals that the adoption of a LTCIP program reduced the likelihood of Medicaid uptake by approximately 1.5 percentage points, which is equivalent to a 13.5% decrease in the likelihood of Medicaid uptake at the 9% pre-partnership Medicaid coverage rate. Estimates are precisely estimated. Column (8) from Table 5.3 reports the fully specified model with individual fixed effects, but these estimates were less precise, and hence are not statistically significant.

**Table 5.3: Baseline Results – impact of LTCIP on private LTCI and Medicaid**

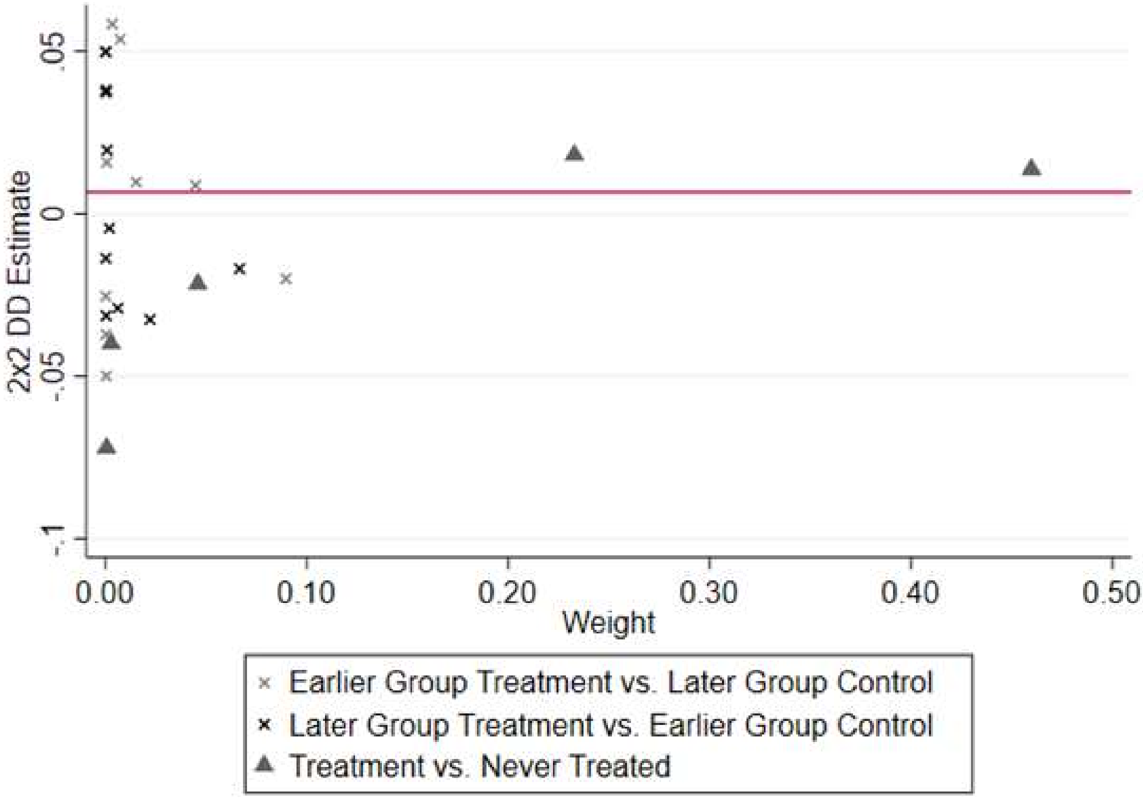
| | Dependent Variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Private-LTCI | | | | Medicaid (or Public-LTCI) | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | | | | | | | | |
| **Partnership** | 0.0144*** | 0.02*** | 0.0164*** | 0.01*** | 0.0107*** | -0.016*** | -0.0147*** | -0.0029 |
| | (0.00349) | (0.00467) | (0.00462) | (0.00371) | (0.00253) | (0.00393) | (0.00363) | (0.00296) |
| | | | | | | | | |
| **State + Year Fixed Effects** | NO | YES | YES | YES | NO | YES | YES | YES |
| **Control Variables** | NO | NO | YES | YES | NO | NO | YES | YES |
| **Individual Fixed Effects** | NO | NO | NO | YES | NO | NO | NO | YES |
| **Number of Obs.** | 148,972 | 148,972 | 148,972 | 148,972 | 148,472 | 148,472 | 148,472 | 148,423 |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates of equation (2). There are two dependent variables namely Private long-term care insurance (LTCI) and public long-term care insurance or Medicaid. The variable 'Partnership' is a treatment variable, which is a binary indicator for whether there is LTCIP available in the state and year after the passage of Deficit Reduction Act (DRA-2005). It is also called as 'New-Partnership' or 'LTCIP'. At first, we estimate the impact of LTCIP on Private-LTCI in which Column (1) includes no variables other than treatment or partnership. Column (2) introduces states and years fixed effects into the model. Column (3) adds control variables namely age, gender, age^2, income, health status, marital status, race, and education. Column (4) introduces Fixed Effect Model that removes time-constant characteristics. Whereas, Columns (5)-(8) follow the similar procedure for Medicaid uptake.

Additionally, as we are dealing with variation in treatment timings, the two-way fixed effects estimator is a weighted average of several group-time treatments (Goodman-Bacon 2021). We run (Goodman-Bacon 2021) decomposition technique and obtain the distribution of weights for various comparison groups (or 2x2 DDs). Figure 5.3 displays the graphical representation of decomposition of the effects of LTCIP on private-LTCI. The red line indicates the weighted average of LTCIP effect on private-LTCI and it comes to be approximately 1%. Two major groups appear to be acquiring almost 75% of weights compared to other groups.

**Figure 5.3 Graphical Decomposition of LTCIP effects on Private-LTCI**




Next, Table 5.4 reports treatment effect measures for various treatment comparisons as suggested by (Callaway and Sant'Anna 2021). Panel A of Table 5.4 reports the estimates of the impact of LTCIP on private-LTCI and Medicaid comparing various treatment groups to that of never treated group. This comparison shows how the effect of introducing LTCIP changes by the amount of time LTCIP was in place for a specific group of treatment states. We find that LTCIP improves the uptake of private-LTCI for all the treatment groups, but the estimates are statistically significant only for Group2008 and Group2010 as most states are covered under these two groups. Similarly, LTCIP is found to reduce Medicaid entitlements for all the treatment groups. The parameters in Panel A reflect the similar trends to that of group-time event study average treatment effects shown in Figure A5.6 and Figure A5.7. The effect of LTCIP on private-LTCI (Medicaid) appears to be positively increasing in the magnitude in the beginning but the effect appears to be slightly fading in later years. However, the effect on Medicaid continues to grow in magnitude the longer states are exposed to LTCIP. Additionally, Panel B compares the treatment groups with not-yet treated groups, whereas Panel C show the estimates of early (control) vs late (treatment) groups comparison. We find mixed results in Panel A and B, but they are not statistically significant.

**Table 5.4: Group-Time Effects – Impact of LTCIP on private-LTCI and Medicaid**

| **Panel A** | **Panel A: Treated Vs Never Treated** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | **Private-LTCI** | | | | **Medicaid** | | | |
| | **Gp2006** | **Gp2008** | **Gp2010** | **Gp2012** | **Gp2006** | **Gp2008** | **Gp2010** | **Gp2012** |
| ***Partnership*** | 0.0213<br>(0.0161) | 0.0193***<br>(0.006) | 0.0228***<br>(0.0071) | 0.008<br>(0.0132) | -0.0251<br>(0.0264) | -0.0153***<br>(0.0045) | -0.0161***<br>(0.006) | -0.035***<br>(0.009) |
| State & Year FE + Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| N | 48,875 | 109,773 | 80,982 | 55,700 | 48,714 | 109,411 | 80,711 | 55,511 |
| | | | | | | | | |
| | | | | | | | | |
| **Panel B** | **Panel B: Treated Vs Not Yet Treated** | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | **Private-LTCI** | | | | **Medicaid** | | | |
| | **Gp2006** | **Gp2008** | **Gp2010** | **Gp2012** | **Gp2006** | **Gp2008** | **Gp2010** | **Gp2012** |
| ***Partnership*** | -0.0095<br>(0.0146) | -0.002<br>(0.0077) | 0.0021<br>(0.007) | -- | 0.125<br>(0.126) | -0.0044<br>(0.005) | -0.003<br>(0.005) | -- |
| State & Year FE + Controls | YES | YES | YES | -- | YES | YES | YES | -- |
| N | 54,259 | 62,435 | 72,699 | -- | 54,159 | 62,310 | 72,530 | -- |
| | | | | | | | | |
| | | | | | | | | |
| **Panel C** | **Panel C: Early Treated (Control) Late Vs Treated (Treatment)** | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | **Private-LTCI** | | | | **Medicaid** | | | |
| | **Gp_2006** | **Gp2008_Vs_10** | **Gp2008_Vs_12** | **Gp2010_Vs_12** | **Gp_2006** | **Gp2008_Vs_10** | **Gp2008_Vs_12** | **Gp2010_Vs_12** |
| ***Partnership*** | -- | -0.005<br>(0.009) | 0.0049<br>(0.0132) | -0.006<br>(0.0145) | -- | -0.0037<br>(0.007) | -0.0104<br>(0.009) | -0.0109<br>(0.01) |
| State & Year FE + Controls | -- | YES | YES | YES | -- | YES | YES | YES |
| N | -- | 42,464 | 31,432 | 14,547 | -- | 42,248 | 31,274 | 14,454 |
| | | | | | | | | |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates of equation (2). There are two dependent variables namely Private long-term care insurance (LTCI) and public long-term care insurance or Medicaid. The variable 'Partnership' is a treatment variable, which is a binary indicator for whether there is LTCIP available in the state and year after the passage of Deficit Reduction Act (DRA-2005). It is also called as 'New-Partnership' or 'LTCIP'. Panel A represents group-time estimates of the impact of LTCIP on Private-LTCI and Medicaid for Treated groups Vs Never Treated Groups. Panel B represents group-time estimates of the impact of LTCIP on Private-LTCI and Medicaid for Treated groups Vs Not-Yet Treated Groups. Panel C represents group-time estimates of the impact of LTCIP on Private-LTCI and Medicaid for Early Treated (Control) Vs Late Treated (Treatment) Groups. Column (4) introduces Fixed Effect Model that removes time-constant characteristics. All models are inclusive of state as well as year fixed effects and control variables, namely age, gender, age^2, income, health status, marital status, race, and education.

***5.5.3. Cumulative Effects***. The effect of LTCIP kicks-in gradually as the program is disseminated among new beneficiaries. This explains why earlier studies showed no evidence of an effect (Bergquist et al. 2018; Lin and Prince 2013). Our estimates differ significantly from those of earlier studies because of two main reasons. Firstly, as discussed in Brown and Finkelstein (2011), the LTCIP tackles one of the two sources of Medicaid implicit tax by delaying the process of qualifying for Medicaid through the inclusion of private insurance coverage towards the means-tested eligibility for Medicaid. Although not entirely, this helps in reducing Medicaid's implicit tax on private insurance and thus increases the demand of private-LTCI to some extent which is also evidenced by our estimates. It must be noted that LTCIP does not change the status of Medicaid as a secondary payer, which is another source of Medicaid implicit tax (Brown and Finkelstein 2011). Secondly, the existence of a lag between the time when a policy is purchased and when people use their coverage, also mentioned by Bergquist et al. (2018), likely delays the uptake of Medicaid until further down the road which is also reflected by the event study plot in Figure A5.5. The effect on Medicaid picks up almost 2-3 years after the implementation of LTCIP. Overall, the evidence we provide suggests that the effect of LTCIP appears over time, and the effect is mostly driven by partnerships set up after 2010 which are not covered by previous studies. Table 5.5 shows the impact of LTCIP on private-LTCI and Medicaid uptake over the post-reform years.

**Table 5.5: Effect Over Time – impact of LTCIP on private LTCI and Medicaid**

| | Private LTCI | | Medicaid | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Partnership | -0.000172<br>(0.00615) | 0.00343<br>(0.00424) | -0.00198<br>(0.00428) | 0.00112<br>(0.0037) |
| Partnership*2010 | 0.0188**<br>(0.0076) | 0.00874<br>(0.00541) | 0.00151<br>(0.00544) | -0.000673<br>(0.00483) |
| Partnership*2012 | 0.0302***<br>(0.00844) | 0.0114*<br>(0.00596) | -0.00679<br>(0.00614) | 0.00236<br>(0.00544) |
| Partnership*2014 | 0.0243***<br>(0.00896) | 0.0119*<br>(0.00645) | -0.0209***<br>(0.00728) | -0.0165***<br>(0.00618) |
| Partnership*2016 | 0.00121<br>(0.00905) | 0.00323<br>(0.00703) | -0.0375***<br>(0.00793) | -0.0211***<br>(0.007) |
| **Controls & State + Year FE** | YES | YES | YES | YES |
| **Individual FE** | NO | YES | NO | YES |
| **Number of obs.** | 148,972 | 148,972 | 148,472 | 148,423 |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are drawn from the sample of Health and Retirement Study, Wave 3-13, 1996-2016. The outcomes are regressed on treatment and other covariates. Both outcome variables are binary variables. Treatment is interacted with four waves post-LTCIP to find the impact of policy over time. Column (1) and (3) include State and Year fixed effects and other covariates, whereas Column (2) and (4) add individual fixed effects and removes time-constant characteristics to obtain the estimated coefficients. Other covariates include age, gender, age^2, income, health status, marital status, race, and education.

***5.5.4. Effects on the Intensive Margin and OOP Expenses***. Next, we test the effect on the intensive margins and on the out-of-pocket medical expenses, which capture among others, the effect of generous insurance policy coverage after the LTCIP program has been introduced because the program allows individuals to secure their assets and meet the asset threshold for Medicaid eligibility, which in turn can be transferred as a bequest (and hence satisfy bequests motives). First, we examine the impact of LTCIP by estimating Equation (1) on the monthly premium of individual's private LTCI plan as a dependent variable, as well as distinguishing whether a purchased plan covers both nursing home care as well as home care. Table 5.6 summarizes the results in which Column (1) and (2) represent the estimated impact of LTCIP on the monthly premium of a private LTCI plan. Column (2) estimates are obtained using a fully specified model with individual fixed effects. LTCIP results in the monthly premium of private LTCI to go down by approximately $0.179, but these estimates are not statistically significant. Similarly, Column (3) and (4) indicate that LTCIP increases the likelihood of purchasing a plan with coverage of both nursing home care as well as home care by 1.4 percentage points (and by 0.7 percentage points without controlling for individual fixed effects). These results indicate that the LTCIP program impacted both intensive as well as extensive margins. The increase in private LTCI premiums after the adoption of LTCIP indicates that some individuals were motivated by the program to secure their assets.

**Table 5.6: Impact of LTCIP on Intensive Margins and Out-of-Pocket Medical Expenses**

| | **Intensive Margins** | | | | **OOP Med Expenses (Extensive Margins)** | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | LTCI Monthly Premium | | LTCI with Home & Nursing care | | OOP>$500 | | OOP>$1k | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | | | | | | | | |
| Partnership | 1.456 | -0.128 | 0.0143*** | 0.0063** | -0.015** | -0.028*** | -0.022*** | -0.03*** |
| | (1.284) | (1.556) | (0.00428) | (0.00341) | (0.007) | (0.006) | (0.007) | (0.006) |
| | | | | | | | | |
| State & Year FE + Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Individual FE | NO | YES | NO | YES | NO | YES | NO | YES |
| Number of obs. | 143,964 | 143,729 | 147,944 | 147,895 | 148,972 | 148,972 | 148,972 | 148,972 |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates for outcomes: Monthly Premium, type of insurance (or long-term care insurance for both nursing home and home care), out of pocket medical expenses above $500, and above $1k. Column (1), (3), (5), and (7) include State and Year fixed effects and other covariates, whereas Column (2), (4), (6), and (8) add individual fixed effects and removes time-constant characteristics to obtain the estimated coefficients. Other covariates include age, gender, age^2, income, health status, marital status, race, and education.

Second, we analyse the impact of LTCIP on extensive margins of out-of-pocket medical expenses viz. expenses above $500 and above $1k. Column (5), (6), (7), and (8) show that LTCIP is associated with decrease in the likelihood of out-of-pocket medical spending. This indicates that LTCIP increases the coverage of private-LTCI and has a negative cascading effect on out-of-pocket medical spending.

***5.5.5. Heterogeneity***. Table 5.7 shows that different sub-samples of the U.S. population differ in the level of pre-partnership private LTCI coverage. The adoption of LTCIP programs differs for different states, with some states adopting LTCIP immediately after the passage of Deficit Reduction Act (2005), whereas other participating states followed a few years later[21]. Thus, the limitation of data prevented previous researchers from identifying the variation in the responsiveness across various observable characteristics. The use of Health and Retirement Survey data provides an advantage to examine how outcomes vary across different sub-populations. Identifying the responsiveness across different factors can help determine both Medicaid eligibility as well as the savings in Medicaid expenditure. Therefore, we estimate the fully specified models to find how various outcomes respond to LTCIP across different observable characteristics such as education, wealth level, gender, retirement status, marital status, health status, and the number of children.

Table 5.7 displays the heterogenous impact of LTCIP on the likelihood of private LTCI coverage and Medicaid uptake across different socioeconomic characteristics. Similarly, Figures 5.3.a and 5.3.b report the effects on LTCI coverage and Medicaid entitlements. We find that LTCIP programs increased the uptake of private LTCI coverage among more affluent individuals, whereas a strong and significant effect can also be observed for individuals with upper-middle level of wealth. In contrast, lower middle-wealth individuals experienced a moderate but no significant increase in private LTCI coverage after the adoption of LTCIP, whereas low wealth individuals witnessed a slight decrease in private LTCI coverage after the reform.

**Table 5.7: Heterogeneity in effect of LTCIP on Private LTCI and Medicaid**

| | **Private LTCI** | | **Medicaid** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |

[21] Previous studies such as Bergquist et al (2018) used the data on insurance contracts provided by National Association of Insurance Commission (NAIC), which do not include individual-level information.

| State & Year FE + Controls | | YES | YES | YES | YES |
|---|---|---|---|---|---|
| Individual FE | | NO | YES | NO | YES |
| Health | Good/Best/Excellent | 0.0153*** | 0.0139*** | -0.0125*** | -0.0102*** |
| | Fair/Poor | 0.02*** | -0.002 ††† | -0.021*** | 0.017*** ††† |
| Gender | Female | 0.0157*** | 0.01*** | -0.0131*** | -0.00320 |
| | Male | 0.017*** | 0.009* | -0.0163*** | -0.0023 |
| Age | 50-62 | 0.01* | 0.0147*** | -0.01** | -0.00685* |
| | 63-75 | 0.0242*** ††† | 0.0077* | -0.02*** †† | -0.0014 |
| Year of Partnership | 2008 | 0.0171*** | 0.01*** | -0.0145*** | 0.00593** |
| | 2010 | 0.0154** | 0.0091** | -0.0148*** | -0.0166*** ††† |
| Education | High School/Less | 0.00824 | -0.00304 | -0.0139*** | 0.0129*** |
| | Some/More College | 0.0226*** †† | 0.0240*** ††† | -0.013*** | -0.02*** ††† |
| Income | Low (< $30K) | 0.013** | -0.0052 | 0.002 | 0.029*** |
| | Middle ( $30K-$60K) | 0.006 | 0.00075 | -0.0146*** †† | -0.0136*** ††† |
| | High (> $60K) | 0.02*** | 0.03*** ††† | -0.0179*** ††† | -0.025*** ††† |
| Wealth | Low (< $138.5K) | 0.0105** | -0.007* | -0.0148*** | 0.021*** |
| | LM ($144K-$421K) | 0.01 | 0.0006 † | -0.0167*** | -0.0162*** ††† |
| | UM ($421K-$981K) | 0.11 | 0.033*** ††† | -0.0118*** | -0.025*** ††† |
| | High (> $981K) | 0.05*** † | 0.044*** ††† | -0.0053 † | -0.029*** ††† |
| Retirement Status | Working | 0.00830 | 0.0127*** | -0.0157*** | -0.008** |
| | Retired | 0.0262*** †† | 0.0074** | -0.0136*** | 0.0009 ††† |
| Marital Status | Not Married | 0.0119* | 0.00134 | -0.0128** | 0.0157*** |
| | Married | 0.019*** | 0.0142*** ††† | -0.0156*** | -0.0135*** ††† |
| Have Children | NO | 0.0232 | 0.0358*** | -0.0282*** | 0.000891 |
| | YES | 0.0152 | 0.0078** ††† | -0.0132*** | -0.003 |
| Ethnicity | Non-White | 0.0115* | -0.0114** | -0.0204** | 0.0271*** |
| | White | 0.0174*** | 0.015*** ††† | -0.0134*** | -0.0107*** ††† |

*denotes significantly different from zero (* significant at 10%; ** significant at 5%; *** significant at 1%) ; + denotes that bottom category estimates are significantly different from top category ones (+ significant at 10%; ++ significant at 5%; +++ significant at 1%)

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates for outcomes private long-term care insurance and Medicaid. Both outcome variables are binary variables. Column (1) and (3) include State and Year fixed effects and other covariates, whereas Column (2) and (4) add individual fixed effects and removes time-constant characteristics to obtain the estimated coefficients. Other covariates include age, gender, age^2, income, health status, marital status, race, and education. Robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level. Each category on the left hand side of the table indicate a separate regression that includes interactions between subgroup indicators and treatment variable ( LTCIP or Partnership).

These results are in line with previous studies conducted by Bergquist et al (2018) and Lin and Prince (2014). Nonetheless, the most striking impact that was observed refers to

Medicaid uptake. Specifically, we observe a decrease in the uptake of Medicaid, with a significant decrease among middle-wealth and high-wealth individuals, and a substantial increase among low-wealth individuals. LTCIP affects high-income individuals more than their low- and middle-income counterparts. However, Medicaid uptake for high- and middle-income groups was significantly reduced after LTCIP compared to low-income groups. The effect of LTCIP on private LTCI coverage is larger among highly educated individuals compared to less-educated ones, whereas the reverse is observed in the case of Medicaid uptake in which highly educated individuals are less likely to take up Medicaid. It must be noted that the effect of education, income, and wealth cannot be fully identified because these characteristics are strongly correlated with each other.

**Figure 5.4(a): Heterogenous effect on private-LTCI by year of LTCIP adoption (2008 vs 2010)**

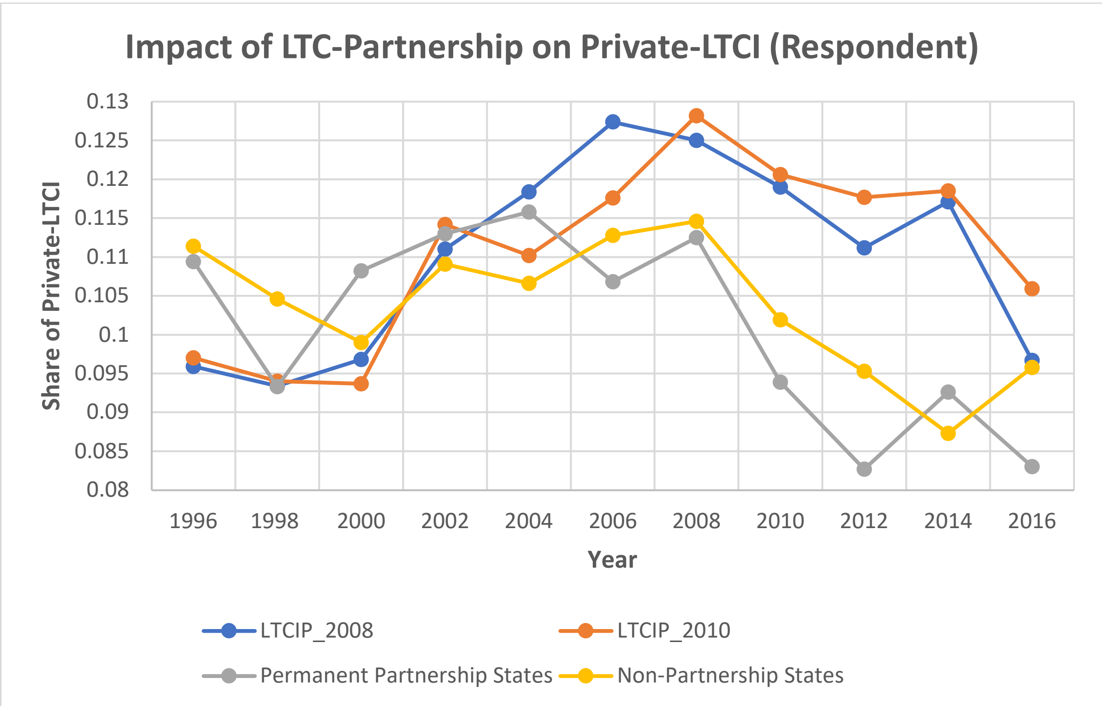
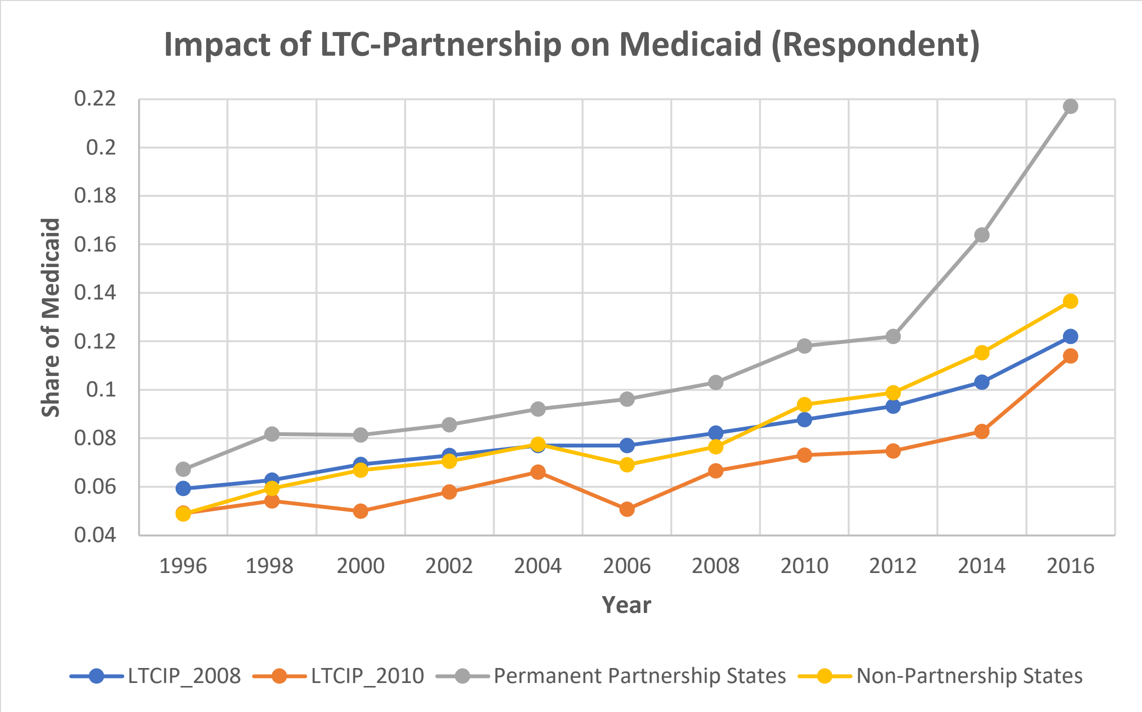



**Figure 5.4(b): Heterogenous effect on Medicaid by year of LTCIP adoption (2008 vs 2010)**




Note : Trends in the percentage of long-term care insurance coverage and Medicaid for partnerships states (2008 vs 2010), permanent partnership states, and non-partnership states using Health and Retirement Study, Wave 3-13, 1996-2016. Each point indicates the average of private-LTCI coverage and Medicaid across four categories of states. LTCIP_2008 indicates the group of states that adopted LTCIP prior to year 2008 ((17 states)), whereas LTCIP_2010 represents the group of states that adopted LTCIP between 2008 and 2010 (18 states).

The evidence suggests that the effect of LTCIP on private LTCI coverage increased more for working individuals. In addition, the purchase of private LTCI significantly increased for healthy individuals but did not increase for older individuals with pre-existing health conditions. This clearly indicates the presence of an adverse selection. Additionally, this result is suggestive of evidence of a positive selection in the case of private LTCI. The LTCIP program is slightly stronger for women and for married individuals which subsequently leads to a decrease in their uptake of Medicaid. The findings suggest that individuals without children are more likely to purchase private LTCI coverage compared to those with children. The effect is not significant in the case of Medicaid uptake. Finally, we find that the purchase of private LTCI after LTCIP increased among white Americans but decreased among ethnic minorities, whereas the effect is significantly reversed in case of Medicaid uptake.

