2017

Essays On Health Care Markets

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Essays On Health Care Markets

Abstract
The two chapters of my dissertation develop and estimate economic models to analyze the demand for and the provision of health care services. Specifically, I analyze the optimal design of health care markets to promote higher quality and lower cost, which can have profound implications for the well-being of people.

The first chapter, ``An Equilibrium Analysis of the Long-Term Care Insurance Market," uses a model of family interactions to explain why the long-term care insurance market has not been growing. By developing and estimating a structural model of family interactions, I study how family care affects the workings of the long-term care insurance market. I argue that private information about the availability of family care induces adverse selection where individuals with limited access to family care heavily select into insurance coverage. I demonstrate that pricing on family demographics substantially mitigates adverse selection by reducing the amounts of private information. I propose child demographic-based pricing as an alternative risk adjustment that could decrease the average premium, invigorate the market, and generate welfare gains.

The second chapter, ``Partial Rating Area Offering in the ACA Marketplaces," joint with Hanming Fang, studies insurance companies' plan offering decisions in the marketplaces established by the Patient Protection and Affordable Care Act of 2010 (ACA). Under the ACA, insurance companies can vary premiums by ``rating areas" which usually consist of multiple counties. In a given rating area, the ACA mandates uniform pricing for all counties, but, it does not mandate universal offering. We first demonstrate that it is not uncommon to observe insurance companies selling plans to only a subset of counties within a rating area. Using both theoretical and empirical approaches, we find evidence that partial rating area coverage is explained by insurers' incentive to risk screen consumers. While the ACA allows price discrimination based on rating areas and not on counties, we argue that insurers are effectively price discriminating consumers based on counties by endogenously determining their service area within a rating area.

Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Economics

First Advisor
Hanming Fang

Subject Categories
Economics

ESSAYS ON HEALTH CARE MARKETS

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A DISSERTATION

in

Economics

Presented to the Faculties of the University of Pennsylvania in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

2017

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ESSAYS ON HEALTH CARE MARKETS

Acknowledgments

This dissertation wouldn't have been possible without the wonderful support that I received from the faculty members at Penn, my friends, and family. First and foremost, I want to express my deepest thanks to my advisor, Hanming Fang. I benefited so much from his guidance and support, and without him, I wouldn't be here writing acknowledgments. I thank Petra Todd and Holger Sieg for their valuable feedback and involvement throughout the construction of this dissertation. I also have benefited a lot from other faculty members at Penn, who comprise a list too long to mention here.

I thank my fellow graduate students, especially Jan Tilly, Nick Janetos, Laura Liu, and Qing Gong for giving me a chance to get away from my computer, and making my days at Penn much more enjoyable.

I'd like to gratefully acknowledge financial support from the Korea Foundation for Advanced Studies and the Center for Retirement Research at Boston College (BC Grant 5002099) sponsored by the Social Security Administration.

I thank my parents for their support and unconditional love. I thank my sister, Ara, for being my best friend. I also wish to thank my uncle and aunt, Eugine Choi and Sunsook Noh, for giving me encouragements when I needed them the most. Lastly, I thank Dongho Song for everything he's done for me. Dongho, you mean the world to me.

ABSTRACT

ESSAYS ON HEALTH CARE MARKETS

Ami Ko

Hanming Fang

The two chapters of my dissertation develop and estimate economic models to analyze the demand for and the provision of health care services. Specifically, I analyze the optimal design of health care markets to promote higher quality and lower cost, which can have profound implications for the well-being of people.

The first chapter, "An Equilibrium Analysis of the Long-Term Care Insurance Market," uses a model of family interactions to explain why the long-term care insurance market has not been growing. By developing and estimating a structural model of family interactions, I study how family care affects the workings of the long-term care insurance market. I argue that private information about the availability of family care induces adverse selection where individuals with limited access to family care heavily select into insurance coverage. I demonstrate that pricing on family demographics substantially mitigates adverse selection by reducing the amounts of private information. I propose child demographic-based pricing as an alternative risk adjustment that could decrease the average premium, invigorate the market, and generate welfare gains.

The second chapter, "Partial Rating Area Offering in the ACA Marketplaces," joint with Hanming Fang, studies insurance companies' plan offering decisions in the marketplaces established by the Patient Protection and Affordable Care Act of 2010 (ACA).

Under the ACA, insurance companies can vary premiums by "rating areas" which usually consist of multiple counties. In a given rating area, the ACA mandates uniform pricing for all counties, but, it does not mandate universal offering. We first demonstrate that it is not uncommon to observe insurance companies selling plans to only a subset of counties within a rating area. Using both theoretical and empirical approaches, we find evidence that partial rating area coverage is explained by insurers' incentive to risk screen consumers. While the ACA allows price discrimination based on rating areas and not on counties, we argue that insurers are effectively price discriminating consumers based on counties by endogenously determining their service area within a rating area.

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Chapter 1

Introduction

The two chapters of my dissertation develop and estimate economic models to analyze the demand for and the provision of health care services. I analyze the optimal design of health care markets to promote higher quality and lower cost, which can have profound implications for the well-being of people.

1.1 "An Equilibrium Analysis of the Long-Term Care Insurance Market"

Over 55 percent of 65-year-olds will incur on average $100,000 in long-term care expenses in their remaining life. Yet only 13 percent of the elderly own private long-term care insurance. Along with relatively low coverage rates, the long-term care insurance market has undergone dramatic changes in premiums and in market structure over the last couple of years. The average premium more than doubled and the number of insurance companies selling policies plunged from over one hundred to a dozen. The primary goal of this paper is to understand how informal care provided by the family can explain the small size of the long-term care insurance market and to explore welfare-improving policies. A second goal of this paper is to understand the reasons for the recent premium increases.

To achieve these goals, I develop and estimate a dynamic non-cooperative model of an elderly parent and an adult child. The parent has preferences over informal and formal care and may value leaving a bequest to the child. The parent makes savings decisions and can have formal care paid by Medicaid if eligible. The child may provide informal care out of altruism or to protect her bequest from formal care expenses. The child's cost of providing informal care includes forgone labor income and a psychological burden, which may vary by the child's demographics. Among other things, the parent's long-term care insurance decision is affected by the likelihood of receiving informal care and the chance of becoming Medicaid eligible. The model is estimated using data from the Health and Retirement Study 1998-2010 by the conditional choice probability (CCP) estimation method. Estimation is based on *actual* premium data over the sample period. Then, I use the estimated model to analyze the counterfactual competitive *equilibrium* of the long-term care insurance market.

In the first set of counterfactuals, I examine mechanisms by which informal care accounts for the small size of the long-term care insurance market and explore welfare-increasing policies. There are two main results. First, private information about the availability of informal care creates substantial adverse selection. In equilibrium, the market only serves high-risk individuals with limited access to informal care. To reduce market inefficiencies arising from adverse selection, I evaluate counterfactual pricing on child demographics that are predictive of family care. Counterfactual results show that child demographic-based pricing increases the equilibrium coverage rate by 56 percent, decreases the average premium by 16 percent, and creates welfare gains. These welfare gains are generated by expanding insurance coverage to low-risk individuals who nevertheless value financial protection against formal care risk. Second, there is a *family moral hazard* effect of insurance and children reduce informal care by almost 20 percent in response to their parents' insurance coverage. This is because insurance protects bequests from formal care expenses and therefore undermines children's informal care incentives. Family moral hazard results in strategic non-purchase of insurance where parents forgo insurance to elicit more informal care from children. I find that family moral hazard reduces the equilibrium ownership rate by 41 percent.

In the second set of counterfactuals, I provide explanations for the recent premium increases in the insurance market. I demonstrate that the average empirical premium before the recent hikes was below the break-even level by 80 percent. I show that the initial risk classification practices of insurance companies underestimated the magnitude of adverse selection and family moral hazard, leading to such underpricing. I further demonstrate that the decreasing availability of informal care for more recent birth cohorts increases the formal care risk of the elderly and puts upward pressure on the equilibrium premium. Without changes in the pricing practices of insurance companies, the model predicts constant premium increases as the ratio of the elderly to working-age population increases.

1.2 “Partial Rating Area Offering in the ACA Marketplace”

The ACA requires that insurers vary premiums only by age, smoking status and “rating area” which usually consists of multiple counties. In a given rating area, the ACA mandates uniform pricing for all counties, but, it does not mandate universal offering. We document the prevalence of a phenomenon that we label as *partial rating area offering* where plans are not sold to all counties within a given rating area. Using individual health plans sold in 34 states with federally-facilitated marketplaces, we find that 57 percent of plans are not sold to all counties in a rating area. We hypothesize two explanations for this phenomenon: 1) insurers may selectively offer plans in order to risk screen consumers, and 2) insurers may use partial rating area offering as a way to avoid competition. We find theoretical and empirical evidence that partial rating area offering is better explained by the risk screening hypothesis. We demonstrate that while the ACA regulation allows price discrimination based on rating areas and not on counties, insurers are effectively price discriminating consumers based on counties by endogenously determining their service area within a rating area.

Chapter 2

An Equilibrium Analysis of the Long-Term Care Insurance Market

2.1 Introduction

Long-term care is one of the largest financial risks faced by elderly Americans. Almost 60 percent of 65-year-olds will spend on average $100,000 on formal long-term care services, including nursing homes, assisted living facilities, and home health aides (Kemper, Komisar, and Alecxih, 2005/2006). Long-term care insurance provides financial protection against this formal care risk. Yet only 13 percent of the elderly own long-term care insurance. Along with relatively low coverage rates, the long-term care insurance market has undergone dramatic changes in premiums and in market structure over the last couple of years. The average premium more than doubled, and the number of insurance companies selling policies plunged from over 100 to a dozen.

The primary goal of this paper is to understand how the availability of informal care provided by families can explain the small size of the long-term care insurance market and to explore welfare-improving policies. A secondary goal is to understand the reasons for recent premium increases. There are two main mechanisms by which informal care can account for the limited size of the insurance market. First, despite the fact that most long-term care is provided informally by adult children, long-term care insurance companies do not price on child demographics. This can result in adverse selection where in equilibrium, the market only serves high-risk individuals with limited access to family care. Second, the desire to use bequests as an effective instrument to elicit informal care can reduce the demand for insurance. If children provide care in part to protect bequests from formal care expenses, then long-term care insurance undermines this informal care incentive as it pays for formal care expenses. If parents prefer informal care to formal care, then they will demand less insurance to avoid distorting children's caregiving incentives.

I first present empirical facts that suggest that there is adverse selection based on the availability of informal care in the long-term care insurance market. I show that conditional on information used by long-term care insurance companies for pricing, individuals' beliefs about the availability of informal care are negatively correlated with formal care risk and long-term care insurance coverage. Next, I present suggestive evidence that children provide care in part to protect bequests from formal care expenses. I show that parents who have financial protection against formal care expenses from long-term care insurance or Medicaid are less likely to receive care from children.

Motivated by these facts, I develop and estimate a model that is a dynamic non-cooperative game between an elderly parent and an adult child who interact over long-term care decisions. The parent has preferences over informal and formal care and may value leaving bequests to the child. The parent makes savings decisions and can have formal care paid by Medicaid if eligible. The child may provide informal care out of altruism or to protect bequests from formal care expenses. The child's cost of providing informal care includes forgone labor income and a psychological burden, which may vary by the child's demographics. Among other things, the parent's long-term care insurance decision is affected by the likelihood of receiving informal care and the chance of becoming Medicaid eligible. I use individual-level panel survey data from the Health and Retirement Study 1998-2010 to structurally estimate the model by conditional choice probability (CCP) estimation method. Estimation is based on actual premium data over the sample period. Then, I use the estimated model to analyze the counterfactual competitive equilibrium of the long-term care insurance market.

In the first set of counterfactuals, I quantify the effects of informal care on equilibrium coverage rates in the long-term care insurance market and explore welfare-increasing policies. There are two main results. First, private information about the availability of informal care creates substantial adverse selection. In equilibrium, the market only serves high-risk individuals who have limited access to informal care. To reduce market inefficiencies arising from adverse selection, I evaluate counterfactual pricing on child demographics that are predictive of family care. Demographic-based pricing is common in insurance markets, and in fact, long-term care insurance companies started gender-based pricing in 2013 as an attempt to fight persistent financial losses. Counterfactual results show that child demographic-based pricing increases the equilibrium coverage rate by 56 percent, decreases the average premium by 16 percent, and creates welfare gains. These welfare gains are generated by expanding insurance coverage to low-risk individuals who nevertheless value financial protection against formal care risk. Second, there is a *family moral hazard* effect of long-term care insurance and children reduce informal care in response to their parents' insurance coverage by 20 percent. This is because insurance protects bequests from formal care expenses and therefore undermines children's informal care incentives. Because parents prefer informal care to formal care, family moral hazard decreases the demand for insurance. It also puts upward pressure on the equilibrium premium by increasing formal care risk of the insured. I find that family moral hazard reduces the equilibrium coverage rate by 41 percent.

In the second set of counterfactuals, I provide explanations for the recent premium increases in the long-term care insurance market. First, I demonstrate that the average empirical premium before the recent hikes is below the equilibrium premium by 80 percent. This number coincides with major long-term care insurance companies' requested premium increases of 80-85 percent on their older blocks of sales (Carrns, 2015). I show that the initial risk classification practices of insurance companies underestimated the magnitude of adverse selection and family moral hazard, leading to such underpricing. Second, I demonstrate that the declining availability of informal care for more recent birth cohorts puts upward pressure on the equilibrium premium. As baby boomers replace the former generation and become the major consumers of the long-term care insurance market, the equilibrium premium increases by 10 percent. This is because baby boomers are at higher risk for using formal care as they have fewer children to rely on for family care. Without changes in the pricing practices of insurance companies, one could expect constant premium increases as the ratio of the elderly to working-age population increases.

The findings in this paper have important implications for the viability of insurance markets. For relatively young insurance markets, such as the long-term care insurance market, pricing on observables that are powerful predictors of risk is crucial for the market's sustainability. This is because initial financial losses from adverse selection could trigger insurance companies to exit the market even when there is an interior equilibrium.[1] In the context of the long-term care insurance market, this paper demonstrates that pricing on the availability of substitutes that have substantial impacts on the insured risk can alleviate adverse selection and generate welfare gains. The value of these findings can be substantial given the aging of the baby boom generation and, consequently, the increasing needs for long-term care. By reducing private information about family care, the long-term care insurance market can increase its viability and continue to provide elderly Americans with insurance against one of their largest financial risks.

This paper contributes to several distinct literatures. First, it is related to the literature on private information in insurance markets. Classical models in the literature assume one-dimensional heterogeneity in risk and analyze adverse selection based on expected risk (Akerlof, 1970; Pauly, 1974; Rothschild and Stiglitz, 1976). There is a growing empirical literature that stresses the importance of heterogeneity in risk preferences such as risk aversion (Finkelstein and McGarry, 2006; Cohen and Einav, 2007), cognitive ability (Fang, Keane, and Silverman, 2008), desire for wealth after death (Einav, Finkelstein,

[1]For example, recent exits of insurance companies from the health insurance exchanges after incurring losses for the first couple of years hint at the importance of getting the pricing right in the first place.

and Schrimpf, 2010), and moral hazard (Einav, Finkelstein, Ryan, Schrimpf, and Cullen, 2013). My analysis contributes to this strand of the literature by allowing selection on risk as well as selection on wealth. As argued in Brown and Finkelstein (2008), the presence of means-tested Medicaid renders wealth an important factor in determining the willingness to pay for long-term care insurance. By developing a model of insurance choice that incorporates risk heterogeneity as well as wealth heterogeneity, this paper promotes a better understanding of selection in private insurance markets in the presence of public insurance programs.

Second, this paper contributes to the literature on strategic bequest motives and insurance choices. Theoretical studies in the literature argue that when parents can use bequests to elicit favorable actions from their children, they may forgo financial protection against risk to avoid distorting children's incentives (Bernheim, Shleifer, and Summers, 1985; Pauly, 1990; Zweifel and Struwe, 1996; Courbage and Zweifel, 2011). The empirical evidence favors this argument. Work by Cox (1987), Cox and Rank (1992), and Norton, Nicholas, and Huang (2013) finds evidence for strategic inter-vivos transfers, and in the context of long-term care, Brown (2006) and Groneck (2016) find evidence that caregiving children are rewarded with more bequests. Despite such empirical evidence, there is no study that structurally quantifies the effect of strategic bequest motives on the insurance choices of the elderly. I fill this gap by developing and structurally estimating a non-cooperative model in which family members interact over insurance decisions with both strategic and altruistic motives.

Third, this paper contributes to the literature that analyzes the small size of the long-term care insurance market. Most studies in this field focus on factors that limit the demand for insurance. Brown and Finkelstein (2008) find that Medicaid imposes a large implicit tax on long-term care insurance for low-wealth individuals, and Lockwood (2016) finds that altruistic bequest motives reduce the demand for long-term care insurance by lowering the cost of precautionary savings. Studies on the supply side of the market find high mark-ups (Brown and Finkelstein, 2007) and they propose substantial amounts of private information (Hendren, 2013) as an explanation for the small size of the market. I provide new explanations by analyzing the effects of family care on equilibrium outcomes in the long-term care insurance market. Recent work by Mommaerts (2015) estimates a cooperative model of the family with limited commitment and shows that family care reduces the overall demand for long-term care insurance. In contrast to her work, I estimate a non-cooperative model of the family with rich family heterogeneity and examine how adverse selection based on informal care and family moral hazard affect equilibrium outcomes. I show that private information about the availability of informal care and strategic motives of the family, both of which are absent in Mommaerts (2015), have important effects on the long-term care insurance market.[2]

The rest of this paper proceeds as follows. Section 2.2 presents empirical facts about long-term care in the U.S. Section 2.3 presents the model. Section 2.4 presents the data and the estimation results. Section 2.5 presents the main results. Section 2.6 concludes.

[2]This paper is also related to the literature on family care arrangements (Kaplan, 2012; Fahle, 2014; Skira, 2015; Barczyk and Kredler, 2016) and the literature on the effects of health risks on elderly savings (Hubbard, Skinner, and Zeldes, 1995; Palumbo, 1999; De Nardi, French, and Jones, 2010; Kopecky and Koreshkova, 2014).