***5.5.6. Robustness Checks***. The reported estimates are robust to various robustness checks. Firstly, we control for state tax subsidy and find that the model produces similar estimates with a very slight change. Table 5.8 indicates the robustness check results. The effect slightly increases from 1.64 percentage points to 1.7 percentage points after controlling for tax subsidy. These two programs were independently active at the same time. Few states had private LTCI available through both partnership as well as tax subsidy programs during the same period. Secondly, we check whether our estimates are influenced by Affordable Care Act (ACA hereafter) Medicaid expansion for low-income individuals up to age 64. McInerney et al. (2020) use HRS data to identify the impact of ACA's Medicaid expansion on Medicaid uptake and find that the Medicaid expansion program significantly increases the uptake of Medicaid by 15 percentage points on average among low-income adults aged 50-64. Thus, it is important to test whether our specification is robust to ACA's Medicaid expansion. Consistently, we interact LTCIP with Medicaid expansion states at time t and observe that ACA's Medicaid expansion has no impact on the purchase of private-LTCI and it decreases the uptake of Medicaid same as our baseline specification. Hence, we conclude that our specifications are robust to the effect of ACA's Medicaid expansion and the effect is driven entirely by LTCIP. In addition, we test our main specification using a probit model and show that its marginal effects are identical to that of linear model. Next, add to our main specifications age specific fixed effects, and we find that the estimates do not change. Simultaneously, we test our specification after controlling for wealth (net-worth) and the uptake of other insurance contracts such as property and vehicle insurance. Our results remain unaltered and overall suggest that same effects as that of our main models. Lastly, to match our specifications to that of previous studies (Lin and Prince, 2013), we include permanent partnership states into the treatment states and run the model again. We observe that this specification change does not affect our result whatsoever and we obtain the exact same estimates as those from our main model. Therefore, this suggests that our estimates are robust to all necessary specification checks.

**Table 5.8: Robustness Checks – Linear Estimates of the effect on LTCI (Private & Public)**

| | Private LTCI | | Medicaid | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Tax-Subsidy** | | | | |
| Partnership | 0.0171*** | 0.0114*** | -0.0141*** | -0.0344 |
| | (0.00475) | (0.00383) | (0.0036) | (0.00291) |
| Subsidy | 0.00506 | 0.0116*** | 0.00374 | -0.0034 |
| | (0.00474) | (0.00396) | (0.00357) | (0.00257) |
| **ACA Medicaid Expansion** | | | | |
| Partnership | 0.0176*** | 0.01*** | -0.0051*** | 0.0007 |
| | (0.00456) | (0.00367) | (0.0035) | (0.003) |
| ACA_ME | -0.00011 | -0.0033 | 0.0381*** | 0.017*** |
| | (0.00613) | (0.0046) | (0.00565) | (0.00476) |
| Partnership*ACA-ME | -0.008 | -0.0065 | -0.0155*** | -0.019*** |
| | (0.00695) | (0.00517) | (0.00644) | (0.00456) |
| **Probit Model** | | | | |
| Partnership | 0.0167*** | | -0.0128*** | |
| | (0.0046) | | (0.003242) | |
| **Inclusion of Age Fixed Effects in place of Age and Age sq.** | | | | |
| Partnership | 0.0162*** | 0.01** | -0.0147*** | -0.003 |
| | (0.00462) | (0.00371) | (0.00363) | (0.003) |
| **Wealth** | | | | |
| Partnership | 0.0163*** | 0.01*** | -0.0146*** | -0.00288 |
| | (0.00461) | (0.00371) | (0.00360) | (0.00296) |
| **Other Insurances** | | | | |
| Partnership | 0.0151*** | 0.01*** | -0.0125*** | -0.00259 |
| | (0.00460) | (0.00372) | (0.0035) | (0.00296) |
| **Include RWJF states as a treatment group (same as Lin and Prince 2013)** | | | | |
| Partnership | 0.0164*** | 0.01*** | -0.0146*** | -0.0029 |
| | (0.00462) | (0.00371) | (0.00360) | (0.00296) |
| **State + Year Fixed Effects** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual FE** | NO | YES | NO | YES |
| **Number of obs.** | 148,972 | 148,972 | 148,472 | 148,423 |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates of equation (2). There are two dependent variables namely Private long-term care insurance (LTCI) and public long-term care insurance or Medicaid. Both outcome variables are binary variables. Column (1) and (3) include State and Year fixed effects and other covariates, whereas Column (2) and (4) add individual fixed effects and removes time-constant characteristics to obtain the estimated coefficients. Other covariates include age, gender, age^2, income, health status, marital status, race, and education. Each category title on the left-hand side of the table refers to a specification change incorporated to check if the baseline model estimates are robust to change in specifications.

***5.5.7. Placebo Test***. To ensure that the estimated effect of LTCIP is not driven by other insurance products such as life insurance or health insurance, and more generally reflects a wider effect, we run our main model using several unrelated dependent variables such as life insurance and employer pension contributions. Table 5.9 reports evidence of statistically insignificant or negligible effects, consistent with the expected estimates of a placebo test.

**Table 5.9: Placebo test – Impact LTCIP on other insurances**

| | Life Insurance | Life Insurance | Employer Health Insurance | Employer Health Insurance |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | | | | |
| **Partnership** | 0.0121* | 0.0056 | 0.0049 | -0.00523 |
| | (0.00717) | (0.00525) | (0.00774) | (0.00567) |
| | | | | |
| **State + Year Fixed Effects** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual FE** | NO | YES | NO | YES |
| **Number of obs.** | 148,972 | 148,972 | 148,472 | 148,423 |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates for alternative insurance coverage namely Life Insurance and Employer Health Insurance. Both dependent variables are binary variables denoting ownership of such insurance products. Column (1) and (3) include State and Year fixed effects and other covariates, whereas Column (2) and (4) add individual fixed effects and removes time-constant characteristics to obtain the estimated coefficients. Other covariates include age, gender, age^2, income, health status, marital status, race, and education.

***5.5.8. Mechanism***. Finally, we examine a number of mechanisms that can underpin the effect of LTCIP as reported in Table 5.10. First, we examine how the LTCIP changed bequest motives or altruistic transfers. We analyse the impact of LTCIP on an individual's probability of leaving any bequest, and we find that the effect on post-reform bequest transfers is negative. The magnitude of the change in bequest motive intensions is almost equivalent to the impact on private LTCI.

## Table 5.10: Possible Mechanisms driving the effects

| **Models** | (1) | (2) |
|---|---|---|
| **State & Year FE + Controls** | YES | YES |
| **Individual FE** | NO | YES |
| ***Bequest*** | | |
| **Partnership** | -0.0017 | -0.0142*** |
| | (0.00635) | (0.00516) |
| ***log(Income)*** | | |
| **Partnership** | 0.0567*** | 0.023 |
| | (0.020) | (0.0151) |
| ***Wealth*** | | |
| **Partnership** | -4,909 | 4,702 |
| | (25,994) | (12,401) |
| ***Total Savings*** | | |
| **Partnership** | 13,401 | 16,792 |
| | (13,524) | (12,084) |
| ***Disability*** | | |
| **Partnership** | -0.000888 | 0.00302 |
| | (0.00248) | (0.002) |
| ***Survival* Probability (Longevity till 100)** | | |
| **Partnership** | 1.208*** | 0.345 |
| | (0.456) | (0.344) |
| ***Death*** | | |
| **Partnership** | -0.0153*** | NA |
| | (0.00492) | |
| ***Self-Reported Health Status*** | | |
| **Partnership** | -0.031* | 0.0111 |
| | (0.0162) | (0.008762) |
| ***BMI*** | | |
| **Partnership** | 0.13 | 0.073*** |
| | (0.0942) | (0.028) |
| ***Mental Health (CESD Score)*** | | |
| **Partnership** | 0.0514 | -0.36** |
| | (0.316) | (0.2) |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates for bequest, wealth and health outcomes. Each category title on the left-hand side of the table refers to a specific outcome regressed on right hand side variables to check if it reveals possible mechanisms driving the effect of LTCIP. Column (1) includes State and Year fixed effects and other covariates, whereas Column (2) adds individual fixed effects and removes time-constant characteristics to obtain the estimated coefficients. Other covariates include age, gender, age^2, income, health status, marital status, race, and education.

Next, we analyse the impact of LTCIP on income, wealth, and savings behaviour as proxying individuals' self-insurance of their LTCSS. However, we do not find a statistically significant effect. Another potential channel refers to the effect on health behaviour outcomes post-reform. Importantly, we find that longevity or the probability of living up to 100 years of age is positively associated with LTCIP. Also, the likelihood of dying decreases with the effect's magnitude equal to that of private LTCI and the estimates are statistically significant. However, we do not observe an impact for disability. Finally, we find a positive and significant effect on self-reported health, body-mass index, and mental health, which suggest evidence of a genuine insurance effect on wellbeing, including physical and mental health.

### 5.6. Medicaid Savings Simulation After the Adoption of LTCIP

This section reports the LTCIP effect on both LTCI uptake as well as Medicaid expenditure. The program was expected to increase the uptake of LTCI especially among median-wealth households (Lin and Prince 2014, Bergquist et al. 2016). The policies purchased through the LTCIP convey extra benefits via additional wealth protection due to higher asset thresholds for Medicaid eligibility, which prevents spending-down effects (Pauly 1990). Previous evidence indicates that low LTCI uptake leads to a rise in both out-of-pocket expenses and public expenditure (via Medicaid) for long-term care (Brown and Finkelstein 2007; 2008; 2011; Goda 2011; Bergquist et al. 2018; Frank 2012). Hence, it is important to evaluate whether LTCIP exerts an effect on Medicaid expenditure. Thus, we decide to implement the simulation model, in line with that of (Goda 2011), with the help of other relevant studies on the topic to predict the impact of LTCIP on fiscal public Medicaid expenditure.

***5.6.1. Simulation procedures***. We follow Goda (2011)'s simulation model for tax subsidy as a reference model for predicting the impact of LTCIP on the Medicaid expenditure. In line with Goda (2011), we simulate the impact of adopting LTCIP programs for a 65-year-old with gender $g$ and wealth decile $i$. We define $C_i(I)$ and $C'_i(I) = C_i(I) + P_i$ as a coverage rate of private LTCI before and after the adoption LTCIP, respectively, in which $P_i$ is the change in private LTCI coverage due to LTCIP. The share of the expected present discounted value (EPDV hereafter) of long-term care expenditures for gender $g$ and wealth decile $i$, with and without private LTCI coverage, are denoted by $M_{i,g}(I)$ and $M_{i,g}(N)$, respectively. Let $M_{i,g}(P)$ and $M'_{i,g}(P)$ be the share of Medicaid before and after the adoption of LTCIP program, respectively. They are defined as:

$$M_{i,g}(P) = C_i(I) * M_{i,g}(I) + (1 - C_i(I)) * M_{i,g}(N) \quad (3)$$

$$M'_{i,g}(P) = C'_i(I) * M_{i,g}(I) + (1 - C'_i(I)) * M_{i,g}(N) \quad (4)$$

Let $E_g(LTC)$ be the EPDV of long-term care costs for a person with gender $g$. Therefore, the expected Medicaid savings due to the adoption of LTCIP program for gender $g$ and wealth decile $i$ is as follows.

$$E_{i,g}(S) = \left( M_{i,g}(P) - M'_{i,g}(P) \right) * E_g(LTC) - E(C) \quad (5)$$

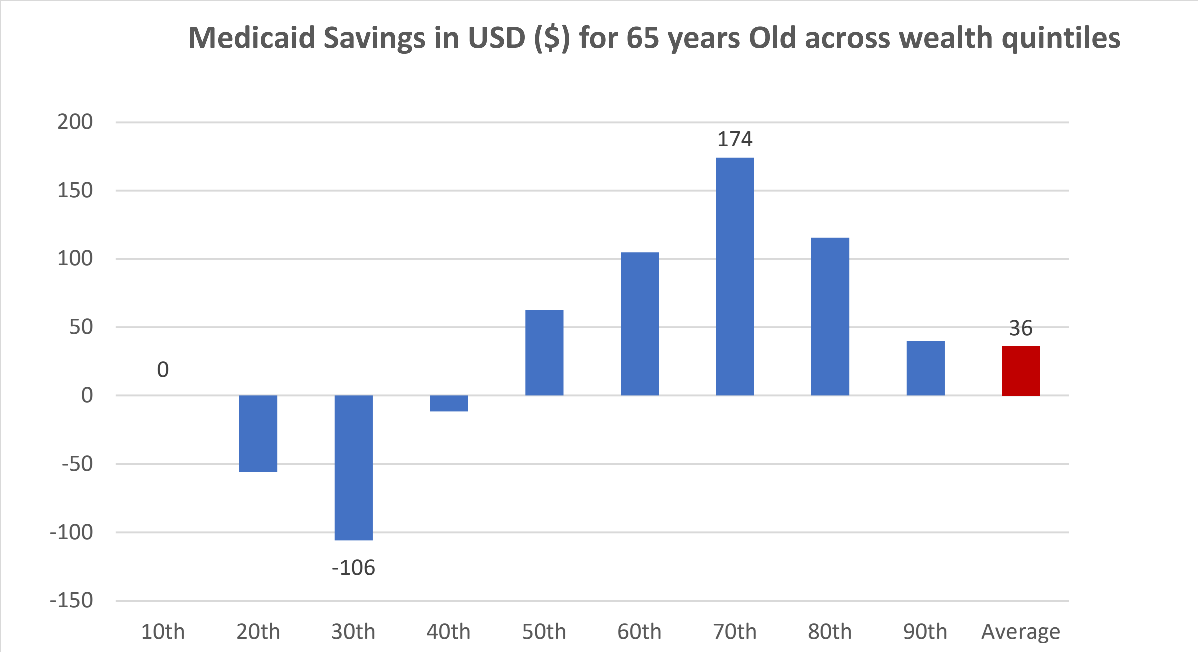
Where E(C) is the expected cost of implementation of LTCIP program per person. The program implementation cost does not differ for individuals with gender $g$ and wealth decile $i$. *In other words, the cost is the same for all individuals.* However, we assume that the implementation of LTCIP incurs little to no costs. Thus, while calculating and reporting the expected Medicaid savings, we insert E(C) = 0 in equation 5.

***5.6.2. Simulation Assumptions***. We use the above model for the prediction of savings in Medicaid expenditure after the adoption of the LTCIP program. However, we need important assumptions concerning the effect of LTCIP on private LTCI coverage rates and premiums, and Medicaid costs (Goda 2011). Column (2) of Table 5.7 indicates our assumption that the impact of LTCIP by Low, Middle, and High wealth levels correspond to $30^{th}$, $60^{th}$, and $80^{th}$ percentile, respectively. We also linearly interpolate responses for the remaining percentiles in our simulation model. Similar to Goda (2011), we use the estimates of $M_{i,g}(I)$ and $M_{i,g}(N)$ which represent the Medicaid share of EPDV for LTC by gender $g$ and wealth decile $i$ for 65-year-old individuals with and without private LTCI coverage, provided by Brown and Finkelstein (2008). We use an annual premium of $\theta$ = \$2,000—which is gender neutral—and assume that private LTCI coverage provides a daily benefit of \$100 for a 65-year-old individual. Brown and Finkelstein (2008) and Goda (2011) use the EPDV of LTC costs by gender, calculated in the year 2000, as $E_f(LTC)$ =\$43,750 for women and $E_m(LTC)$ = \$17,500 for men. However, we calculate these values of EPDV for the year 2006. Thus, we use $E_f(LTC)$ =\$52,523 for women and $E_m(LTC)$ = \$21,021 for men, in our simulation model.

***5.6.3. Simulation Results****:* Assuming that the implementation of LTCIP incurs little to no administrative costs, Figures 5.5 reports the net Medicaid savings across different levels of wealth. The net Medicaid savings is non-monotonically related to wealth. The net savings for an individual at the $10^{th}$ percentile of wealth is zero but becomes negative for the $20^{th}$, $30^{th}$, and $40^{th}$ percentile in the amount of \$56, \$106, and \$12 respectively. The $30^{th}$ percentile corresponds to the lowest net saving. Net savings recovers for the $40^{th}$ percentile to -\$12 and subsequently becomes positive afterward, attaining a peak of \$174 at the $70^{th}$ percentile, and begins to decline as the wealth percentile increases. The net Medicaid savings is \$40 at the high end of the wealth distribution (the $90^{th}$ percentile). Overall, the federal government saves[22], on average, \$36 per 65-year-old in Medicaid expenditure. The 95% confidence interval ranges from -\$23 to \$95. Overall, this indicates that an increase in the purchase of private LTCI through LTCIP adoption increases the savings in government expenditure via Medicaid.

[22] However, the savings estimates alter if we use results from Column (1) of Table 7 that does not incorporate individual level fixed effects. Figure VII in the appendix represents net Medicaid savings, and we observe that average net savings increases to \$105 per 65-year-old individual if we use the model without individual fixed effects.

**Figure 5.5: Estimated total net savings from LTCIP for 65 years old individual by wealth decile**




Note: These saving estimates are calculated using the estimated effects across wealth levels obtained from Column (2) of Table 7. Average Medicaid savings for 65 years old calculated using a simulation technique similar to Goda (2011). Authors calculate, with reference to year 2006, the expected present discounted value (EPDV) of long term-care costs or E(LTC) of $21021 for men and $52523 for women, using the values assumed by Brown and Finkelstein (2007) and Goda (2011) for the year 2000. Low, Middle, and High wealth levels correspond to 30th, 60th, and 80th percentile respectively. The horizontal axis represents wealth percentiles, and the vertical axis represents amount saved in USD.

The phenomenon that leads to this non-monotonic relationship can be explained in several ways. Firstly, wealth levels below the median can be expected to generate less savings after the LTCIP, because more individuals in these groups opt for Medicaid after the exhaustion of their savings in comparison to individuals above the median-wealth level. Although the response to private LTCIP is slightly negative at the lower levels of wealth, over-insuring on the part of low-income individuals can, on average, yield positive savings in federal Medicaid expenditure. Secondly, the savings begin to decrease as the wealth percentiles move towards the higher end of the wealth distribution e.g., after 70$^{th}$ percentile. This can be explained by the stigma of Medicaid. In the U.S., richer individuals are less likely to opt for Medicaid in conservative states because of unpopular and negative opinions about public insurance programs (Sommers et al. 2012; Allen et al. 2014). In addition, the increase in private LTCI coverage for high-wealth individuals does not significantly alter their Medicaid expenditure for long-term care (Goda 2011). Our findings also suggest that the response to LTCIP is the highest among high-wealth individuals, but these groups account for lower Medicaid savings because there is both no resulting change in their share of Medicaid uptake as well as a high prevalence of stigma for Medicaid among these individuals.

***5.6.4. Sensitivity analysis***: Consistent with (Goda 2011), we perform a sensitivity analysis on the simulation model that we use to calculate Medicaid savings for 65-year-old individuals. As part of the sensitivity analysis, we first calculate the expected long-term care costs ($E_g$(LTC) or EPDV) at a 10% tolerance in both directions and then replace the EPDVs from our main simulation with the adjusted ones for 65-year-old individuals with gender g. The results from Table 5.11 indicate that changing EPDVs at a 10% tolerance level alters the Medicaid savings by $4 above and below the baseline value of $36. Medicaid savings at +10% and -10% of EPDV are $40 and $32, respectively. Similarly, we calculate the expected Medicaid savings by altering the discount rate assumption of 3% in the baseline simulation model. First, we adjust the discount rate to 1.5% and obtain the Medicaid savings estimate of $85 per 65-year-old individual. The lower discount rate increases the present value of long-term care costs relative to baseline discount rate of 3% and yields higher Medicaid savings. However, raising the discount rate to 4.5% decreases the Medicaid savings to $17.

**Table 5.11: Sensitivity Analysis for Simulation Output**

| | | **Total Medicaid Savings** |
|---|---|---|
| ***Main model*** | Baseline | $36 |
| | +2SD | $95 |
| | -2SD | -$23 |
| $Eg(LTC)$ | 1.1*EPDV (or +10%) | $40 |
| | 0.9*EPDV (or -10%) | $32 |
| ***Discount Rate*** | 1.5% | $85 |
| | 4.5% | $17 |

Note: The expected present discounted value (EPDV) of long term-care costs or E(LTC) for men (women) is $21021 ($52523).

## 5.7. Welfare Analysis: A MVPF Approach

We attempt to evaluate and explain the scenarios where LTCIP generates Medicaid savings and also has the welfare impact. Therefore, to analyse the partnership insurance policy, we use Marginal Value of Public Funds (MVPF hereafter) approach suggested by (Hendren 2013; Finkelstein and Hendren 2020; Hendren and Sprung-Keyser 2020). The MVPF is an elegant way of linking causal estimates of a policy to the welfare analysis of that policy. As per Hendren (2016) and Finkelstein and Hendren (2020), the MVPF is defined as the ratio of marginal benefits to the marginal cost of the policy.

$$MVPF = \frac{\text{"}Benefits\text{"}}{\text{"}Costs\text{"}} \tag{6}$$

The numerator refers to the benefit received by a recipient after a policy change. This is equivalent to the willingness to pay for the increased expenditure due to policy (Finkelstein and Hendren 2020; Hendren and Sprung-Keyser 2020). The denominator reflects the costs to the government for the implementation of a policy. It consists of two categories of costs viz. Mechanical Cost and Fiscal Externality of the policy. The mechanical cost of the policy refers to increase in government expenditure post-adoption of LTCIP unaccompanied by any behavioural response. In the context of LTCIP, we assume that the mechanical cost is either zero or miniscule, because the direct cost of the LTCIP program consists of administrative costs of making the policy available for purchase. Such costs are miniscule as a recipient can choose an option of LTCIP in place of regular insurance policy while buying a contract from the same provider. Therefore, we continue to assume the mechanical cost of LTCIP as zero or miniscule.

The fiscal externality (FE) refers to costs incurred due to the behavioural response after the adoption of policy. In case of LTCIP, the behavioural response can occur through A) Decrease/increase in labour participation after the adoption of LTCIP. Decrease in labour participation means that an individual does not need to accumulate money to finance their future long-term care costs once they are covered and their assets are protected through LTCIP. This leads to decrease in income tax revenue collected by government, a negative fiscal externality. However, an increase in labour participation means that individual may intend to accumulate money to satisfy other motives including transfer of bequest which in turn increases the income tax revenue collected by the government and results in a positive fiscal externality for the government. Our estimates (ref. Appendix) indicate that LTCIP increases the labour participation for elderly, but they are not significant. B) Another behavioural response of the policy can result in increase in government expenditure (or decrease in costs) if an individual happens to purchase more coverage than the assets she intends to protect. Such an additional coverage may ultimately result in decrease in Medicaid costs to government, a positive fiscal externality for government. Hence, we infer that the Medicaid savings we find in our simulation analysis comes from such a behavioural response to the policy. Equation (7) includes the various components of benefits and costs after LTCIP adoption. For numerator, let A, C, & P indicate the protected assets, insurance coverage, and premium in $ respectively; for denominator, let M, t, & X indicate Medicaid costs, tax on earnings, and additional coverage in $ respectively.[23]

$$MVPF = \frac{"Benefits"}{MC + FE} = \frac{A + C - P}{(0) + (M \pm t - X)} \tag{7}$$

For simplicity, we take an example of a median wealth individual with a wealth of $144,000 for our analysis and observe that the welfare analysis of LTCIP results in three different scenarios depending upon how a marginal beneficiary behaviourally responds to the adoption of LTCIP (National Institute on Aging and The Social Security Administration 2018). We

[23] It is difficult to distinguish between a policy purchased through LTCIP and using tax-subsidy, but our estimates are robust to the inclusion of tax subsidy in the model. It is not straightforward to calculate the cost of implementation of LTCIP but given that the LTCIP policy can be purchased through the same exchanges we can assume that the adoption of LTCIP incurred minimal or no cost to the government. It is also difficult to identify the costs imposed on the government via Medicaid by an individual holding LTCIP policy and getting qualified for Medicaid after exhausting her coverage. Therefore, our welfare analysis of LTCIP does not include the exact cost of Medicaid in the MVPF formula.

continue to assume that a policy can be purchased at an annual premium of θ = $2,000 and that private LTCI coverage provides a daily benefit of $100 for a 65-year-old individual. We observed that, in the absence of LTCIP, a median wealth individual needed to spend down her assets to $2000 before qualifying for Medicaid. Thus, a median wealth individual required to spend $142,000 of her assets, after the exhaustion of private insurance coverage, before becoming eligible for a public insurance via Medicaid. The MVPF associated with no-LTCIP is shown in row 1 of Table 5.12.

However, in the presence of LTCIP, an individual is provided with an option of discounting her assets before qualifying for Medicaid. In an optimal scenario, a median wealth individual can protect all of her assets by purchasing LTCIP policy with a private coverage equivalent to her assets ($144,000 - $2000 = $142,000). It is important to notice that the exact optimal planning via LTCIP does not affect the Medicaid expenditure and Medicaid costs remains same with or without LTCIP. Nevertheless, it can be observed that the benefits received by an individual with LTCIP policy increase by an amount of assets she protects under the provision of LTCIP. For an individual with private insurance coverage and keeping other things constant, we find that MVPF of LTCIP (row 2 of Table 5.12) is greater than MVPF without LTCIP (row 1). Additionally, if a median wealth individual purchases insurance through LTCIP with a coverage less than her total assets (<$142,000), then she pays the difference between amount of coverage and Medicaid threshold out of her own pocket before qualifying for Medicaid.[24] Let that difference be represented by 'd'. But once again it is important to note that this will not change the government expenditure of providing public insurance via Medicaid (ref. row 3 of Table 5.12).

[24] For example, if she buys a coverage of $100,000, then the difference she needs to pay out of her pocket would be $42,000. Overall, it is not optimal for a median individual to purchase coverage less than $142,000.

Finally, given that the insurance premium varies by gender, age, health conditions, benefit multiplier, and couple status, and comes in several standardized packages. Therefore, buying an optimal coverage becomes a rare possibility, and an individual may end up purchasing a coverage greater than her assets. However, this additional coverage has a direct impact on the Medicaid costs; it leads to savings in Medicaid and reduce the fiscal burden on the government. Let 'X' be the additional coverage purchased by an individual, row 4 of Table 5.12 indicates the MVPF with coverage above optimal level. We find that MVPF associated with row 4 of Table 5.12 will be greater than previous cases. These negative costs to the government also signify that the government spending pays for itself and MVPF is defined as infinite (Hendren and Sprung-Keyser 2020). Overall, LTCIP reduces Medicaid costs when an individual purchases private-LTCI coverage greater than her total assets and in-turn also improves the welfare of an individual without raising the costs to the government for providing Medicaid.

**Table 5.12: Welfare Analysis using MVPF Approach.**

| Sr No | Scenarios | Coverage | MVPF |
|---|---|---|---|
| 1) | No LTCIP | ------ | $= \frac{C-P-A}{(M \pm t)}$ |
| 2) | LTCIP – Optimal | C = \$142,000 | $= \frac{A+C-P}{(M \pm t)}$ |
| 3) | LTCIP – Below Optimal | C < \$142,000 | $= \frac{A+C-P-d}{(M \pm t)}$ |
| 4) | LTCIP – Above Optimal | C > \$142,000 | $= \frac{A+C-P}{(M \pm t - X)}$ |

Note: This table consists of four different scenarios and their corresponding marginal values of public funds (MVPF) respectively. The coverage estimates, indicative of average individual wealth, comes from the Health and Retirement study (1996-2016).

### 5.8. Benefits, Ordeals, and Target Efficiency

One of the major reasons for low uptake of LTCI in the US is the secondary payer status of Medicaid, which imposes implicit tax on private LTCI (Brown and Finkelstein 2008; 2011). Medicaid's implicit tax on LTCI can be eliminated to a certain extent, by delaying the process of qualifying for Medicaid, via the adoption of LTCIP (Brown and Finkelstein 2011). Thus, the effect of LTCIP must also be looked through the lens of ordeals. The main purpose of ordeals is to achieve target efficiency by reaching out to those who need it the most (Nichols and Zeckhauser 1982; Zeckhauser 2021). Table 5.13 represents four types of potential beneficiaries of Medicaid via LTCIP, labelled as A, B, C, and D. The richer the individual gets, then greater the $ amount in coverage she buys. If each individual protects 100% of her leftover assets after paying a premium for LTCIP, then the main goal of partnership program is to serve group D individuals. As group B individual is relatively rich and more likely to have greater coverage, her required LTSS expenses will be majorly financed by private insurance (LTCIP). Similarly, group A and C individuals only need some form of LTSS support, which will be covered under LTCIP. Thus, they do not have to go through the ordeal of qualifying for Medicaid. Hence, LTCIP can achieve target efficiency even in the presence of Medicaid's implicit tax on private-LTCI.

**Table 13: Intended and actual beneficiary of Medicaid via LTCIP**

| **Class** | **Some LTSS** | **Full LTSS** |
|---|---|---|
| *Rich* | *A* | B |
| *Middle Class* | *C* | D |

### 5.9.Discussion

This paper has examined the effect of the rollout of LTCIP on private LTCI and public Medicaid uptake. Unlike previous studies that focus on short-term effects, we find robust evidence that the adoption of LTCIP increases insurance uptake. More specifically, our results reveal that the rollout of LTCIP increased the uptake of LTCI coverage by 1.64 percentage points on average, which is equivalent to 86% of the effect of income on private-LTCI (ref. Appendix - Column 2 of Table A5.4), and reduced Medicaid uptake by 1.46 percentage points. This result is suggestive of the important interaction between public and private long-term care insurance and to the possibility of limiting Medicaid expenditure and potential crowding-out effects by way of a partnership design. We draw on more than two decades worth of data from the Health and Retirement Study (from 1996 through 2016) and take advantage of recent developments in a generalised DiD design to exploit the progressive adoption of LTCIP over time after the passage of the federal Deficit Reduction Act (DRA-2005). Evidence from our simulation analysis suggests that LTCIP generates $36 in Medicaid savings per 65-year-old. Although the response to private-LTCI is smaller in magnitude, it appears to significantly reduce the uptake of Medicaid, leading to generous savings in Medicaid. The main reasons behind these generous savings are: 1) Little to no expected government costs associated with the implementation of LTCIP, and 2) LTCIP allows individuals with medium level of wealth to purchase insurance coverage to fund their future long-term care costs, which otherwise would have been paid for by Medicaid. Hence, LTCIP delays the uptake of Medicaid by incentivising the purchase of private-LTCI.