2.2 Empirical Facts

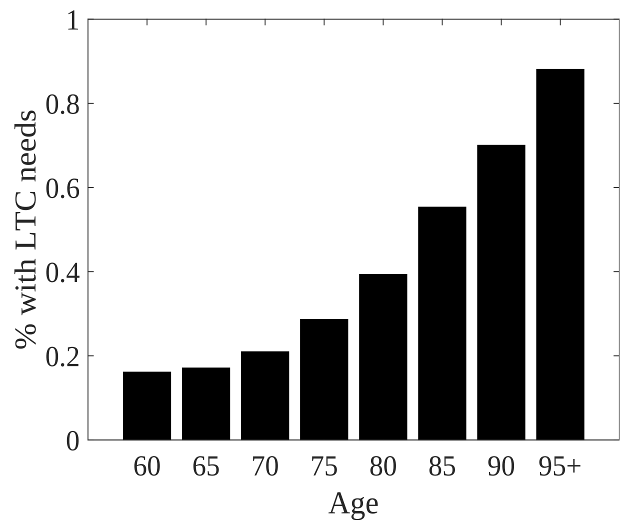
I start by providing empirical facts about long-term care in the U.S. The main data for this paper come from the Health and Retirement Study (HRS), which surveys a representative sample of Americans over the age of 50 every two years since 1992. I use seven interviews from the HRS 1998-2010. I present evidence that private information about the availability of informal care is a source of adverse selection in the long-term care insurance market. Next, I show data patterns that suggest that bequests may be important in shaping children's informal care incentives. Finally, I present evidence on underpricing of insurance products that cannot be explained by existing studies on the supply of long-term care insurance.

2.2.1 Long-Term Care in the U.S.

I first provide a brief background on the long-term care sector in the U.S. For more institutional details, see Commission on Long-Term Care (2013), Society of Actuaries (2014), and Fang (2016).

Long-term care risk. Long-term care is formally defined as assistance with basic personal tasks of everyday life, called Activities of Daily Living (ADLs) or Instrumental Activities of Daily Living (IADLs). Examples of ADLs include bathing, dressing, using the toilet, and getting in and out of bed. IADLs refer to activities that require more skills than ADLs such as doing housework, managing money, using the telephone, and taking medication. Declines in physical or mental abilities are the main reasons for requiring long-term care. Using individuals aged 60 and over in the HRS 1998-2010, Figure 2.1

Figure 2.1: Long-Term Care Needs by Age



Notes: Figure reports the share of respondents who have ADL/IADL limitations or are in the bottom 10 percent of the cognitive score distribution. Sample is limited to individuals aged 60 and over in the HRS 1998-2010.

reports, for each age group, the share of individuals who have ADL/IADL limitations or are cognitively impaired. Long-term care needs rise sharply with age and 62 percent of individuals over the age of 85 need assistance with daily tasks. While a substantial share of the elderly have long-term care needs toward the end of their lives, some people never experience difficulties with basic daily tasks until death. Using the HRS 1998-2010, I estimate the Markov transition probabilities of long-term care needs conditional on age and gender.[3] I find that about 26 percent of the elderly will never experience physical or cognitive disabilities, suggesting that individuals face risks about how much long-term care they would need.

Informal care. Unpaid long-term care provided by the family - which I will refer to as

[3]I provide details about the estimation in Section 2.4.2.

informal care in this paper - plays a substantial role in the long-term care sector. This is because unlike acute medical care, long-term care does not require professional training; it simply refers to assistance with basic personal tasks. Several studies have found evidence that informal care is the backbone of long-term care delivery in the U.S. For example, work by Barczyk and Kredler (2016) shows that informal care accounts for 64 percent of all help hours received by the elderly. Using the HRS 1998-2010, I find that 62 percent of individuals with long-term care needs receive help from children. This implies that children play a central role in delivering long-term care to the elderly.

Formal care. Another way to meet one's long-term care needs is to use formal long-term care services, such as nursing homes, assisted living facilities, and paid home care. These formal care services are labor-intensive and costly; the median annual rate is $80,300 for a semi-private room in a nursing home, $43,200 for assisted living facilities, and $36,500 for paid home care.[4] Work by Kemper, Komisar, and Alecxih (2005/2006) shows that almost 60 percent of 65-year-olds will incur $100,000 in formal care expenses over their lives. Formal care is therefore one of the largest financial risks faced by elderly Americans.

Long-term care insurance. Private long-term care insurance provides financial protection against these formal care risks. The long-term care insurance market is relatively young and modern insurance products were introduced in the late 1980s.[5] Typical long-term care insurance policies cover both facility care and paid home care provided by employees of home care agencies; most policies do not cover informal care. Policies are

[4] See Genworth (2015). The cost estimate for paid home care assumes that the help is used for 5 hours per day.

[5] National Care Planning Council, https://www.longtermcarelink.net/.

guaranteed renewable and specify a constant and nominal annual premium. Premiums are conditional on age, gender, and underwriting class determined by health conditions. Gender-based pricing is new and started in 2013. The average purchase age is 60 years, but most people do not use insurance until they turn 80 (Broker World, 2009-2015). Despite substantial formal care risks, the private long-term care insurance market is small; I find that the insurance coverage rate is only 13 percent among individuals aged 60 and over in the HRS 1998-2010.

Sources of formal care payments. Formal long-term care expenses totaled over $200 billion in 2011, which is about 1.4 percent of GDP (Commission on Long-Term Care, 2013). There are three main sources of payments. First, long-term care insurance covers about 12 percent. The role of private insurance is small due to the low coverage rates. Second, Medicaid covers over 60 percent. Medicaid is a means-tested public insurance program and pays formal care costs for individuals with limited resources. At $123 billion in 2011, Medicaid spending on long-term care imposes severe fiscal constraints at both state and federal government levels (Commission on Long-Term Care, 2013). Third, out-of-pocket money covers about 22 percent. This suggests that self-insurance in the form of savings is an important way by which elderly individuals prepare for formal care risks.

2.2.2 Private Information in the Long-Term Care Insurance Market

Despite the fact that informal care plays a critical role in delivering long-term care, long-term care insurance companies do not collect any information about children from their consumers. This is not because of regulation as there are no restrictions on the characteristics that may be used in pricing (Brown and Finkelstein, 2007). I now provide evidence that conditional on information used by insurance companies for pricing, subjective beliefs about the availability of informal care are powerful predictors of formal care risk and long-term care insurance coverage.[6]

I use the HRS question that asks about the availability of future informal care: "Suppose in the future, you needed help with basic personal care activities like eating or dressing. Will your daughter/son be willing and able to help you over a long period of time?" I use an individual's answer to this question as a measure of his beliefs about the availability of informal care. The HRS also asks individuals about their self-assessed probability of entering a nursing home: "What is the percent chance (0-100) that you will move to a nursing home in the next five years?" Several studies have used this question to construct a measure of private information about formal care risk (Finkelstein and McGarry, 2006; Hendren, 2013). I examine the predictive power of beliefs about informal care as well as the predictive power of beliefs about nursing home entry by estimating the following probit equations:

$$Pr(NH_{i,t\sim t+6} = 1) = \Phi(\alpha_1 B_{it}^{IC} + \beta_1 B_{it}^{NH} + X_{it}\gamma_1) \quad \text{and} \tag{2.2.1}$$

$$Pr(LTCI_{it} = 1) = \Phi(\alpha_2 B_{it}^{IC} + \beta_2 B_{it}^{NH} + X_{it}\gamma_2). \tag{2.2.2}$$

The term $NH_{i,t\sim t+6}$ is an indicator for staying in a nursing home for more than 100 nights in the next six years since the interview.[7] $LTCI_{it}$ is an indicator for current long-term

[6]The empirical strategy used in this section follows that in Finkelstein and McGarry (2006).

[7]Short-term nursing home stays following acute hospitalization are covered by Medicare up to 100 days. To distinguish nursing home stays that are covered by private long-term care insurance from those

Table 2.1: Beliefs about Informal Care, Nursing Home Use, and Insurance Coverage

	(1) Believe children will help	(2) Do not believe children will help
Subsequent NH Use	0.014	0.024
LTCI	0.139	0.186
Observations	2553	2552

Notes: Column (1) reports the subsequent nursing home (NH) utilization rate and the long-term care insurance (LTCI) coverage rate of respondents who believe their children will help with long-term care needs. Column (2) reports the nursing home utilization and insurance coverage rates of respondents who do not believe their children will help. Sample is limited to individuals with children who are between ages 70-75 and do not have rejection conditions based on underwriting guidelines in Hendren (2013).

care insurance holdings. B_{it}^{IC} is an indicator for whether the individual thinks children will help. If the individual believes some child will help, I set B_{it}^{IC} to one. If the individual believes no child will help, then I set B_{it}^{IC} to zero. B_{it}^{NH} is the individual's self-assessed probability of entering a nursing home rescaled to be between zero and one. X_{it} is a vector of individual characteristics used by insurance companies for pricing that includes age, gender, and various health conditions.[8] X_{it} does not include any information about children as such information is not collected by insurance companies.

I restrict the sample to individuals who are healthy enough to buy long-term care insurance at the time of interview, and old enough to have long-term care needs over the next six years since the interview. I use individuals aged 70-75 who have children and do not have conditions that render them ineligible to buy long-term care insurance.[9] Table 2.1 reports the subsequent nursing home utilization rate and the long-term care

covered by Medicare, I use nursing home stays lasting more than 100 nights.

[8]I follow Finkelstein and McGarry (2006) and Hendren (2013) to control for pricing covariates.

[9]I follow Hendren (2013) to identify rejection conditions. I exclude individuals who have ADL/IADL limitations, have experienced a stroke, or have used nursing homes or paid home care in the past.

Table 2.2: Results from the Asymmetric Information Test

	(1) Subsequent NH use		(2) LTCI	
Believe children will help	-0.010**	(0.004)	-0.041***	(0.012)
Subjective prob of future NH use (0-1)	-0.011	(0.012)	0.186***	(0.029)
Female	0.063	(0.157)	0.350	(0.390)
Age	0.004**	(0.002)	0.004	(0.004)
Female*Age	-0.001	(0.002)	-0.005	(0.005)
Psychological condition	0.004	(0.007)	-0.017	(0.024)
Diabetes	0.019***	(0.005)	-0.035*	(0.019)
Lung disease	0.010	(0.007)	-0.059**	(0.025)
Arthritis	-0.008*	(0.004)	-0.000	(0.013)
Heart disease	-0.002	(0.005)	-0.014	(0.017)
Cancer	0.000	(0.006)	-0.017	(0.018)
High blood pressure	0.005	(0.004)	-0.013	(0.014)
Cognitive score (0-1)	-0.106***	(0.020)	0.324***	(0.050)
Observations	5105		5105	

Notes: Reported coefficients are marginal effects from probit estimation of Equations (2.2.1) and (2.2.2). Standard errors are clustered at the household level and are reported in parentheses. Dependent variable in Column (1) is an indicator for staying in a nursing home for more than 100 nights in the next 6 years. Mean is 0.019. Dependent variable in Column (2) is an indicator for long-term care insurance ownership. Mean is 0.163. Sample is limited to individuals with children who are between ages 70-75 and do not have rejection conditions based on underwriting guidelines in Hendren (2013). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

insurance coverage rate of the sample broken down by their beliefs about the availability of informal care. About one half of the sample believes children will help. These beliefs appear reasonable because in the data, about 60 percent of respondents with long-term care needs actually receive care from their children. Individuals who believe children will help are less likely to enter a nursing home in the future and to own long-term care insurance.

Table 2.2 reports the results from probit estimation. Column (1) shows that individual beliefs about the availability of informal care are powerful predictors of subsequent nursing home use. Individuals who believe their children will help are 1 percentage point less likely to enter a nursing home in the future. This is a substantial effect as 2 percent of the sample use nursing homes in the next 6 years.[10] What is surprising is that individual beliefs about nursing home entry have no power in predicting subsequent nursing home use - the relationship is indeed negative and statistically insignificant.[11] If beliefs about nursing home entry reflect information about unobserved health conditions, the insignificant relationship suggests that the amounts of private information about health are small. Column (2) indicates that there is a negative and significant relationship between beliefs about the availability of informal care and insurance holdings. Individuals who believe their children will help are 4 percentage points less likely to own long-term care insurance. Given the coverage rate of 16 percent among the sample, this finding serves as evidence that private information about informal care has a substantial effect on insurance choices.

Taken together, Table 2.2 provides evidence that (1) the dimension of private information that could be the most relevant to insurance companies is private information about the availability of informal care, and (2) individuals with less access to informal care are more likely to select into insurance, creating potential adverse selection.

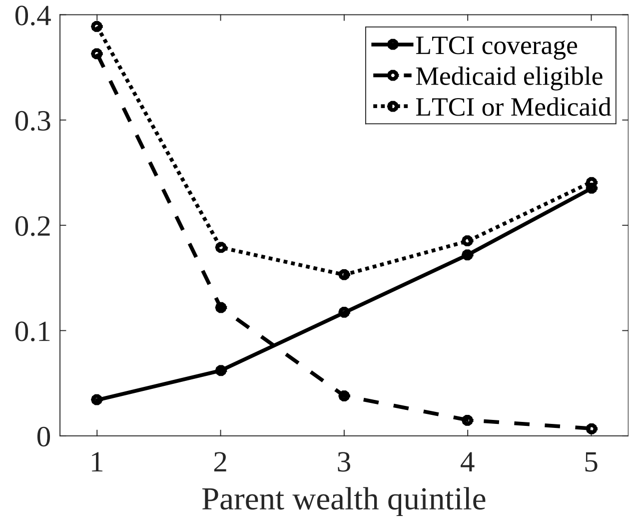
2.2.3 Informal Care and Bequests

I now provide descriptive statistics that suggest that bequests may play an important role in shaping the caregiving incentives of children. Given the costly nature of formal care,

[10] The negative and significant correlation between beliefs about informal care and subsequent nursing home use holds true when I measure nursing home use over a longer time horizon.

[11] This result is consistent with Hendren (2013), who finds little predictive power of beliefs about nursing home entry among individuals who are eligible to buy long-term care insurance. The fact that beliefs about the availability of informal care have predictive power, while beliefs about nursing home entry do not, suggests individuals' imperfect ability to incorporate all relevant information in forming these beliefs. As argued in Finkelstein and McGarry (2006), if B^{NH} is a sufficient statistic for private information about nursing home use, conditional on B^{NH}, all other individual information (including B^{IC}) should have no power in predicting nursing home use.

Figure 2.2: Long-Term Care Insurance Coverage and Medicaid Eligibility by Wealth

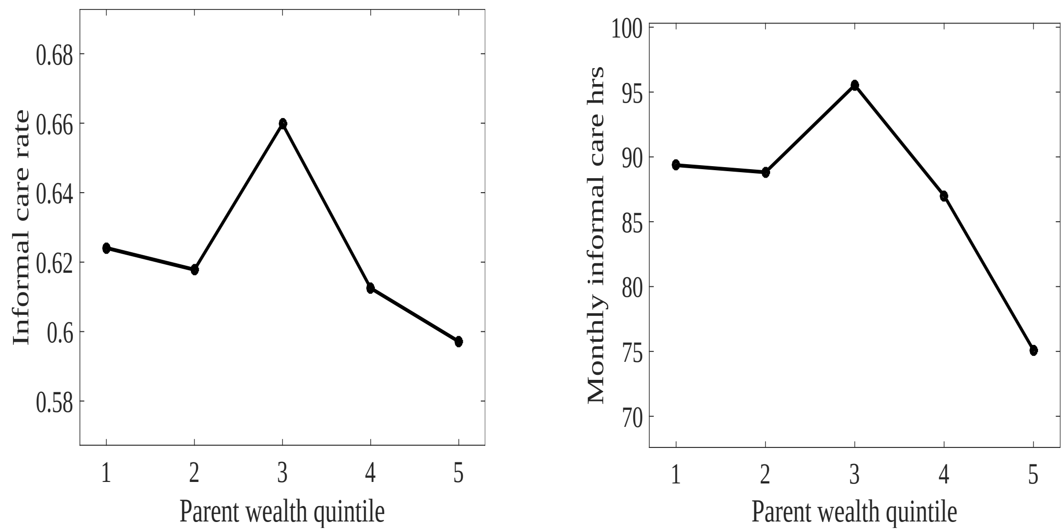


Notes: Solid line represents the long-term care insurance coverage rate by wealth quintile. Dashed line represents the share of respondents on Medicaid. Dotted line represents the share of respondents who have either long-term care insurance or Medicaid benefits. Sample is limited to single respondents aged 60 and over in the HRS 1998-2010.

children may provide care themselves to protect bequests from formal care expenses. If that is the case, the out-of-pocket costs of formal care that parents face may be an important factor in children's caregiving decisions. For example, if parents face zero out-of-pocket costs of formal care by having full long-term care insurance or being Medicaid eligible, children will not have any strategic incentive to provide informal care. Based on this intuition, I look for data patterns that suggest a positive relationship between informal care provision and the out-of-pocket costs of formal care faced by parents.

Figure 2.2 reports the long-term care insurance coverage rate (solid line) and the share of Medicaid eligibles (dashed line) by wealth quintile. The long-term care insurance coverage rate increases in wealth while the share of Medicaid eligibles decreases in wealth. Individuals in the middle of the wealth distribution face the largest out-of-pocket costs

Figure 2.3: Informal Care from Children by Parent Wealth



Notes: Left panel reports the share of respondents receiving care from children, by respondent wealth quintile. Right panel reports the average monthly care hours provided by children. Sample is limited to single respondents aged 60 and over who have long-term care needs in the HRS 1998-2010.

of formal care as the share covered by either long-term care insurance or Medicaid is the lowest. Indeed, Figure 2.3 shows that there is an inverted-U pattern of informal care; middle-wealth parents receive the most informal care from children at the extensive and intensive margins. While other factors, such as children's opportunity costs, may contribute to the inverted-U pattern of informal care, the positive relationship between children's informal care behaviors and parents' out-of-pocket costs of formal care serves as suggestive evidence that children may provide informal care to protect bequests from formal care expenses.[12]

Several empirical studies also find a significant relationship between bequests and children's informal care behaviors. Brown (2006) uses inclusion in life insurance policies and

[12]In Appendix A.1, I show further descriptive evidence that long-term care insurance undermines children's informal care incentives.

wills as proxies for bequests and finds that caregiving children are more likely to receive end-of-life transfers from parents. Groneck (2016) uses the actual bequest data obtained from the HRS exit interviews and finds a positive and significant correlation between children's informal care behaviors and the amounts of the bequests they receive. Motivated by such evidence, this paper develops and estimates a structural model to quantify how strategic incentives of the family surrounding bequests affect various dimensions of long-term care decisions.