Our findings suggest that LTCIP stimulates the purchase of private-LTCI, which subsequently reduces the uptake of Medicaid provide *fresh evidence that the implicit tax on private-LTCI can be minimized to some extent by reducing means testing*. Our results strengthen the claims made by Brown and Finkelstein (2011) suggesting that the Partnership program has a direct impact on means testing component of the implicit tax on private-LTCI and that reinventing LTCIP can be a way forward for eliminating the implicit tax completely. We also discuss how LTCIP can achieve target efficiency even though Medicaid imposes implicit tax on private-LTCI. Most importantly, our findings certainly create a ground for more research on how LTCIP can be redesigned to address the implicit tax completely by removing Medicaid's role as a secondary payer.

## 5.10. Appendix

**Figure A5.1.: Coverage of private long-term care insurance (LTCI) over time.**

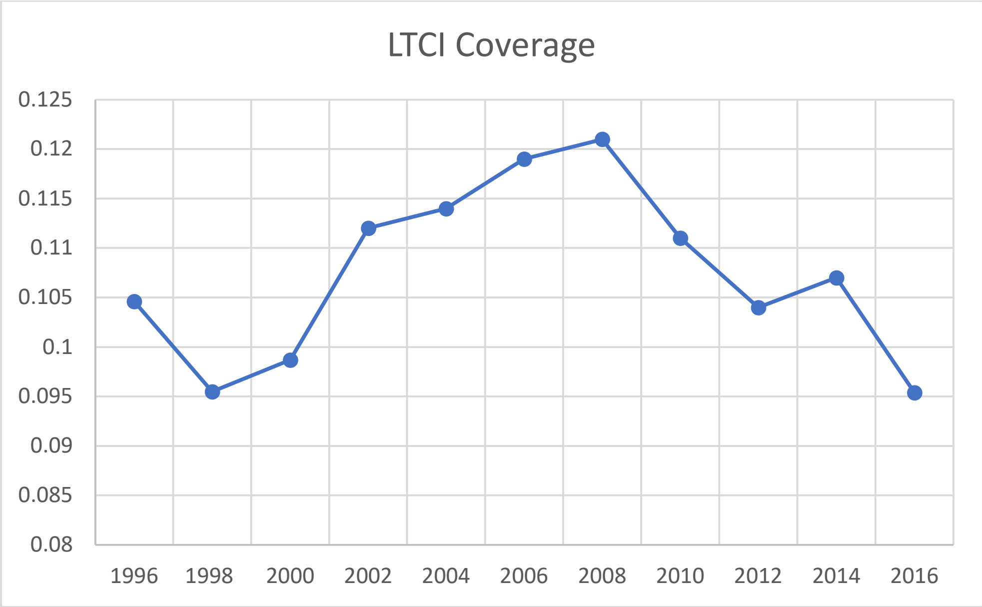



**Figure A5.2.: The Uptake of Medicaid entitlements over time.**

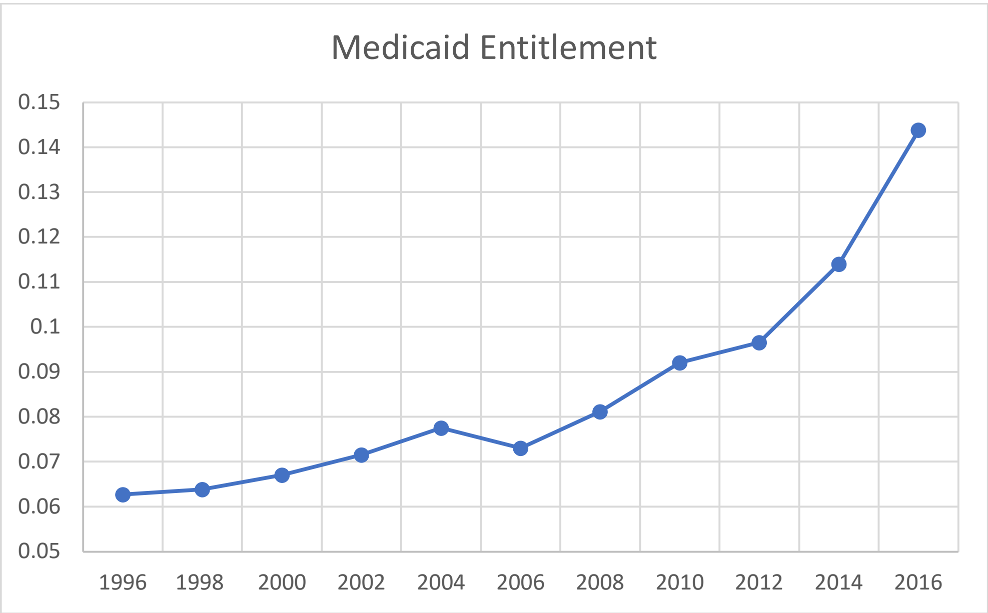



**Figure A5.3: Spouse – Effect of LTCIP on purchase of private long term-care insurance (LTCI) over time**

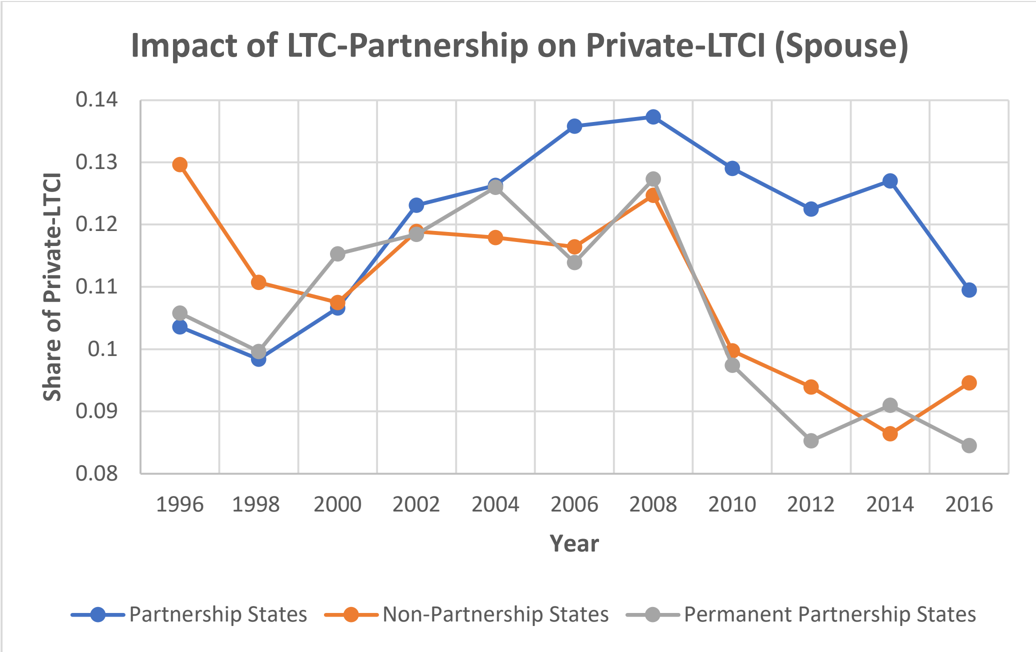
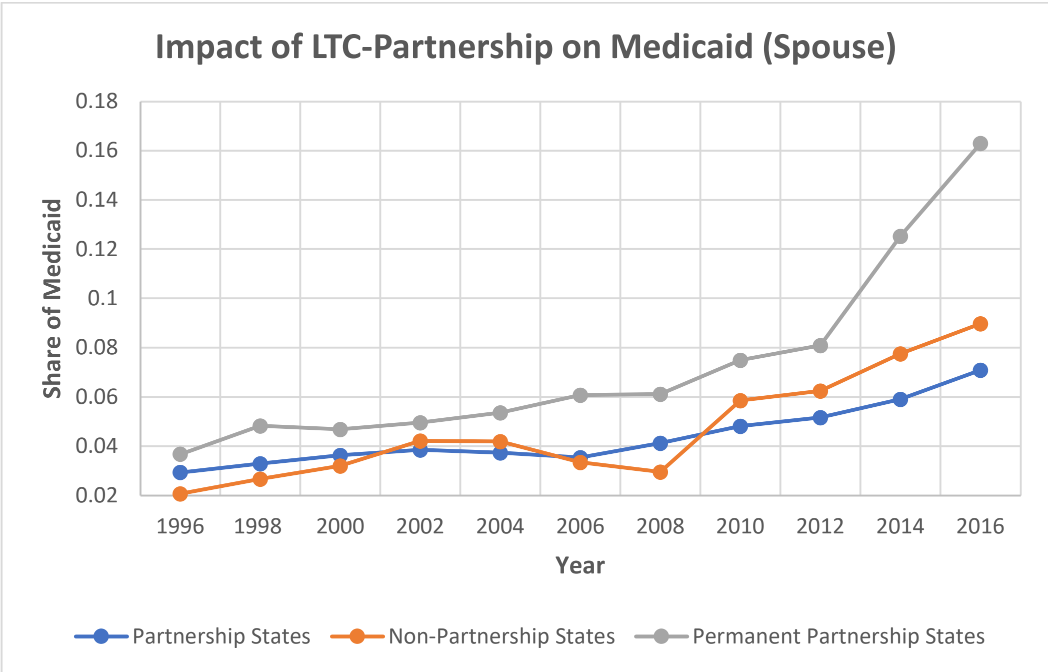



**Figure A5.4.: Spouse – Effect of LTCIP on the uptake of Medicaid over time**




### *5.10.1. Event Study Design*

Panel event study methods are at the core of the recent developments in quasi-experimental techniques as they attempt to estimate the impacts of events occur at different time periods. A growing number of studies tests a combination of complex identifying assumptions in this regard and attempts to provide a guidance on accurately estimating the impact of staggered adoption of policies (Athey and Imbens 2021; Borusyak and Jaravel 2017; Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfoeuille 2019; Abraham and Sun 2020; Goodman-Bacon 2021). One of the major concerns of using two-way fixed effects is that the interpretation of the estimated coefficient is not straightforward due to heterogeneity in treatment effects (Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfoeuille 2019; Goodman-Bacon 2021). However, a panel event study design can address the concern arises from heterogenous treatment effects when treatment occurs in different time periods for different units (Abraham and Sun 2020; Clarke and Schythe 2020). We initially estimate a non-parametric event study specification to obtain the event study trends on the aggregate data, defining the event (t=0) as the adoption of the DRA 2005 which opens the door to LTCIP programs. We use Health and Retirement Survey data for the study, which is a biannual survey, therefore we only observe the introduction of the DRA 2006 (or Wave 8), and we define indicator variables relative to the event for New-Partnership states and non-Partnership states. The non-parametric event study allows us to visually investigate the outcome pattern subject to the adoption of LTCIP by each state. We rely on two identifying assumptions: 1) The parallel trend assumption suggesting that the baseline outcome is mean-independent of the timing of LTCIP adoption, and 2) The anticipation of treatment (event) should not occur.

The non-parametric specification is as follows:

$$\boldsymbol{Y}_{it} = \boldsymbol{\delta}_t + \boldsymbol{\beta X}_{it} + \boldsymbol{\theta}_s + \textstyle\sum_{r=-2}^{-5} \boldsymbol{\Phi}_r + \sum_{r=0}^{5} \boldsymbol{\Phi}_r + \left(\sum_{r=-2}^{-5} \boldsymbol{\Psi}_r + \sum_{r=0}^{5} \boldsymbol{\Psi}_r\right) * \boldsymbol{NewPS} + \mathrm{V}_{it} \quad \textbf{(A1)}$$

In equation A1, $\delta t$ and $\theta s$ indicate year and state fixed effects, respectively. It must be noted that $r$=0 corresponds to year 2006 i.e., the interview was conducted one year after the adoption of DRA-2005. Because HRS is a biannual survey, we do not observe the data recorded for year 2005. The $X_{it}$ indicates other control variables and $\Psi r$ represents coefficients on leads and lags for New-Partnership states (*NewPS*) relative to the omitted category $\Psi_{-1}$, whereas $\Phi r$ represents coefficients for leads and lags for non-Partnership states. Subsequently, we estimate Partnership group-time average treatment effects, under the parallel trend and no anticipation effect assumptions, using event study method for several group-time combinations suggested by (Callaway and Sant'Anna 2021).

### *5.10.2. Results (Event Study)*

Figures A5.5.(a) and A5.5.(b) plot the estimated coefficients, obtained after estimating the aggregate non-parametric event study regression (A1) for both private and public long-term care insurance. They report the impact of the introduction of a LTCIP in a specific state on the uptake of private-LTCI and Medicaid in such states compared to non-partnership states. We document that the effect of LTCIP on private LTCI builds up over time and reaches a peak after 2 to 3 waves of the HRS. Similarly, the effect of LTCIP on Medicaid uptake follows the impact on private LTCI, as a comparison between Figure A5.5.(a) and A5.5.(b) reveals. Both figures show comparable linear trends in the pre-LTCIP period for both private and public insurance. The evidence suggests that LTCIP exerts a statistically significant impact on the purchase of private LTCI and the uptake of Medicaid in the post-DRA 2005 era[25], implying that LTCIP is associated with an increase in private insurance purchases and a subsequent decrease in the uptake of public insurance (Medicaid).

**Figure A5.5.(a) Event Study: Impact of LTCIP on private long-term care insurance.**

[25] We also plot event study by assuming that the reform began in 2008 instead of 2006. Figure V and VI of the Appendix represent event study plot for LTCI and Medicaid respectively. We observe that the event study trends are almost unaffected due to the change in reform. This happens because only the state of Idaho began adopting LTCIP in 2006. Thus, we obtain similar event study trends.

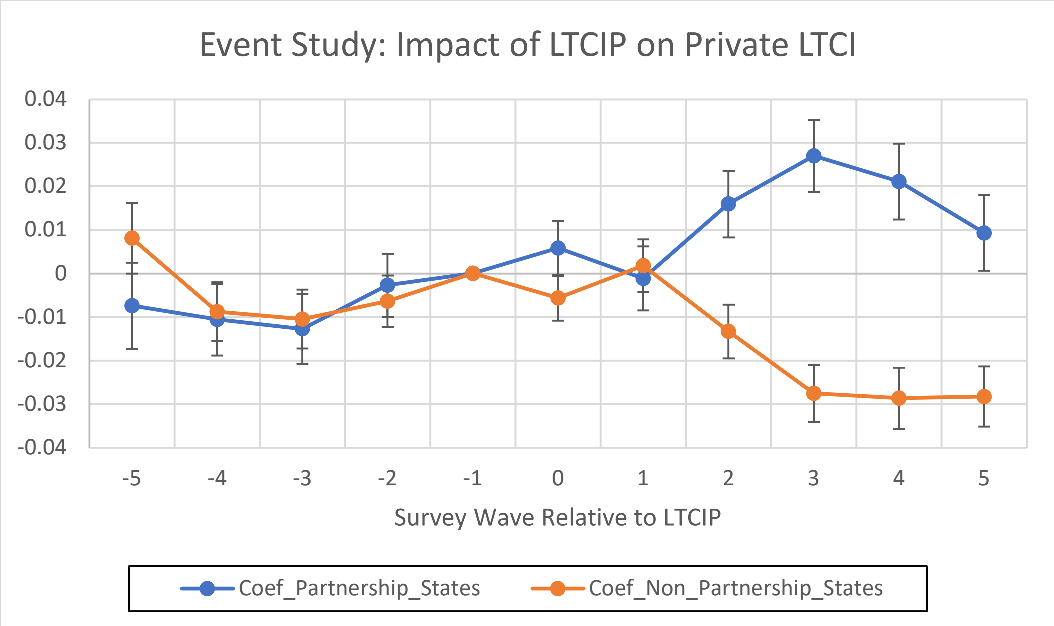
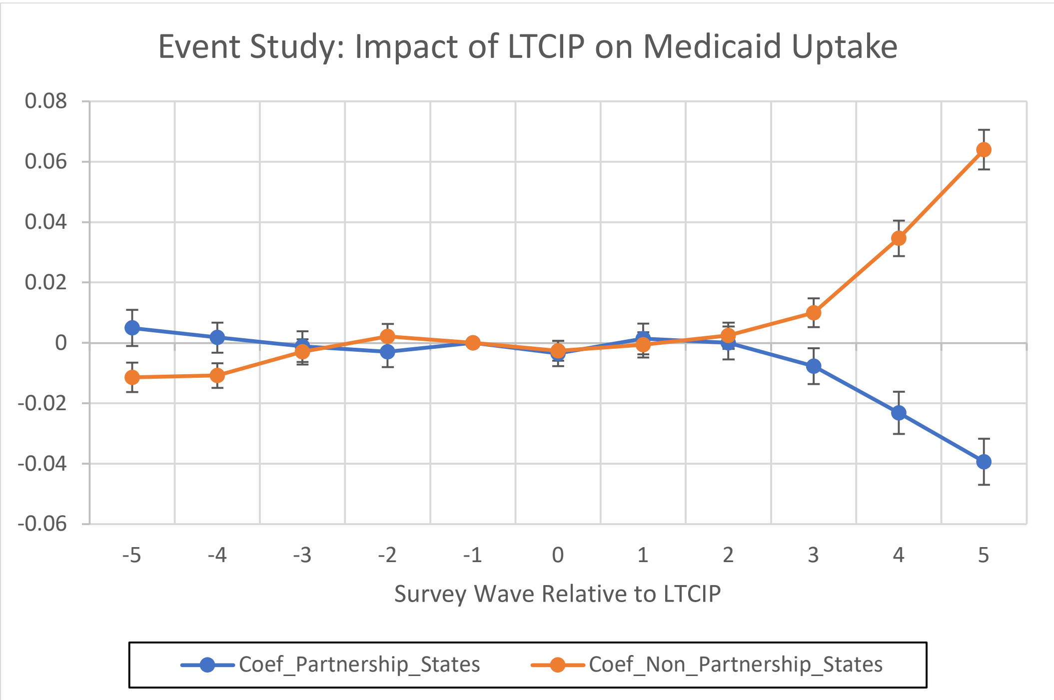



**Figure A5.5.(b) Event Study: Impact of LTCIP on Medicaid.**

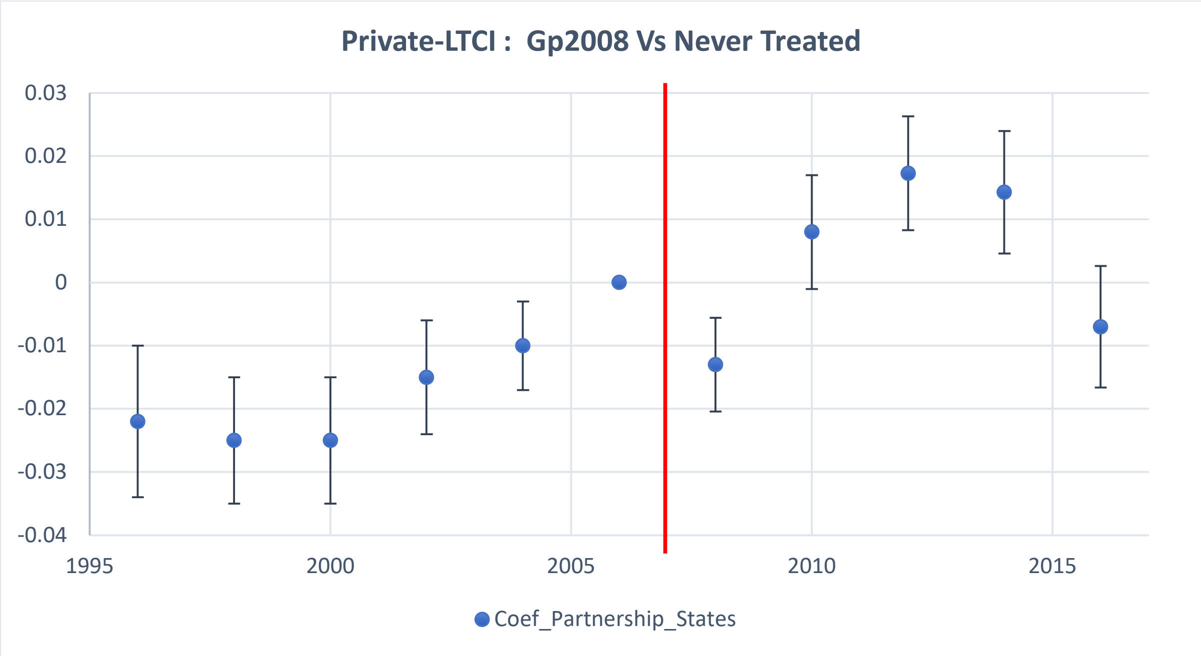



*Notes*: Each point in the figure A5.5. (a) and (b) indicates the effect of LTCIP relative to event time estimated using non-parametric event study in equation (A1), with survey wave for the year 2006 reporting the LTCIP for the first time after DRA-2005 is designated as Wave 0. As the HRS is a biannual survey, the points on X-axis are two years apart. The bars associated with each point on the plot represent 95% confidence interval for the associated coefficient. Each figure has coefficients plotted for two categories, LTCIP states vs non-Partnership states. All the coefficient estimates are weighted using survey weights at person-level.

Next, we report, in Figures A5.6. and A5.7., the group-time average treatment effects for various groups along with respective 95% confidence intervals. All the estimates are obtained after clustering the standard errors at the state level. Figures A5.6.a, A5.6.b, and A5.6.c represent event study plots for private-LTCI in terms of group of states introducing partnership reform in 2008 (16 states), 2010 (18 states), and 2012 (2 states) respectively, whereas Figures A5.7.a, A5.7.b, and A5.7.c do the same for Medicaid. We exclude the state of Idaho that introduced the reform in 2006 from group-time event study analysis because it's a relatively small state and the HRS sample contains only minimal observations for Idaho which makes the comparison very insignificant. The group-time estimates support the finding that LTCIP increases the uptake of private-LTCI followed by decrease in Medicaid entitlements. Further, Figure A5.6.d represents the Early group (2008, control) Vs Late group (2012, treatment) comparison effects for private-LTCI., whereas Figure A5.7.d represents the similar comparison for Medicaid. We find that the effect takes a while to appear which can be termed as marginally less significant comparison. Overall, we observe that the main effect of LTCIP on private-LTCI is driven by the states adopting LTCIP in 2010, which is not covered by previous studies.

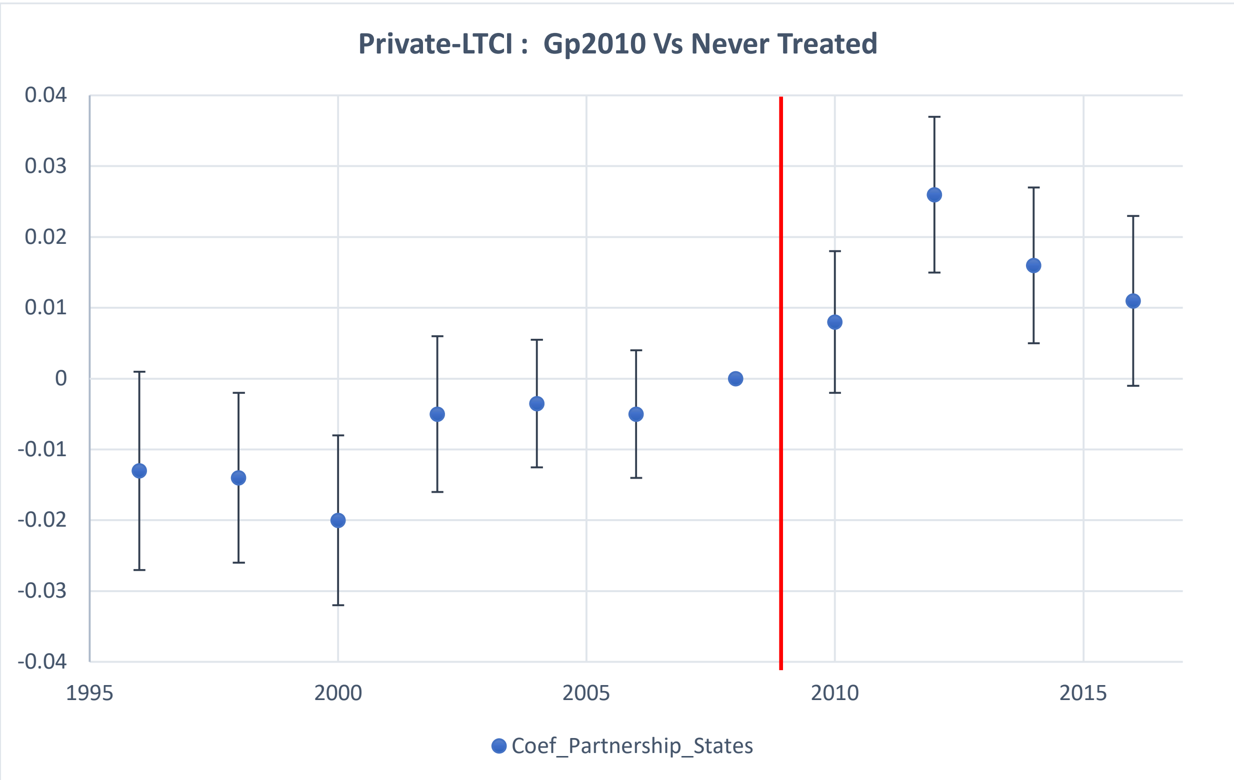
**Figure A5.6.: Event Study: Group-Time Effects – Private-LTCI**