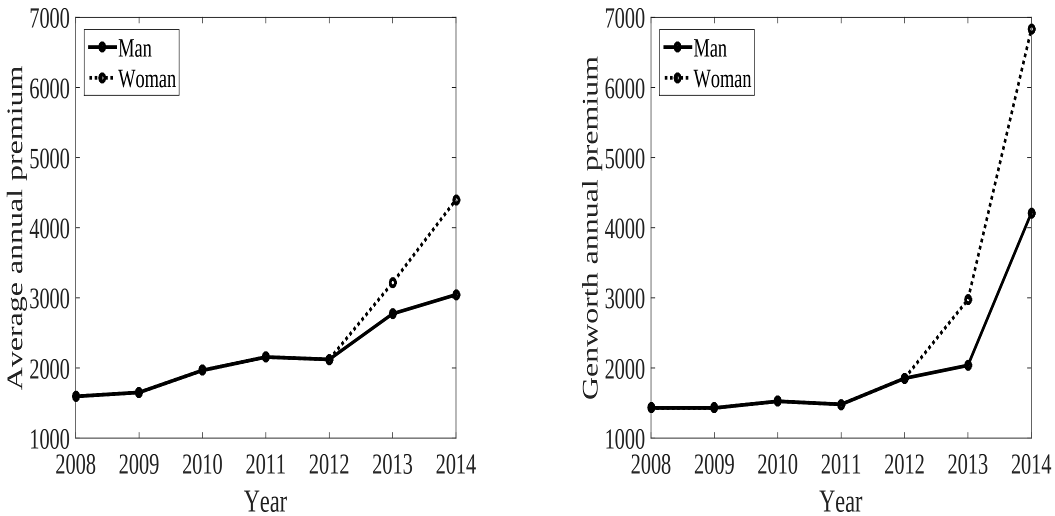
2.2.4 Recent Changes in the Long-Term Care Insurance Market

The last few years have witnessed drastic changes in the long-term care insurance market, and there have been debates on the market's viability. The left panel in Figure 2.4 presents changes in the average premium of a specific long-term care insurance policy that pays formal care expenses up to $100 per day for three years.[13] From 2008 to 2014, the average premium of this policy doubled for men and almost tripled for women. The right panel reports the premium trend of this policy separately for Genworth, which is the biggest insurance company with more than one third of the market share. The figure shows that Genworth tripled the premium for men and almost quintupled it for women. Figure 2.4 also reveals that, despite the well-known fact that women are more likely to use formal care than men (Brown and Finkelstein, 2007), gender-based pricing only started in 2013.

Existing policies were no exceptions to such premium hikes. Long-term care insurance contracts specify a constant nominal premium that is usually not subject to changes over

[13] The data are collected by Broker World, and major insurance companies - which account for more than 90 percent of industry sales - participate in the survey. The data period is from 2008 to 2014. The drastic changes in the long-term care insurance market started after 2010. The sample period of 2008-2014 is therefore suitable to capture these changes.

Figure 2.4: Soaring Premiums



Notes: Figure reports nominal annual premiums for policies with the following features: (1) they are sold to 60-year-olds who belong to insurance companies' most common underwriting class, (2) they have a maximal daily benefit of \$100, which increases at the nominal annual rate of 5 percent, (3) they provide benefits for three years, and (4) they have a 90-day elimination period. Left panel reports the average premium of policies with these features by year (the number of policies surveyed varies from 15 to 34 across years). Right panel reports changes in Genworth's product that has the described features. Data are from Broker World 2009-2015.

the life of the contract. However, state regulators approve premium increases on existing policies if insurance companies are successful in demonstrating that they had "under-priced" their products. Most major insurance companies requested premium increases starting in 2012 and were granted substantial ones. For example, Genworth requested premium increases of 80 to 85 percent on policies sold before 2011, and had received approvals from 41 states by the end of 2013 (Carrns, 2014, 2015).

In the midst of insurance companies seeking premium increases, a substantial number of insurance companies left the market altogether. Using financial data submitted by the universe of insurance companies operating in the individual long-term care line of business, I find that out of 128 insurance companies that had in-force policies in 2015, only 16 companies are actively in the market, that is, selling new policies.[14] According to an industry report which surveyed insurance companies that had exited the market, the failure to meet profit objectives was the primary reason for the exit decisions (Cohen, 2012).

In this paper, using an equilibrium model of the long-term care insurance market, I examine whether premiums before the recent hikes were indeed underpriced. The existing literature actually has evidence opposite to what insurance companies claim about underpricing and financial losses. Brown and Finkelstein (2007) use an actuarial model of formal long-term care utilization probabilities to calculate mark-ups of long-term care insurance policies sold in 2002. They find that the premiums are above actuarially fair levels and that insurance companies pay out only 82 cents in benefits for every dollar they receive in premiums. However, the actuarial model used in their analysis predicts formal care risk *unconditional* on ownership status of long-term care insurance, which may underpredict formal care risk in the presence of adverse selection or family moral hazard. By estimating a model of insurance selection that incorporates these two factors, I aim to compute more accurate mark-ups of these policies and provide explanations for the recent soaring premiums.

2.3 Model

To understand family interactions over long-term care and to explore the possible scope for welfare-increasing policies, I develop a dynamic non-cooperative game model played

[14]The data are collected by the National Association of Insurance Commissioners (NAIC) and compiled by SNL Financial. Insurance companies that no longer sell policies still have to honor their existing policies.

between a single elderly parent and an adult child.[15] The parent makes long-term care insurance purchase decisions when relatively young and healthy. The child makes labor market participation decisions, and when the parent has long-term care needs, she decides how much time to spend on taking care of the parent. If the child does not provide care, the parent chooses the type of formal care services that she would use. The parent can have formal care costs paid by Medicaid if eligible. The parent makes savings decisions, and she leaves a share of her wealth as bequests to the child.

Key features of the model are the following. First, the model describes a non-cooperative decision-making process of the parent and the child. The non-cooperative approach is motivated by several studies that find that strategic motives may be important in understanding long-term care decisions of the family.[16] Moreover, almost 70 percent of the children in the data are married. As most parents and children in the data belong to separate households, it is unrealistic to assume that they cooperate on various dimensions of decisions such as consumption, labor market participation, and leisure. Second, the model incorporates altruism. The parent is altruistic toward the child in that she may value leaving her wealth to the child. The child is altruistic toward the parent in that she may derive warm-glow utility from providing informal care. Third, the model captures the possibility of multiple children providing care in a reduced-form way. In the data, about one quarter of parents receive care from multiple children, and parents with many children use nursing homes less compared to parents with few children. Based on

[15] I assume the parent is single to abstract away from spouse-provided care, and to focus on family care provided by children. Also, in the data, most of family care received by the elderly comes from adult children.

[16] See Bernheim, Shleifer, and Summers (1985), Pauly (1990), Zweifel and Struwe (1996), and Courbage and Zweifel (2011) for theoretical studies, and Brown (2006) and Groneck (2016) for empirical evidence.

this fact, I allow the parent's formal care preferences to depend on the number of children and mitigate the possible bias from describing the informal care behaviors of one child. Fourth, the model incorporates rich child-level heterogeneity to allow for possible insurance selection based on the availability of informal care. The child's caregiving utility and forgone labor market income depend on various child demographics, which result in heterogeneous informal care incentives. Fifth, Medicaid is incorporated as a means-tested public program that pays formal care costs for impoverished parents. Lastly, the model describes the parent's savings decisions (1) to incorporate self-insurance as an alternative financial protection against formal care risk, (2) to examine the parent's bequest motives, and (3) to determine Medicaid eligibility.

2.3.1 Model Description

The model starts when the single elderly parent (with superscript P) is 60 years old and her adult child (with superscript K) is 60-Δ years old. Model period $a = 60, 62, ..., 100$, represents the parent's age and increases biennially.[17] The model incorporates three sources of uncertainty: parent health transitions, parent wealth shocks, and parent and child choice-specific preference shocks. The state vector, s_a, represents variables that are commonly observed by the family at the beginning of each period a, after the resolution of uncertainty about parent health and wealth:

$$\begin{aligned} s_a &= (w_a^P, a, ltci_a^P, h_a^P, \mathbb{I}_{cg_{a-2}^K=0}, e_{a-2}^K; X) \\ \text{where} \quad X &= (female^P, y^P, female^K, edu^K, married^K, close^K, home^K, \mathbb{I}_{N_k \geq 4}). \end{aligned}$$

[17] This is to match the fact that HRS interviews occur every two years.

w_a^P is the parent's wealth after the wealth shock, $ltci_a^P$ is an indicator for the parent's long-term care insurance holdings, h_a^P is the parent's health status, $\mathbb{I}_{cg_{a-2}^K=0}$ is an indicator for the child not providing informal care in the previous period, and e_{a-2}^K is the child's employment status in the previous period. The parent's health status can take four values: the parent can be healthy ($h_a^P = 0$), have light long-term care needs ($h_a^P = 1$), have severe long-term care needs ($h_a^P = 2$), or be dead ($h_a^P = 3$). The health transition probabilities follow a Markov chain and depend on the parent's gender, age, and current health status.[18] X represents a vector of family demographics where $female^P$ is an indicator for the parent being female, y^P is the parent's permanent income, $female^K$ is an indicator for the child being female, edu^K is an indicator for the child having some college education, $married^K$ is an indicator for the child being married, $close^K$ is an indicator for the child living within 10 miles of the parent, $home^K$ is an indicator for the child being a homeowner, and $\mathbb{I}_{N_k \geq 4}$ is an indicator for the parent having four or more children.

In each period a while the parent is alive, the child makes informal care and employment decisions. $cg_a^K \in \{0, 1, 2\}$ is the child's informal care choice where $cg_a^K = 0$ is no informal care, $cg_a^K = 1$ is light informal care, and $cg_a^K = 2$ is intensive informal care. The intensity of informal care is defined in terms of time devoted to caregiving. $e_a^K \in \{0, 1\}$ is the child's employment choice where $e_a^K = 0$ is not working, and $e_a^K = 1$ is working full-time. When the parent is healthy, the child's informal care choice is set to $cg_a^K = 0$.[19]

[18]This suggests that the parent's health transition process is exogenous and does not depend on the receipt of informal or formal care. This is based on previous studies that find that the evolution of long-term care needs is largely unaffected by the use of long-term care (Byrne, Goeree, Hiedemann, and Stern, 2009).

[19]In the data, almost no children provide care to parents without any ADL limitations.

Let $d_a^K = (cg_a^K, e_a^K)$ denote the child's informal care and employment choices in period a.

The parent moves after observing the child's choices.[20] The parent makes long-term care insurance purchase and formal care utilization decisions, followed by a consumption decision. $buy_a^P \in \{0, 1\}$ is the parent's once-and-for-all long-term care insurance choice where $buy_a^P = 1$ means purchase, and $buy_a^P = 0$ means non-purchase. The parent can buy long-term care insurance only when she is 60 years old and healthy.[21] $fc_a^P \in \{0, 1, 2\}$ is the parent's formal care choice where $fc_a^P = 0$ is no formal care, $fc_a^P = 1$ is paid home care, and $fc_a^P = 2$ is nursing homes. The parent can use formal care only when she has long-term care needs, and the child does not provide care.[22] In all other states (the parent is healthy or the child provides care), the parent does not use formal care. Let $d_a^P = (buy_a^P, fc_a^P)$ denote the parent's insurance and formal care choices in period a. Following her discrete choice d_a^P, the parent chooses consumption $c_a^P \in R_+$. In the period of the parent's death, the child inherits a share of the parent's wealth and the model closes. The parent dies for sure at the age of 100.

Preferences when the parent is alive. The child's per-period utility while the parent

[20]I make this sequential-move assumption in order to avoid the potential existence of multiple equilibria in a simultaneous-move version of the game.

[21]The average purchase age of long-term care insurance policies is around 60 (Broker World, 2009-2015), and insurance companies do not sell policies to individuals who already have long-term care needs (Hendren, 2013).

[22]In the model, informal and formal care are therefore perfect substitutes. This is based on several studies (Charles and Sevak, 2005; Coe, Goda, and Van Houtven, 2015) that find strong empirical evidence for the substitutability of informal and formal care.

is alive is

$$\tilde{\pi}^K(d_a^K, s_a, \epsilon_a^K) = \underbrace{\theta_c^K \log(c_a^K) + \theta_l^K \log(l_a^K) + \omega^K(cg_a^K, s_a)}_{\pi^K(d_a^K, s_a)} + \epsilon_a^K(d_a^K). \tag{2.3.1}$$

The child's per-period utility depends on consumption (c_a^K), leisure (l_a^K), informal care (cg_a^K), and choice-specific preference shocks (ϵ_a^K) associated with each possible discrete choice $d_a^K = (cg_a^K, e_a^K)$. The child's consumption is equal to her income, which is determined by her work choice and demographics. The child's leisure is residually determined by her work and informal care choices. ϵ_a^K is privately observed by the child and follows an *i.i.d.* extreme value type I distribution with scale one. The function ω^K represents the child's warm-glow utility from providing informal care and captures the child's possible altruism toward the parent. For $h_a^P \in \{1, 2\}$, ω^K is defined as

$$\omega^K(cg_a^K, s_a) = \begin{cases} 0 \quad \text{if} \quad cg_a^K = 0, \\ \theta^K_{h_a^P, cg_a^K} + \theta^K_{male}\mathbb{I}_{female^K=0} + \theta^K_{far}\mathbb{I}_{close^K=0} \\ \qquad\qquad + \theta^K_{start}\mathbb{I}_{cg^K_{a-2}=0} \quad \text{if} \quad cg_a^K \in \{1, 2\}. \end{cases} \tag{2.3.2}$$

The child's utility from providing no informal care is normalized to zero. The child's utility from providing light or intensive informal care depends on the parent's health status $h_a^P \in \{1, 2\}$. Moreover, the child's caregiving utility depends on her gender, whether or not she lives within 10 miles of the parent, and whether or not she provided care to the parent in the previous period.[23] As the child's informal care choice is set to $cg_a^K = 0$

[23]In the data, the informal care behaviors of children vary substantially by gender and residential proximity. Also, there is persistence in caregiving behaviors in that children who provide care tend to

when the parent is healthy, I normalize ω^K to zero for $h_a^P = 0$.[24]

The parent's per-period utility when she is alive is given by

$$\tilde{\pi}^P(d_a^K, d_a^P, c_a^P, s_a, \epsilon_a^P) \quad = \quad \underbrace{\theta_c^P \log(\hat{c}_a^P) + \omega^P(cg_a^K, fc_a^P, s_a)}_{\pi^P(d_a^K, d_a^P, c_a^P, s_a)} + \epsilon_a^P(d_a^P). \tag{2.3.3}$$

$\hat{c}_a^P$ is the sum of the parent's consumption spending and the consumption value from residing in a nursing home (c_{nh}) :

$$\hat{c}_a^P = c_a^P + c_{nh}\mathbb{I}_{fc_a^P=2}. \tag{2.3.4}$$

The parent's per-period utility depends on this total consumption value, the child's informal care choice (cg_a^K), the parent's formal care choice (fc_a^P), and choice-specific preference shocks (ϵ_a^P) associated with each possible discrete choice $d_a^P = (buy_a^P, fc_a^P)$.[25] ϵ_a^P is privately observed by the parent and follows an *i.i.d.* extreme value type I distribution with scale one. The function ω^P represents the parent's utility from informal and formal care. For $h_a^P = 0$, I normalize ω^P to zero as the parent does not use any long-term care when

continue to do so.

[24]As the parent's health transition is exogenous, this normalizing value has no impact on the child's choices.

[25]The parent's per-period utility does not include leisure utility. This is because I assume the parent is retired and spends her total available time on leisure. As I assume additively separable leisure utility, including leisure utility has no impact on the parent's choices.

she is healthy.[26] For $h_a^P \in \{1,2\}$, ω^P is defined as

$$\omega^P(cg_a^K, fc_a^P, s_a) = \begin{cases} 0 & \text{if } \; cg_a^K \in \{1,2\}, \\ \theta^P_{h_a^P} & \text{if } \; cg_a^K = 0 \;\text{ and }\; fc_a^P = 0, \\ \theta^P_{h_a^P} + \theta^P_{h_a^P, fc_a^P, \mathbb{I}_{N_k \geq 4}} & \text{if } \; cg_a^K = 0 \;\text{ and }\; fc_a^P \in \{1,2\}. \end{cases} \tag{2.3.5}$$

The parent's utility from receiving informal care is normalized to zero. If the parent chooses not to use any formal care when the child does not provide care, then she experiences $\theta^P_{h_a^P}$. So $\theta^P_{h_a^P}$ can be interpreted as the parent's disutility from not receiving any long-term care when her health status is $h_a^P \in \{1,2\}$. If the parent uses formal care $fc_a^P \in \{1,2\}$, then she experiences a utility gain of $\theta^P_{h_a^P, fc_a^P, \mathbb{I}_{N_k \geq 4}}$. This formal care utility depends on the parent's health status and whether or not she has four or more children. This is to reflect the possibility that the child within the model may not be the only source of informal care, and to rationalize the data pattern that parents with many children use less formal care. As the parent's utility from receiving informal care is normalized to zero, levels of $\theta^P_{h_a^P} + \theta^P_{h_a^P, fc_a^P, \mathbb{I}_{N_k \geq 4}}$ can be interpreted as how much the parent prefers formal care to informal care.[27]

Preferences when the parent is dead. In the case of the parent's death, she leaves her wealth to the family and derives bequest utility. Following Lockwood (2016), I pa-

[26]As previously mentioned, this normalizing value has no impact on the model as the health transition probabilities are exogenous to the choices made within the model.

[27]The parent's formal care choices only identify the differences across formal care utilities, i.e., $\theta^P_{h_a^P, fc_a^P, \mathbb{I}_{N_k \geq 4}}$. $\theta^P_{h_a^P}$ is identified from the parent's long-term care insurance purchase and consumption choices. I discuss identification of these parameters in Section 2.4.4.

rameterize the parent's altruistic bequest utility as

$$\pi_d^P(w_a^P) \quad = \quad (\theta_d^P)^{-1} w_a^P. \tag{2.3.6}$$

Bequests are luxury goods and the parent is less risk-averse over bequests than over consumption. This parametrization is useful in that it has an easy-to-interpret parameter, θ_d^P. As I assume utility from consumption c is $\theta_c^P \log(c)$, for a parent in a two-period model who dies for sure in the second period and decides between consumption and bequests, $\theta_c^P \theta_d^P$ can be interpreted as the threshold consumption below which she does not leave any bequests.[28]

I use two empirical facts to determine the child's share of bequests. First, caregiving children, on average, receive bequest amounts that are twice as much as those received by non-caregiving children (Groneck, 2016). Second, the average number of children in the data is around three. Based on these, I assume that the child in the model inherits one half of the parent's wealth. The model closes when the parent dies and the child's terminal value is given as

$$\pi_d^K(w_a^P) = \theta_d^K \Pi_d^K(0.5 w_a^P). \tag{2.3.7}$$

The function Π_d^K represents the child's inheritance value. This is calculated by assuming that the child optimally allocates and consumes the bequests over the next T_0 periods. Details on how I compute Π_d^K are given in Appendix A.2.