a) Private-LTCI: Group2008 States Vs Never Treated States



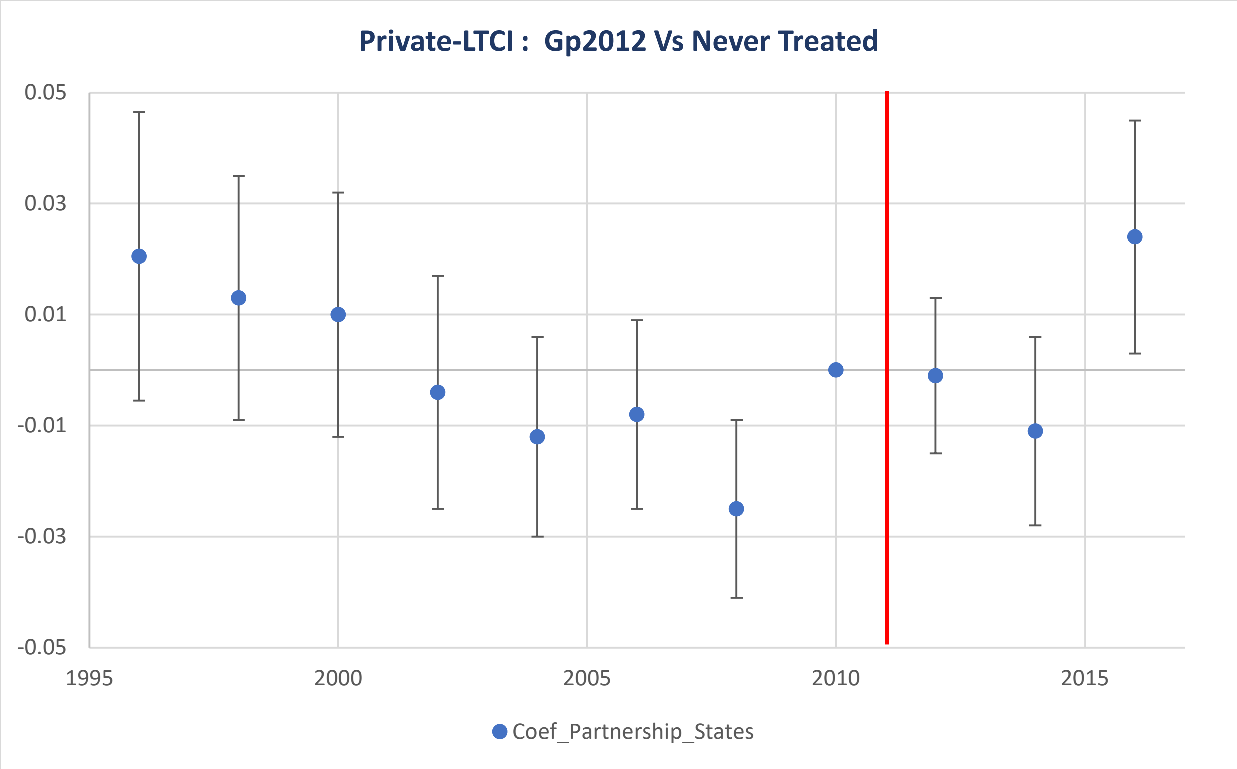

Note: The verticle red line represents the adoption year (2007-08) of LTCIP

b) Private-LTCI: Group2010 States Vs Never Treated States



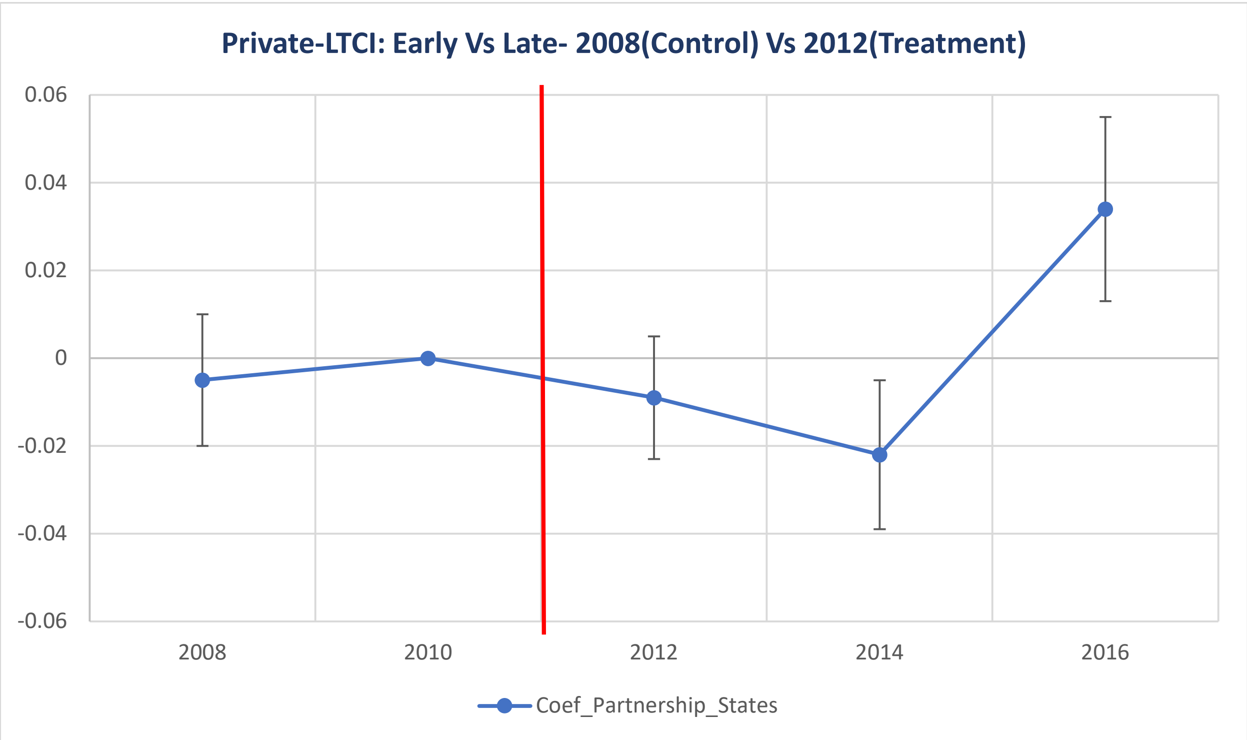

Note: The verticle red line represents the adoption year (2009-10) of LTCIP

c) Private-LTCI: Group2012 States Vs Never Treated States




Note: The verticle red line represents the adoption year (2011-12) of LTCIP

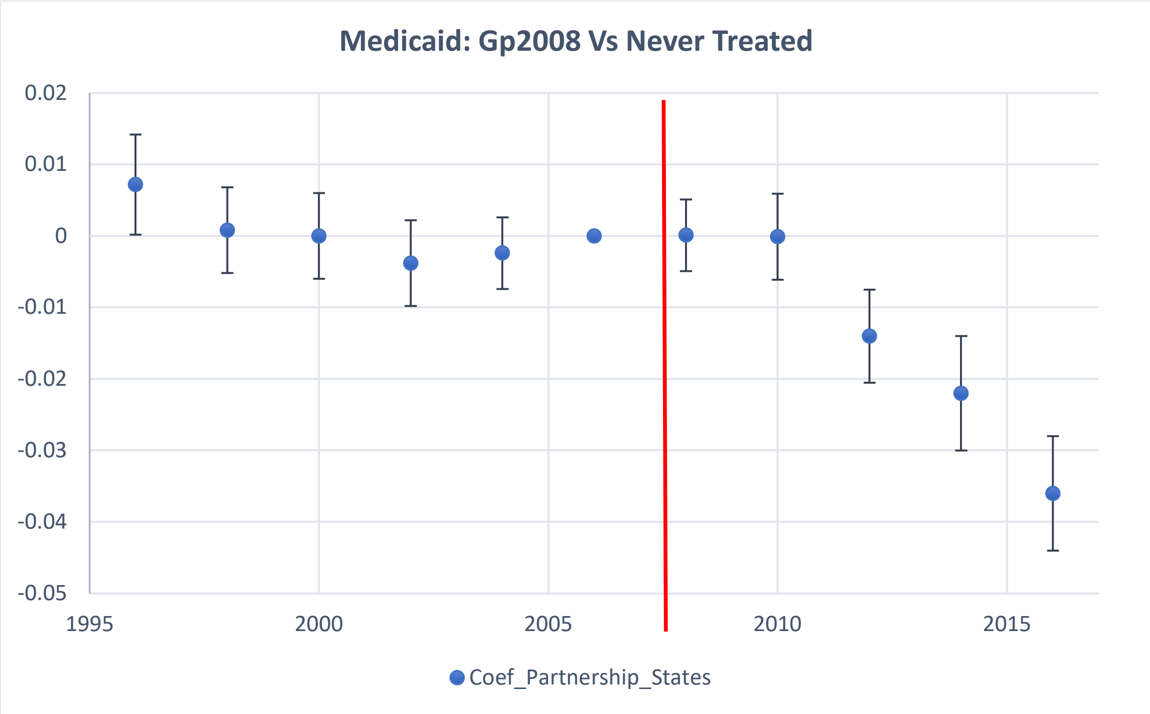
d) Private-LTCI: Group2008 (Control) States Vs Group2012 (Treatment) States




Note: The verticle red line represents the adoption year (2011-12) of LTCIP

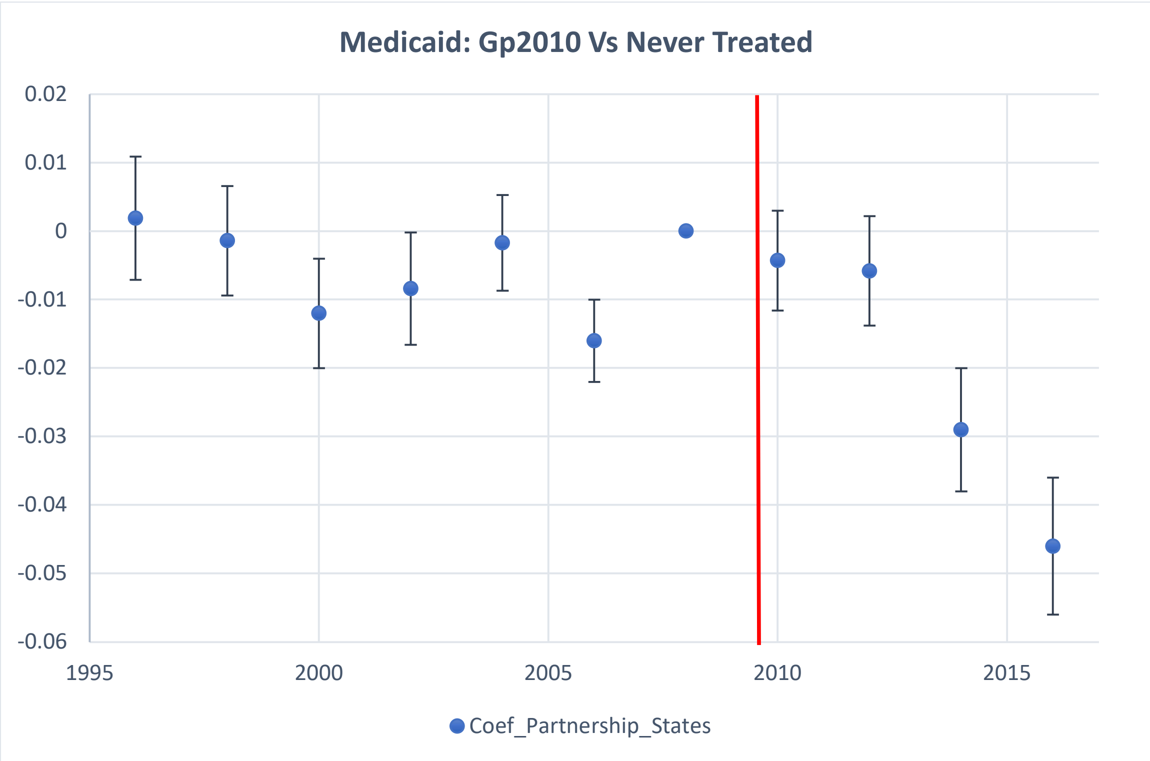
**Figure A5.7.: Event Study: Group-Time Effects – Medicaid**

a) Medicaid: Group2008 States Vs Never Treated States



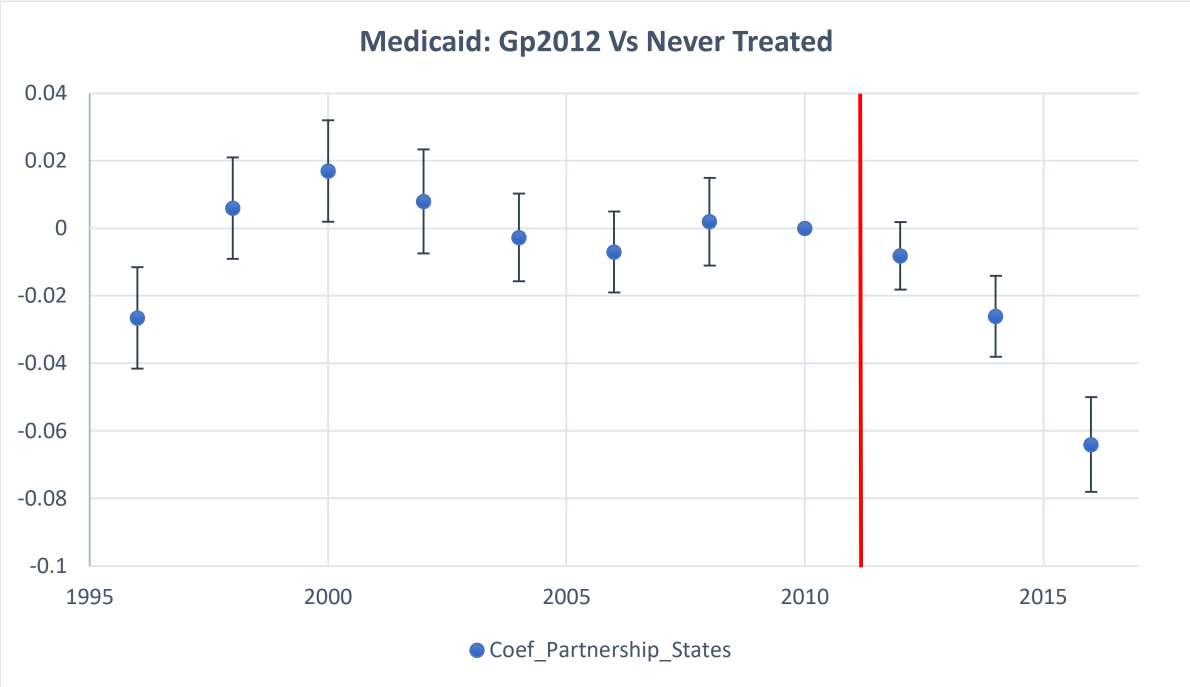

Note: The verticle red line represents the adoption year (2007-08) of LTCIP

b) Medicaid: Group2010 States Vs Never Treated States



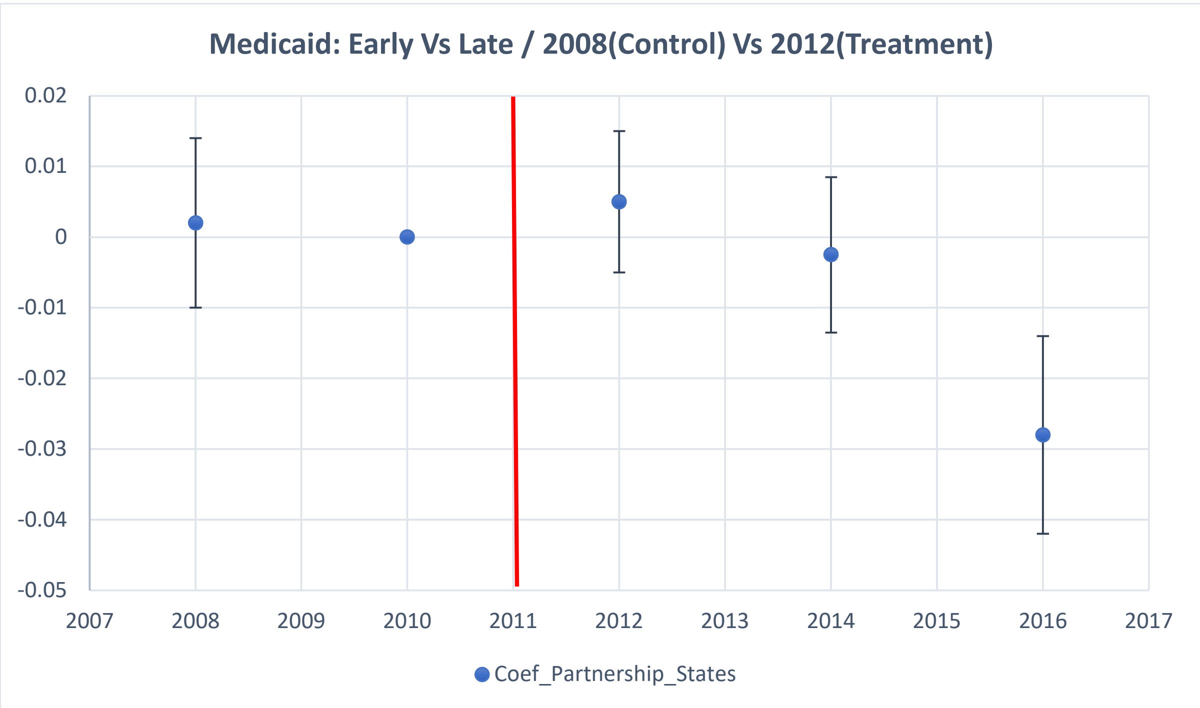

Note: The verticle red line represents the adoption year (2009-10) of LTCIP

c) Medicaid: Group2012 States Vs Never Treated States




Note: The verticle red line represents the adoption year (2011-12) of LTCIP

d) Medicaid: Group2008 (Control) States Vs Group2012 (Treatment) States




Note: The verticle red line represents the adoption year (2011-12) of LTCIP

**Figure A5.8.: Event Study: LTCI - Assuming LTCIP began in 2008 not in 2006**

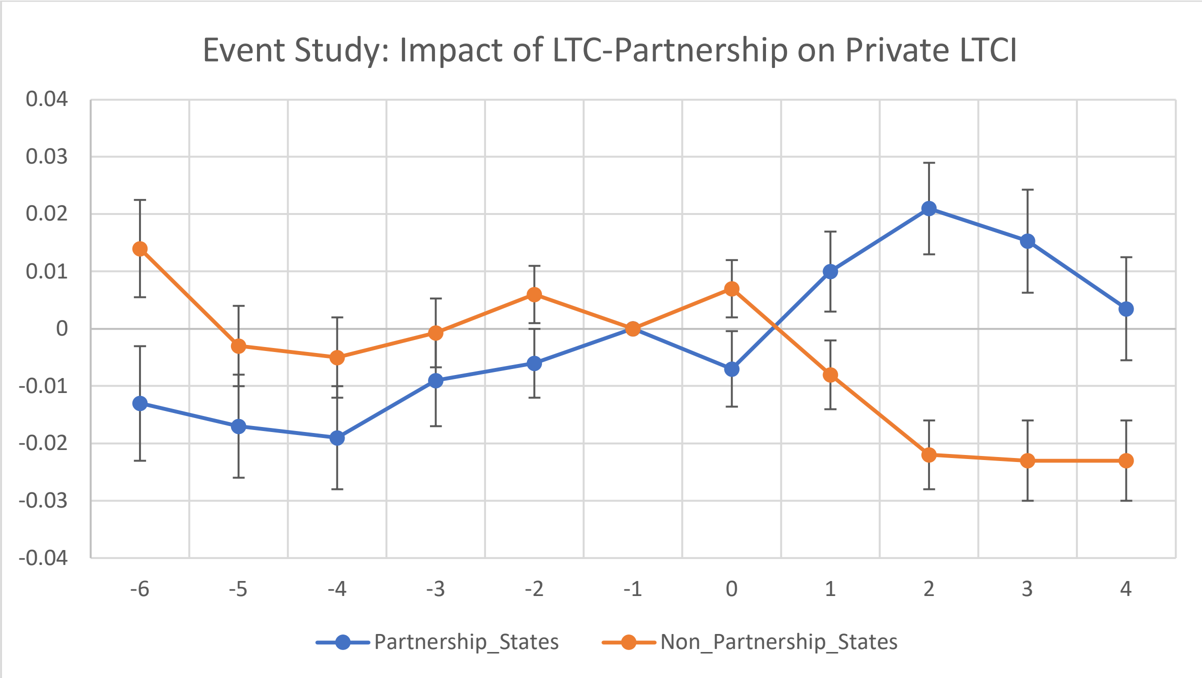



**Figure A5.9. Event Study: Medicaid-Assuming LTCIP began in 2008 not in 2006**

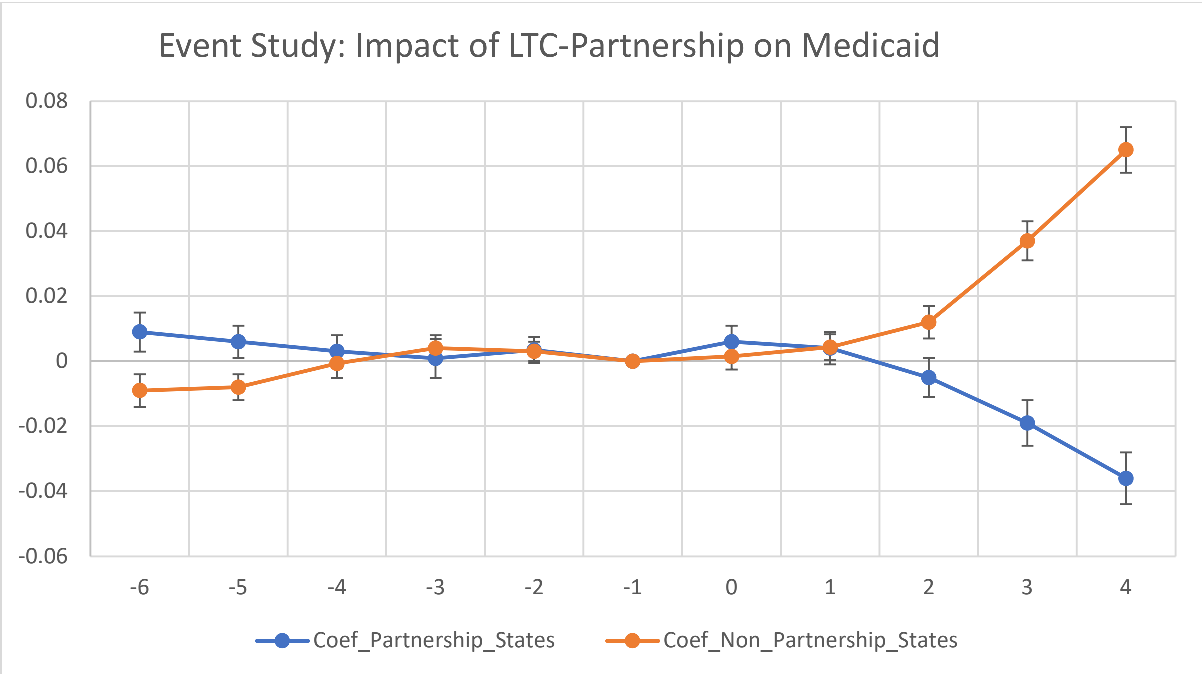
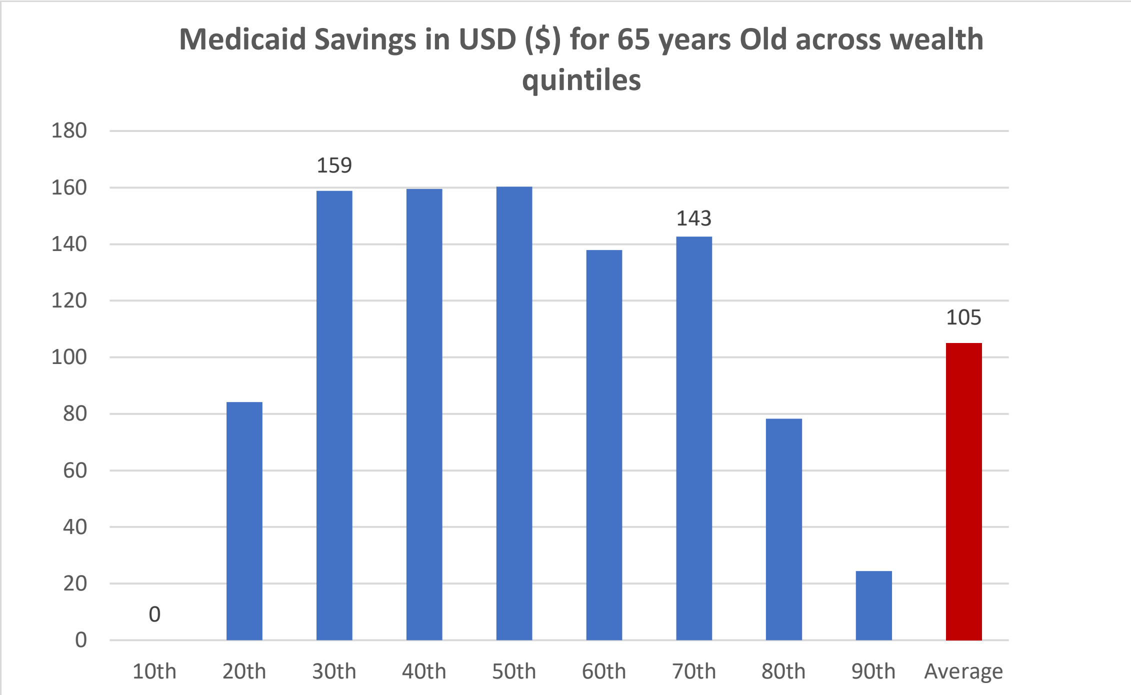
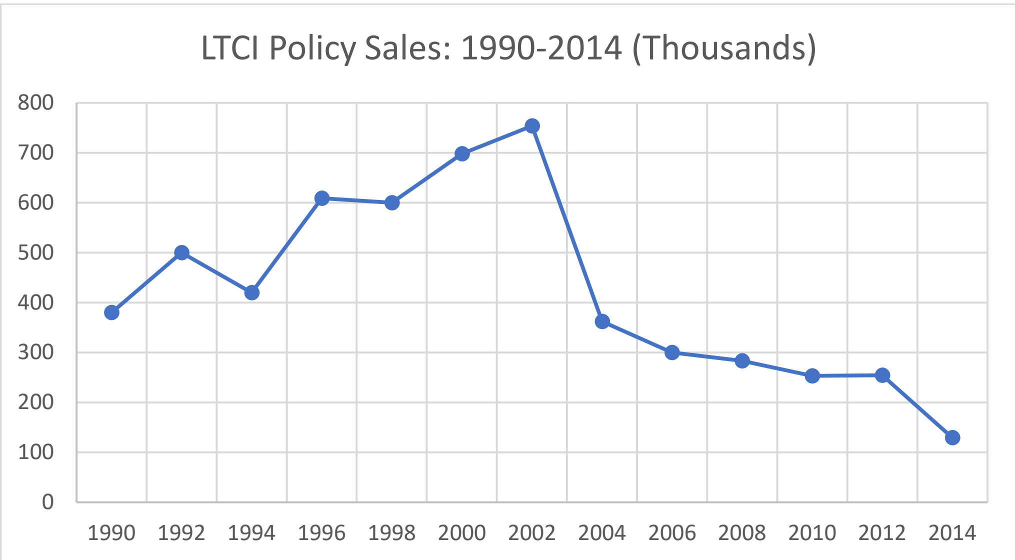


**Figure A5.10.: Estimated total net savings from LTCIP for 65 years old: Model without Person FE**




Note: These saving estimates are calculated using the estimated wealth effects obtained from Column (1) of Table 7. Average Medicaid savings for 65 years old calculated using a simulation technique similar to Goda (2011). Authors calculate, with reference to year 2006, the expected present discounted value (EPDV) of long term-care costs or E(LTC) of $21021 for men and $52523 for women, using the values assumed by Brown and Finkelstein (2007) and Goda (2011) for the year 2000. Low, Middle, and High wealth levels correspond to 30th, 60th, and 80th percentile respectively. The horizontal axis represents wealth percentiles and the vertical axis represents amount saved in USD.

**Figure A5.11.: Private-LTCI Individual Market Sales: 1990-2014 (Thousands)**




Source: Ameriks et at. (2016), contributed for National Association of Insurance Commissioners and The Center for Insurance Policy and Research.

**Table A5.1. Descriptive Statistics for Sample, Insurance Holders, and Insurance Holders from Partnership State**

| | Private-LTCI | | | | |
|---|---|---|---|---|---|
| | Sample Mean | LTCI-Purchasers | LTCI-Purchasers from Partnership states | Difference LTCIP- Mean | Difference LTCIP-LTCI |
| | (1) | (2) | (3) | (3) - (1) | (3) - (2) |
| **Income** | 68,131 | 96,147 | 93,754 | 25,623 | -2,393 |
| **Wealth** | 414,383 | 736,146 | 691,614 | 277,231 | -44,532 |
| **Age** | 62.82 | 64.28 | 64.32 | 1.5 | 0.040 |
| **Male** | 0.431 | 0.416 | 0.413 | -0.018 | -0.003 |
| **Married** | 0.66 | 0.728 | 0.74 | 0.08 | 0.012 |
| **College/More** | 0.447 | 0.61 | 0.61 | 0.163 | 0.000 |
| **Children** | 0.93 | 0.92 | 0.924 | -0.006 | 0.004 |
| **White** | 0.753 | 0.83 | 0.85 | 0.097 | 0.020 |
| **Retired** | 0.55 | 0.62 | 0.63 | 0.08 | 0.010 |
| **Fair/Poor Health** | 0.274 | 0.167 | 0.166 | -0.108 | -0.001 |
| | | | | | |
| | Medicaid | | | | |
| | Sample Mean | Medicaid-Takers | Medicaid-takers from Partnership states (MediciadP) | Difference MedicaidP - Mean | Difference MedicaidP - Medicaid |
| | (4) | (5) | (6) | (6) - (4) | (6) - (5) |
| **Income** | 68,131 | 17,438 | 17023 | -51,108 | -415 |
| **Wealth** | 414,383 | 47,663 | 43120 | -371,263 | -4,543 |
| **Age** | 62.82 | 63.11 | 63.4 | 0.58 | 0.29 |
| **Male** | 0.431 | 0.34 | 0.338 | -0.093 | -0.002 |
| **Married** | 0.66 | 0.315 | 0.303 | -0.357 | -0.012 |
| **College/More** | 0.447 | 0.203 | 0.188 | -0.259 | -0.015 |
| **Children** | 0.93 | 0.903 | 0.91 | -0.02 | 0.007 |
| **White** | 0.753 | 0.496 | 0.528 | -0.225 | 0.032 |
| **Retired** | 0.55 | 0.777 | 0.821 | 0.271 | 0.044 |
| **Fair/Poor Health** | 0.274 | 0.638 | 0.647 | 0.373 | 0.009 |

Note: This table compares means of important variables across three categories using Health and Retirement Study, Waves 3-13, year 1996-2016. The present sample is restricted to age 50-75. The sub-sample mean among insurance holders from Partnership states in Column (3) and (6) compared with Sample mean (Column (1) & (4)) and subsample mean of insurance holders (Column (2) & (5)).

## Table A5.2.: Adoption of Long-Term Care Partnership Insurance Across States

| What States Have Approved Long-Term Care Partnership Insurance for Sale (Updated: April 2017) | | |
|---|---|---|
| **State** | **Effective Date (As of April 2017)** | **Policy Reciprocity** |
| Alabama | 03/02/09 | Yes |
| Alaska | Not Filed | --- |
| Arizona | 07/01/08 | Yes |
| Arkansas | 07/01/08 | Yes |
| California | Original Partnership | No |
| Colorado | 01/02/08 | Yes |
| Connecticut | Original Partnership | Yes |
| Delaware | 11/02/11 | Yes |
| District of Columbia | Not Filed | --- |
| Florida | 01/01/07 | Yes |
| Georgia | 01/01/07 | Yes |
| Hawaii | Pending | --- |
| Idaho | 11/02/06 | Yes |
| Illinois | Pending | --- |
| Indiana | Original Partnership | Yes |
| Iowa | 01/01/10 | Yes |
| Kansas | 04/01/07 | Yes |
| Kentucky | 06/16/08 | Yes |
| Louisiana | 10/01/09 | Yes |
| Maine | 07/01/09 | Yes |
| Maryland | 01/01/09 | Yes |
| Massachusetts | Proposed | --- |
| Michigan | Work stopped | --- |
| Minnesota | 07/02/06 | Yes |
| Mississippi | Not Filed | --- |
| Missouri | 08/01/08 | Yes |
| Montana | 07/01/09 | Yes |
| Nebraska | 07/01/06 | Yes |
| Nevada | 01/01/07 | Yes |
| New Hampshire | 02/16/10 | Yes |
| New Jersey | 07/01/08 | Yes |
| New Mexico | Not Filed | --- |
| New York | Original Partnership | Yes |
| North Carolina | 03/07/11 | Yes |
| North Dakota | 01/01/07 | Yes |
| Ohio | 09/10/07 | Yes |
| Oklahoma | 07/01/08 | Yes |
| Oregon | 01/01/08 | Yes |
| Pennsylvania | 09/15/07 | Yes |
| Rhode Island | 07/01/08 | Yes |
| South Carolina | 01/01/09 | Yes |
| South Dakota | 07/01/07 | Yes |
| Tennessee | 10/01/08 | Yes |
| Texas | 03/01/08 | Yes |
| Utah | Not Filed | --- |
| Vermont | Not Filed | --- |
| Virginia | 09/01/07 | Yes |
| Washington | 01/01/12 | Yes |
| West Virginia | 17/01/2011 | Yes |
| Wisconsin | 01/01/09 | Yes |
| Wyoming | 06/29/09 | Yes |

Source: American Association of Long-Term Care Insurance website, which comes under U.S. Government Accountability Office's Consumer Information Center. http://www.aaltci.org/long-term-care-insurance/learning-center/long-term-care-insurance-partnership-plans.php)

## Table A5.3.: Baseline Models – Impact of LTC-Partnership on Private-LTCI and Medicaid

| VARIABLES | (1) RLTCI | (2) RLTCI | (3) RLTCI | (4) RLTCI | (5) Medicaid | (6) Medicaid | (7) Medicaid | (8) Medicaid |
|---|---|---|---|---|---|---|---|---|
| Partnership(LTCIP) | 0.0144*** | 0.00670** | 0.0164*** | 0.00951*** | 0.0107*** | 0.0108*** | -0.0146*** | -0.00282 |
| | (0.00348) | (0.00342) | (0.00462) | (0.00371) | (0.00252) | (0.00240) | (0.00360) | (0.00296) |
| PermPP | -0.00243 | -0.00487 | -0.0491 | 0.0472 | 0.0317*** | 0.0251*** | 0.0648 | 0.0545 |
| | (0.00497) | (0.00491) | (0.121) | (0.0946) | (0.00425) | (0.00373) | (0.0548) | (0.0750) |
| age | | 0.00102 | 0.00148 | -0.00343 | | 0.00212 | 0.00167 | 0.000979 |
| | | (0.00354) | (0.00357) | (0.00281) | | (0.00258) | (0.00261) | (0.00221) |
| age2 | | 2.59e-05 | 2.25e-05 | 3.71e-05** | | -1.60e-05 | -1.24e-05 | -1.16e-05 |
| | | (2.80e-05) | (2.83e-05) | (1.63e-05) | | (2.04e-05) | (2.06e-05) | (1.28e-05) |
| Male | | -0.0140*** | -0.0139*** | | | -0.0129*** | -0.0127*** | |
| | | (0.00398) | (0.00395) | | | (0.00255) | (0.00252) | |
| College_edu | | 0.0663*** | 0.0663*** | | | -0.0461*** | -0.0476*** | |
| | | (0.00392) | (0.00392) | | | (0.00264) | (0.00268) | |
| Married | | 0.0256*** | 0.0249*** | 0.0110*** | | -0.0811*** | -0.0803*** | -0.0276*** |
| | | (0.00398) | (0.00397) | (0.00324) | | (0.00326) | (0.00323) | (0.00255) |
| Income | | 3.32e-08** | 3.30e-08** | 4.00e-09 | | -1.90e-08** | -2.06e-08** | -6.70e-09*** |
| | | (1.66e-08) | (1.67e-08) | (3.27e-09) | | (7.62e-09) | (8.28e-09) | (2.59e-09) |
| White | | 0.0231*** | 0.0211*** | | | -0.0802*** | -0.0768*** | |
| | | (0.00353) | (0.00380) | | | (0.00465) | (0.00467) | |
| Fair/Poor Hlth | | -0.0349*** | -0.0333*** | -0.00587*** | | 0.113*** | 0.111*** | 0.0120*** |
| | | (0.00313) | (0.00312) | (0.00221) | | (0.00381) | (0.00378) | (0.00174) |
| Constant | 0.106*** | -0.112 | -0.0455 | 0.0844 | 0.0582*** | 0.115 | 0.0879 | 0.00574 |
| | (0.00222) | (0.111) | (0.165) | (0.152) | (0.00175) | (0.0801) | (0.0978) | (0.120) |
| STATE + YEAR FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Individual FE | NO | NO | NO | YES | NO | NO | NO | YES |
| Observations | 148,972 | 148,972 | 148,972 | 148,972 | 148,472 | 148,472 | 148,472 | 148,423 |
| R-squared | 0.001 | 0.028 | 0.036 | 0.008 | 0.002 | 0.119 | 0.127 | 0.017 |
| Number of respd_id | | | | 32,182 | | | | 32,139 |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-13, 1996-2016. Each coefficient indicates OLS estimates of equation (2). There are two dependent variables namely Private long-term care insurance (LTCI) and public long-term care insurance or Medicaid. The variable 'Partnership' is a treatment variable, which is a binary indicator for whether there is LTCIP available in the state and year after the passage of Deficit Reduction Act (DRA-2005). It is also called as 'New-Partnership' or 'LTCIP'. At first, we estimate the impact of LTCIP on Private-LTCI in which Column (1) includes no variables other than treatment or partnership. Column (2) introduces states and years fixed effects into the model. Column (3) adds control variables namely age, gender, age^2, income, health status, marital status, race, and education. Column (4) introduces Fixed Effect Model that removes time-constant characteristics. Whereas Column (5)-(8) follow the similar procedure for Medicaid uptake.

**Table A5.4.: Standardized Coefficients – Impact of LTC-Partnership on Private-LTCI and Medicaid**

| | LTCI | | Medicaid | |
|---|---|---|---|---|
| VARIABLES | (1)<br>***b*** | (2)<br>***bstdXY*** | (3)<br>***b*** | (4)<br>***bstdXY*** |
| Partnership (LTCIP) | 0.0164***<br>(0.00462) | 0.025 | -0.0146***<br>(0.00360) | -0.028 |
| PermPP | -0.0491<br>(0.121) | -0.061 | 0.0648<br>(0.0548) | 0.102 |
| age | 0.00148<br>(0.00357) | 0.031 | 0.00167<br>(0.00261) | 0.041 |
| age2 | 2.25e-05<br>(2.83e-05) | 0.060 | -1.24e-05<br>(2.06e-05) | -0.039 |
| Male | -0.0139***<br>(0.00395) | -0.022 | -0.0127***<br>(0.00252) | -0.026 |
| College_edu | 0.0663***<br>(0.00392) | 0.105 | -0.0476***<br>(0.00268) | -0.094 |
| Married | 0.0249***<br>(0.00397) | 0.038 | -0.0803***<br>(0.00323) | -0.15 |
| Income | 3.30e-08**<br>(1.67e-08) | 0.029 | -2.06e-08**<br>(8.28e-09) | -0.022 |
| White | 0.0211***<br>(0.00380) | 0.025 | -0.0768***<br>(0.00467) | -0.114 |
| Fair/Poor Hlth | -0.0333***<br>(0.00312) | -0.106 | 0.111***<br>(0.00378) | 0.19 |
| Constant | -0.0455<br>(0.165) | -- | 0.0879<br>(0.0978) | -- |
| STATE + YEAR FE | YES | YES | YES | YES |
| Individual FE | NO | NO | NO | No |
| Observations | 148,972 | 148,972 | 148,472 | 148,423 |
| R-squared | 0.036 | 0.036 | 0.127 | 0.127 |
| Number of respd_id | | | | |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level. All the coefficient estimates are weighted using survey weights at person-level.

Note: The standardized estimates of ***bstdXY*** in clomn 2 and 4 are obtained using *listcoef, help* command of stata.

# 6. Self-Insuring Care Effects? Wealth Shocks and Public and Private Long-Term Care Insurance

## 6.1.Abstract

The funding of long-term care services and supports (LTSS), relies heavily on self-insurance either via housing or financial wealth at old age. We examine the effect of wealth shocks resulting from both housing prices, and variation in financial shocks prices on the uptake of private long term care insurance (LTCI) and on the individual eligibility for public insurance (Medicaid sponsored care). Using restricted data from the relevant waves of the Health and Retirement Study (1994-2018), we explore *local variation* stemming from housing prices and, individual variation in the US stock market wealth. Consistently with the hypothesis of 'self-insuring care effect', we document that housing and stock wealth shocks significantly reduce the probability of purchasing private-LTCI without significantly altering Medicaid eligibility among owners of housing and financial assets. We find that the effect of liquid wealth strongly dominates over the effect of housing wealth. A 100K increase in financial (housing) wealth reduces the likelihood of buying private-LTCI by 4.7 (0.6) percentage points.

Keywords: long term care insurance, housing assets, Medicaid, House prices. Stock market price index. Instrumental variables.

JEL No. I18, J14

## 6.2.Introduction

One of the central social policy questions in the aging western societies is how best to fund long-term care services and supports (LTSS). Before they pass away, almost half of persons who reach the age of 65 might anticipate utilising some long-term services and supports (Favreault and Dey, 2015). The predicted present discounted value of the services used by persons who will use LTSS is estimated to be $133,700 in 2015 dollars. Before they pass away, about 5% of men and 12% of women over 65 will spend more than $250,000 in present-day, discounted 2015 dollars on LTSS (Favreault and Dey, 2015). Purchases of private long-term care insurance (LTCI) in turn are limited, and in the United States about 12% of people 65 years of age and older have such policies. However, in the absence of a flourishing private insurance market, Medicaid has increasingly been the main funder of long-term care (Frank, 2012) in addition to individuals self-financing. In the absence of private insurance and eligibility for Medicaid, the alternative funding mechanism is self-funding by using available assets, both Housing and financial. Housing assets are traditionally the main source of non-pensionable wealth of Americans (Venti and Wise, 1990) and this is especially the case at old age as 80% of elderly Americans are homeowners and continue to be so at old age (Engelhardt, 2008). Although housing assets are generally exempt when determining a person's eligibility for Medicaid, many people count on being able to sell their house in order to pay out-of-pocket for LTSS. Similarly, individuals holding financial wealth can rely on such wealth as a self-funding mechanism for future LTSS, which we denote as 'self-insuring care effect'. Thus, understanding how a wealth shocks, both housing and financial, might affect individuals' long-term care funding decisions is needed for estimating the costs of possible public policies for financing LTSS.

Studies examining housing downsizing find that it is not until individuals become frail elders that they might end-up depleting their housing assets (Walker, 2004). The cost of home care and nursing home care can routinely impoverish older Americans, and it is not uncommon for some to rely on Medicaid for funding, especially if they do not hold LTCI. So far weak evidence that individuals strategically spend down to become eligible for Medicaid funded care. Individuals must technically be qualified for Supplemental Security Income (SSI) or have a level of income and assets below the SSI restrictions in order to be eligible for Medicaid. The current SSI asset and income limits for single people are $2,000 and $564, respectively. However, different states might apply special rules so that the threshold becomes slightly higher or lower across states, generally more restrictive criteria. Although there is some level of stigma in Medicaid uptake, once an individual is using LTSS a negative wealth shock could increase the chances of older adults to qualify for Medicaid, especially single individuals, though couples too. Household wealth are expected to influence the capacity to self-fund for LTSS, though the identification of wealth effects is complicated due to unobservables that drive wealth accumulation might as well determine the demand for long-term care (Garber, 1989) in addition to the weak wealth and health nexus effect (Meer, Miller, and Rosen, 2003). Thomas Davidoff (2010) suggests in his paper (containing numerical evidence) that home equity pays out cash in a way similar to LTCI, and he concludes that if homeowners manage to anticipate using home equity to pay for LTSS, it provides a case for a more extensive use of housing assets in the Medicaid eligibility tests.

One way to examine the wealth effects drawing on exogenous wealth shocks either at the individual (e.g., lottery wins, bequests etc.) or local area level (e.g., changes in house) or at aggregate level (eg., stock indices). The home equity is one of the largest components of wealth for most households, whereas the share of stock equity has been consistently growing among Americans in recent decades. Such dramatic and largely unexpected changes in house and stock prices can influence consumer's decisions, especially at old age when individuals tend to draw on their housing assets more than proportionally. Among wealth shocks, the exogenous nature of rapid and unexpected house and stock prices – which in some countries has engendered housing and stock bubbles-, followed by subsequent house and stock price drops – or bubble bursting phenomenon- stands out as a clear example to examine. The evidence on the effect of housing assets on public and private long-term care insurance is almost negligible. The exception is Davidoff (2008) which carries out an empirical exercise with data before 2006 to examine the effect of the proportion of housing assets to total wealth on long-term care insurance. However, the impact of stock wealth on long-term care insurance is not known and needs to be identified for the comprehensive understanding of self-funding mechanism for LTSS.

In this paper, we focus on estimating the effects of a wealth shock on the uptake of Medicaid and private long-term care insurance (LTCI) in the United States, being the default option individual's self -insurance of care needs. We take advantage of the exogenous variation in both housing and stock wealth on public and private insurance for LTSS. That is, we estimate the effect of a wealth shock on the extensive margin of (individual level probability to qualify for) Medicaid or, the purchase LTCI. The period examined includes wide variation in house prices, beginning with a housing boom was in the first quarter of 1999 (Q1), and the start of the housing bubble burst was in the first quarter of 2006(Q1) (Cohen et al., 2012). That is, after a decade of price increases, housing prices reached their peak in early 2006, and at the end of that year, there was a sudden, unexpected, and historically largest drop in history of 18.9%. From there, prices showed more moderate price decreases until 2009, when prices seemed to have risen again[26]. Changes are heterogeneous across the territory; housing prices tended to rise much faster in metropolitan areas in the East and West Coast regions than in the country's

[26] See Figure A6.1 in the Appendix

interior (Cohen, Coughlin, and Lopez, 2012)[27]. Similarly, the last two decades experienced two different bubbles in the US stock market: The Dot-com bubble of mid 1990s and mid 2000's housing bubble due to sub-prime mortgage crisis. We show that pro-cyclical home and stock equity gains (losses) for owners generate positive health effects through increased (reduced) reliance of Medicaid and use of long-term care[28].

The degree of property price changes varies greatly between households both geographically and over time. Local economic conditions, which are likely to have an impact on people's health in ways other than through home equity impacts, are a contributing factor in local house price changes, even if they are exogenous to individual households. By including local-level and time dummies into our econometric model, we condition our estimates on location and temporal effects. We also calculate how changes in local housing costs affect the health of *renters* who go through same housing consumption conditions as owners without experiencing the direct wealth gains or losses due to house price movements.

This paper reports quasi-experimental environment for evaluating the effect of wealth shocks on the uptake of private-LTCI and the means-tested public insurance (Medicaid) at the extensive margin. More specifically, we document the effect of exogenous changes in housing assets exerted on the probability of purchasing private-LTCI. We rely on the HRS 1994 -2014 data waves, and we use time, state and house prices and stock market changes to identify the effect of wealth change on private-LTCI purchase as well as Medicaid. We draw on the exogenous source of variation of wealth to investigate the effect of wealth on access to long term care. Given the significant variation in the effects of the housing bubble across the

[27] So prices in Boston during the boom increased by 121% and during the bust dropped by 15%, whilst in LA they increase by 231% during the boom and dropped by 40% during the burst. In contrast in Detroit, the price changes was more balanced out with an increase during the boom was 46% and the house decline was 44%.
[28] The two main indexes that are regarded as reliable are the Standard & Poor's (S&P)/Case-Shiller house price index and the Federal Housing Finance Agency (FHFA) Purchase-Only. However, although variation is larger in the former, the two indexes are remarkably similar in the timing of the changes. Overall, metropolitan areas with the larger booms tended to have larger busts.

territory of the United States, examining wealth changes over time is particularly important. To ensure the experimental nature of exercise, we have tested the instruments' robustness and conducted reduced forms. All of these tests show that wealth is endogenous, and that stock market and housing market fluctuations are effective instruments for measuring this variation in wealth. We have considered the factors that may have an impact on elderly caregiving and housing options. By including time and state dummies in our regression estimations, we can adjust for crucial sources of variance such as time- and state-specific effects. Additionally, we include specific fixed effects in our regression model. At the same time, we examine the effects of changes in house prices on renters and of changes in stock market on no-stock holders, who would not exhibit a wealth effect.

Our work offers two clear advantages. First, we exploit data on the exogenous wealth changes at the individual level, conditional on the controls we can include in our estimating equation. We find that a $100,000 change in both housing and total assets reduces the likelihood of purchasing private-LTCI by 0.59 and 0.47 percentage points respectively, whereas $100,000 change in stock and total assets reduces the probability of buying private-LTCI by 4.7 percentage points and 6.8 percentage points, respectively. These estimates clearly indicate the substitution between two goods, self-insurance and private-LTCI. Second, we find no significant effect on the probability of Medicaid entitlement.

The structure of the paper is as follows. The next section provides background about housing and stock wealth and the current financing of LTSS, followed by a section describing our data and empirical strategy. In section four we discuss our estimation results and in the final section we discuss the implications of the results.

### 6.3. Background

***6.3.1. Housing at old age.*** The steady rise in the homeownership rate among people 65 and older, which is explained by an increase in social security benefits, has been one of the most striking trends in US housing markets (Engelhardt, 2008). According to Venti and Wise (1990), the elderly has a strong desire to age in place, and there is a link between homeownership among the old and income. Housing wealth is actually consumed, albeit the evidence would seem to show that this occurs more in very old life. Walker (2004) demonstrates that rather than age, the primary determinant of housing sales in senior housing for single households is health. Surging attention and research interests on relationships between house price fluctuations as a proxy for wealth shocks.

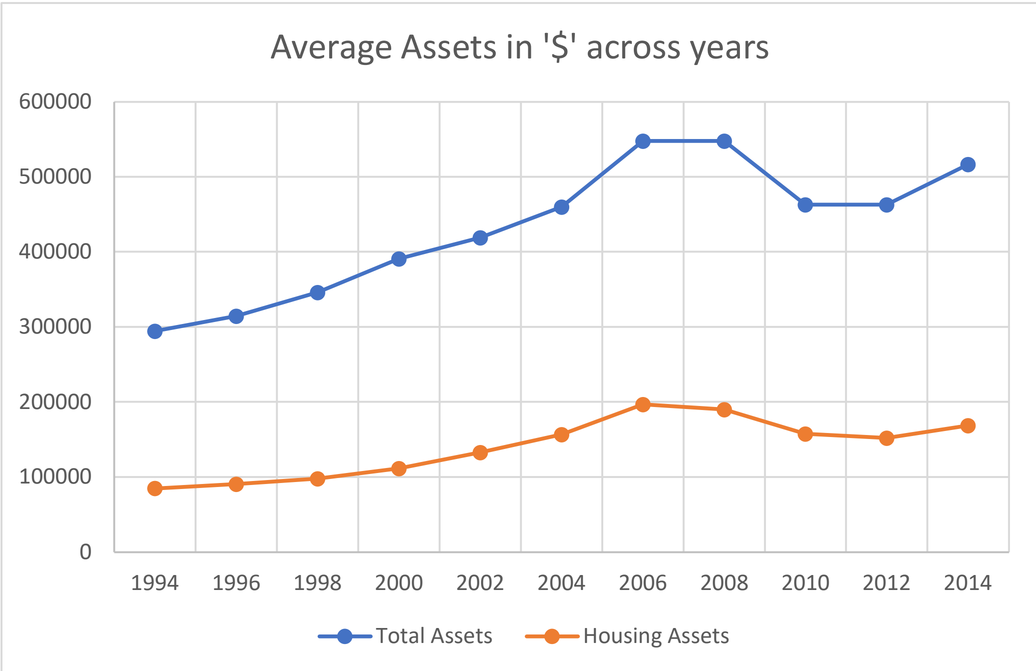
***6.3.2. Housing wealth effects***. According to Poterba, Venti, and Wise (2011), net worth increases steadily or more slowly with age for wealthier households (those in the top three quintiles of baseline health status), but not for healthier households (those in the bottom three). (Case, Quigley, and Shiller 2005), and (Campbell and Cocco 2005), examine the housing wealth effect by looking at whether households will modify consumption in response to house price changes. There is some difference between immediate and long-run effects, but overall, the difference is suggestive of an effect. Case et al., (2005) show that changes in aggregate housing expands consumption with an elasticity that can be as high as 0.1. When long-run effects are identified, then housing wealth elasticity drops to 0.04 but remains significant (Carroll, Otsuka, and Slacalek 2011). Bostic, Gabriel, and Painter (2009) find higher elasticities on housing wealth on consumption than that of financial wealth and in the UK, Disney, Gathergood, and Henley (2010) found slightly smaller estimates, which were different for positive and negative wealth shocks. However, it is important to distinguish perfectly anticipated housing prices from unanticipated ones. We concentrate on housing price shocks in this study since they are orthogonal to human decision-making. The latter is due in part to the fact that housing has consumption implications and people do not always view it as an investment. However, investment consequences can become more noticeable in the event of a health and wealth shock together. Downsizing impacts later in life are another situation where investment effects become apparent (Campbell and Cocco, 2005). The economic downturn allows for examining the impact of wealth shocks on several economic decisions. Lovenheim et al. (2013) show that housing wealth rise increases fertility among homeowners but not among renters. Goda et al. (2011) conclude that a positive permanent income shock decreases the demand for nursing facility care and raises the demand for paid home care services using data from the social security notch, which would have differentially affected retirees' income.

House prices exhibit pro-cyclical business cycle dynamics, illustrated in Figures 6.1.1 & 6.1.2, which employ the Health and Retirement Survey (HRS) to show the evolution of total assets of individuals over the age of 50. As expected, we find a significant wealth expansion from 1994 on to 2006 where we find a wealth reduction (in the form of a wealth shocks) that on average is of a magnitude of 15-20%. This pattern almost certainly matches that of Figure 6.1.2 that shows the evolution of house prices over the same period using Federal Housing Finance Agency (FHFA) Purchase-Only prices. Overall, the trends are suggestive of a change in assets, with a slight decrease towards 2008-10 for the older individuals than their younger counterparts who are less likely to require LTSS but experience greater decline in assets during the same time. However, it is also evident that the economic recovery began to take place after 2012.

Such dramatic and largely unexpected changes in house prices can influence the financing of LTSS, given that at old age individuals tend to draw on their housing assets more than proportionally. After retirement, individuals rely on their pension income and wealth in housing assets as a self-insurance against long-term care, which in turn takes a more central stage in maintaining the elderly’s consumption levels and, when dependency hits, granting access to long-term care. In the latter case, it can be reasonable to expect a specific effect of housing assets on the choice of long-term care, specifically influencing the potential substitution between different formal LTSS (e.g., nursing home care, assisted living and home health) and informal care within the household. The latter still today is the predominant form of support for elderly in need of LTSS in the United States. More generally, a change in housing assets might have impacted the capacity to finance planned long-term care services with the remaining net wealth.

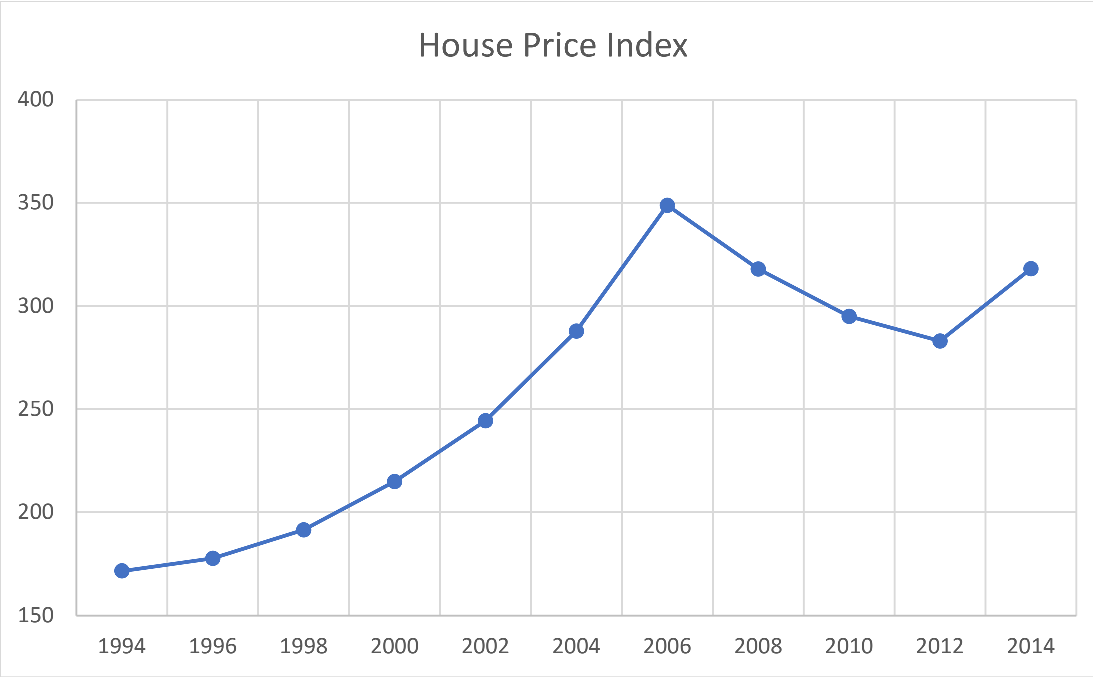
**Figure 6.1. Total Assets of Elderly American Households, House Prices Index and Population without Housing Assets**

**6.1.1. Evolution of Total and Housing Assets**



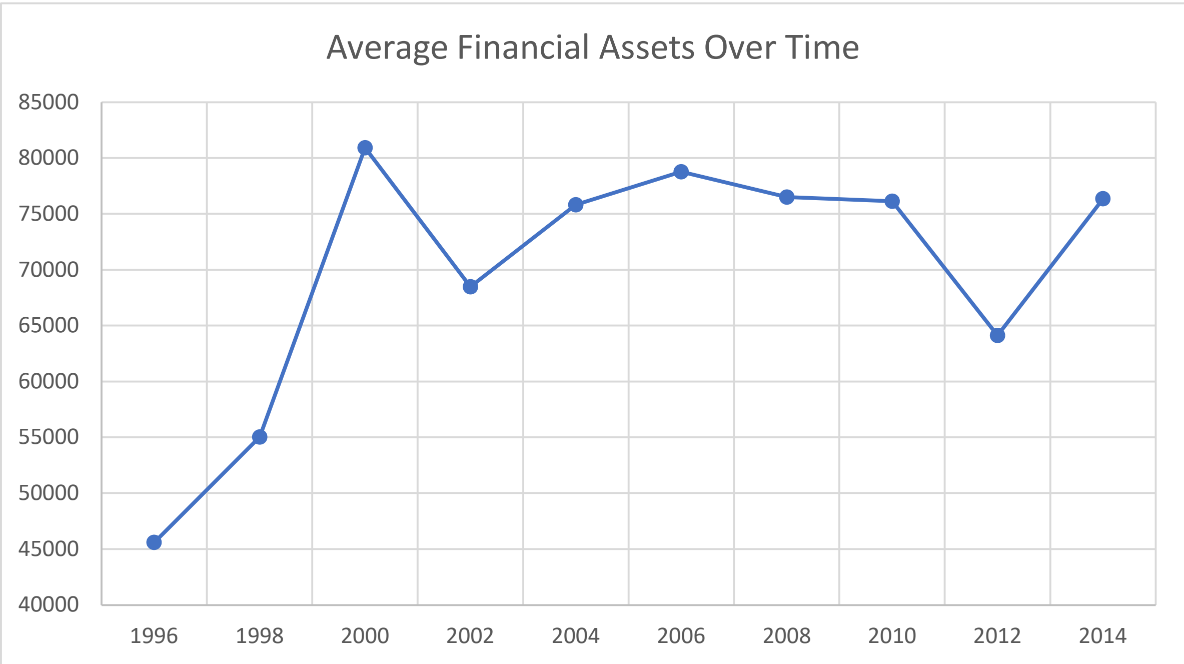

Source: Health and Retirement Study, waves 2 -12.

**6.1.2. House prices (FHFA Index- by MSA and County)**




Source: HHFA 2014. [Note: Places with missing MSA-level indexes are assigned county level index values.]

### 6.1.3. Evolution of Financial Assets Over Time




Source: Health and Retirement Study, waves 3 -12. Wave 2 (Year 1994) is excluded due to lack of observations.

The influence of housing assets on LTC financing can take place through different pathways. A negative change in housing assets can influence the individual's ex-ante planning for old age care. Arguably, it might increase the probability of long-term care insurance purchase by making self-insurance less of an option. It is important empirical question that needs to be answered given the efforts led in the past two decades by both federal and state governments to stimulate the purchase of private-LTCI for limiting the public expenditure on Medicaid (public insurance). However, given that the housing price shocks potentially exerts an unexpected effect on homeowner individual's wealth, it seems reasonable to interpret the effects as exogenous to the individual, and hence causality is more likely to be established. Another potential effect is that of a change of housing assets on the health, and more specifically the probability of disability at old age even though the effects appear to be weak to date (Meer et al., 2003). Alternatively, it might increase the probability of an individual to qualify for Medicaid. Older adults that were at the point of becoming dependent at the time of the exogenous change in housing assets, when liquidising such assets arguably becomes prominent, would have suffered a significant loss in wealth to face some wealth losses which arguably had an impact on their household caregiving decisions. It is an empirical question first ascertain whether this was indeed the case. Wealth effects result from increases (reductions) in asset values on consumer decision, especially among old age elderly who need long-term care. Also, one can refer to income effects resulting from a decline (expansion) in income and employment.