[28] θ_c^P and θ_d^P are not separately identified from the parent's consumption choices. The parent's discrete choices (insurance purchase and formal care choices) separately identify these two structural parameters. I discuss identification in Section 2.4.4.

Long-term care insurance and Medicaid. I consider one standardized long-term care insurance policy. The features of this policy are based on typical long-term care insurance products sold during my sample period (Brown and Finkelstein, 2007; Broker World, 2009-2015). The policy is sold to healthy 60-year-olds, covers both paid home care and nursing homes, has a maximal per-period benefit cap b, and provides benefits for life. The policy pays benefits for formal care expenses only when the parent has long-term care needs. If the parent owns the long-term care insurance policy, she pays a constant premium, p, in every period when she is not receiving benefits. Premium payments are waived when the parent is receiving insurance benefits.

After receiving benefits from long-term care insurance, if any, the parent's out-of-pocket cost of formal care is $x_{fc_a^P,h_a^P} - \min\{b, x_{fc_a^P,h_a^P}\}$ where $x_{fc_a^P,h_a^P}$ is the price for formal care fc_a^P in health status h_a^P. The parent can reduce the out-of-pocket cost if she is Medicaid eligible by satisfying the following means test:

$$w_a^P + y^P - \Big(x_{fc_a^P,h_a^P} - \min\{b, x_{fc_a^P,h_a^P}\}\Big) \quad \leq \quad \bar{w}_{fc_a^P}. \tag{2.3.8}$$

Medicaid requires that the parent's net resources after paying the out-of-pocket cost of formal care be less than $\bar{w}_{fc_a^P}$. This threshold depends on the parent's formal care choice, as the resource threshold for paid home care is substantially higher than that for nursing home care.[29] If the parent is Medicaid eligible, then her out-of-pocket cost of formal care

[29]The modal income threshold for paid home care was \$545 per month, while it was only \$30 per month for nursing homes in 1999 (Brown and Finkelstein, 2008).

is reduced to $\max\{0, w_a^P + y^P - \bar{w}_{fc_a^P}\}$ and Medicaid pays the remaining cost:

$$x_{fc_a^P,h_a^P} - \min\{b, x_{fc_a^P,h_a^P}\} - \max\{0, w_a^P + y^P - \bar{w}_{fc_a^P}\}.$$

Two important features of Medicaid emerge. First, Medicaid is a secondary payer by law. So if the parent has private long-term care insurance and is also Medicaid eligible, long-term care insurance pays first, then Medicaid. This suggests that from the perspective of insurance companies, the parent's Medicaid eligibility is irrelevant as Medicaid starts paying only after insurance companies pay out benefits. Second, the parent becomes Medicaid eligible only after having spent down her net resources to the Medicaid threshold. Medicaid therefore provides very limited financial protection against formal care risks.

Budget constraints. The parent's wealth after paying the long-term care insurance premium and the out-of-pocket cost of formal care, if any, is

$$\tilde{w}_a^P = \begin{cases} w_a^P + y^P - \max\{0, w_a^P + y^P - \bar{w}_{fc_a^P}\} = \min\{w_a^P + y^P, \bar{w}_{fc_a^P}\} & \text{if Medicaid,} \\ w_a^P + y^P - \left(x_{fc_a^P,h_a^P} - \min\{b, x_{fc_a^P,h_a^P}\}\right) - p & \text{otherwise.} \end{cases} \tag{2.3.9}$$

To make sure that the parent maintains strictly positive consumption, there is a government transfer up to $g_{fc_a^P}$, which depends on the parent's formal care choice. This can be thought of as the Supplemental Security Income (SSI) benefits, which vary by beneficiaries' nursing home residency. The parent's wealth after this government transfer is

$$\hat{w}_a^P(s_a, d_a^P) := \max\{\tilde{w}_a^P, g_{fc_a^P}\}. \tag{2.3.10}$$

There is no borrowing and the parent's consumption is constrained by $c_a^P \leq \hat{w}_a^P(s_a, d_a^P)$. The parent's wealth at the beginning of the next period is given by

$$w_{a+2}^P = \max\left\{0, (1+r)\left(\hat{w}_a^P(s_a, d_a^P) - c_a^P\right) - m_{a+2}^P\right\} \tag{2.3.11}$$

where r is the real per-period interest rate, and m_{a+2}^P is the wealth shock realized at the beginning of the next period for which the parent is liable up to $\hat{w}_a^P(s_a, d_a^P) - c_a^P$. The wealth shock follows an *i.i.d.* normal distribution.

The HRS data provide very limited information about children's assets. In the data, I only observe children's family income and whether or not they own a house. Owing to such data limitations, I assume the child does not save and consumes all her family income, y_a^K.[30] The child's family income is a deterministic function of the child's work choice, work choice in the previous period, and various demographics, including her gender, education, marital status, and home ownership status:

$$y_a^K = f(e_a^K; s_a). \tag{2.3.12}$$

[30]The assumption that the child cannot save may underestimate the cost of informal care. This is because adult children usually provide care when they are in their prime saving years (Barczyk and Kredler, 2016). Also, the child's value from bequests may vary by her wealth. While limited, rich child-level heterogeneity incorporated in the model mitigates these issues. The child's forgone labor income and caregiving utility depend on various demographics to better capture her cost of informal care. The child's value from bequests also depends on her education level which may be highly correlated with her wealth.

The child's time constraint is

$$T_{cg_a^K} + T_{e_a^K} + l_a^K = T_{total}$$

where T_{total} is her total available time, $T_{cg_a^K}$ is the required time for caregiving choice cg_a^K, and $T_{e_a^K}$ is the required time for work choice e_a^K.

2.3.2 Equilibrium

Let σ^i denote a set of decision rules for player $i \in \{K, P\}$. For the child, $\sigma^K = \{\sigma^K(s_a, \epsilon_a^K)\}$ is a mapping from the common state space, S, and the space of the child's private preference shocks, $R^{|\mathbb{C}^K|}$, to the set of the child's informal care and employment choices, $\mathbb{C}^K$:

$$\sigma^K : S \times R^{|\mathbb{C}^K|} \rightarrow \mathbb{C}^K.$$

For the parent, $\sigma^P = (\sigma^{P,d}, \sigma^{P,c})$ is composed of decision rules for discrete choices ($\sigma^{P,d}$) and consumption ($\sigma^{P,c}$). The parent makes discrete choices after observing the child's choice, so $\sigma^{P,d} = \{\sigma^{P,d}(s_a, d_a^K, \epsilon_a^P)\}$ is a mapping from the common state space, the child's choice set, and the space of the parent's private preference shocks, $R^{|\mathbb{C}^P|}$, to the set of the parent's discrete insurance and formal care choices, $\mathbb{C}^P$:

$$\sigma^{P,d} : S \times \mathbb{C}^K \times R^{|\mathbb{C}^P|} \rightarrow \mathbb{C}^P.$$

The parent chooses consumption after her discrete choices. $\sigma^{P,c} = \{\sigma^{P,c}(s_a, d_a^K, d_a^P)\}$ is a mapping from the common state space, the child's choice set, and the parent's set of discrete choices to the strictly positive real line:[31]

$$\sigma^{P,c} : S \times \mathbb{C}^K \times \mathbb{C}^P \to R_+.$$

Let $\tilde{V}^K(s_a, \epsilon_a^K; \sigma)$ denote the child's value if she behaves optimally today and in the future when the parent behaves according to her decision rules specified in $\sigma = (\sigma^K, \sigma^P)$. In states where the parent is dead, with a slight abuse of notation, define $\tilde{V}^K = \pi_d^K(w_a^P)$. By Bellman's principle of optimality, the child's problem in periods where the parent is alive can be recursively written as

$$\tilde{V}^K(s_a, \epsilon_a^K; \sigma) = \max_{d_a^K \in \mathbb{C}^K(s_a)} \left\{ \pi^K(d_a^K, s_a) + \epsilon_a^K(d_a^K) + \beta E\left[\tilde{V}^K(s_{a+2}, \epsilon_{a+2}^K; \sigma) \middle| s_a, d_a^K; \sigma \right] \right\} \tag{2.3.13}$$

where the expectation is over the parent's private preference shocks of the current period, the parent's health and wealth shocks of the next period, and the child's private preference shocks of the next period. $\mathbb{C}^K(s_a)$ denotes the set of the child's feasible informal care and employment choices in state s_a. Define $V^K(s_a; \sigma)$ as the expected value function, $V^K(s_a; \sigma) = \int \tilde{V}^K(s_a, \epsilon_a^K; \sigma) g(\epsilon_a^K)$ where g is the probability density function of ϵ_a^K. Define the choice-specific value function, $v^K(s_a, d_a^K; \sigma)$, as the per-period payoff of

[31] As the parent's preference shocks (ϵ_a^P) are additively separable and serially independent, conditional on the parent's discrete choices, these shocks are irrelevant to consumption choices.

choosing d_a^K minus the preference shock plus the expected value function:

$$v^K(s_a, d_a^K; \sigma) = \pi^K(d_a^K, s_a) + \beta E\Big[V^K(s_{a+2}; \sigma)\Big| s_a, d_a^K; \sigma\Big]. \tag{2.3.14}$$

I similarly define value functions for the parent. Let $\tilde{V}^P(s_a, d_a^K, \epsilon_a^P; \sigma)$ denote the parent's value if the parent behaves optimally today and in the future when the child behaves according to her decision rules specified in σ. Again, with a slight abuse of notation, define $\tilde{V}^P = \pi_d^P(w_a^P)$ in states where the parent is dead. The parent's problem when she is alive can be written as

$$\begin{aligned}\tilde{V}^P(s_a, d_a^K, \epsilon_a^P; \sigma) = \max_{d_a^P \in \mathbb{C}^P(s_a, d_a^K), c_a^P \in (0, \hat{w}_a^P(s_a, d_a^P))]} \Big\{ & \pi^P(d_a^K, d_a^P, c_a^P, s_a) + \epsilon_a^P(d_a^P) \\ & + \beta E\left[\tilde{V}^P(s_{a+2}, d_{a+2}^K, \epsilon_{a+2}^P; \sigma)\Big| s_a, d_a^K, d_a^P, c_a^P; \sigma\right]\Big\}\end{aligned} \tag{2.3.15}$$

where the expectation is over the parent's wealth, health, and preference shocks of the next period, and the child's private preference shocks of the next period. $\mathbb{C}^P(s_a, d_a^K)$ denotes the set of the parent's feasible insurance and formal care choices in state s_a when the child's choice is d_a^K. As there is no borrowing, consumption cannot be greater than the wealth after the government transfer, $\hat{w}_a^P(s_a, d_a^P)$. I define the parent's expected value function as $V^P(s_a, d^K; \sigma) = \int \tilde{V}^P(s_a, d_a^K, \epsilon_a^P; \sigma) g(\epsilon_a^P)$. I denote the parent's choice-specific value function as $v^P(s_a, d_a^K, d_a^P; \sigma)$, and it is defined as the parent's per-period payoff of choosing discrete choice d_a^P minus the preference shock plus her expected value function,

$$\begin{aligned} v^P(s_a, d_a^K, d_a^P; \sigma) &= \pi^P(d_a^K, d_a^P, \sigma^{P,c}(s_a, d_a^K, d_a^P), s_a) \\ &\quad + \beta E\Big[V^P(s_{a+2}, d_{a+2}^K; \sigma)\Big| s_a, d_a^K, d_a^P, \sigma^{P,c}(s_a, d_a^K, d_a^P); \sigma\Big] \end{aligned} \tag{2.3.16}$$

where I replaced c_a^P by $\sigma^{P,c}(s_a, d_a^K, d_a^P)$, the implied consumption contained in σ.

Definition. A strategy profile $\sigma^* = (\sigma^{K,*}, \sigma^{P,*})$ is a Markov perfect equilibrium (MPE) of the model if for any $(s_a, \epsilon_a^K) \in S \times R^{|\mathbb{C}^K|}$,

$$\sigma^{K,*}(s_a, \epsilon_a^K) = \underset{d_a^K \in \mathbb{C}^K(s_a)}{\operatorname{argmax}} \left\{ v^K(s_a, d_a^K; \sigma^*) + \epsilon_a^K(d_a^K) \right\}, \tag{2.3.17}$$

for any $(s_a, d_a^K, \epsilon_a^P) \in S \times \mathbb{C}^K \times R^{|\mathbb{C}^P|}$,

$$\sigma^{P,d,*}(s_a, d_a^K, \epsilon_a^P) = \underset{d_a^P \in \mathbb{C}^P(s_a, d_a^K)}{\operatorname{argmax}} \left\{ v^P(s_a, d_a^K, d_a^P; \sigma^*) + \epsilon_a^P(d_a^P) \right\}, \tag{2.3.18}$$

and for any $(s_a, d_a^K, d_a^P) \in S \times \mathbb{C}^K \times \mathbb{C}^P$,

$$\begin{aligned} \sigma^{P,c,*}(s_a, d_a^K, d_a^P) = \underset{c_a^P \in (0, \hat{w}_a^P(s_a, d_a^P)]}{\operatorname{argmax}} & \Big\{ \pi^P(d_a^K, d_a^P, c_a^P, s_a) \\ & + \beta E\Big[V^P(s_{a+2}, d_{a+2}^K; \sigma^*)\Big| s_a, d_a^K, d_a^P, c_a^P; \sigma^*\Big]\Big\}. \end{aligned} \tag{2.3.19}$$

2.3.3 Solution Method

As the preference shocks, ϵ_a^K and ϵ_a^P, are unobserved by the econometrician, I define a set of conditional choice probabilities (CCP) corresponding to discrete choice rules σ^K and

$\sigma^{P,d}$ as

$$P^{K,\sigma}(d_a^K|s_a) = \int \mathbb{I}\left\{\sigma^K(s_a, \epsilon_a^K) = d_a^K\right\} g(\epsilon_a^K) \quad \text{and} \tag{2.3.20}$$

$$P^{P,\sigma}(d_a^P|s_a, d_a^K) = \int \mathbb{I}\left\{\sigma^{P,d}(s_a, d_a^K, \epsilon_a^P) = d_a^P\right\} g(\epsilon_a^P), \tag{2.3.21}$$

respectively, and define $P^\sigma := (P^{K,\sigma}, P^{P,\sigma}, \sigma^{P,c})$. Compared to σ, P^σ represents the *expected* or *ex-ante* discrete choices of the child and the parent while they both specify the parent's consumption decision rules in the same manner. As the value functions in Equations (2.3.17), (2.3.18), and (2.3.19) only depend on σ through P^σ, rather than solving for a MPE σ^*, I solve for $P^* := P^{\sigma^*}$ instead. I discretize the parent's wealth into a fine grid and use linear interpolation for wealth points not contained in the grid. As the wealth shocks are assumed to be normally distributed, I use Gauss-Hermite quadrature to numerically integrate over the wealth shocks. I start with the terminal period when the parent is 100 years old and dies for sure. The terminal values for the child and the parent are given as $V^K = \pi_d^K(w_a^P)$ and $V^P = \pi_d^P(w_a^P)$, respectively. I proceed backward in time, and for period $a < 100$, I apply the following steps:

(a) I obtain the parent's optimal consumption by solving Equation (2.3.19).

(b) I obtain the parent's optimal CCP by solving Equation (2.3.18) and integrating out ϵ_a^P. As ϵ_a^P is *i.i.d.* and follows an extreme value type I distribution with scale one, I obtain a closed-form expression for $P^{P,*}$:

$$P^{P,*}(d_a^P|s_a, d_a^K) = \frac{\exp\left(v^P(s_a, d_a^K, d_a^P; P^*)\right)}{\sum_{d_a^P \in \mathbb{C}^P(s_a, d_a^K)} \exp\left(v^P(s_a, d_a^K, d_a^P; P^*)\right)}. \tag{2.3.22}$$

(c) I obtain the child's optimal CCP by solving Equation (2.3.17) and integrating out ϵ_a^K. As ϵ_a^K is *i.i.d.* and follows an extreme value type I distribution with scale one, I obtain a closed-form expression for $P^{K,*}$:

$$P^{K,*}(d_a^K|s_a) = \frac{\exp\left(v^K(s_a, d_a^K; P^*)\right)}{\sum_{d_a^K \in \mathbb{C}^K(s_a)} \exp\left(v^K(s_a, d_a^K; P^*)\right)}. \tag{2.3.23}$$

2.3.4 Model Discussion

I close this section by discussing some of the key implications of the model. I start with discussions on strategic interactions of the family. The child's strategic incentive to provide care results from the assumption that the child inherits the parent's wealth. As informal care and formal care are assumed to be perfect substitutes, the child has an incentive to provide care to eliminate formal care expenses. This strategic incentive is affected by the parent's wealth (w_a^P) and the parent's long-term care insurance ownership status ($ltci_a^P$). For example, if the amounts of bequests are small or if the parent's formal care expenses are covered by long-term care insurance or Medicaid, then the child's strategic caregiving incentive is reduced. This suggests that if the parent prefers informal care to formal care, she will have an incentive to save more and demand less long-term care insurance to elicit more informal care. The model therefore incorporates not only the altruistic but also the strategic bequest motives of the parent. It it worth noting that the effects of strategic bequest motives on insurance demand and savings depend on the parent's relative preference for informal versus formal care. For example, if the parent prefers formal care, then she will demand more insurance or dis-save to disincentivize the child's caregiving behaviors.

I now turn to the model's implications for selection in the long-term care insurance market. I focus on how the willingness to pay for insurance is affected by heterogeneity in formal care risk and heterogeneity in wealth. First, the parent's willingness to pay for insurance increases in formal care risk. This is straightforward as the precise role of long-term care insurance is to offer financial protection against formal care expenses. What is worth highlighting is that this formal care risk is not a model primitive. The parent's formal care risk is determined by exogenous health transitions that vary by gender *and* endogenous informal care choices of the child.[32] As a result, the parent's formal care risk is endogenously determined as an equilibrium outcome of the game played between the parent and the child. As the model incorporates rich family demographics, the model generates heterogeneous informal care likelihood across families. This implies that the model allows standard adverse selection whereby individuals with a higher formal care risk have a higher willingness to pay for insurance.