***6.3.3. Stock Wealth Effects***: Stock market wealth can be comparable to the housing wealth because the stock ownership in the US constitutes the largest share of household financial assets Maggio, Kermani, and Majlesi (2018). There is mixed evidence of the effects of stock market wealth and household consumption. Davis and Palumbo (2001), Case et al. (2005, 2013), Carroll, Otsuka, and Slacalek (2011), Carroll and Zhou (2012), and Bostic, Gabriel, and painter (2009) identify the stock market wealth effects by analysing aggregate or micro level data and found that the stock market wealth is weakly correlated with household consumption with marginal propensity to consume is lower than 5%. In addition, Poterba (2000) concludes that the direct wealth effect of stock market wealth increase is likely to be small due to the skewness in distribution of stock wealth ownership. He also infers the possibility of spill-over effect of stock prices increase on household spending through consumer confidence for those who do not own stocks (Poterba 2000). However, Dynan and Maki (2001) and Maggio et al. (2018) found that increase in stock wealth is strongly correlated with household consumption spending and that the estimated MPC is greater than 5%.

Long-term care is an important component of elderly's consumption expenditure. The expected effect of stock ownership on long-term care has never been explored before. Increase in stock ownership in recent decades creates a possibility that individual might use stock wealth towards self-insuring against future long-term care costs. Therefore, it is important to disentangle the impact of stock market wealth on the uptake of long-term care insurance, both public and private.

***6.3.4. Private Long-Term Care Insurance***. Private long-term care insurance is a product that contain characteristics similar to health and life insurance. An insurance purchaser chooses to buy specific amount of insurance coverage to protect against the future long-term care costs. However, unlike medical insurance, long-term care insurance providers directly pay beneficiary the selected daily maximum amount agreed in the insurance contract (KFF, 2013). An insurance policy pays for long-term care services and support received at home or in nursing care centres. Nevertheless, as per the Health and Retirement Survey, close to 12% Americans above 50 years buy such insurance coverage (Health and Retirement Study, 2016). The small share of private LTCI is one of the most worrying concerns of old age Americans given their low savings. Thus, in the event of needed long-term care, lack of LTCI increases not only the individuals' out-of-pocket expenses but also the public expenditure for long-term care via Medicaid (Goda, 2011). Comprehensive studies (Brown and Finkelstein, 2009; Norton, 2000;

Norton and Sloan, 1997) point out various reasons, including public insurance crowding out of LTCI, adverse selection, and moral hazards, for this lack of LTCI in developed countries.

***6.3.5. Medicaid***. Medicaid does not only assist poorer Americans, but richer people impoverished by nursing home and other medical expenses who are otherwise uninsured get to benefit form Medicaid. Spillman and Kemper (1995) reveals that 44% paid out of pocket for nursing home, 16% began as private payers and were converted to Medicaid, and Medicaid covered 27% upon admission. An analysis of elderly people's saving patterns reveals that those who anticipate needing long-term care have more savings than those who don't, and those most likely to be eligible for Medicaid experienced a slower rate of savings decline, as they aged, than wealthy elderly (Webb, 2001). One of the consequences of a house price reduction is that it eases Medicaid eligibility, especially among single individuals. However, some previous evidence shows that that does not necessarily encompasses an expansion of nursing home care utilisation (Grabowski and Gruber, 2007), suggestive of a nursing home care market with an inelastic demand. The Deficit Reduction Act (DRA) gives States a lot of the latitude they've been looking for to make big changes to their Medicaid programmes over the years. Under this DRA provision, States can make targeted reforms to strengthen the community-based infrastructure so that individuals have a choice of where they live and receive services. The legislation tightens asset transfer regulations to lessen the likelihood that seniors will give significant sums of money and other assets to family members in order to qualify for Medicaid-funded long-term care services. The "look back" duration is increased from three to five years.

## 6.4.Data and Sample

The data for this paper comes from the Health and Retirement Study (HRS), which is a publicly available data set that has been sponsored by the National Institute on Ageing. The

HRS data is biannual and follows respondents that were born in 1931-1941 after 1992 and their spouses. There is a separate sample, AHEAD, which considers cohorts born before 1923, the war baby sample was made of those born between 1942-1947, and the children of the depression age are cohorts born between 1924-30. Given that long-term care can potentially affect all those cohorts, we did include them all. Therefore, we obtain the sample using the RAND HRS data and documentation file that contains the data from 1992 through 2014. We remove the first wave from our sample due to the vagueness in the way questions are worded. This choice is made on quality of data consistently with previous studies (Goda, 2011, Finklestein and McGarry, 2006). However, unlike previous studies, we do not limit our analysis to a specific age group primarily because we are interested on the effect of a wealth shock (self-insurance) on both private-LTCI and public insurance (Medicaid). Overall, the survey is very rich in socio-economics controls, demographics, health status, housing wealth and wealth more generally, income and insurance coverage.

We were able to obtain restricted access to examine changes in housing wealth at the Metropolitan Statistical Area (MSA) level and the county level. The housing bubble and burst took place mainly in certain MSAs and counties, hence. It provides sufficient variability to obtain a local average treatment effect (LATE). House prices were a relevant and statistically significant instrument for wealth among homeowners. The latter is because of the orthogonal effects the unexpected changes in house prices have on individual's wealth. However, the unanticipated wealth change is difficult to identify unless an event such as an economic bubble and burst of house prices takes place. In the absence of a housing market shock, some have argued that a change in the emphasis from institutional care to home health care can impact on the housing market, and the distribution of wealth when there is only one resident in the property who is disabled (Bell and Rutherford, 2012). Similarly, it is possible to argue that wealth and housing characteristics impact on health even when the effects are found to be small (Meer et al., 2003).

The final sample contains the data from 1996 through 2014 and has 134,592 observations for 24,195 sample individuals. However, sample size differs for different observations. The dependent variable in the regressions is a set of binary variables that refer to a yearly entitlement to Medicaid, as well as the purchase of private long-term care insurance (LTCI). Whereas the average net worth (total assets), the total housing and financial assets are treatment variables in the regression and are potentially endogenous. We use house price index (HPI) and Constructed Stock-Market wealth shocks (CWS) using SP500 indices as an instrumental variable to address the endogeneity of housing assets and of financial assets, respectively. Table 6.1 displays the descriptive statistics and sample size. The table shows that about 12% of the sample has private-LTCI coverage and 4.32% are covered under Medicaid. The table summarises then the average net worth (total assets), total housing assets, and total financial assets. Also, we show the descriptive statistics for other individual level characteristics of the sample such as income, health status, and other demographic variables. This is a broad indicator of how single-family home values have changed. It acts as a timely, precise indication of regional variations in housing price trends. Additionally, it gives housing economists a tool for analysis that they may use to predict changes in the rates of prepayments, defaults, and housing affordability in particular regions. The HPI is a metric created to track changes in the value of single-family homes across the United States, in different regions, and in more localised locations like counties and MSAs. Using information from Freddie Mac and Fannie Mae, the Federal Housing Finance Agency (FHFA) publishes the HPI. Table 6.2 displays sample features according to insurance status (both public and private). It suggests that people with greater wealth, better incomes, and higher levels of education favour private-LTCI. On the contrary, Medicaid is associated with lower assets, lower income, and lower levels of education. There is no substantial difference in age, gender, and being parent by insurance status. On average, more retired individuals are covered under private or public insurance than working individuals. Lastly, the Standard and Poor 500 (S&P500) stock market index's monthly stock market data is used to match with the month of interview of the Health and Retirement Study (HRS) data. We further construct stock market wealth shocks as suggested by Coile and Levine (2006) and Schwandt (2019) and use it as an instrumental variable to exploit the exogenous variations occur in stock and total assets, due to the change in S&P500 indices, for establishing the causal relationship between stock wealth and long-term care insurance (Both public and private). While selecting the samples for both housing and financial wealth, we separately run the reduced form regressions and decide whether non-treated groups to be included in the main analysis (Ref. Appendix – Table A6.2). In the original sample, approximately 22% of sample responses had no housing wealth and were living on rental basis, whereas remaining 78% of observations forms our main analysis sample. The reduced form regression for renters shows no significant effect of house prices on long-term care insurance, thus we restrict our sample to houseowners as we use regional variation in house prices to identify the effect. In addition, we observe that approximately 96% of the main sample observations responded to the question on the probability of leaving considerable amount of bequest ($10k and above) to their children. The high responses for bequest variable allow us to use this variable as one of the potential mechanisms driving the effect of housing wealth on public and private long-term care insurance. In case of financial wealth sample, approximately 57% (102,996 out of 180,618) of observations from the original sample responded to the question of owning stocks or shares. Thus, the final sample for financial wealth contains 102,996 observations from which 67% of them reported having zero wealth in stocks and shares at the time of interview. The reduced form regression for those with zero financial wealth yields significant impact of CWS on private-LTCI, hence we include such observations into the analysis because it is sensible to assume that some individuals only temporarily maintain the net zero portfolio of financial assets.

**Table 6.1 Descriptive Statistics: Sample Characteristics**

| | **Individual Level Characteristics of the Sample** | | | | |
|---|---|---|---|---|---|
| | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| | (1) | (2) | (3) | (4) | (5) |
| ***Private-LTCI*** | 134,592 | 0.126 | 0.332 | 0 | 1 |
| ***Medicaid*** | 134,145 | 0.0435 | 0.204 | 0 | 1 |
| ***Total Wealth*** | 134,592 | 453863 | 755649 | -935000 | 9988097 |
| ***Income*** | 134,592 | 67,087 | 450801 | 0 | 7395714 |
| ***Housing Wealth*** | 134,592 | 147,140 | 182932 | -1028586 | 6810739 |
| ***Financial Wealth*** | 102,996 | 70,692 | 288718 | 0 | 9000000 |
| ***Age*** | 134,592 | 67 | 9.87 | 50 | 104 |
| ***Male*** | 134,592 | 0.443 | 0.5 | 0 | 1 |
| ***Married*** | 134,539 | 0.702 | 0.457 | 0 | 1 |
| ***College/More*** | 134,378 | 0.45 | 0.5 | 0 | 1 |
| ***Have Children*** | 132,991 | 0.94 | 0.24 | 0 | 1 |
| ***White*** | 134,497 | 0.83 | 0.374 | 0 | 1 |
| ***Retired*** | 115,026 | 0.642 | 0.48 | 0 | 1 |
| ***Fair/Poor Health*** | 134,519 | 0.25 | 0.43 | 0 | 1 |

Note: Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

**Table 6.2. Summary Statistic for Insurance Holders**

| . | **Dependent Variables** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Private-LTCI** | | | | **Medicaid (or Public-LTCI)** | | | |
| | **NO** | | **YES** | | **NO** | | **YES** | |
| | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** | **Mean** | **Std Dev** |
| ***Total Wealth*** | 409558 | 720693 | 680490 | 878470 | 456551 | 758210 | 103817 | 223510 |
| ***Housing Wealth*** | 137504 | 178875 | 183101 | 193209 | 146038 | 182553 | 71822 | 133805 |
| ***Financial Wealth*** | 62393 | 277502 | 128972 | 350576 | 73968 | 295245 | 3990 | 47091 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ***Income*** | 65533 | 483105 | 86199 | 103672 | 70303 | 462123 | 20410 | 57706 |
| ***Age*** | 66.23 | 10 | 68.3 | 9.46 | 66.23 | 9.9 | 69.86 | 10.44 |
| ***Age_sq*** | 4486 | 1379 | 4757 | 1312 | 4491 | 1364 | 4989 | 1491 |
| ***Male*** | 0.45 | 0.5 | 0.424 | 0.494 | 0.449 | 0.497 | 0.376 | 0.484 |
| ***College/More*** | 0.425 | 0.49 | 0.6 | 0.49 | 0.459 | 0.5 | 0.154 | 0.361 |
| ***Married*** | 0.705 | 0.456 | 0.723 | 0.45 | 0.72 | 0.45 | 0.428 | 0.495 |
| ***White*** | 0.823 | 0.382 | 0.886 | 0.32 | 0.84 | 0.367 | 0.615 | 0.487 |
| ***Retired*** | 0.61 | 0.49 | 0.709 | 0.454 | 0.612 | 0.49 | 0.875 | 0.33 |
| ***Have Children*** | 0.94 | 0.237 | 0.925 | 0.263 | 0.94 | 0.24 | 0.93 | 0.255 |
| ***Fair/Poor Health*** | 0.26 | 0.44 | 0.17 | 0.377 | 0.233 | 0.422 | 0.603 | 0.49 |

Note: Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

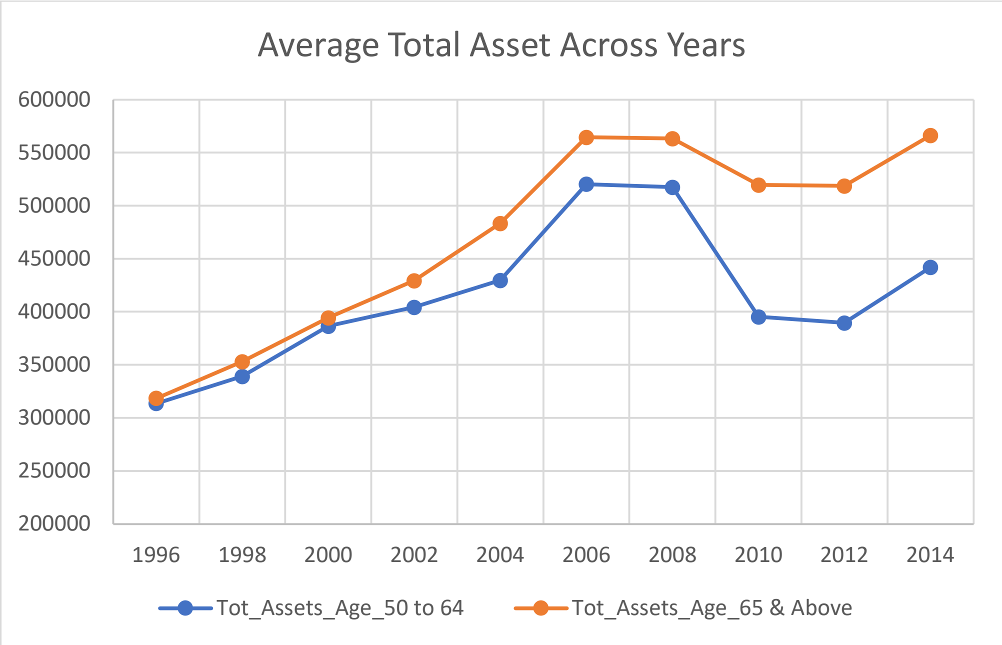
## 6.5. Empirical Strategy

We exploit the variation in the effective price of dwellings as well as in the stock market indices (S&P500) in the US. Armed with these data from the health and retirement survey (HRS), we estimate instrumental variable model to estimate an exogenous variation on individual's wealth on Medicaid uptake and purchase of private-LTCI around the time of this reform. Given that changes in house prices did not affect individuals who were not homeowners, we examine the effect among those who were renting a property before and after 2007-8 (interpreted as one control group not affected by a decline on property prices) to changes for individuals that indeed owned a property. Since we control for fixed effects for each state, each year, and each individual, the effect of the policy is identified.

Some key features play a crucial role in our identification strategy. Second, Figure 6.2 we examine difference in total (Figure 2.1), housing assets (Figure 6.2.2), and financial assets (Figure 6.2.3) by age group. The figure shows that both groups exhibit an expansion in housing assets which peaks in 2006 and exhibits a sharp decline in 2008 and onwards, whereas the financial assets across age groups capture boom and bursts of past two decades. Overall, for housing, we find that both groups are comparable till 2006, but differs greatly after 2008; for financial assets, we observe that both groups are comparable till 2008, but differs greatly in terms of recovery after great recession.

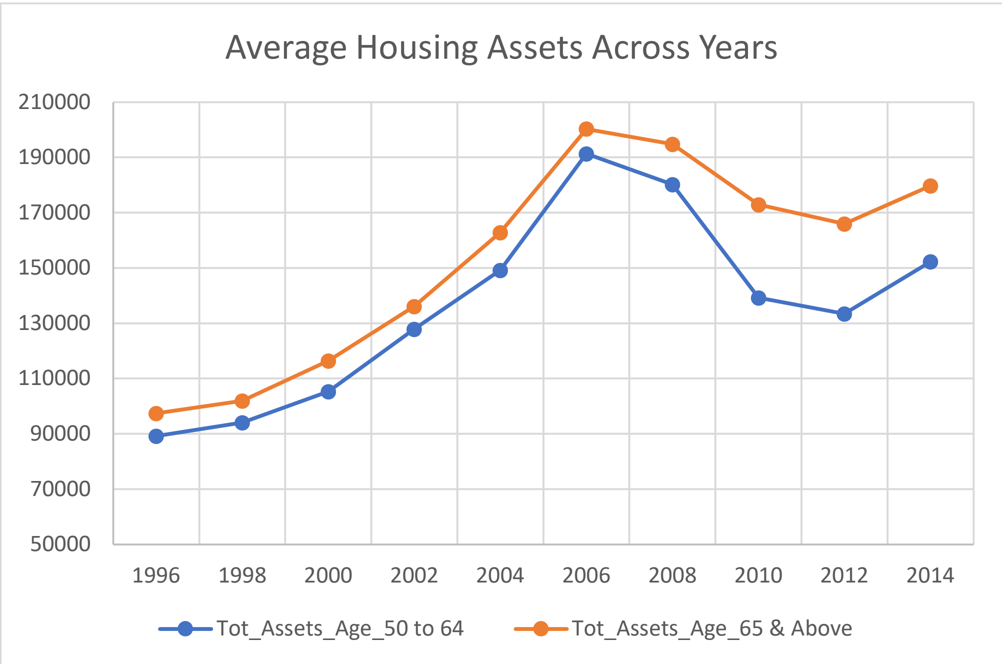
**Figure 6.2. Evolution of Total, Housing, and Financial Assets by age groups**

**6.2.1 Total Assets**



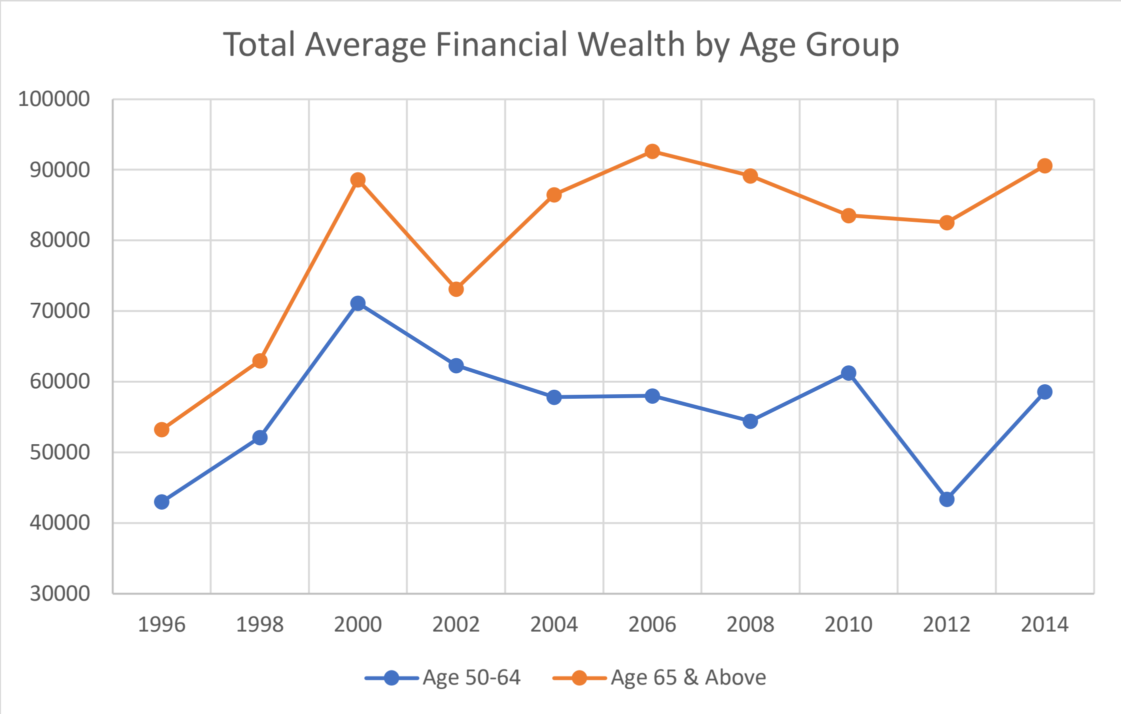

Source: Health and Retirement Study, waves 3 -12.

**6.2.2 Housing Assets**




Source: Health and Retirement Study, waves 3 -12.

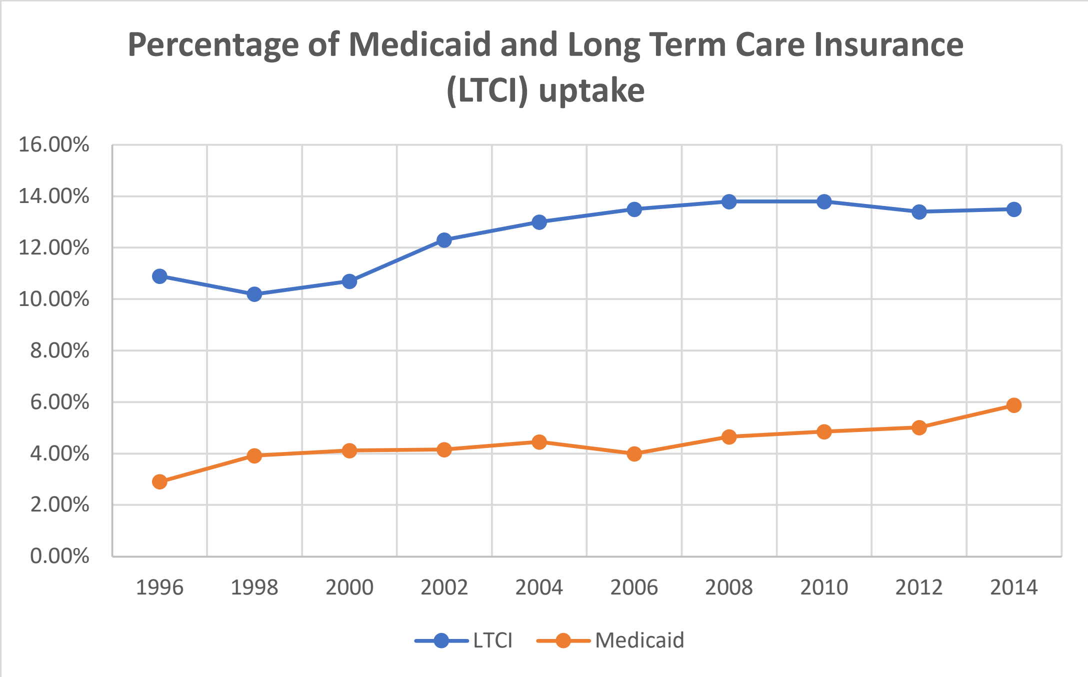
### 6.2.3 Financial Assets




Source: Health and Retirement Study, waves 3 -12. Wave 2 (Year 1994) is excluded due to lack of observations.

Next, Figures 6.3, 6.4.1, and 6.4.2 show the time and age-specific trends in LTCI and Medicaid uptake. Overall Figure 3 depicts a moderate expansion in the update of instance over time for both Medicaid and private-LTCI, but the rate of change is considerably small. In contrast, when we break down the effect by age group, we find that individuals with age 65 and above are more likely to increase the use of Medicaid and to take up LTCI while the effect on younger group is smaller. That is, we find that when we distinguish trends by age group the previously identified spike refers to individuals over the age of 65 who are more likely than younger individuals to qualify for Medicaid. Additional descriptive evidence confirms that consistently with other studies, we find that Medicaid entitlement is more common among low and middle-income individuals, but some individuals at the third and top quantile of income do qualify too. However, after 2006, we find that the distribution of Medicaid uptake increases, especially for younger individuals, consistently with an impoverishment argument resulting from the housing and financial downturn.

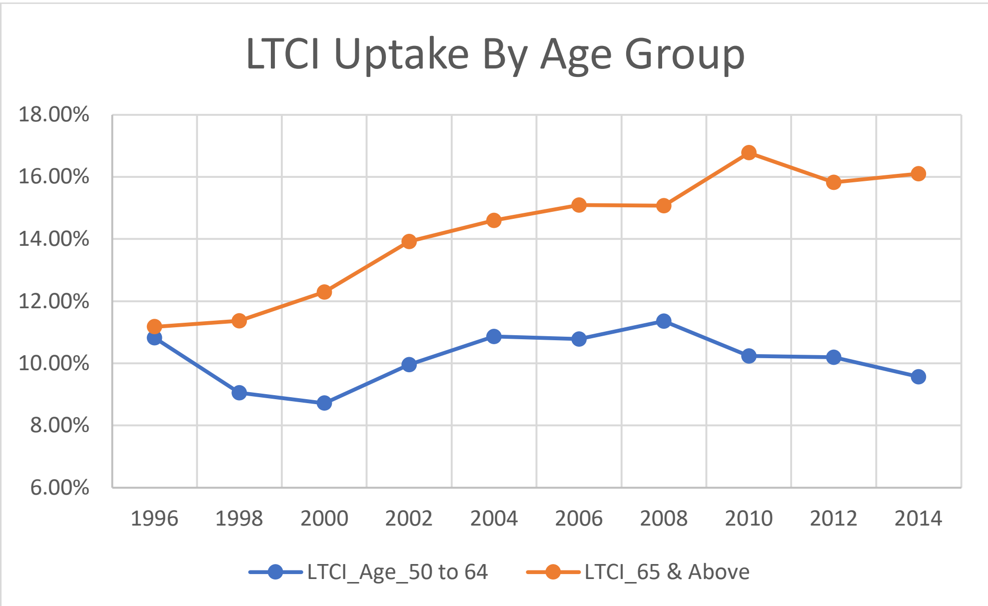
**Figure 6.3. Percentage of Medicaid and Private Long-Term Care Insurance (LTCI) uptake**




Source: Health and Retirement Study, waves 3 -12.

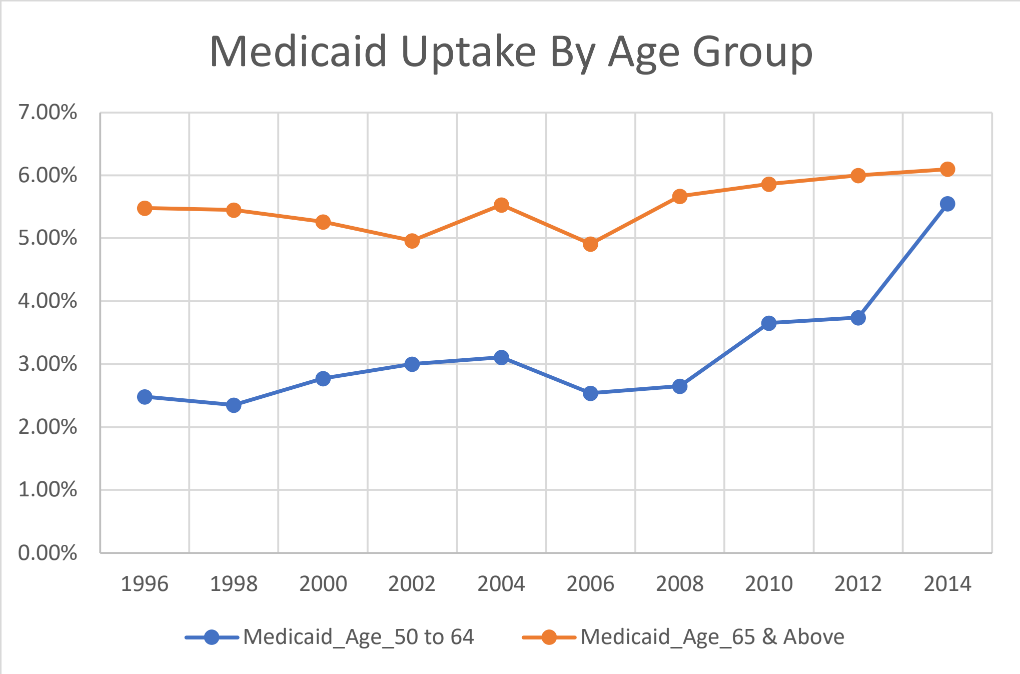
**Figure 6.4. Percentage of Medicaid and Private Long-Term Care Insurance (LTCI) uptake by age group**

**6.4.1 LTCI by Age**




Source: Health and Retirement Study, waves 3 -12.

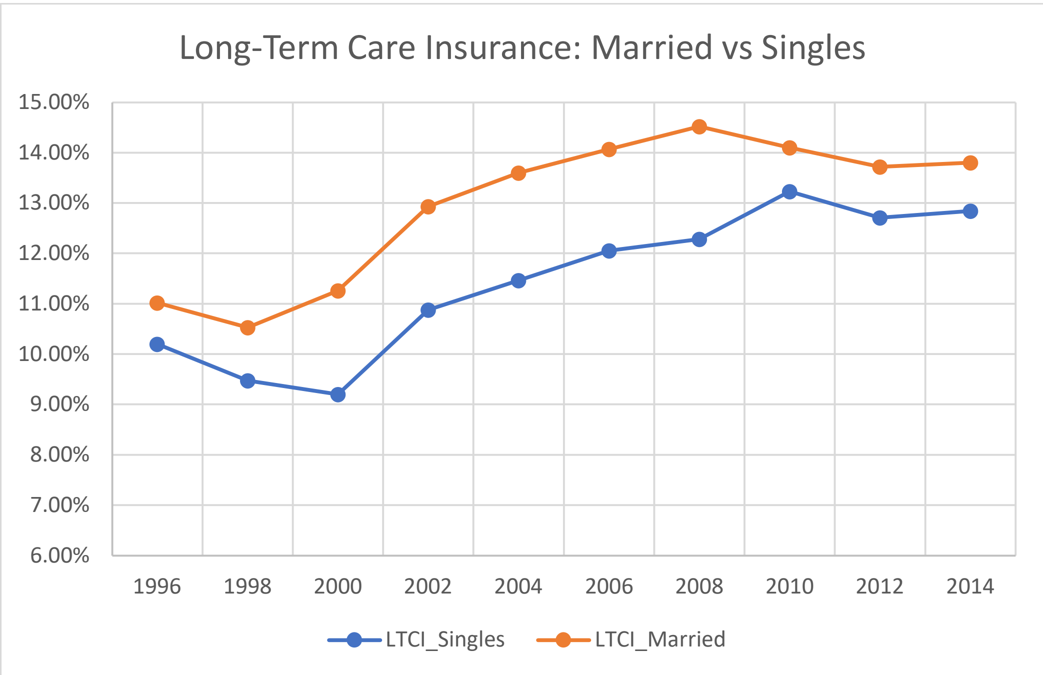
### 6.4.2 Medicaid by Age




Source: Health and Retirement Study, waves 3 -12.

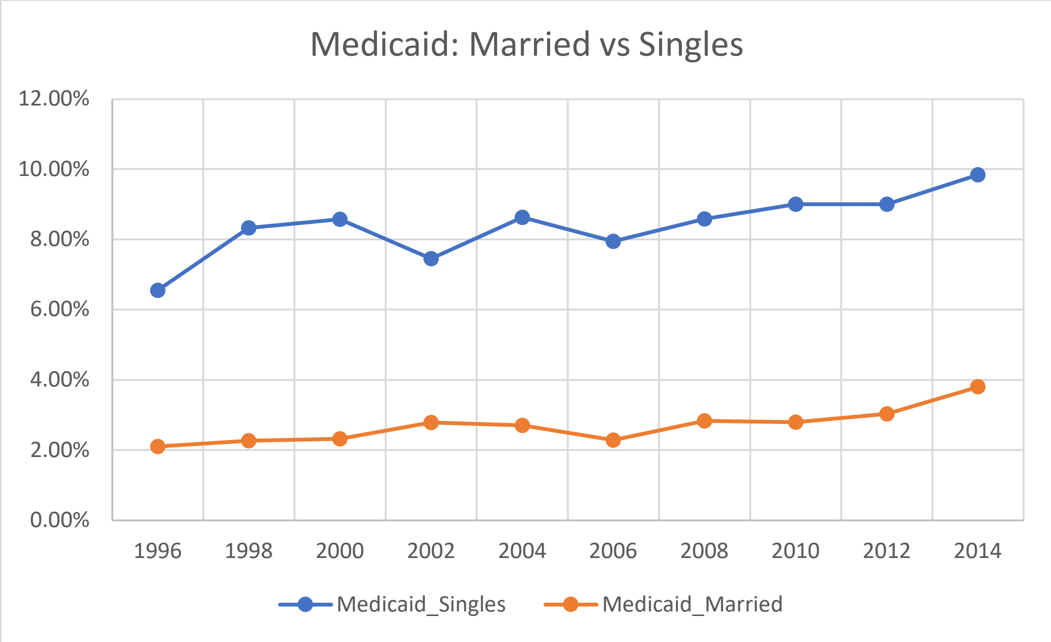
**Figure 6.5. Percentage of Medicaid and Private Long-Term Care Insurance (LTCI) uptake by Marital Status**

### 6.5.1 LTCI: Married Vs Singles




Source: Health and Retirement Study, waves 3 -12.

### 6.5.2 Medicaid: Married Vs Singles




Source: Health and Retirement Study, waves 3 -12.

Finally, Figures 6.5.1 and 6.5.2 show the trends by Marital status in LTCI and Medicaid uptake. Figure 6.4.1 indicate a moderate expansion in the uptake of private-LTCI, but the rate of change is considerably small and both groups show similar trends. However, when we break down the effect for Medicaid, we find that single individuals are more likely than married couples to use Medicaid more often. It is important to note that the rate of Medicaid uptake slightly began to increase, for both groups, after 2006.

Based on the latter considerations, this study attempts to examine the effect of the change in housing as well as financial assets exerted on the uptake of private-LTCI and Medicaid entitlement. We take advantage of a unique and unexpected event that have modified the expectation individuals build in paying (self-insuring) for long-term care, namely the house prices and Stock market wealth shocks. The effect of the bubble bursting on house prices and on S&P500 indices has different impacts; one lies in the direct self-insurance effect. The other lies in the lower bequeathing that it encompasses. Third, the effect was large particularly for property owners and for stockholders that rely on housing and financial assets for old age decisions, respectively. Our basic estimating equation is an instrumental variables equation of the following form:

$$(\boldsymbol{Y_{ist}}) = \boldsymbol{\gamma_t} + \boldsymbol{\mu_i} + \boldsymbol{X_{ist}} \cdot \boldsymbol{\delta} + \boldsymbol{\beta} \cdot \widehat{\boldsymbol{ASSETS}}_{\boldsymbol{ist}} + \boldsymbol{\theta_s} + \boldsymbol{\varepsilon_{ist}} \qquad \textbf{(1)}$$

$$ASSETS_{ist} = \boldsymbol{a_t} + \boldsymbol{b_i} + \boldsymbol{d_s} + \boldsymbol{Z_{ist}} \cdot \boldsymbol{\varphi} + \boldsymbol{c}(CWSi/HPI_{\ st}) + \boldsymbol{u_{ist}} \qquad \textbf{(2)}$$

Where $Y_{ist}$ denotes Medicaid or private-LTCI entitlement for an individual $(i)$ in a state *(s)* at year $(t)$; $\gamma_t$ denotes a set of time dummies (survey waves), θs denotes a set of state dummies, $\mu_i$ represents individual fixed effects that removes time-invariant individual level controls, $X_{ist}$ is a vector of covariates that act as controls (age, gender, married, education, health status etc.) which are exogenous (especially time variant ones). $Z_{ist}$ is a vector of covariates that act as controls and all-time constant variables between different locations are controlled for. HPI indicates House Price Indices, whereas CWS indicates Constructed Stock Market Wealth Shocks. The CWS is calculated using equation 3 stated below (Schwandt 2020).

$$\boldsymbol{CWSi} = \frac{\boldsymbol{SWi, t-1}}{\boldsymbol{TWi, t-1}} * \frac{\boldsymbol{\Delta SPt}}{\boldsymbol{SPt-1}} \qquad (\mathbf{3})$$

Where $SW_{i,t-1}$ stock market wealth for individual *i* at time *t-1*, $TW_{i,t-1}$ indicates total wealth of an individual *i* for time *t-1*, and $\frac{\boldsymbol{\Delta SPt}}{\boldsymbol{SPt-1}}$ is the percentage change in the S&P500 index between *t* and *t-1*. Overall, we have estimated different specifications using different dependent variables such as uptake of Medicaid and private-LTCI, which we have examined the effect by income group too. Furthermore, we consider a number of placebo tests and reduced forms of house prices and of CWS to confirm that first stage regressions are indeed suggestive of an experiment as described in the results section.

## 6.6.Results

***6.6.1. Reduced forms***. As a way to test for the validity of our instruments, we begin our empirical analysis by estimating reduced forms using house price indexes as well as CWS, and also including income, and other covariates (Table 6.1 & 6.2 contain the descriptive statistic of the main covariates we control for). We control for state and year fixed effects by including state and wave dummies into the model. Our specification also includes individual fixed effects, which omits time-invariant individual characteristics. Column 1-2 of Panel A (B) of Table 6.3 reports the effect of a change in the house prices index (CWS) on the uptake of Medicaid and private-LTCI. As expected, most covariates exhibited the expected sign, such as income and health conditions. While an increase in housing price indexes reduced the probability of the purchase of private-LTCI, no significant effect is found for the uptake of Medicaid. However, an increase in CWS decreases the probability of private-LTCI but increases the probability of Medicaid uptake.

***6.6.2. Validity of the instruments***. Next, we examine the validity of instruments in predicting total housing assets as well as total financial assets.  We find that that as expected a change in the index would significantly change both total assets and total housing assets respectively (Column 3&4 of Panel A of Table 6.3). The F-tests of the first stage is 677 (t-stat=23.16) for total assets and 6673 (t-stat=82.3) for housing assets. Similarly, we observe that one unit change in CWS is positively associated with total assets as well as total financial assets (Column 3&4 of Panel B of Table 6.3) and the values of respective F-tests are also much above the tradition thresholds. Table 6.5 (Panel A & B) examines the effects of wealth on LTCI (both private and public) for non-homeowners as well as for non-stockholders as a placebo test and consistently finds no effect. Hence, from our analysis we conclude that the effect of house prices (CWS) does exert a change in housing (financial) and total assets, and the evidence of larger F-statistic suggests that it is indeed a strong instrument.

**Table 6.3. Reduced form and First Stage Regressions – (OLS)**

| | **PANEL A: Housing Market** | | | |
|---|---|---|---|---|
| | **Reduced Form** | | **First Stage** | |
| | **Private LTCI** | **Medicaid** | **Total Wealth (in \$100k)** | **Housing Wealth (in \$100k)** |
| | (1) | (2) | (3) | (4) |
| **House Price Index** | -1.74e-05* | -1.89e-06 | 0.004*** | 0.00318*** |
| | (9.12e-06) | (5.78e-06) | (0.000158) | (4.0e-05) |
| **First Stage t-statistic** | -- | -- | 25.24 | 79.67 |
| **N** | 134,165 | 133,724 | 134,165 | 134,165 |
| | | | | |
| | **PANEL B: Stock Market** | | | |
| | **Reduced Form** | | **First Stage** | |
| | **Private LTCI** | **Medicaid** | **Total Wealth (in \$100k)** | **Stock Wealth (in \$100k)** |
| | (1) | (2) | (3) | (4) |
| Constructed Stock Wealth Shock | -0.0765*** | 0.0129*** | 1.041*** | 1.574*** |
| | (0.019) | (0.00422) | (0.389) | (0.367) |
| **N** | 99,867 | 101,177 | 101,676 | 101,676 |
| **State + Year Fixed Effects** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual FE** | YES | YES | YES | YES |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level.

Note: All the models include state, year, and individual fixed effects. Columns 1 and 2 correspond to reduced form models in which Private-LTCI and Medicaid are regressed on house price Indexes and on Constructed Stock-Market Wealth Shocks, whereas Column 3 and 4 correspond to first stage regression models in which total and housing wealth are regressed on house price indexes in Panel A and also total and stock wealth are regressed on Constructed Stock-Market Wealth Shock in Panel B. Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than \$10 million.

***6.6.3. Effect on Private-LTCI Purchase***. Changes in total, housing, and financial wealth would be expected to decrease the number of people that would purchase private-LTCI. Table 6.3 reports a naïve regression, namely a reduce form of the house price index (CWS) on the uptake of private-LTCI and Medicaid, and consistently finds a negative and significant coefficient in case of private-LTCI, whereas effect on Medicaid is negative but non- significant (positive and significant). Table 6.4 reports the baseline estimates for the effect of total, housing, and financial assets on the uptake of private-LTCI and Medicaid. We report both OLS and IV estimates obtained using fully specified models (Panel A & B) that accounts for state, year, and individual fixed effects. The estimates suggest that as expected a change in housing and financial assets reduced purchase of private-LTCI. Most importantly, we find that IV estimates from Panel A (B) for total and housing (financial) assets are not significantly different, but these estimates are significantly different from zero. The magnitude of the effect of housing (financial) wealth on the uptake of private-LTCI is slightly greater (lower) than that of total wealth. The effect sizes indicate that \$100 thousand increase in the housing assets (total assets) decreases the likelihood of purchasing private-LTCI by 0.6% (0.47%), whereas \$100 thousand increase in financial (total) assets reduces the purchase of private-LTCI by 4.73% (6.84%). These results exhibit presence of substitution, between insurance and self-insurance for long-term care, occurs due to change in the value of housing as well as financial assets.

Table 6.4 also reports the effect of a change in housing (financial) and total assets on the probability of Medicaid uptake. We find that total and housing (financial) assets correlate negatively (positively) with the uptake of Medicaid. However, we do not find a significant effect on the uptake of Medicaid.

**Table 6.4. Effect of a type of wealth on Private-LTCI and Medicaid**

| **Linear Baseline Estimates of the effect of Wealth on LTC-Insurance (Private & Public)** | | | | |
|---|---|---|---|---|
| | **Dependent Variables** | | | |
| | **Private-LTCI** | | **Medicaid** | |
| **Treatment** | **OLS** | **IV** | **OLS** | **IV** |
| ***PANEL A: Housing Market*** | **(1)** | **(2)** | **(3)** | **(4)** |
| **1) Total Wealth (in \$100k)** | 0.0015*** | -0.00436* | -0.0005*** | -0.00047 |
| | (0.000174) | (0.00257) | (0.00011) | (0.00138) |

| | | | | |
|---|---|---|---|---|
| **F-Statistic for Excluded Instrument Test** | | **634** | | **637** |
| | | | | |
| **2) Housing Wealth (in $100k)** | 0.00353*** | -0.0055* | -0.002*** | -0.00059 |
| | (0.0007) | (0.00321) | (0.00043) | (0.00174) |
| **F-Statistic for Excluded Instrument Test** | | **6347** | | **6349** |
| **N** | **134,165** | **133,459** | **133,724** | **132,996** |
| | | | | |
| ***PANEL B : Stock Market*** | **(1)** | **(2)** | **(3)** | **(4)** |
| **1) Total Wealth (in $100k)** | 0.0015*** | -0.0684*** | -0.0005*** | 0.0123 |
| | (0.000252) | (0.018) | (0.000074) | (0.008) |
| **F-Statistic for Excluded Instrument Test** | | **25.2** | | **22.6** |
| | | | | |
| **2) Stock Wealth (in $100k)** | 0.00127*** | -0.0473*** | -0.0004*** | 0.008 |
| | (0.000475) | (0.0084) | (0.000095) | (0.005) |
| **F-Statistic for Excluded Instrument Test** | | **233** | | **224.7** |
| **N** | **99,857** | **96,544** | **101,177** | **97,940** |
| | | | | |
| **State + Year Fixed Effects** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level.

Note: All the models include state, year, and individual fixed effects. Panel A represents Housing Market Regressions and Panel B represents Stock Market related regressions. Columns 1 and 2 correspond to first set of regressions where Private-LTCI is regressed on total, housing, and stock wealth in which Columns 1 & 3 correspond to Ordinary Least Square (OLS) regression and Column 2 & 4 refer to Instrumental Variable regression (known as 2SLS or Two stage least squares). Similarly, Columns 3 and 4 correspond to second set of regressions where Medicaid is regressed on total, housing, and stock wealth in which Column 3 corresponds to OLS regression and Column 4 refers to IV regression. Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

***6.6.4. Placebo effects***. Panel A and B of Table 6.5 present the placebo tests where we estimate the IV estimates but for a sample of renters and non-stockholders. Consistently, we find no evidence of a change in the probability of LTCI or Medicaid uptake as a result of a change in house prices or CWS.

**Table 6.5. Placebo Test – Impact of Wealth Shock for Renters and Non-stockholders**

| **Placebo test – Impact LTC-partnership on other insurances** | | |
|---|---|---|
| | Private-LTCI | Medicaid |
| | (1) | (2) |

| | | |
|---|---|---|
| **Panel A: Housing Market (Renters Only)** | | |
| **Total Wealth (in $100k)** | 0.0764 | 0.139 |
| | (0.0996) | (0.143) |
| **Housing Wealth (in $100k)** | 32.19 | 67.27 |
| | (80.65) | (157.3) |
| | | |
| **Panel B: Stock Market (Non-Stockholders Only)** | | |
| **Total Wealth (in $100k)** | 0.217 | -0.0263 |
| | (0.134) | (0.0314) |
| **Stock Wealth (in $100k)** | -- | -- |
| | -- | -- |
| | | |
| **State + Year Fixed Effects** | YES | YES |
| **Control Variables** | YES | YES |
| **Individual FE** | YES | YES |
| | | |

*Significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level.

Note: All the models include state, year, and individual fixed effects. Panel A represents Housing Market Regressions and Panel B represents Stock Market related regressions. Column 1 and 2 correspond to Instrumental Variable (IV) regressions where each outcome, Private-LTCI and Medicaid, is regressed on total, housing, and stock wealth, respectively. The instrument used is: House Price Index (or HPI) and Constructed Stock-Market Wealth Shocks. This Sample only includes renter or non-homeowners as well as non-stockholders and is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

***6.6.5. Heterogeneity***. The housing boom and bursts differ across states, with some states experience severe impact of the housing shock, whereas the effect on other states is usually insubstantial. The Health and Retirement study include detailed information about the important characteristics of elderly population in the US. We obtain heterogenous treatment effects by interacting housing (financial) and total wealth with available socioeconomic variables, including gender, age, income, education, marriage, ethnicity, nursing home stay, recession, and housing bubble states. In Table 6.6, we summarize the effects obtained after repeating analysis for different subsamples. We find that females are less likely than males to purchase private-LTCI in response to change in housing (financial) and total wealth, whereas the uptake of Medicaid remains unaltered for females, but males are less (more) likely to use Medicaid after the change in housing (financial) wealth. The use of Medicaid in response to change in assets is expected to decrease for college graduates, whereas high school graduates are less likely to purchase private-LTCI after the increase in housing (financial) wealth. Single individuals are expected to self-insure themselves after increase in both housing (financial) and total wealth, whereas change in housing asset has no significant effect on married individuals. Subsequently, we find that having children decreases the likelihood of purchasing private-LTCI with the change in housing (financial) and total wealth, but exactly opposite is observed for individuals without children as they are more likely (no significant impact) to purchase private-LTCI after the positive wealth shock.

Non-white Americans are expected to self-insure themselves with increase in both housing and total wealth, but at the same their likelihood of uptake of Medicaid increases. The reversed is observed in case of financial wealth where white Americans are more likely to self-insure with increase in financial wealth, but no significant impact was observed for non-white Americans. Similarly, we observe that in case of housing individuals with income below-median are less likely to purchase private-LTCI and more likely to become eligible for Medicaid uptake. These individuals prefer to self-insure after the positive wealth shock, but the change in housing (financial) wealth does not affect (reduces) the probability of buying private-LTCI for individuals with income above median. In addition, individuals belonging to states, which experienced severe impact of boom and bursts, are more likely to self-insure themselves after the change in housing and total wealth, but residents of remaining states show no significant impact on private-LTCI uptake and are less likely to enrol in Medicaid after wealth shock. Most importantly, it is found that people used to self-insure more with increase in housing (financial) assets before the great recession hits the US in late 2006.

## Table 6.6. Heterogeneity in Response to change in Total, Housing and Stock Wealth

| | | PANEL A : HOUSING MARKET | | | | PANEL B : STOCK MARKET | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | TOTAL WEALTH (in $100k) | | HOUSING WEALTH (in $100k) | | TOTAL WEALTH (in $100k) | | STOCK WEALTH (in $100k) | |
| | | Private LTCI | Medicaid | Private LTCI | Medicaid | Private LTCI | Medicaid | Private LTCI | Medicaid |
| State & Year FE + Controls | | YES | YES | YES | YES | YES | YES | YES | YES |
| Individual FE | | YES | YES | YES | YES | YES | YES | YES | YES |
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ALL | | | | | | | | | |
| Health | Good/Best/Excellent | -0.00373* | -0.00135 | -0.0045 | -0.00196 | -0.0765*** | 0.0147** | -0.0516*** | 0.01*** |
| | Fair/Poor | -0.008*** ††† | 0.00122 †† | -0.0108*** † | 0.00235 †† | -0.045*** †† | 0.0054 ††† | -0.0272*** †† | 0.0002 ††† |
| Gender | Female | -0.00551*** | 0.00059 | -0.00691** | 0.0013 | -0.0723 | 0.0034 | -0.0566*** | 0.00758*** |
| | Male | -0.0038* | -0.0022 †† | -0.0048 | -0.0035* †† | -0.064 | 0.022 | -0.038*** | 0.0087** |
| Age | Below 65 | -0.00633** | 0.000113 | -0.00783** | 0.00057 | -0.0618*** | 0.0105*** | -0.0738*** | 0.0157*** |
| | 65 and Above | -0.0044** | -0.00077 | -0.0053* | -0.0011 | -0.025*** ††† | 0.0015 ††† | -0.0214*** ††† | 0.0011 ††† |
| Partnership Status | Non-Partnership | -0.00462** | -0.0007 | -0.00667** | -0.000324 | -0.0755*** | 0.0146* | -0.054*** | 0.0115** |
| | Partnership | 0.00046 †† | -0.00422** †† | 0.0032 †† | -0.0073** †† | -0.0455*** ††† | 0.004 ††† | -0.025*** ††† | -0.0026 ††† |
| Education | High School/Less | -0.0190*** | 0.00624*** | -0.0254*** | 0.0097*** | 0.111 | -0.285 | -0.0684** | 0.0231** |
| | Some/More College | 0.00175 ††† | -0.0039*** ††† | 0.0046* ††† | -0.0067*** ††† | -0.1162 | 0.098 | -0.043*** | 0.0049** |
| Income | Above Median | -0.0018 | 0.0004 | -0.015 | -0.00145 | -0.072*** | 0.0123 | -0.049*** | 0.0077* |
| | Below Median | -0.02*** ††† | 0.032*** ††† | -0.021*** ††† | 0.034*** ††† | -0.055** | 0.014 | -0.039** | 0.012 |
| Housing Bubble | Non-Bubble States | -0.0014 | -0.004** | -0.000633 | -0.0066** | -0.0156 | 0.00242 | 0.0368*** | -0.009*** |
| | Bubble States | -0.00483** † | -0.00061 ††† | -0.00671** | -0.000135 ††† | -0.18 | 0.032 | -0.069*** | 0.0117** |
| Recession | Non-Recession Period | -0.008*** | 0.000088 | -0.0104*** | 0.000348 | -0.0667*** | 0.0114** | -0.0557*** | 0.0116*** |
| | Recession Period | -0.0028 ††† | -0.00125 | -0.00244 ††† | -0.002 † | -0.029** ††† | -0.00001 ††† | -0.0142** ††† | -0.00475*** ††† |
| Nursing Home | Not Stayed at NH | -0.00465** | -0.000465 | -0.0059** | -0.000564 | -0.0657*** | 0.01** | -0.0467*** | 0.00727*** |
| | Stayed at NH | -0.0047 | -0.0089*** ††† | -0.0058 | -0.012*** ††† | -0.034* | -0.0145* ††† | -0.0237 | -0.028** ††† |
| Marital Status | Singles | -0.00781** | 0.000325 | -0.0097** | 0.00086 | -0.0428*** | -0.000156 | -0.0246* | -0.00613 |
| | Married | -0.0035 † | -0.0012 | -0.00415 | -0.0019 | -0.067*** | 0.0115** ††† | -0.048*** | 0.0086*** ††† |
| Have Children | NO | 0.0219*** | 0.00461 | 0.0377*** | 0.0079* | -0.00985 | 0.00209 | -0.000304 | 0.00056 |
| | YES | -0.0068*** ††† | -0.001 †† | -0.0095*** ††† | -0.0015 †† | -0.088** †† | 0.015** †† | -0.054*** ††† | 0.0087*** †† |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Ethnicity | Non-White | -0.0246*** | 0.0177*** | -0.0335*** | 0.0268*** | 0.05 | -0.0732 | -0.0329 | -0.0481 |
| | White | -0.00038 ƗƗƗ | -0.00482*** ƗƗƗ | -0.000061 ¥¥¥ | -0.00685*** ƗƗƗ | -0.077*** | 0.0188** | -0.048*** | 0.0092*** |
| | | | | | | | | | |

*denotes significantly different from zero (* significant at 10%; ** significant at 5%; *** significant at 1%) ; + denotes that bottom category estimates are significantly different from top category ones (Ɨ significant at 10%; ƗƗ significant at 5%; ƗƗƗ significant at 1%)

Note: The estimates are obtained using the sample from Health and Retirement Study, Waves 3-12, 1996-2014. Each coefficient indicates IV estimates for outcomes, private long-term care insurance and Medicaid for both Panel A and B. Panel A represents Housing Market Regressions and Panel B represents Stock Market related regressions. Both outcome variables are binary variables. All the models include state, year, and individual fixed effects. Column (1), (2), (5) and (6) regress outcomes on total wealth, whereas Column (3) and (4) regress outcomes on housing wealth and Column (7) and (8) regress outcomes on Stock wealth. Other covariates include age, gender, age^2, income, health status, marital status, race, and education. Each category on the left-hand side of the table indicates a separate regression that includes interactions between subgroup indicators and treatment variable.

In terms of health and aging differences, we estimate that individuals with fair or poor health are less likely to buy private-LTCI if their wealth is increased, whereas no significant effect is observed on the uptake of Medicaid. We also find that younger cohorts are only slightly more than older individuals to self-insure if their wealth increases. Those who stayed in nursing home in the previous year are less likely to enrol in Medicaid after wealth change, but no significant impact found in their probability of purchasing private-LTCI. However, for those who did not stay at nursing home previously are more likely to self-insure themselves. Finally, we find that partnership program actually decreased the probability of Medicaid uptake, whereas individuals living in non-partnership states are more likely to self-insure themselves after the positive housing shock.

***6.6.6. Robustness Check***. Panel A & B of Table 6.7 indicate the results after running the fully specified model using four different specification changes: 1) A Control function approach, 2) Lagged wealth as a treatment, 3) After removing respondents who are disabled & on Medicare benefits, and 4) After controlling for life insurance. As expected, we obtain similar estimates as that of main models after incorporating a control function approach Wooldridge (2010) and removing disabled respondents with Medicare. However, replacing contemporary treatment with lagged treatment yields no effect on the private-LTCI, but negative effect on Medicaid uptake. In addition, we observe only a slight variation in the main effects of housing (financial) and total wealth, on private-LTCI and Medicaid, when controlled for life insurance in our models. Hence, the results are robust to different specifications and to the inclusion of other insurance as a control into the models.

**Table 6.7. Robustness Check: Effect of Wealth on LTC-Insurance (Private & Public)**

| **Table 3 : Robustness Check: Effect of Wealth on LTC-Insurance (Private & Public)** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Control Function Models** | | **Lagged Wealth as treatment** | | **Removing Disabled w Medicare** | | **Controlling for Life Insurance** | |
| | Private LTCI | Medicaid | Private LTCI | Medicaid | Private LTCI | Medicaid | Private LTCI | Medicaid |
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| **PANEL A: HOUSING MARKET** | | | | | | | | |
| ***I) Control Function Model*** | | | | | | | | |
| 1) Total Wealth (in $100k) | -0.00472** | -0.000773 | -0.00089 | -0.0026* | -0.00453** | -0.00122 | -0.00447* | -0.0007 |
| | (0.00221) | (0.00138) | (0.0024) | (0.0015) | (0.00225) | (0.00136) | (0.00232) | (0.00145) |
| 2) Housing Wealth (in $100k) | -0.00597** | -0.000971 | -0.0011 | -0.0034* | -0.0058** | -0.00155 | -0.0056* | -0.0009 |
| | (0.0028) | (0.00175) | (0.003) | (0.0019) | (0.00285) | (0.00173) | (0.0028) | (0.00181) |
| **PANEL B: STOCK MARKET** | | | | | | | | |
| ***I) Control Function Model*** | | | | | | | | |
| 1) Total Wealth (in $100k) | -0.074** | 0.0124 | --- | --- | -0.0704*** | 0.0132 | -0.067** | 0.0122 |
| | (0.017) | (0.008) | | | (0.0186) | (0.008) | (0.0176) | (0.008) |
| 2) Stock Wealth (in $100k) | -0.0487*** | 0.00818 | --- | --- | -0.049*** | 0.0088* | -0.0465*** | 0.00808 |
| | (0.008) | (0.005) | | | (0.00863) | (0.00501) | (0.00834) | (0.005) |
| | | | | | | | | |
| **State + Year Fixed Effects** | YES | YES | YES | YES | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES | YES | YES | YES | YES |
| **Individual FE** | YES | YES | YES | YES | YES | YES | YES | YES |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level.