Second, the parent's willingness to pay for insurance increases in wealth in the presence of Medicaid. For low-wealth individuals, long-term care insurance is not an appealing product as Medicaid already covers their formal care expenses. Brown and Finkelstein (2008) measure "the extent to which long-term care insurance is redundant of benefits that Medicaid would otherwise have paid" and define it as Medicaid's implicit tax on long-term care insurance. As the model incorporates heterogeneity in wealth, the model predicts that high-wealth individuals who face Medicaid's small implicit tax are more

[32]The parent's health transitions also depend on the parent's age and current health status. However, as only healthy 60-year-olds buy insurance, there is no heterogeneity on these dimensions.

likely to select into insurance. The model's prediction on the nature of overall selection is therefore ambiguous. As the parent's willingness to pay for insurance is determined by both heterogeneity in formal care risk and heterogeneity in wealth, it is not a priori obvious whether individuals who have a higher willingness to pay for insurance are at higher risk. I now turn to estimation of the model to empirically investigate the model's predictions.

2.4 Data and Estimation

The main data for estimation come from the HRS 1998-2010. I use single parents with children to construct the estimation sample. To incorporate rich family heterogeneity and maintain estimation tractability, I use two-stage conditional choice probability (CCP) estimation (Hotz and Miller, 1993). All monetary values presented henceforth are in 2013 dollars unless otherwise stated.

2.4.1 Data

Sample selection. From the HRS 1998-2010, I restrict the sample to single respondents aged 60 and over in 1998 who do not miss any interviews as long as they are alive. I further restrict the sample to respondents with at least one adult child who is alive over the sample period. The model describes the informal care decisions of one adult child.[33] Therefore, I have to select one child for respondents with multiple children. I apply the following selection rules. For respondents who ever receive help with daily activities

[33]While the model endogenizes the informal care choices of one child, it still incorporates the possibility of multiple children providing care by allowing the parent's formal care preferences to depend on the number of children.

from children, I pick the primary caregiving child based on the intensity of informal care provided over the sample period.[34] For respondents who do not receive any help from any of their children, I randomly select one child. I do not select children based on their demographics, because I am interested in identifying child demographics that are predictive of the informal care likelihood. In the end, my sample consists of 4,183 families and 19,292 family-year observations.

Data on parent wealth, income, and health. I measure the parent's wealth as the net value of total assets less debts. This measure of wealth includes real estate, housing, vehicles, businesses, stocks, bonds, checking and savings accounts, and other assets. The parent's income is measured as the sum of capital income, employer pension, annuity income, social security retirement income, and other income. As the model assumes the parent's income is time-invariant, for each parent in the sample, I compute the average income over the sample period.

I use self-reported difficulties with ADLs and cognitive impairment to define health. The survey asks about a total of five ADLs: bathing, dressing, eating, getting in/out of bed and walking across a room. The HRS also provides cognitive scores based on various tests that are designed to measure cognitive ability.[35] I categorize a respondent as cognitively impaired if she is in the bottom 10 percent of the cognitive score distribution. The model assumes that Medicaid and long-term care insurance cover formal care

[34] I sequentially use the following measures of informal care intensity until ties are broken. First, I use the number of interviews in which the child is reported to help. Second, I use the number of total help hours over the sample period. Third, I use the number of total help days. For the very few observations left with ties, I randomly select one child.

[35] These tests include word recall, subtraction, backward number counting, object naming, date naming, and president naming.

expenses to eligible individuals when they have long-term care needs ($h^P \in \{1, 2\}$). The health-related benefit triggers used by Medicaid and most insurance companies require an individual to have at least two ADL limitations or a severe cognitive impairment (Brown and Finkelstein, 2007). I define the parent's health statuses such that the model reflects these health-related benefit triggers. Specifically, I classify a respondent as healthy ($h_a^P = 0$) if she is not cognitively impaired and has zero or one ADL limitation. I classify a respondent as having light long-term care needs ($h_a^P = 1$) if she is not cognitively impaired but has two or three ADL limitations. I classify a respondent as having severe long-term care needs ($h_a^P = 2$) if she is cognitively impaired or has four or more ADL limitations.

Data on endogenous choices within the model. The model assumes that insurance selection is once-and-for-all and takes place at the age of 60. To obtain data on insurance choices, I use respondents aged 60-69 who were healthy in 1998. I do not restrict the sample to respondents who are exactly 60 as the number of such observations is too small. While the average purchase age is around 60, purchases happen up to 79.[36] To reflect the possibility that insurance selection may take place later in life, I use the insurance ownership statuses over the sample period to infer insurance purchases as in Lockwood (2016). Specifically, a respondent is treated as an insurance buyer if she reports having a private long-term care insurance policy for almost half of the interview waves. Out of 4,183 parents in the estimation sample, 1,053 parents were aged 60-69 and healthy in 1998. Of these individuals, 14.4 percent are classified as insurance buyers.

[36] About 99 percent of sales are made to individuals aged 79 and less. About 20 percent of sales are made to people aged 65-79 (Broker World, 2009-2015).

I use children whose parents have long-term care needs to obtain data on informal care choices.[37] The HRS asks respondents the number of hours children helped in the last month prior to the interview. A child is classified as a light caregiver if her monthly help hours are over zero and below 100. She is classified as an intensive caregiver if the monthly help hours are equal to or greater than 100. For children's work choices, I use the HRS question that asks respondents about their children's employment. A child is classified as working if she is reported as working full-time. A child is classified as not working if she is reported as unemployed or working part-time.

I use parents with long-term care needs who do not receive informal care from children to obtain data on formal care choices.[38] A parent is classified as a nursing home user if she reports having spent more than 100 nights in a nursing home in the last two years. A parent is classified as a paid home care user if she reports having used paid home care in the last two years.[39] If a respondent reports having used paid home care and stayed in a nursing home for more than 100 days, she is classified as a nursing home user.[40]

The HRS does not ask respondents about their consumption behaviors. A subsample of the HRS respondents were selected at random and surveyed about their consumption behaviors biennially from 2003 to 2013 in the Consumption and Activities Mail Survey (CAMS). About 25 percent of my sample is found in the CAMS data. I use the CAMS data to impute consumption for the remaining sample. I use information about respon-

[37]In my sample, almost no children provide care to parents without long-term care needs.

[38]For respondents who report using both informal and formal care, I apply the following rules. If the respondent is a nursing home user, then I assume the type of long-term care used is nursing homes. Otherwise, I assume the respondent receives informal care.

[39]The HRS does not ask about the intensity of paid home care utilization.

[40]This is rare as the question about paid home care use is largely skipped for nursing home residents.

dents' assets, income, age, health, and education as well as their children's demographics to impute consumption.

Data on child demographics. To examine possible insurance selection based on the availability of informal care, the model incorporates rich child-level heterogeneity such as gender, education, home ownership, residential proximity to the parent, and marital status. The child is considered to have some college education if her completed schooling years exceed 13. As the model assumes that the child's home ownership, residential proximity to the parent, and marital status are time-invariant, I use modal values of these variables over the sample period.

Summary statistics. Table 2.3 presents the summary statistics for the parent sample. About 80 percent of the parents are female. The mean wealth is \$203,651 and the mean annual income is \$21,576. The average number of children is around three, and 40 percent have four or more children. Among respondents who were aged 60-69 in 1998, 14 percent purchased long-term care insurance. Almost 40 percent of the parents have long-term care needs; 45 percent of these parents receive care from their children. Among respondents who have long-term care needs and do not receive care from children, 37 percent use paid home care and 26 percent use nursing homes.

Table 2.4 presents the summary statistics for the child sample. Compared to children who never provide care over the sample period, caregiving children are more likely to be female and live closer to parents. They are less likely to have a college education and work full-time. Only 5 percent of the caregiving children are ever paid to help, suggesting that direct financial compensation for family care is rare.

Table 2.3: Summary Statistics on the Parent Sample

	Mean	Median
Female	0.79	
Age	78	
Have 4+ children	0.40	
Wealth	203651	88000
Annual income	21576	17448
Annual consumption	37812	34473
Buy LTCI	0.14	
Have LTC needs	0.37	
Receive informal care	0.45	
Use paid home care	0.37	
Use nursing homes	0.26	

Notes: Table reports mean/median values of the parent sample. Monetary values are in 2013 dollars. Long-term care needs are defined based on ADL limitations and cognitive impairments (see text for details). The insurance purchase rate is among respondents who were healthy and aged 60-69 in 1998. The informal care receipt rate is among respondents who have long-term care needs. The formal care utilization rates are among respondents who have long-term care needs and do not receive informal care.

Table 2.4: Summary Statistics on the Child Sample

	(1) All	(2) Never caregivers	(3) Caregivers
Female	0.56	0.49	0.67
Age	48	47	50
Have some college education	0.45	0.47	0.42
Married	0.66	0.68	0.64
Live within 10 mi of the parent	0.55	0.42	0.74
Homeowner	0.61	0.62	0.60
Work full-time	0.66	0.69	0.62
Ever paid to help			0.05
Observations	4183	2438	1745

Notes: Table reports mean values of the child sample. Column (1) reports summary statistics of all children in the sample. Column (2) reports summary statistics of children who never provide informal care over the sample period. Column (3) reports summary statistics of children who provide some informal care over the sample period.

Table 2.5: Parameters Estimated Outside the Model

Parameter description	Notation	Source	Value
Shocks			
Health shocks	h^P	HRS	See Table 2.6
Wealth shocks	m^P	HRS	$N(\$10{,}805,\ \$41{,}484^2)$
Choice-specific shocks	ϵ^P, ϵ^K		EV type 1 with scale 1
Formal care costs			
Paid home care	$x_{fc^P=1,h^P}$	MetLife (2008)	\$15,330 for $h^P = 1$
			\$30,660 for $h^P = 2$
Nursing homes	$x_{fc^P=2,h^P}$	MetLife (2008)	\$70,080 for $h^P = 1, 2$
Long-term care insurance			
Max benefits	b	BF (2008)	\$49,056
Premiums	p	BF (2008)	\$3,195
Benefit period		Broker World (2009-2015)	Lifetime
Public programs			
Medicaid thresholds	$\bar{w}_{fc^P=1}$	BF (2008)	\$9,156
	$\bar{w}_{fc^P=2}$	Lockwood (2016)	\$0
Gov. transfers (SSI)	$g_{fc^P=1}$		\$9,156
	$g_{fc^P=2}$		\$0
Child budget and time constraints			
Total endowed time	T_{total}		5,840 hours
Caregiving time	$T_{cg^K=1}$		1,095 hours
	$T_{cg^K=2}$		2,190 hours
Employment time	$T_{e^K=1}$		2,190 hours
Family income process	$f(e^K; s)$	HRS	See Appendix A.3
Other			
Nursing home cons. value	c_{nh}		\$9,156
Parent income	y^P	HRS	\$10,500, \$19,000, \$37,500
Discount factor	β	BF (2008)	$\frac{1}{0.03}$
Real rate of return	r	BF (2008)	0.03
Age difference	Δ	HRS	29 years

Notes: Table reports annual values of parameters that are estimated outside the model. Monetary values are in 2013 dollars. BF (2008) refers to Brown and Finkelstein (2008).

2.4.2 Parameters Estimated Outside the Model

I now describe parameters that are estimated outside the model. These parameters are summarized in Table 2.5. While each period within the model is two years, Table 2.5 reports annual values for easier interpretation.

Health shocks. The parent's health transition probabilities follow a Markov process. The next period health is determined by the parent's gender, age, and current health.

Table 2.6: Health Probabilities for a 60-year-old at Subsequent Ages

	68	78	88	98	
Male					
Healthy	0.7305	0.4014	0.0966	0.0026	
Light LTC needs	0.0601	0.0632	0.0320	0.0021	
Severe LTC needs	0.0462	0.0746	0.0536	0.0050	
Dead	0.1631	0.4608	0.8179	0.9902	
Ever have LTC needs					0.6756
Female					
Healthy	0.7607	0.4786	0.1304	0.0031	
Light LTC needs	0.0820	0.0940	0.0575	0.0044	
Severe LTC needs	0.0591	0.1044	0.1113	0.0203	
Dead	0.0982	0.3230	0.7007	0.9722	
Ever have LTC needs					0.8149

Notes: Table reports probabilities of different health statuses for a healthy 60-year-old ($h_{60}^{P} = 0$) at different subsequent ages. The health transition probabilities take the logistic functional forms and are estimated using maximum likelihood estimation.

From the HRS 1998-2010, I estimate the biennial transition probabilities by maximum likelihood estimation using a logit that is a flexible function of health, age, and gender. Table 2.6 reports the probabilities of different health statuses for a healthy 60-year-old at different subsequent ages. A 60-year-old man has a 68 percent chance of ever experiencing long-term care needs, while a 60-year-old woman has an 81 percent chance. These estimates are consistent with previous findings in the literature (Kemper, Komisar, and Alecxih, 2005/2006).

Wealth shocks. Using 25 percent of the parent sample for whom I observe consumption choices in the CAMS data, I use the wealth accumulation law of the model to compute the sample distribution of the wealth shock. I then fit it to a normal distribution. The estimated mean is \$10,805 and the standard deviation is about four times the mean.

Formal care costs. I calibrate formal care costs based on the average formal care prices in 2008; the average price for a semi-private room in a nursing home was \$178, and the hourly rate for paid home care was \$20 (MetLife, 2008). The mean age of the parent sample was 85 years in 2008. As long-term care is a late-life risk, formal care prices in 2008 are likely to represent the actual costs that the majority of my sample had to pay. I assume that the parent uses paid home care for 2 hours per day if she has light long-term care needs and 4 hours per day if she has severe long-term care needs. I assume if the parent enters a nursing home, she stays in the facility for the entire period.

Long-term care insurance. In the model, there is one standard long-term care insurance contract that provides benefits for life. During my sample period, a substantial share of policies offered such unlimited benefit period options.[41] I assume the standard contract pays 70 percent of nursing home costs at most. This is based on the observation that most long-term care insurance policies have daily or monthly benefit caps that are around 60-80 percent of nursing home costs (Broker World, 2009-2015). During my sample period, policies with such benefits were sold at an average premium of \$3,195 to healthy 60-year-olds.[42] In estimating the model, I assume this is the premium that the parent pays if she has long-term care insurance.

Public programs. To receive Medicaid benefits with nursing home costs, the parent's assets after incurring formal care expenses and receiving any long-term care insurance benefits must be no greater than zero. This is consistent with Medicaid's stringent re-

[41] For example, in 2008, 75 percent of policies offered unlimited benefit period options (Broker World, 2009-2015).

[42] This is the median premium (in 2013 dollars) of policies sold to healthy 60-year-olds in 2002 that have (1) a \$100 maximum daily benefit (in 2002 dollars) that increases at the nominal annual rate of 5 percent, (2) a 0 day deductible, and (3) an unlimited benefit period (Brown and Finkelstein, 2007).

strictions on assets for nursing home residents.[43] On the other hand, to receive Medicaid benefits with paid home care, the parent is allowed to have up to $9,156 after incurring net formal care expenses. This is based on Medicaid's modal income threshold for paid home care, which was $545 per month in 1999 (Brown and Finkelstein, 2008). I assume that the consumption value of nursing home services is also $9,156 per year. The parent not in a nursing home receives government transfers to top up her wealth to $9,156. The parent in a nursing home does not receive such transfers as the nursing home already generates a consumption value of an equal amount.

Child budget and time constraints. The child is endowed with 5,840 hours per year that she can use for work, leisure, or informal care. Light caregiving takes 1,095 hours per year, while intensive caregiving takes 2,190 hours per year. Full-time employment also takes 2,190 hours per year. I estimate the child's family income process outside the model using the HRS data. The HRS asks respondents to report their children's family income as one of the stated bracketed values. I use these values to estimate the child's family income process as a deterministic function of the child's work choice and demographics. Details are given in Appendix A.3.

Other values. I consider three values of the parent's income that correspond to the 20th, 55th, and 80th percentiles of the parent income distribution of my sample. The child is 29 years younger than the parent, which is the average age difference between parents and children in my sample. I assume that the annual real interest rate and the discount rate are each equal to 0.03 (Brown and Finkelstein, 2008).

[43]Following Lockwood (2016), I do not use small positive values as it does little in changing the results of estimation while complicating the analysis.

2.4.3 Estimation Strategy

The structural parameters that I estimate within the model are denoted by θ in the model description section (Section 2.3.1).[44] I now describe my strategy to estimate these parameters. To incorporate rich individual heterogeneity and maintain estimation tractability, I use two-stage conditional choice probability estimation (Hotz and Miller, 1993). CCP estimation has a computational advantage as it does not require solving the model to estimate the structural parameters. The first stage involves regressing the observed choices on the observed states to obtain the empirical policy functions. The second stage uses the empirical policy functions from the first stage to estimate value functions that are then used to estimate the structural parameters of the model. I now provide details of the estimation.

Empirical policy function estimation. I start by estimating the equilibrium decision rules, $P^* = (P^{K,*}, P^{P,*}, \sigma^{P,c,*})$, directly from the data. To estimate $P^{K,*}$ and $P^{P,*}$, I use flexible logits. Specifically, to estimate $P^{K,*}$, I regress the child's employment and caregiving choices (d_a^K) on flexible functions of common state variables (s_a). To estimate $P^{P,*}$, I regress the parent's insurance purchase or formal care utilization choices (d_a^P) on flexible functions of s_a and the child's choice in the current period (d_a^K). To estimate the parent's equilibrium consumption strategy, $\sigma^{P,c,*}$, I regress the log of imputed consumption from the CAMS data on flexible functions of s_a, d_a^K, and d_a^P. I denote the resulting empirical policy functions as $\hat{P} = (\hat{P}^K, \hat{P}^P, \hat{\sigma}^{P,c})$. Appendix Table A.2 compares simulated moments generated with these first-stage policy function estimates

[44] For the list of these parameters, see Tables 2.7 and 2.8.

to data moments.

Value function estimation. Next, I estimate the equilibrium value functions, $V^{K,*}$ and $V^{P,*}$, using the empirical policy functions, $\hat{P}$. Following Hotz, Miller, Sanders, and Smith (1994) and Bajari, Benkard, and Levin (2007), I use forward simulation. For each state, I use $\hat{P}$ and the known distributions of shocks to obtain a simulated path of choices until the parent is dead. I repeat the simulation $N_S = 500$ times and average the child's and the parent's discounted sum of flow payoffs over the N_S simulated paths. I denote the estimated value functions as $\hat{V}^K$ and $\hat{V}^P$.

Pseudo maximum likelihood estimation. Finally, I use the estimated value functions to construct a *pseudo* likelihood function and search for the parameters that maximize this function. Intuitively, the pseudo likelihood function represents the likelihood that the child's and the parent's observed choices in a given period are their "current optimal" choices when they optimize in the current period, and starting in the next period, they behave according to $\hat{P}$, which may not be optimal.

Before I define this pseudo likelihood function, I first define the likelihood function, which can be obtained by fully solving the model. The data available for estimation consist of $\{s_{a_{nt}}, d^K_{a_{nt}}, d^P_{a_{nt}}; t = 1, ..., T_n, n = 1, ..., N\}$ where T_n is the number of interviews in which the nth parent-child pair is observed.[45] The likelihood function is given as

$$L^*(\theta) = \prod_{n=1}^{N} Pr(s_{a_{n1}}) \prod_{t=1}^{T_n-1} P^{K,*}(d^K_{a_{nt}}|s_{a_{nt}};\theta)P^{P,*}(d^P_{a_{nt}}|s_{a_{nt}}, d^K_{a_{nt}};\theta)Pr(s_{a_{n,t+1}}|s_{a_{nt}}, d^K_{a_{nt}}, d^P_{a_{nt}}) \tag{2.4.1}$$

where $P^{K,*}$ and $P^{P,*}$ are the optimal conditional choice probabilities obtained from solving the model backward at candidate parameter value θ. As there are no unobserved permanent types and all shocks are serially independent, the initial conditions can be treated as exogenous. The transition of the common state variables is deterministic except for the parent's wealth and health. While the parent's health transition is exogenous to the model, the conditional density of the parent's wealth in the next period depends on endogenous choices of the model. Using the wealth accumulation law in Equation (2.3.11), the conditional density of wealth is given as

$$\begin{aligned} f(w^P_{a+2}|s_a, d^P_a, c^P_a) &= f_m\left((1+r)(\hat{w}^P_a(s_a, d^P_a) - c^P_a) - w^P_{a+2}\right)^{\mathbb{I}(w^P_{a+2}>0)} \\ &\quad \times \left(1 - F_m\left((1+r)(\hat{w}^P_a(s_a, d^P_a) - c^P_a)\right)\right)^{\mathbb{I}(w^P_{a+2}=0)} \end{aligned}$$

where f_m and F_m are the probability and the cumulative density functions of the parent's wealth shock, respectively. The distribution of the wealth shock is estimated outside the model as shown in Table 2.5. In place of c^P_a, I use the model's prediction on optimal consumption, $\sigma^{P,c,*}$. Getting rid of the terms that are irrelevant in estimating the structural

[45] For pseudo maximum likelihood estimation, I do not use the parent's imputed consumption based on the CAMS data. I instead use the parent's wealth transition to incorporate the parent's consumption choices.

parameters of the model, the likelihood function can be redefined as

$$L^*(\theta) = \prod_{n=1}^{N} \prod_{t=1}^{T_n-1} P^{K,*}(d^K_{a_{nt}}|s_{a_{nt}};\theta) P^{P,*}(d^P_{a_{nt}}|s_{a_{nt}}, d^K_{a_{nt}};\theta) \times f\Big(w^P_{a_{n,t+1}}\Big| s_{a_{nt}}, d^P_{a_{nt}}, \sigma^{P,c,*}(s_{a_{nt}}, d^K_{a_{nt}}, d^P_{a_{nt}};\theta)\Big). \tag{2.4.2}$$

The pseudo likelihood function instead uses an approximation of $P^* = (P^{K,*}, P^{P,*}, \sigma^{P,c,*})$, thereby avoiding the need to solve the model. I repeat the steps (a)-(c) outlined in the model solution section (Section 2.3.3), but use $\hat{V}^K$ and $\hat{V}^P$ in place of equilibrium value functions. These steps can be summarized by the following:

(a′) I obtain the parent's current optimal consumption by solving

$$\Psi^{P,c}(s_a, d^K_a, d^P_a; \hat{P}, \theta) = \underset{c^P_a \in (0, \hat{w}^P_a(s_a, d^P_a)]}{\operatorname{argmax}} \Big\{ \pi^P(d^K_a, d^P_a, c^P_a, s_a;\theta) + \beta E\Big[\hat{V}^P(s_{a+2}, d^K_{a+2}; \hat{P}, \theta)\Big| s_a, d^K_a, d^P_a, c^P_a; \hat{P}\Big]\Big\}. \tag{2.4.3}$$

(b′) I obtain the parent's current optimal discrete choice probabilities as

$$\Psi^{P,d}(d^P_a|s_a, d^K_a; \hat{P}, \theta) = \frac{\exp\Big(\hat{v}^P(s_a, d^K_a, d^P_a; \hat{P}, \theta)\Big)}{\sum_{d^P_a \in \mathbb{C}^P(s_a, d^K_a)} \exp\Big(\hat{v}^P(s_a, d^K_a, d^P_a; \hat{P}, \theta)\Big)}. \tag{2.4.4}$$

(c′) I obtain the child's current optimal discrete choice probabilities as

$$\Psi^K(d^K_a|s_a; \hat{P}, \theta) = \frac{\exp\Big(\hat{v}^K(s_a, d^K_a; \hat{P}, \theta)\Big)}{\sum_{d^K_a \in \mathbb{C}^K(s_a)} \exp\Big(\hat{v}^K(s_a, d^K_a; \hat{P}, \theta)\Big)}. \tag{2.4.5}$$

For $i \in \{K, P\}$, $\hat{v}^i$ is defined as in Equations (2.3.14) and (2.3.16) but $\hat{P}$ and $\hat{V}^i$ are used in place of σ and V^i. The function $\Psi = (\Psi^K, \Psi^{P,d}, \Psi^{P,c})$ is called the policy iteration operator or the policy improvement mapping as it updates the policy function estimates $(\hat{P})$ by embedding the agents' optimizing behaviors of the current period (Aguirregabiria and Mira, 2002). The pseudo likelihood function is given as

$$L(\theta; \hat{P}) = \prod_{n=1}^{N} \prod_{t=1}^{T_n - 1} \Psi^K(d^K_{a_{nt}} | s_{a_{nt}}; \hat{P}, \theta) \Psi^{P,d}(d^P_{a_{nt}} | s_{a_{nt}}, d^K_{a_{nt}}; \hat{P}, \theta) \times f\Big(w^P_{a_{n,t+1}} \Big| s_{a_{nt}}, d^P_{a_{nt}}, \Psi^{P,c}(s_{a_{nt}}, d^K_{a_{nt}}, d^P_{a_{nt}}; \hat{P}, \theta)\Big). \tag{2.4.6}$$

The CCP estimator, denoted by $\hat{\theta}$, maximizes this pseudo likelihood function:

$$\hat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmax}} \; L(\theta; \hat{P}). \tag{2.4.7}$$

This CCP estimator is consistent if the first-stage estimator of the equilibrium policy functions is consistent (Aguirregabiria and Mira, 2007). My first-stage policy function estimator is consistent as it uses the flexible functions of the state variables. To compute standard errors, I use bootstrapping as in Bajari, Benkard, and Levin (2007).

2.4.4 Identification

Before I present the estimation results, I provide heuristic arguments for identification of the structural parameters. I first discuss identification of the parameters that govern the child's decisions. The child's consumption utility (θ^K_c) and leisure utility (θ^K_l) are identified by variation in income and leisure across work and informal care choices. As children with healthy parents do not provide informal care, their choices help identify consumption utility and leisure utility separately from warm-glow caregiving utility and inheritance utility (θ_d^K).[46]

The child's inheritance utility is identified from her informal care choices. For strong identification of the child's inheritance utility, the expected inheritance should vary sufficiently by informal care choices. Substantial formal care prices and the assumption that informal care eliminates the need for formal care result in enough variations in expected inheritances across informal care choices.

The child's informal care choices are governed not only by inheritance utility but also by warm-glow caregiving utility. The child's warm-glow caregiving utility is separately identified from inheritance utility using the informal care choices of children whose parents have low wealth or are Medicaid eligible. This is because these children's informal care choices are mostly governed by altruism and not strategic motives. Informal care choices of children whose parents have long-term care insurance also provide a source of identification by the same argument. Exclusion restrictions also help separate identification. While warm-glow caregiving utility is unaffected by the parent's wealth, inheritance utility crucially depends on the parent's wealth.

I now discuss identification of the parameters that govern the parent's decisions. The parent's consumption utility (θ_c^P) and altruistic bequest utility (θ_d^P) are not separately identified from savings choices. This is because savings is a continuous choice and only the relative ratio of the consumption-bequest trade-off matters. The feature of the data that helps identification is parents' formal care and insurance purchase choices. Variations in consumption and expected bequests across these discrete choices allow separate

[46] By warm-glow caregiving utility, I refer to structural parameters that enter ω^K in Equation (2.3.2).

identification of θ_c^P and θ_d^P.

The parent's formal care choices identify the *differences* among formal care utilities ($\theta^P_{h_a^P, fc_a^P, \mathbb{I}_{N_k \geq 4}}$). The *levels* of formal care utilities ($\theta^P_{h_a^P}$) are not identified from formal care choices. As shown in Equation (2.3.5), $\theta^P_{h_a^P}$ is included in the parent's utility for all three formal care choices (no formal care, paid home care, and nursing home). I do this because I have already normalized the utility from receiving informal care to zero. Owing to this normalization, the levels of formal care utilities can be interpreted as how much the parent prefers formal care to informal care. As a result, the parent's choices that affect the likelihood of informal care identify these levels of formal care utilities. In other words, the parent's choices that are affected by her strategic bequest motives provide a source of identification. Long-term care insurance and savings are such choices. The parent's insurance ownership status affects the child's informal care incentives through the family moral hazard effect of insurance. Savings also influence the child's informal care incentives by changing bequests that are at stake.

The parent's insurance and savings choices are governed not only by strategic bequest motives but also by altruistic bequest motives (θ_d^P). These two different motives are separately identified by the following argument. The parent's strategic bequest motives affect the parent's insurance and savings decisions only through the child's caregiving responses. Such responses are affected by the child's demographics that determine the cost of informal care. As the parent's altruistic bequest motives are unrelated to the child's demographics, child demographics serve as exclusion restrictions that identify strategic bequest motives from altruistic bequest motives.

Lastly, the parent's formal care choices are governed not only by formal care utilities

Table 2.7: Parent Structural Parameter Estimates

Description	Notation	Estimate	S.E.
Consumption utility	θ_c^P	4.596	0.034
Bequest utility	θ_d^P	19646	1431
Formal care utility when $h_a^P = 1$			
No formal care	$\theta^P_{h_a^P=1}$	-3.014	0.388
Paid home care, 4- children	$\theta^P_{h_a^P=1,fc_a^P=1,0}$	1.466	0.085
Paid home care, 4+ children	$\theta^P_{h_a^P=1,fc_a^P=1,1}$	1.380	0.126
Nursing home, 4- children	$\theta^P_{h_a^P=1,fc_a^P=2,0}$	0.575	0.177
Nursing home, 4+ children	$\theta^P_{h_a^P=1,fc_a^P=2,1}$	0.230	0.245
Formal care utility when $h_a^P = 2$			
No formal care	$\theta^P_{h_a^P=2}$	-6.283	0.230
Paid home care, 4- children	$\theta^P_{h_a^P=2,fc_a^P=1,0}$	2.990	0.119
Paid home care, 4+ children	$\theta^P_{h_a^P=2,fc_a^P=1,1}$	2.368	0.104
Nursing home, 4- children	$\theta^P_{h_a^P=2,fc_a^P=2,0}$	4.788	0.062
Nursing home, 4+ children	$\theta^P_{h_a^P=2,fc_a^P=2,1}$	3.149	0.078

Notes: Table reports estimates for the parent's structural parameters. Standard errors are computed using 100 bootstrap samples.

but also by consumption and bequest motives. For example, the parent may not use formal care because she would rather spend her wealth on consumption or increase bequests. Parents with long-term care insurance or Medicaid benefits help separate identification. This is because these parents' formal care choices are largely unaffected by consumption or bequest motives as they can use formal care without drawing down their wealth.

2.4.5 Estimates and Model Fit

Table 2.7 reports the estimates of the parent's structural parameters. Several findings emerge from the estimates. First, the parent prefers informal care to formal care. This is shown by the fact that estimates of $\theta^P_{h_a^P} + \theta^P_{h_a^P, fc_a^P, \mathbb{I}_{N_k \geq 4}}$ are always negative. This is consistent with Mommaerts (2015) who also finds that parents have a distaste for formal care relative to informal care. Second, the parent's relative preferences for different formal care services vary by health status. Parents with light long-term care needs ($h_a^P = 1$) prefer paid home care to nursing home care.[47] This is consistent with the broad perception that most individuals want to remain in their homes and delay facility care until they absolutely need it. Preferences for nursing home care are substantially higher when the parent has severe long-term care needs ($h_a^P = 2$). Third, preferences for formal care are smaller for parents with many children. This is consistent with the data pattern that parents with four or more children use less formal care. Lastly, the parent has altruistic bequest motives. The magnitude of altruistic bequest motives is smaller than that found in Lockwood (2016).[48] While the parent in his model only has altruistic bequest motives, the parent in my model has both altruistic *and* strategic bequest motives. Because the parent prefers informal care to formal care, strategic bequest motives induce the parent to save more. To the extent that both models try to rationalize the same savings patterns, my estimation of the model finds lower altruistic bequest motives as it attributes some of the savings to strategic bequest motives.

Table 2.8 reports the estimates of the child's structural parameters. Several findings emerge from the estimates. First, children providing care to parents with light long-term care needs derive higher caregiving utility than those providing care to parents with severe long-term care needs. This implies that taking care of parents with severe daily living limitations is stressful to children. This is consistent with Skira (2015), who also finds higher caregiving utility when the parent has modest rather than severe long-term

[47]The estimates of nursing home preferences are net of consumption value from nursing home care (c_{nh}) as I have explicitly included it in the parent's consumption utility. See Equation (2.3.4).

[48]He considers a life-cycle model of a single parent who makes long-term care insurance and savings decisions, abstracting away from strategic interactions with the family.

Table 2.8: Child Structural Parameter Estimates

Description	Notation	Estimate	S.E.
Consumption utility	θ_c^K	1.137	0.027
Leisure utility	θ_l^K	0.688	0.032
Inheritance utility	θ_d^K	5.077	0.195
Warm-glow caregiving utility			
$h_a^P = 1$, light informal care	$\theta^K_{h_a^P=1,cg_a^K=1}$	1.141	0.048
$h_a^P = 1$, intensive informal care	$\theta^K_{h_a^P=1,cg_a^K=2}$	0.711	0.053
$h_a^P = 2$, light informal care	$\theta^K_{h_a^P=2,cg_a^K=1}$	-0.208	0.052
$h_a^P = 2$, intensive informal care	$\theta^K_{h_a^P=2,cg_a^K=2}$	0.563	0.035
Male	θ^K_{male}	-1.019	0.043
Live far	θ^K_{far}	-1.148	0.046
Initiate caregiving	θ^K_{start}	-0.987	0.046

Notes: Table reports estimates for the child's structural parameters. Standard errors are computed using 100 bootstrap samples.

care needs. Second, the psychological burden of providing care varies substantially by child demographics. Sons find caregiving more burdensome than daughters, and children who do not live within 10 miles of their parents experience higher caregiving costs than children who do. Third, there is a substantial cost in initiating informal care. This may reflect switching or adjustment costs. The model generates persistence in informal care, consistent with Skira (2015). Lastly, the child values bequests. The model therefore generates family moral hazard whereby children reduce informal care in response to their parents' insurance coverage.

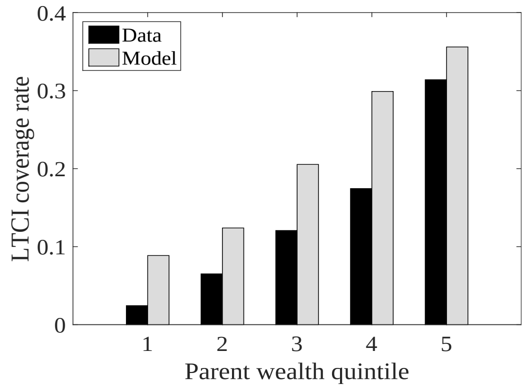
I now discuss the model fit. Figure 2.5 shows that the model does a good job of matching the empirical long-term care insurance coverage rate by wealth quintile. In particular, the model is able to replicate the monotonically increasing ownership rate in wealth. Figure 2.6 reports the actual and simulated parent median wealth by age, and the fit is reasonable. Table 2.9 shows that the model is able to match the paid home care and nursing home utilization rates as well as the light and intensive informal care rates, conditional on the intensity of the parent's long-term care needs. Figure 2.7 further breaks down the formal care moments by parent wealth. The model is able to replicate the fact that the paid home care utilization rate increases in wealth, and parents in the bottom wealth quintile have the highest nursing home utilization rate.

Figure 2.8 reports the actual and simulated formal care utilization rates by whether or not parents have four or more children. In the data, the paid home care utilization rate is almost the same between parents with few children and parents with many children. On the other hand, the nursing home utilization rate for parents with many children is lower by 30 percent compared to that for parents with few children. Figure 2.8 shows that the model is able to rationalize these patterns.

Figure 2.9 reports the informal care rate by parent wealth. The model is able to reproduce the inverted-U pattern across wealth, although the pattern is slightly shifted to the right compared to the data pattern. Figures 2.10 and 2.11 report informal care and employment moments by child gender and residential proximity to the parent, respectively. The fit of these moments confirm that the model is capable of matching the child's empirical moments conditional on various demographics. Table 2.10 reports the fit of informal care transition probabilities. The model is able to reproduce the persistent caregiving pattern in the data.

Finally, Table 2.11 compares the simulated lifetime formal care expenses for a healthy 65-year-old to those found in Kemper, Komisar, and Alecxih (2005/2006). Similar to their findings, the model predicts large formal care risks; half of 65-year-olds will not incur any formal care expenses while the other half will spend on average \$100,146 on

Figure 2.5: Long-Term Care Insurance Coverage by Parent Wealth



Notes: Figure reports data and simulated long-term care insurance coverage rates by parent wealth. Simulated moments are generated using the estimated model.

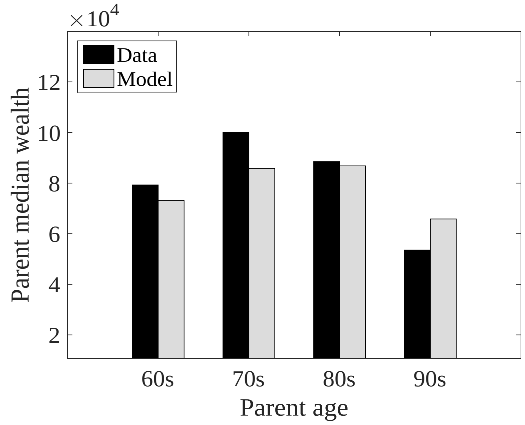
formal care. The model predicts that almost 40 percent of these expenses will be paid by Medicaid, which is also similar to what the other study finds.