Note: All the models include state, year, and individual fixed effects. Panel A represents Housing Market Regressions and Panel B represents Stock Market related regressions. Column 1 and 2 correspond to Instrumental Variable models. Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

*Testing non-linearity using Spline Function:* In addition to above specification checks, we make a use of Spline function in Stata to test the non-linearity of wealth and age variables

(Hubbard, Skinner, and Zeldes, 1994), which are likely to have non-linear relationship with public and private long-term care insurance. Spline function help mathematically reproduce flexible shapes in which several knots can be placed within a specific data range to identify different functional pieces joined together. We run mkspline function in Stata and produce estimates for total wealth, housing wealth, and age and plot those coefficients for private-LTCI and Medicaid outcomes. Table 6.8 represents various regressions' output obtain after transforming total wealth, housing wealth, and age variables, using Spline function. Panel A of Table 6.8 represents regression output of knotted total wealth variable (TW1-TW5), indicating coefficients on each interval obtained using spline function. These coefficients indicate that the variable total wealth is in a non-linear relationship with the private-LTCI as well as Medicaid, because the magnitudes and directions of these coefficients are different. Thus, assuming linear relationship between total wealth and insurance (private-LTCI and Medicaid) is not straightforward. The estimates for private-LTCI indicate that the coefficient is decreasing as wealth increases, but the rate of decrease is not constant across wealth percentiles. The results from Panel B indicates the non-linear relationship between housing wealth and insurance (private-LTCI and Medicaid). Similarly, the results from Panel C indicate that age and insurance show non-linear relationship. Table 6.9 indicates the values for the knots for total wealth, housing wealth, and age.

**Table 6.8. OLS Estimates using Spline Function**

| | **Dependent Variables** | | | |
|---|---|---|---|---|
| | **Private-LTCI** | | **Medicaid** | |
| **Treatment Variables** | **β** | **S.E.** | **β** | **S.E.** |
| ***PANEL A: Total Wealth* (in $100k)** | **(1)** | | **(2)** | |
| **TW1** | 0.0048*** | (0.00041) | -0.0018*** | (0.00026) |
| **TW2** | 0.00165*** | (0.00039) | -0.00026 | (0.00024) |
| **TW3** | -0.00152** | (0.0007) | 0.000058 | (0.00046) |
| **TW4** | 0.00037 | (0.0013) | -0.00042 | (0.0008) |
| **TW5** | 0.003 | (0.0024) | -0.0002 | (0.0015) |
| ***PANEL B: Housing Wealth* (in $100k)** | | | | |
| **HW1** | 0.0093*** | (0.001) | -0.004*** | (0.00064) |

| | | | | |
|---|---|---|---|---|
| **HW2** | -0.003*** | (0.001) | -0.00049 | (0.00085) |
| **HW3** | 0.0027 | (0.0056) | -0.00028 | (0.0035) |
| **HW4** | -0.0027 | (0.0084) | 0.0005 | (0.0053) |
| **HW5** | -0.015 | (0.017) | -0.0174 | (0.01) |
| ***PANEL C: Age in Years*** | | | | |
| **Age1** | 0.0013 | (0.002) | -0.00064 | (0.0013) |
| **Age2** | 0.004* | (0.002) | 0.0002 | (0.0012) |
| **Age3** | -0.0007 | (0.002) | -0.0007 | (0.0013) |
| **Age4** | -0.0037 | (0.0021) | 0.0025 | (0.0013) |
| **Age5** | -0.01** | (0.005) | 0.0055 | (0.0032) |
| **N** | 134,165 | | 133,724 | |
| **State + Year Fixed Effects** | YES | | YES | |
| **Control Variables** | YES | | YES | |
| **Individual Fixed Effects** | YES | | YES | |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household.

Note: All OLS models include state, year, and individual fixed effects. Column 1 (2) of Panel A regresses private-LTCI (Medicaid) on knotted variables for total wealth (4 knots, 5 variables) obtained using mkspline function in stata. Similarly, Panel B and Panel C represent estimates obtained for transformed housing and age variables, using mkspline function, separately. Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

**Table 6.9. - Values at knots obtained using Spline Function**

| | Knot 1 | Knot 2 | Knot 3 | Knot 4 |
|---|---|---|---|---|
| **Total Wealth (in $100k)** | 12.5 | 34.34 | 56.2 | 78.03 |
| **Housing Wealth (in $100k)** | 5.4 | 21.07 | 36.75 | 52.43 |
| **Age in years** | 60.8 | 71.6 | 82.4 | 93.2 |

Note: The above estimates are obtained using mkspline function of Stata.

***6.6.7. Mechanism***. The decrease in the likelihood of purchasing private-LTCI after the increase in housing (financial) and total wealth could be driven by multiple factors, and the motivation behind self-insuring oneself depends upon which mechanisms led to the estimated treatment effects. However, identifying the precise mechanism that has mostly driven the observed effect is difficult due to the limitation of survey data. Thus, we attempt to provide evidence of possible mechanisms through which the observed treatment effect is generated. The evidence suggests that there are possibly three different explanations behind the resulted effect: 1) Bequest motives - Increase in both housing and total wealth can stimulate the bequest seeking behaviour of children or relatives, which increases the care options available to the individual in need of long-term care. Subsequently, it might increase individuals' probability of leaving bequest to their caretaking children or relatives. Estimates from Column 1 of Table 6.10 clearly indicate that increase in both housing (financial) and total wealth significantly increases the probability of leaving any bequest of $10k or above, suggesting that individuals prefer to pay for long-term care expenses through bequest transfer to their children or relatives instead of purchasing private-LTCI. 2) Improvement in health status – In case of the elderly, transitioning from fair/poor health to better/excellent health can significantly reduce the need of long-term care services and support. Therefore, an individual can anticipate lesser needs of LTSS leading to decrease in the likelihood of purchasing private-LTCI. Column 2 of Table 6.10 shows that change in housing and total wealth significantly decreases the probability of a person being in a fair/poor health, meaning that there is an improvement in health status occurs due to increase in overall wealth which leads to decrease in the usage of LTSS. Subsequently, an improvement in overall health status also results in decrease in probability to retire from employment. Column 5&6 of Table 6.10 report the estimated impact of housing and total wealth change on the likelihood of retirement for respondent and spouse, respectively. However, this mechanism is not evident in case of stock-market wealth. 3) Income – Individuals save money today to fund their future LTSS costs. A positive housing (financial) wealth shock leads to the appreciation of both housing (financial) and total assets, and it also increases the rent (dividend) on properties (stocks) and other assets. In addition, individuals invest more towards retirement benefits leading to increase in pension and annuity income post-retirement. These events subsequently generate a source of additional income for individuals holding such housing assets, and ultimately lead to increase in total income. Overall, this continuous source of income act as a self-insurance and each additional increase in total income increases the probability of self-insuring oneself against the future LTSS expenses.

**Table 6.10. Mechanisms**

| | P(leaving Bequest) | log(Income) | Pension Annuity | Fair/Poor Health | Respondent Retired | Spouse Retired |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Housing Market** | | | | | | |
| **Total Wealth ( in $100k)** | 0.0075** | 0.0148** | 779*** | -0.00533* | -0.007*** | -0.0064* |
| | (0.0035) | (0.0059) | (180) | (0.0031) | (0.0031) | (0.0038) |
| **Housing Wealth ( in $100k)** | 0.00951** | 0.019** | 978*** | -0.0067* | -0.009*** | -0.0088* |
| | (0.00443) | (0.0075) | (222) | (0.00385) | (0.004) | (0.00474) |
| **N** | 120,584 | 133,439 | 134,165 | 134,165 | 114,638 | 81,271 |
| | | | | | | |
| **Panel B: Stock Market** | | | | | | |
| **Total Wealth (in $100k)** | 0.0328* | 0.116*** | -791.4 | 0.0156 | 0.003 | 0.0077 |
| | (0.018) | (0.0315) | (913) | (0.0163) | (0.0147) | (0.0182) |
| **Stock Wealth (in $100k)** | 0.0231* | 0.0881*** | -523.3 | 0.0103 | 0.00245 | 0.00503 |
| | (0.0119) | (0.02) | (596) | (0.0105) | (0.0106) | (0.0119) |
| **N** | 90,735 | 101,184 | 101,676 | 101,676 | 86,729 | 79,765 |
| | | | | | | |
| **State & Year FE + Controls** | YES | YES | YES | YES | YES | YES |
| **Individual FE** | YES | YES | YES | YES | YES | YES |

*significant at 10%; ** significant at 5%; *** significant at 1%, robust standard error clustered at state and household level.

Note: Sample is obtained from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million. Panel A represents Housing Market Regressions and Panel B represents Stock Market related regressions. Each column of the table refers to a specific outcome regressed on total, housing, and stock wealth. Other covariates include age, gender, age^2, income, health status, marital status, race, and education. All the models include state, year, and individual fixed effects.

## 6.7.Discussion

This article exploits the quasi-experiment resulting from wealth shocks in both housing and financial assets on the uptake of private and public (Medicaid) long term care insurance among both owners of housing and financial assets. That is, we exploit the local effects of the timing and strength of the housing boom and bursts across US on means-tested public insurance (Medicaid) and uptake of private-LTCI among homeowners. We also exploit the exogenous variation that occurs in financial wealth due to the dot com bubble and the great recession using the SP500 indices to identify the impact in the parallel world. We find robust evidence of a causal evidence of a reduction (increase) of private-LTCI purchase after a housing as well as financial bubble (burst) controlling for regional time trends and individual fixed effects. Overall, we find that a $100 thousand increase in the housing assets (total assets) decreases the likelihood of purchasing private-LTCI by 0.6% (0.47%)., whereas $100 thousand increase in the financial assets (total assets) decreases the probability of private-LTCI by 4.73% (6.84%). We did not find such effect for renters (non-stockholders) and does not vary much when we examine the effect on total and housing (financial) assets. Consistent with (Davidoff, 2010), we observe that individuals view their housing assets as a form of self-insurance for funding their future long-term care costs. However, we do not find significant evidence that a positive wealth shock decreases the uptake of Medicaid. An explanation is that at the time of the 2006-2008 economic downturns different heterogeneous effects were going in different directions. Nonetheless, the last effect indicates no significant decrease in demand for Medicaid after the housing (financial) bubble burst.

Together these results suggest that the market for private LTCI is likely to offer some answers to the demand for risk protection for the baby boom generation. This is evidenced by the finding that the demand of private-LTCI significantly responds to changes in wealth. The results indicate that housing (financial) value is an important source of risk protection, for older adults, in the form of self-insurance. This suggests the potential for policies and products that aid adults to efficiently liquidate assets for the purpose of purchasing services for support in response to illness and disability.

## 6.8.Appendix

**Table A6.1. Variable Description**

| Variables | Definition |
|---|---|
| **Dependent Variables** | |
| *Private-LTCI* | Equals 1 if respondent is on Medicaid, else 0. |
| *Medicaid* | Equals 1 if respondent has purchased LTCI, else 0. |
| **Assets and House Prices** | |
| *House Price Index* | FHFA Index- Census Divisions- MSA |
| *Total Wealth* | Total household Assets |
| *Housing Wealth* | Total household housing Assets |
| *Stock Wealth* | Total Value of Financial Assets (Stocks, Mutual Funds, and Other Investments) |
| *Income* | Total household income |
| **Demographic Controls** | |
| *Married* | Equals 1 if respondent is married, else 0. |
| *Male* | Equals 1 if respondent is Male, else 0. |
| *Child* | Equals 1, if respondent has any children, else 0. |
| *Age* | Age of a respondent |
| *College_Education* | Equals 1 if respondent has college education or more, else 0 |
| **Respondents Health** | |
| *Fiar/Poor Health* | Equals 1 if respondent has fair or poor health, else 0. |

**Table A6.2. Reduced Form Regressions – Selection of the Sample**

| | PANEL A : Housing Market (Renters) | |
|---|---|---|
| | **Reduced Form** | |
| | **Private LTCI** | **Medicaid** |
| | (1) | (2) |
| House Price Index | 0.000018<br>(0.000012) | 0.000013<br>(0.0000182) |
| **N** | 40,618 | 40,917 |
| | | |
| | **PANEL B : Stock Market (Non-Stockholders)** | |
| | **Reduced Form** | |
| | **Private LTCI** | **Medicaid** |
| | (1) | (2) |
| Constructed Stock Wealth Shock | -0.13***<br>(0.029) | 0.02<br>(0.0235) |
| **N** | 66,651 | 67,516 |
| **State + Year Fixed Effects** | YES | YES |
| **Control Variables** | YES | YES |
| **Individual FE** | YES | YES |

*significant at 10%; ** significant at 5%; *** significant at 1%.

Note: All the models include state, year, and individual fixed effects. Column 1 (2) correspond to first set of regressions where Private-LTCI (Medicaid) is regressed on house price index in Panel A and on CWS in Panel B. Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

**Table A6.3. Baseline Estimates – Fully Specified Version – Total Wealth**

| Linear Estimates of the effect of Total Wealth on LTC-Insurance (Private & Public) | | | | |
|---|---|---|---|---|
| | **Dependent Variables** | | | |
| | **Private-LTCI** | | **Medicaid** | |
| | **OLS** | **IV** | **OLS** | **IV** |
| | (1) | (2) | (3) | (4) |
| **Total Wealth (in $100k)** | 0.0016*** | -0.00468** | -0.00056*** | -0.00077 |
| | (0.000166) | (0.00221) | (0.000104) | (0.00137) |
| **Age** | 0.0127*** | 0.0153*** | -0.00293** | -0.00285* |
| | (0.00235) | (0.00253) | (0.00147) | (0.00157) |
| **Age2** | -8.23e-05*** | -9.98e-05*** | 2.04e-05*** | 2.01e-05*** |
| | (8.92e-06) | (1.08e-05) | (5.59e-06) | (6.74e-06) |
| **Married** | 0.0047 | 0.0089** | -0.0182*** | -0.0183*** |
| | (0.0031) | (0.00346) | (0.00194) | (0.00216) |
| **Income** | 5.15e-10 | 3.25e-08** | 4.45e-09 | 5.58e-09 |
| | (8.75e-09) | (1.43e-08) | (5.48e-09) | (8.84e-09) |
| **fair/Poor Health** | -0.00534** | -0.0067*** | 0.00681*** | 0.00671*** |
| | (0.00216) | (0.00223) | (0.00136) | (0.00138) |
| **Constant** | -0.0454* | | 0.0129 | |
| | (0.271) | | (0.0171) | |
| **F-Statistic for Excluded Instrument Test** | | **677.4** | | **696.3** |
| **State + Year Fixed Effects** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES |
| **N** | 145,642 | 142,028 | 147,532 | 143,967 |
| **R-squared** | 0.024 | 0.012 | 0.012 | 0.012 |
| **Number of respd_id** | 27,402 | 24,042 | 27,456 | 24,141 |

*significant at 10%; ** significant at 5%; *** significant at 1%.

Note: All the models include state, year, and individual fixed effects. Column 1 and 2 correspond to first set of regressions where Private-LTCI is regressed on total and housing wealth in which Column 1 corresponds to Ordinary Least Square (OLS) regression and Column 2 refers to Instrumental Variable regression (known as 2SLS or Two stage least squares). Similarly, Column 3 and 4 correspond to second set of regressions where Medicaid is regressed on total and housing wealth in which Column 3 corresponds to OLS regression and Column 4 refers to IV regression. Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

**Table A6.4. Baseline Estimates – Fully Specified Version – Housing Wealth**

| **Linear Estimates of the effect of Housing Wealth on LTC-Insurance (Private & Public)** | | | | |
|---|---|---|---|---|
| | **Dependent Variables** | | | |
| | **Private-LTCI** | | **Medicaid** | |
| | **OLS** | **IV** | **OLS** | **IV** |
| | (1) | (2) | (3) | (4) |
| **Housing Wealth (in $100k)** | 0.00338*** | -0.00592** | -0.00216*** | -0.000979 |
| | (0.000638) | (0.00278) | (0.0004) | (0.00174) |
| **Age** | 0.0131*** | 0.0138*** | -0.00301** | -0.00309** |
| | (0.00235) | (0.00236) | (0.00147) | (0.00148) |
| **Age2** | -8.23e-05*** | -8.95e-05*** | 2.1e-05*** | 2.18e-05*** |
| | (8.92e-06) | (9.01e-06) | (5.59e-06) | (5.64e-06) |
| **Married** | 0.00532* | 0.00651** | -0.0182*** | -0.0187*** |
| | (0.0031) | (0.00312) | (0.00194) | (0.00196) |
| **Income** | 8.21e-09 | 9.5e-09 | 1.92e-09 | 1.8e-09 |
| | (8.71e-09) | (8.73e-09) | (5.48e-09) | (5.46e-09) |
| **Fair/Poor Health** | -0.00553** | -0.006*** | 0.00684*** | 0.00683*** |
| | (0.00216) | (0.00217) | (0.00136) | (0.00136) |
| **Constant** | -0.0476* | | 0.0137 | |
| | (0.271) | | (0.0171) | |
| **F-Statistic for Excluded Instrument Test** | | **6673** | | **6813** |
| **State + Year Fixed Effects** | YES | YES | YES | YES |
| **Control Variables** | YES | YES | YES | YES |
| **Individual Fixed Effects** | YES | YES | YES | YES |
| **N** | 145,642 | 142,028 | 147,532 | 143,967 |
| **R-squared** | 0.023 | 0.022 | 0.012 | 0.012 |
| **Number of respd_id** | 27,402 | 24,042 | 27,456 | 24,141 |

*significant at 10%; ** significant at 5%; *** significant at 1%.

Note: All the models include state, year, and individual fixed effects. Column 1 and 2 correspond to first set of regressions where Private-LTCI is regressed on total and housing wealth in which Column 1 corresponds to Ordinary Least Square (OLS) regression and Column 2 refers to Instrumental Variable regression (known as 2SLS or Two stage least squares). Similarly, Column 3 and 4 correspond to second set of regressions where Medicaid is regressed on total and housing wealth in which Column 3 corresponds to OLS regression and Column 4 refers to IV regression. Sample is drawn from Health and Retirement Study (HRS), Waves 3-12, 1996-2014. Sample excludes individuals below age 50 and those with wealth greater than $10 million.

# 7. Conclusions

## 7.1. Summary of the Findings

The main objective of this thesis has been to analyse caregiving and care financing situations for elderly individuals in the US. Informal caregiving in the US is not sustainable and there are substantial health and wellbeing costs associated with some or other aspects of informal caregiving. Similarly, like other social preferences, informal caregiving can have impact not just on present but on future generation through intergenerational transmission of role modelling effects. These aspects are relevant to understand how an access to health insurance is critical for majority of caregivers in general and how a policy in the past can impact next generation of caregivers through role modelling effects. Additionally, analysing care financing aspects is important from the socio-economic and fiscal point of view as the lack of demand for private-LTCI not only puts pressure on public expenditure via Medicaid but also increases the likelihood of self-financing of care should the wealth of an individual rises. More specifically, the caregiving part of this thesis is focused on two research questions and the care-financing part of this thesis studied the remaining two research questions.

In the first chapter, I examined whether the expansion of public health insurance via Medicaid after the passage of Affordable Care Act (ACA) improves access to health insurance to low-income individuals and impacts the mental health and wellbeing of spousal caregivers. Limited health insurance can have serious negative effects on caregiver wellness generally because it makes it more difficult for them to get the screenings and preventative care they need and raises the stress they experience from their everyday responsibilities. Caregiver without insurance may experience depressed episodes if they put off or postpone necessary medical care. Since there are no ready-made direct programmes and instruments to mitigate the subsequent detrimental economic and health effects of caregiving in the United States, knowing the experiences and mental health wellbeing of low-income caregiver spouses is crucial. As these spousal caregivers from low-income households, who previously had limited access to health insurance, were then could qualify under Medicaid as the ACA reform increased the poverty threshold in the participated states through the expansion of Medicaid coverage. The ACA Medicaid expansion reform created a quasi-experimental change which was exploited to identify the estimated effect of ACA Medicaid on mental health and wellbeing of adult spousal caregivers. The results showed that access to health insurance can significantly reduce the mental burden associated with informal caregiving. The ACA Medicaid reform also had a spill over effect on spouses being cared for as it significantly improves their mental wellbeing. The findings from this chapter offer important solutions from the point of view of sustainable arrangement of informal caregiving.

Similarly, the second chapter of this thesis studied the intergenerational transmission of caregiving duties. This paper exploits a state level quasi-experimental Medicare Interim Payment System (IPS) reform of 1997 that restricts the public provision of home health care services available for elderly individuals to identify the extent to which caregiving duties are transmitted from one generation to another. The paper finds that the IPS reform increased the likelihood of providing care to parents by approximately 5% points. This suggests that restricting the public provision of home health care increases the demand for informal care at household level. Further, the results indicated that the informal caregiving duties are transmitted from one generation to another via role modelling effects as evidenced by various mechanisms that drive the effect. More specifically, the respondents who cared for their parents in the past are 5% points more likely to receive care from their children and grandchildren in the future. These results are important as it indicated that the household attempts to manage a care crisis, occurs due to reduction in public provision of home health care, by increasing the provision of informal care at household level. This behaviour is further transmitted from one generation to another via role modelling effect. Thus, a policy of present can have long-term impact after 30 years and can affect the various socio-economic outcomes of future generations. Therefore, the findings from this study recommend a formulation of policies that can address the care-crisis, which causes due to ageing societies, to ensure the welfare of a household across generations.

The remaining two chapters focused on financing aspects of long-term care. The lack of demand for private-LTCI posed various challenges related to public financing of long-term care. Thus, an introduction of innovative reforms was needed to stimulate the purchase of private-LTCI. In the third chapter, I investigated whether the long-term care insurance partnership (LTCIP) changed the uptake of both public and private-LTCI and simulated whether it was successful in reducing Medicaid expenditure per 65-year individual per year using the calculations suggested by (Brown and Finkelstein 2008; 2011; Goda 2011). The results indicate that the LTCIP reform estimated to have increased the likelihood of purchase of private-LTCI and have reduced the uptake of public insurance (Medicaid). In addition, the most conservative results of simulation analysis suggests that the LTCIP reform was successful in average Medicaid saving of $36 per 65-year individual per year. Although the effect size is small, these results are suggestive of future possibilities of reducing implicit tax on private-LTCI if the reforms such as LTCIP can be incentivised again to attract more middle-income consumers of private-LTCI.

Finally, the fourth chapter of this thesis studied how a change in wealth can shift household level care financing decisions and the impact it has on Medicaid and private-LTCI. This paper takes advantage of natural experiments that occurred due to shocks in housing as well as financial markets. The exogenous variations in housing and financial wealth, occur due to change in house price indices and S&P 500 stock market indices, help identify the estimated impact of wealth on the uptake of Medicaid and private-LTCI. The results indicated that increase in wealth decreases the likelihood of purchasing private-LTCI indicating the presence of self-insuring care effects. Although there is evidence of substitution between self-insurance and private-LTCI, there is no significant effect of change in wealth on the probability of Medicaid entitlement. This paper supports the hypothesis established by (Davidoff, 2010) that individuals accumulate housing wealth such that in need of care it can act as a form of self-insurance. These results indicate that the demand for private-LTCI negatively responds to change in housing as well as financial wealth. Additionally, the demand for private-LTCI can also respond to variables other than housing and financial wealth some of which are also covered in this thesis.

### 7.2. Limitations and Further Research

Although the thesis was able to prove most of its hypotheses for various chapters, there are certain limitations which the thesis couldn't overcome. I discuss below some of these limitations that are notable and offer some directions to enhance our understanding of caregiving and care financing provisions in the US.

The thesis relies on secondary data for testing its hypotheses and the survey data does come with some limitations. Chapter 1 attempts to identify the impact of ACA Medicaid on mental well-being of spousal caregivers. This chapter focuses only on spousal caregivers because the information on socioeconomic indicators of other caregivers including children and friends isn't available in the HRS and this also led to greater reduction in the sample size. Thus, this limitation of HRS data does not allow us to analyse mental wellbeing of other caregivers who are most likely to benefit from access to health insurance via ACA Medicaid. From the broader policy perspective, it would be important to investigate the impact of ACA Medicaid on mental wellbeing of other caregivers using more comprehensive data. In addition, as the access to health insurance has greater health and financial implications for low-income spousal caregivers, it would be interesting to analyse the impact of ACA Medicaid on long-term physical and mental health of such caregivers.

The analysis of Chapter 2 provided evidence for transmission of caregiving from one generation to another. However, the initial waves of HRS data suffer from issues with variable coding and improper wordings. This restricts us from analysing the full sample to investigate the impact of Interim Payment System (IPS) reform on the supply of informal care to elderly parents in the first segment of the analysis. Therefore, the analysis of Chapter 2 could only find the impact of IPS on care provided by respondents to their parents but could not investigate the financial help provided by respondents. The provision of financial help can help mitigate the impact of restricting public home care by substituting it with private home care. Also, it would be interesting to understand whether or not the trait of providing financial help to parents can be transmitted from one generation to another. This can help us predict the proportion of population, who are capable of substituting caregiving responsibilities with care financing, for designing the sustainable arrangements of public care provisions in the US.

The third chapter of the thesis showed that LTCIP stimulates the purchase of private-LTCI and reduces the public expenditure via Medicaid due to reduction in the uptake of Medicaid. Although the effect is just equivalent to 1%, this indicates that programs such as LTCIP can help reduce the implicit tax on private-LTCI. However, the HRS survey does not include a specific question of whether Medicaid is used for long-term care services or other health services. Also, it is hard to separate long-term care beneficiaries from other beneficiaries of Medicaid. This forced me to make a stronger assumption about Medicaid that it is used only for long-term care services whilst I performed the simulation for cost-benefit analysis to calculate the savings in Medicaid after the implementation of LTCIP. The future researchers can separate Medicaid beneficiaries qualifying through LTCIP from those who qualify without LTCIP to accurately retrieve the effect of LTCIP on Medicaid which this study could not identify due to the limitation of the existing HRS sample used for analysis of this chapter.

Finally, the last chapter of this thesis established, in line with (Davidoff, 2010), that individuals prefer to substitute private-LTCI with self-insurance when their housing and financial wealth increase. This also helps us understand why the market for private-LTCI is less efficient in the US. Unfortunately, the House Price Indices, which were used as instrument for housing wealth, were only available at MSA as well as at county level, not allowing the exploitation of the variation at much smaller level (such as zip-code level). Therefore, the analysis of this chapter could only capture variation at broader level to identify the impact of housing wealth on private-LTCI. Exploiting variation in house prices at micro level areas can help us identify the true effect of how likely individuals are to go for self-insuring should their housing wealth increases. Future researchers who can access the house price data at micro level can immensely contribute to the literature on financing of care and housing wealth.

### 7.3. Policy Recommendation

Globally, care needs of elderly and disabled individuals are usually taken care by caregiving duties performed by family members. However, the provision of informal care comes at the significant cost of financial, health, and wellbeing sacrifices made by caregivers. Thus, in order for informal caregiving system to be maintained sustainably, it is important that caregivers are supported at various levels through government policies to protect their interests.

The wellbeing of such caregivers can be improved, especially in a country like the US, by providing access to health insurance for individuals belonging to low-income households. Limited health insurance impact caregiver's ability to engage in preventative activities (e.g., flu shots, preventive care, and screenings) and increases the stress associated with their caregiving duties. If uninsured caregivers delay or forgo needed health care, it may give rise to depressive episodes.

The first chapter of this thesis studied the impact of access to health insurance via ACA Medicaid for low-income spousal caregivers in the US. It finds that the access to health insurance improves the wellbeing and reduces depressing symptoms for spousal caregivers. As the global society is aging and the demand for informal care is expected to rise, the ACA Medicaid experience in the US is enlightening for countries which do not have universal health care system and mostly rely on means testing arrangements for health insurance access. Nevertheless, the potential mechanisms suggests that the access to health insurance significantly reduces the out-of-pocket expenses which in-turn improves the wellbeing of these low-income spousal caregivers. This is the first study that investigates the impact of access to health insurance on wellbeing of spousal caregivers. Thus, supporting modal caregivers in the US can help maintain the sustainable arrangement of informal caregiving system in the US.

The second chapter shows that caregiving duties performed by family members are generally transmitted from one generation to another via role modelling effect, meaning that respondents' caregiving behaviour in the past influences their children to provide care should the need arises. This indicates a greater problem that a policy of present can impact the next generation of individuals and can affect future generations' economic decisions due to presence of role modelling effect. This behaviour can have greater implications not just at household level policies but also at macroeconomic level policies as it can impact the labour market decisions at mass level as the society ages and could eventually add to gross economic productivity of the nation.

While Chapter 1 & 2 touched upon important aspects of caregiving, the remaining chapters of this thesis reveal important findings in terms of care financing which has greater policy implications for the US and elsewhere. Chapter 3 shows that incentivising the purchase of private-LTCI can help stimulate the purchase of private insurance and reduce the public expenditure via Medicaid. The results have greater implications for reducing implicit tax on private-LTCI, also suggested by (Brown and Finkelstein 2011) that the LTCI Partnerships impacts the means testing component of implicit tax, imposed by Medicaid, on private-LTCI. The market for private-LTCI is in the matured stage in the US. Therefore, these findings are important because what happens in the US can have major policy implications for the market for private-LTCI in other OECD countries and elsewhere.

Lastly, Chapter 4 shows that individuals view their housing and financial wealth as a form of self-insurance, so when housing as well as financial wealth increase then their likelihood of purchasing private-LTCI decreases. The changes in wealth do not affect the low-income populations on Medicaid. Thus, this chapter provides insights on substitution between private-LTCI and self-insurance due to changes in wealth. This has greater policy implications for the market for private-LTCI in the US and elsewhere. Therefore, the wealth aspects need to be considered while designing the incentives for stimulating the market for private-LTCI for the sustainable arrangements of care-financing in the US.

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