2.5 Equilibrium Analyses

I use the estimated model to conduct equilibrium analyses of the long-term care insurance market. To do this, I augment the model by incorporating competitive insurance companies. I use the augmented framework to examine how private information about informal care and family moral hazard affect the equilibrium outcomes, and to shed light on the recent soaring premiums.

One standardized policy is offered in the competitive long-term care insurance market. Risk-neutral insurance companies compete by setting premiums. The standard policy is sold to healthy 60-year-olds at a constant premium and has benefit features that are described in Section 2.3.1: (1) it has a maximal per-period benefit cap, (2) it provides benefits for life, and (3) premium payments are waived while policyholders are receiving

Figure 2.6: Parent Wealth by Age



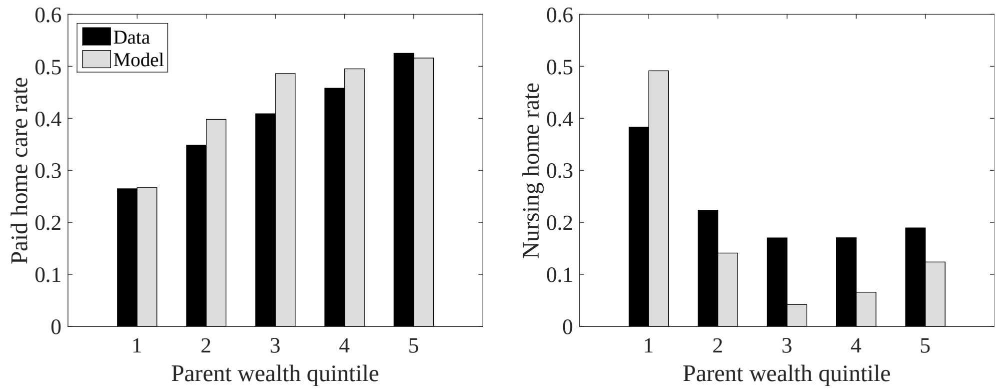
Notes: Figure reports data and simulated median wealth by parent age. Simulated moments are generated using the estimated model.

Table 2.9: Long-Term Care Utilization

	Data	Model
Among parents w/ light LTC needs		
Light informal care rate	0.37	0.35
Intensive informal care rate	0.18	0.10
Paid home care rate	0.50	0.46
Nursing home rate	0.07	0.04
Among parents w/ severe LTC needs		
Light informal care rate	0.09	0.10
Intensive informal care rate	0.29	0.23
Paid home care rate	0.30	0.27
Nursing home rate	0.36	0.33

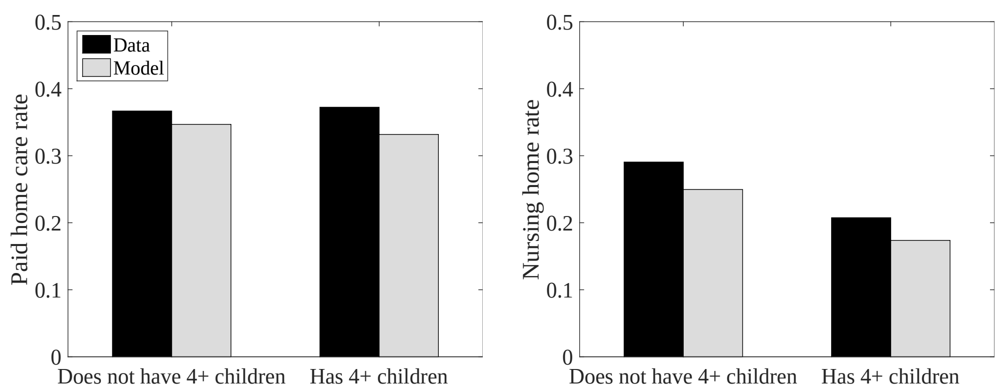
Notes: Table reports data and simulated moments. Simulated moments are generated using the estimated model. Formal care rates are among parents who have specified health statuses and do not receive informal care from children.

Figure 2.7: Formal Care by Parent Wealth



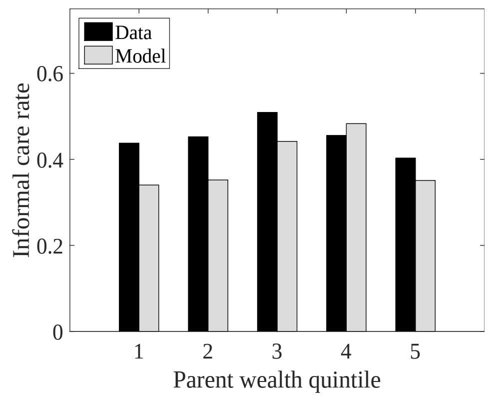
Notes: Figure reports data and simulated paid home care and nursing home utilization rates among parents who have long-term care needs and do not receive any informal care. Simulated moments are generated using the estimated model.

Figure 2.8: Formal Care by Number of Children



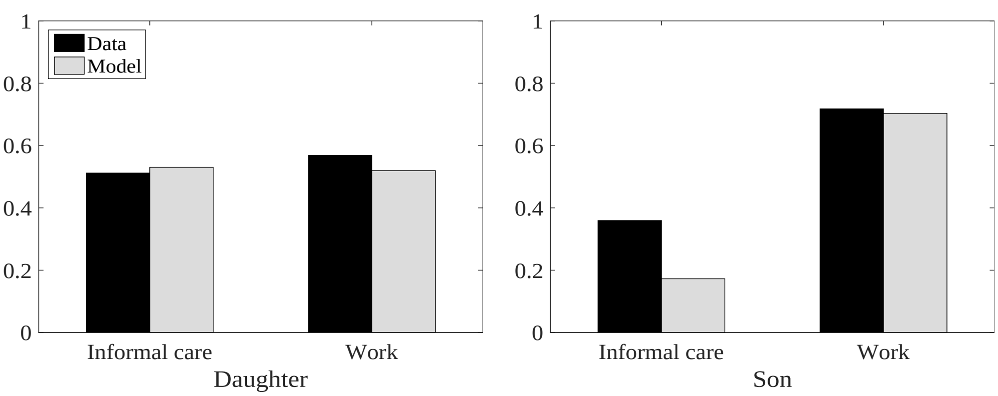
Notes: Figure reports data and simulated paid home care and nursing home utilization rates among parents who have long-term care needs and do not receive any informal care. Simulated moments are generated using the estimated model.

Figure 2.9: Informal Care by Parent Wealth



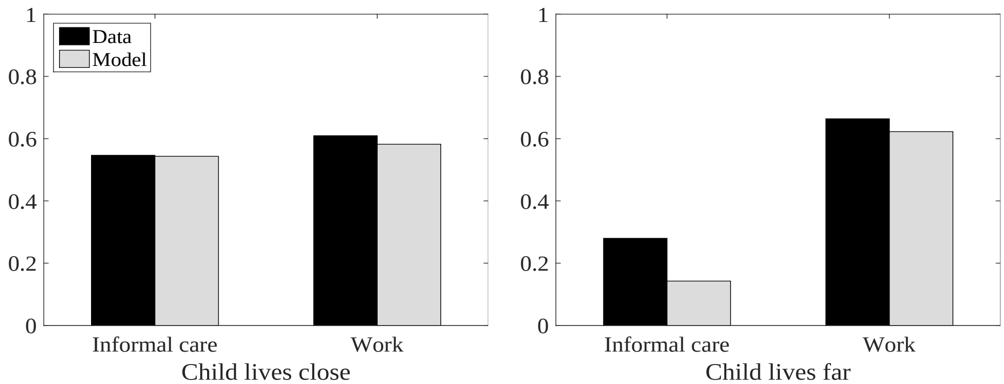
Notes: Figure reports data and simulated informal care rates. Informal care rates are computed among parents with long-term care needs. Simulated moments are generated using the estimated model.

Figure 2.10: Informal Care and Employment by Child Gender



Notes: Figure reports data and simulated employment and informal care rates of children. Informal care rates are computed among parents with long-term care needs. Simulated moments are generated using the estimated model.

Figure 2.11: Informal Care and Employment by Child Residential Proximity



Notes: Figure reports data and simulated employment and informal care rates of children. Informal care rates are computed among parents with long-term care needs. Simulated moments are generated using the estimated model.

Table 2.10: Informal Care Transitions

	No informal care	Informal care
No informal care	90%	10%
	[92%]	[8%]
Informal care	40%	60%
	[46%]	[54%]

Notes: Table reports data and simulated informal care transitions. Simulated transitions are generated using the estimated model and are given in brackets. Informal care transitions are computed using children whose parents are alive for two consecutive periods.

Table 2.11: Present-Discounted Value of Lifetime Formal Care Expenses for a 65-year-old

	Literature	Model
Mean expenses	$55,930	$50,073
Mean expenses cond'l on ever using formal care	$96,431	$100,146
% of 65-year-olds ever using formal care	58%	50%
% of expenses paid by Medicaid	37%	36%

Notes: Table reports the model-simulated present-discounted value of lifetime formal care expenses for a healthy 65-year-old and that found in Kemper, Komisar, and Alecxih (2005/2006). The values are on a unisex basis. Monetary values are inflated to 2013 dollars.

benefits. The maximal annual benefit is 70 percent of the annual nursing home costs. Formal care costs grow at the annual real growth rate of 2 percent (Genworth, 2015). The annual benefit also increases at the same rate such that the policy always pays 70 percent of the nursing home costs at most. I analyze the equilibrium outcomes of this policy for my sample period. Specifically, I examine the equilibrium outcomes when the policy is sold to healthy 60-year-olds in 2002. In 2002, premiums varied only by age and three or four underwriting classes determined by health conditions at the time of initial purchase. Under this pricing rule, all healthy 60-year-olds pay the same premium.

The equilibrium price of the standard policy, p^*, is determined by the zero profit condition, which requires that insurance companies break even on average. p^* is characterized as the lowest break-even price:

$$p^* = \min\{p : AR(p) = AC(p)\}. \tag{2.5.1}$$

$AR(p)$ is the average revenue curve and is defined as the average of the present-discounted value of the lifetime premium payments of individuals who select into insurance at premium p. $AC(p)$ is the average cost curve and is defined as the average of the present-discounted value of the lifetime claims of individuals who select into insurance at premium p. Henceforth, I will refer to $AR(p)$ as the average revenue curve, and $AC(p)$ as the average cost curve.

I build the simulation sample by selecting healthy 60- and 61-year-olds from the HRS 2002. I match one adult child to each parent using the selection criteria described earlier in Section 2.4.1. The simulation sample includes both single and married individuals. I do

Table 2.12: Summary Statistics on the Simulation Sample

	Mean	Median
Parents		
Married	0.75	
Female	0.57	
Wealth	393788	194973
Have 4+ children	0.45	
Children		
Female	0.48	
Age	35	
College education	0.50	
Married	0.57	
Live within 10 mi of the parent	0.48	
Homeowner	0.45	
Observations	1982	

Notes: Table reports the mean and the median values of the simulation sample. Monetary values are in 2013 dollars. Parents in the simulation sample are healthy 60- and 61-year-olds in the HRS 2002.

not restrict the sample to single individuals because in 2002, all healthy 60-year-olds paid the same premium regardless of their marital status.[49] Table 2.12 presents the summary statistics of the simulation sample. It consists of 1,982 parent-child pairs. Three quarters of the parents are married and 57 percent are women. The average wealth is around $400,000 and the median is around $200,000. Of the children, 48 percent are female, one half have a college education, and 48 percent live within 10 miles of their parents. I make 200 duplicates for each parent-child pair.

For each candidate equilibrium premium p, I solve the model backward using the estimated structural parameters. Then, I use the equilibrium policy functions to forward simulate choices of families in the simulation sample. Using parents who select into insurance, I obtain the average cost curve $AC(p)$ and the average revenue curve $AR(p)$.

[49] As the model is estimated using single individuals, the estimated model may overpredict informal care from children for married individuals. However, this issue is mitigated by the fact that (1) long-term care needs are late-life risks and (2) the share of singles increases sharply with age.

I look for the premium where the average cost equals the average revenue. I now present main findings of this paper.

2.5.1 Equilibrium Effects of Informal Care

I conduct various counterfactuals to examine how informal care affects the equilibrium outcomes in the long-term care insurance market. First, I show that private information about informal care results in substantial adverse selection. To reduce market inefficiencies created by adverse selection, I consider counterfactual pricing rules that reduce private information about family care, and examine their coverage and welfare effects. Next, I demonstrate that some parents forgo insurance as insurance undermines the effectiveness of bequests in eliciting informal care. Finally, I show how the existence of informal care limits the size of the long-term care insurance market.

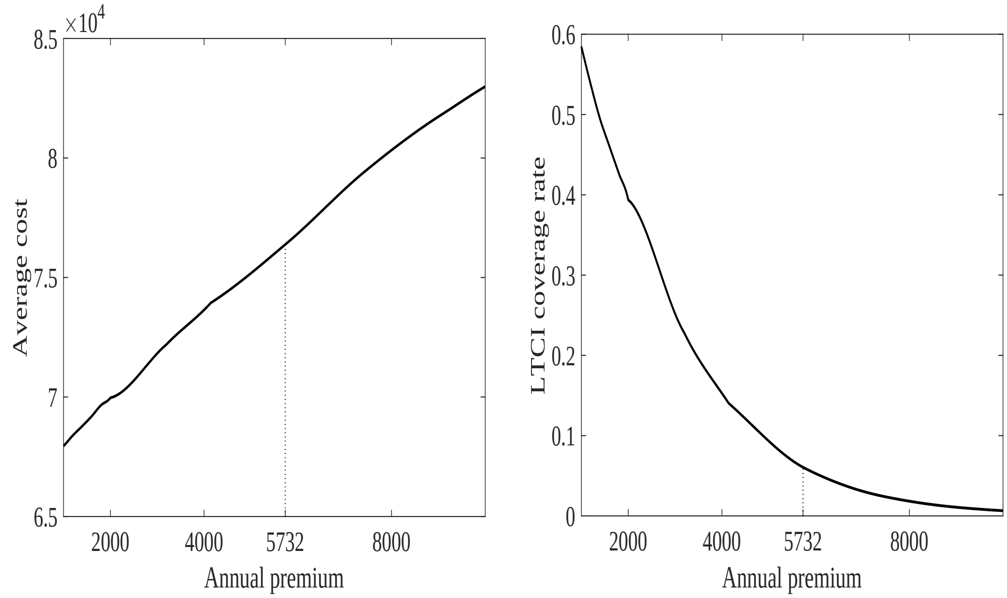
Adverse Selection on Informal Care

The left panel of Figure 2.12 reports the simulated average cost curve in premium. The increasing average cost curve in premium shows that individuals who have a higher willingness to pay for insurance are indeed more expensive to insurance companies.[50] This finding serves as direct evidence of adverse selection in the long-term care insurance market.[51] As shown in Appendix Figure A.4, while there is a quantitatively meaningful selection on wealth (the demand for insurance sharply increases in wealth), there is no

[50] The fact that I do not allow for heterogeneity in risk aversion may overpredict the magnitude of adverse selection. Finkelstein and McGarry (2006) find a negative correlation between risk aversion and risk in the long-term care insurance market that mitigates adverse selection based on risk.

[51] Several studies use a cost curve increasing in price as the definition of the adverse selection property in insurance markets (Einav, Finkelstein, and Cullen, 2010; Einav and Finkelstein, 2011; Handel, Hendel, and Whinston, 2015).

Figure 2.12: Adverse Selection Property

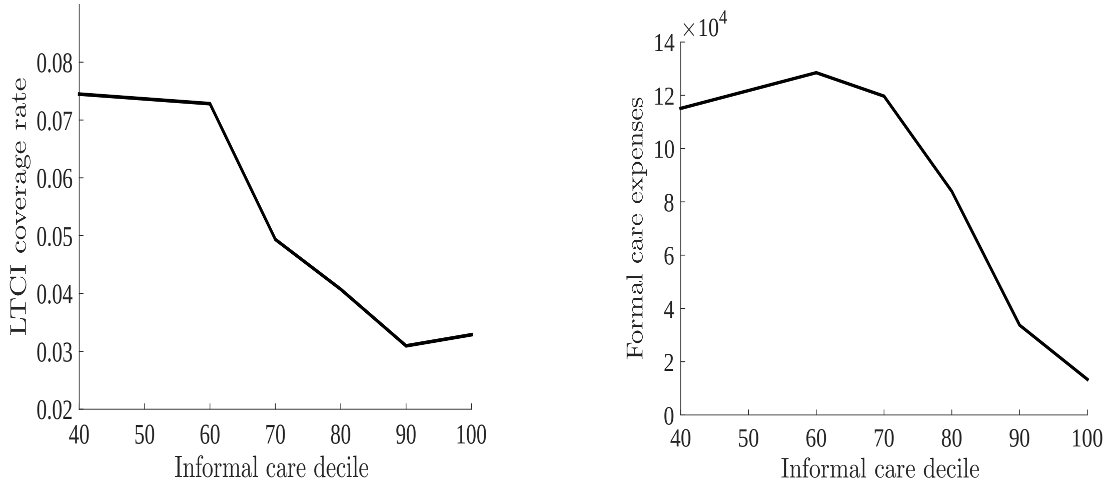


Notes: Left panel reports $AC(p)$, the average cost curve in premium. $AC(p)$ is defined as the average of the present-discounted value of the lifetime claims of individuals who select into insurance at premium p. Right panel reports the coverage rate in premium. Appendix Figure A.2 reports the average cost curve and the average revenue curve together in premium. The equilibrium premium for the standard policy is $5,732 and the equilibrium coverage rate is 6.1 percent. The standard policy is sold to healthy 60-year-olds and provides benefits for life (see main text for details).

meaningful relationship between wealth and formal care risk. As a result, adverse selection based on formal care risk largely determines the overall nature of selection in the long-term care insurance market. The right panel of Figure 2.12 reports the coverage rate in premium. Appendix Figure A.2 reports the average cost curve and the average revenue curve together in premium. The equilibrium premium is $5,732 and the equilibrium coverage rate is 6.1 percent.

I now quantify how private information about informal care accounts for the detected adverse selection. As emphasized earlier, heterogeneity in formal care risk is driven by heterogeneity in health transition probabilities (which vary by gender) and heterogeneity

Figure 2.13: Informal Care and Insurance Selection



Notes: Left panel reports the fraction of parents who buy long-term care insurance at the equilibrium premium, by each decile of the informal care measure. Right panel reports the average present-discounted value of the lifetime formal care expenses when the parent owns long-term care insurance. The informal care measure is defined as the number of informal care periods divided by the number of bad health periods when there is no private long-term care insurance. Quantiles start at the 40th percentile because there is a big mass at zero (about 55 percent of parents never receive informal care). This is consistent with the data patterns; Table 2.3 shows that among parents with long-term care needs, 55 percent do not receive any informal care from children.

in family care. To quantify how heterogeneity in informal care provided by the primary caregiving child contributes to adverse selection, in the left panel of Figure 2.13, for each decile of "informal care measure," I report the fraction of parents who select into insurance at the equilibrium premium. For each family in the simulation sample, I define this informal care measure as the number of total informal care periods divided by the number of total bad health periods when there is no private long-term care insurance (see Appendix Figure A.3 for the density of this informal care measure). The negative slope shows that parents who expect less informal care under no insurance are more likely to select into insurance at the equilibrium premium. Quantitatively, moving from the 10th percentile to the 90th percentile of the informal care distribution is associated with a

4-percentage-point decrease in the demand for insurance. Given the equilibrium coverage rate of 6.1 percent, the finding suggests that there is substantial selection on informal care. To quantify how adverse this selection is, the right panel of Figure 2.13 reports, for each decile of the informal care measure, the average present-discounted value of lifetime formal care expenses when the parent has long-term care insurance. Qualitatively, the slope is negative as expected. Quantitatively, moving from the 10th percentile to the 90th percentile of the informal care measure is associated with an \$81,000 reduction in lifetime spending on formal care. Together, the results in Figure 2.13 show that private information about informal care is a substantial source of adverse selection.

The empirical finding that there is substantial adverse selection based on the availability of informal care provides a new explanation for the small size of the long-term care insurance market. Private information about informal care hinders the efficient workings of the insurance market where, in equilibrium, the market only serves high-risk individuals with limited access to informal care. Low-risk individuals who nevertheless value financial protection against formal care expenses forgo insurance owing to adverse selection. This finding suggests that policies that are intended to reduce the amounts of private information about informal care may increase the market size and generate welfare gains. I now examine the equilibrium and welfare effects of such policies.

Equilibrium Effects of Pricing on Child Demographics

To explore practical policies that could reduce adverse selection in the long-term care insurance market, I consider counterfactual pricing rules where prices are conditional on observables that predict formal care risk. In addition to gender-based pricing that was adopted by insurance companies in 2013, I consider pricing on child demographics. The estimation results in Table 2.8 show that the primary caregiving child's gender and residential proximity substantially affect her informal care incentives.[52] Furthermore, the estimation results in Table 2.7 reveal that parents with more children are less likely to use formal care. Based on these findings, I consider a counterfactual risk adjustment where prices are conditional on the primary caregiving child's gender and residential proximity, and whether or not an individual has at least four children. Depending on the number of values that priced demographics can take, the market results in multiple market segments. For example, under gender-based pricing, there are two market segments: one for women and one for men. Under child demographic-based pricing, there are eight market segments. For each market segment of each pricing rule, I find the break-even premium that satisfies Equation (2.5.1).

Table 2.13 compares the equilibrium outcomes of default pricing (first row), gender-based pricing (second row), child demographic-based pricing (third row), and hybrid pricing on gender and child demographics (fourth row). For each pricing rule, I examine the welfare effects by computing the one-time wealth transfer needed to make a parent under default pricing indifferent to counterfactual pricing.

By price discriminating women from men, gender-based pricing reduces private information about formal care risk (see Table 2.14 for the equilibrium outcomes of each market segment). The ownership rate increases by 18 percent, and the average cost of the insured drops by 14 percent. Table 2.14 shows that these effects are generated by

[52] As shown in Table A.1, the child's gender is also an important factor in labor market income, which determines her opportunity cost of providing care.

Table 2.13: Equilibrium and Welfare Effects of Counterfactual Pricing

Pricing rule	Average premium	Ownership	*AC*	Medicaid spending	Welfare
Default	5732	0.061	76381	21669	0
Gender	5761	0.072	65927	21658	375
Child demographics	4835	0.095	58890	21311	1002
Gender & child demographics	4813	0.102	54300	21416	1255

Notes: Table reports equilibrium outcomes of the standard policy under various pricing rules. The standard policy is sold to healthy 60-year-olds and provides benefits for life (see main text for details). First row reports the equilibrium outcomes under default pricing where all healthy 60-year-olds pay the same price. Second row reports the equilibrium outcomes when prices are conditional on the gender of a consumer. Third row reports the equilibrium outcomes when prices are conditional on the primary caregiving child's gender and residential proximity, and whether or not a consumer has at least four children. Fourth row reports the equilibrium outcomes when prices are conditional on the gender of a consumer, and the three variables used for child demographic-based pricing. Except for the first row where there is one market segment, Average premium represents the average of the equilibrium premiums of multiple market segments. Ownership represents the share of the simulation sample that buys insurance. *AC* represents the average present-discounted value of the lifetime claims of the insured. Medicaid spending represents the average present-discounted value of lifetime Medicaid expenditures per individual. Welfare represents the average wealth transfer needed to make a parent under default pricing indifferent to counterfactual pricing.

more men selecting into insurance as they are no longer pooled with women who have a higher risk of using formal care. Gender-based pricing generates welfare gains for men who face a lower equilibrium premium, but it generates welfare losses for women who face a higher equilibrium premium. Overall, there is an average welfare gain of $375 per individual.

Pricing on child demographics substantially reduces private information about formal

Table 2.14: Equilibria under Gender-Based Pricing

Gender	Premium	Ownership	*AC*
Male	4548	0.13	57525
Female	6974	0.03	96272

Notes: Table reports equilibrium outcomes of each market segment under gender-based pricing. *AC* represents the average present-discounted value of the lifetime claims of individuals who buy insurance in each market segment.

Table 2.15: Equilibria under Child Demographic-Based Pricing

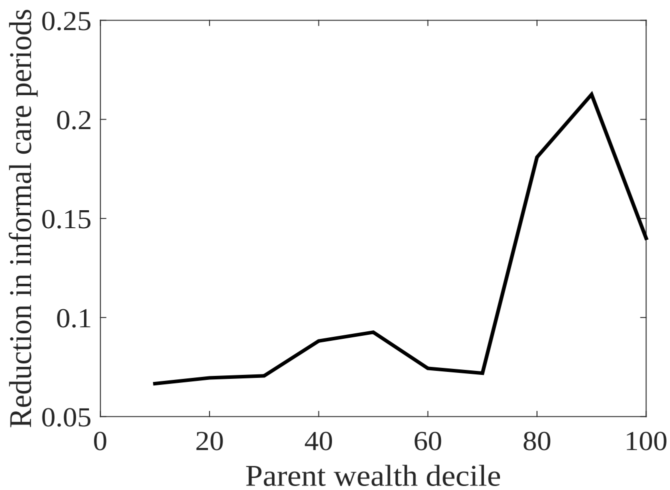
(Daughter,	Live close,	4+ Children)	Premium	Ownership	AC
Yes	Yes	Yes	2412	0.154	33797
Yes	No	Yes	5072	0.067	67397
No	Yes	Yes	4897	0.064	65738
No	No	Yes	5907	0.067	77972
Yes	Yes	No	2539	0.182	36007
Yes	No	No	5693	0.066	75891
No	Yes	No	5441	0.064	72524
No	No	No	6722	0.096	88100

Notes: Table reports equilibrium outcomes of each market segment under counterfactual pricing on child demographics. Priced child demographics are the primary caregiving child's gender (Daughter) and residential proximity (Live close), and whether or not a consumer has at least 4 children (4+ Children). AC represents the average present-discounted value of the lifetime claims of individuals who buy insurance in each market segment.

care risk (see Table 2.15 for the equilibrium outcomes of each market segment). Compared to default pricing, the equilibrium coverage rate increases by 56 percent, the average premium decreases by 16 percent, and the average cost of the insured decreases by 23 percent. Table 2.15 shows that these effects are generated by increased coverage rates among parents with family demographics that indicate high availability of informal care. Increases in the coverage rates relieve Medicaid's burden of paying formal care expenses, and the average lifetime Medicaid spending per individual falls by \$358. Pricing on child demographics results in an average welfare gain of \$1,002 per individual.

Finally, hybrid pricing on gender and child demographics generates the biggest increase in the coverage rate and produces the largest welfare gain. These findings suggest that complementing current gender-based pricing with child demographic-based pricing can substantially reduce adverse selection, invigorate the market, and create welfare gains to the elderly.

Figure 2.14: Family Moral Hazard by Parent Wealth



Notes: Figure reports for each parent wealth decile, the average reduction in total informal care periods as parents move from the No LTCI Regime to the Mandatory LTCI Regime (wealth is measured at parent age 60). Under the No LTCI regime, (1) children on average provide informal care for 0.67 period over parents' lifetime (a period is 2 years), and (2) conditional on ever providing informal care, they provide informal care for 1.95 periods. Under the Mandatory LTCI regime, (1) children on average provide informal care for 0.56 period over parents' lifetime, and (2) conditional on ever providing informal care, they provide informal care for 1.87 periods.

Family Moral Hazard and Strategic Non-Purchase of Insurance

The results so far show that private information about family care limits the size of the long-term care insurance market by creating adverse selection. Estimates of the structural parameters reveal another mechanism by which informal care can account for the small size of the market: children value inheritance and parents prefer informal care to formal care. As a result, the strategic non-purchase of long-term care insurance as argued in several theoretical papers may be a potential explanation for the small size of the insurance market.

I first quantify the magnitude of family moral hazard. To do this, I examine how informal care choices change as I move parents from having no insurance (No LTCI Regime) to having insurance (Mandatory LTCI Regime).[53] For each parent-child pair, I measure the magnitude of family moral hazard by computing the reduction in total informal care periods over the parent's lifetime. I find that children on average reduce informal care periods by almost 20 percent in response to their parents' insurance coverage. Figure 2.14 reports the reduction in total informal care periods by parent wealth. The magnitude of family moral hazard is substantially smaller for low-wealth parents than for high-wealth parents. Children with low-wealth parents have weak strategic incentives to provide care as the bequests they can protect by providing informal care are small. On the other hand, children with high-wealth parents reduce informal care by greater magnitudes as their sizable bequests are now protected by long-term care insurance.

I quantify how this family moral hazard affects the size of the long-term care insurance market. To this end, I conduct a counterfactual exercise with no family moral hazard. I remove family moral hazard by forcing the child whose parent owns long-term care insurance to make the same informal care choices as she would when the parent did not own insurance. In this counterfactual scenario, the parent no longer worries about insurance undermining the effectiveness of bequests in eliciting informal care.

The results of this counterfactual are summarized in Table 2.16. The first row shows the equilibrium of the benchmark model where children are allowed to show behavioral responses to parents' insurance coverage. The second row shows the partial equilibrium when there is no family moral hazard but the premium is held constant at the benchmark

[53]For the rest of the section, the standard policy uses default pricing where all healthy 60-year-olds pay the same premium.

Table 2.16: Equilibrium without Family Moral Hazard

	Ownership	Premium	*AC*
Benchmark equilibrium	0.061	5732	76381
Partial equilibrium without FMH	0.067	5732	71382
Equilibrium without FMH	0.086	5286	70765

Notes: Table reports the equilibrium coverage rate, equilibrium premium, and average present-discounted value of the lifetime claims under each of the specified equilibrium scenarios. First row reports the equilibrium outcomes of the benchmark model where children can respond to parents' insurance coverage. Second row reports the partial equilibrium outcomes when there is no family moral hazard and the premium is held constant at the benchmark equilibrium premium. Third row reports the new equilibrium outcomes when there is no family moral hazard. Under no family moral hazard scenario, children whose parents own long-term care insurance are forced to make the same informal care choices as they would when their parents did not own insurance.

equilibrium of $5,732. Without family moral hazard, the demand increases by 10 percent. There is a noticeable reduction in the average risk of the insured population. This is because children provide the same amount of informal care despite the fact that their parents are insured. As a result, the insured parents are less likely to use formal care compared to the benchmark model where insurance undermines children's informal care incentives. Finally, the third row reports the competitive equilibrium without family moral hazard. As the risk of the insured population decreases, the equilibrium premium falls to $5,286 and the coverage rate increases by 41 percent. Figure A.5 in the Appendix graphically summarizes the results.

These findings suggest that family moral hazard reduces parents' willingness to pay for insurance as they prefer informal care over formal care. Family moral hazard further reduces the equilibrium coverage rate by increasing the formal care risk of insured parents and increasing the equilibrium premium. The overall equilibrium effect of family moral hazard is substantial, which highlights the value of estimating a game model of family long-term care decisions.

Table 2.17: Equilibrium without Informal Care

	Ownership	Premium	*AC*
Benchmark equilibrium	0.061	5732	76381
Partial equilibrium without informal care	0.150	5732	87129
Equilibrium without informal care	0.095	6741	88071

Notes: Table reports the equilibrium coverage rate, equilibrium premium, and average present-discounted value of the lifetime claims under each of the specified equilibrium scenarios. First row reports the equilibrium outcomes of the benchmark model where children can provide informal care. Second row reports the partial equilibrium outcomes when children cannot provide informal care and the premium is held constant at the benchmark equilibrium premium. Third row reports the new equilibrium outcomes when children cannot provide care.

Existence of Informal Care and the Long-Term Care Insurance Market

I now examine how the *existence* of informal care affects the equilibrium of the long-term care insurance market. To do this, I compute the equilibrium of the long-term care insurance market when there is no informal care. In this counterfactual experiment, children's caregiving choices are always set to no informal care. Table 2.17 summarizes the results. The first row shows the benchmark equilibrium outcomes. The second row shows the partial equilibrium without informal care when the premium is held constant at the benchmark equilibrium. The results in this row can be interpreted as the effects of informal care on the demand for insurance. Taking away the option of informal care sharply increases the demand by 9 percentage points. However, the formal care risk of the entire population (not just the insured population) increases, because without informal care, formal care becomes the only way to receive long-term care. The third row shows the competitive equilibrium when there is no informal care. The equilibrium premium increases to reflect the increased risk in the absence of informal care. The overall increase in the equilibrium coverage rate is 3.4 percentage points. Figure A.6 in the Appendix graphically reports the results in Table 2.17.

These results suggest that while the existence of informal care substantially reduces the demand for insurance, its effect on reducing the equilibrium coverage rate is much smaller. This is because informal care reduces the overall formal care risk of the elderly thereby lowering the equilibrium premium. Combined with the results in Table 2.13, the most salient impact of informal care on limiting the size of the long-term care insurance market does not arise from its existence alone. The failure to account for heterogeneity in informal care creates market inefficiencies that have as powerful an effect on limiting the size of the market.

2.5.2 Explanations for Soaring Premiums

As a final set of counterfactuals, I use the equilibrium model of the insurance market to shed light on the recent soaring premiums. I show that the failure to account for selection and moral hazard led to substantial underpricing. I also demonstrate that the decreasing availability of informal care for baby boomers results in a higher formal care risk and puts upward pressure on the equilibrium premium.

Underpricing

The average empirical premium of the standard policy considered throughout this section was $3,195 in 2002.[54] The model predicts that the zero-profit premium for this policy is

[54] This is the median premium (in 2013 dollars) of policies sold to healthy 60-year-olds in 2002 that have (1) a $100 maximum daily benefit (in 2002 dollars) that increases at the nominal annual rate of 5 percent, (2) a 0 day deductible, and (3) an unlimited benefit period (Brown and Finkelstein, 2007). The average nursing home cost in 2002 was around $143, implying that these policies cover 70 percent of nursing home costs at most, as assumed for the standard policy. Using the annual inflation of 3 percent, the maximum benefits of these policies grow at the real annual rate of 2 percent, as assumed for the standard policy.

$5,732. This finding suggests that long-term care insurance products were indeed initially underpriced, and were below the break-even level by almost 80 percent. This number coincides with Genworth's requested premium increases of 80-85 percent on existing policies (Carrns, 2015).

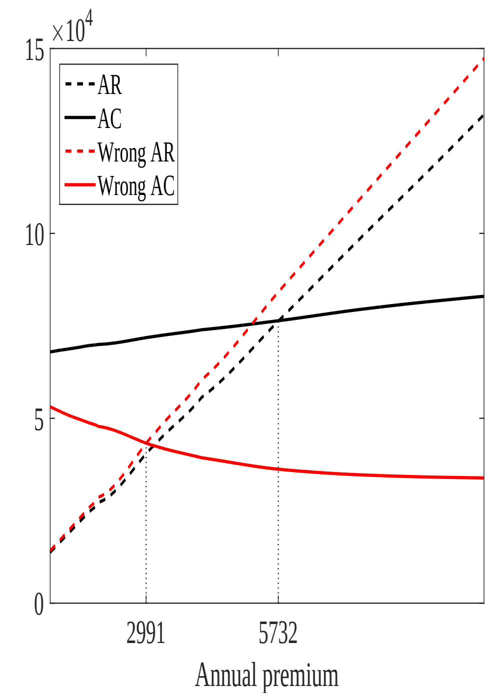
I now provide potential explanations for such substantial underpricing. The initial actuarial model, which was widely used by long-term care insurance companies to price their products predicts formal care risks unconditional on ownership status of long-term care insurance.[55] This may be due to the underestimated adverse selection/moral hazard or a lack of sufficient claims data. While individuals typically buy long-term care insurance in their sixties, most of them do not use it until they turn 80.[56] Such a time lag between the purchase and the use of insurance suggests that it takes almost two decades for insurance companies to learn about the risk of their policyholders. As modern long-term care insurance products were introduced in the late 1980s, it has only been a few years since insurance companies have had access to sufficient claims data.

To examine how the failure to account for adverse selection and moral hazard affects pricing, I compute the premium where the average formal care expenses of the *entire* population equals the average premium payment. Figure 2.15 presents this exercise. The black solid line and the black dashed line represent the correct average cost curve and average revenue curve, respectively. The red solid line - denoted as the wrong average cost curve - represents the average counterfactual claim of the entire population. This is

[55] See Brown and Finkelstein (2007) for more details about the widespread use of this actuarial model. For more details about the actuarial model itself, see Robinson (1996, 2002).

[56] Figure 2.1 shows that long-term care is a late-life risk. Also, the average age at first entry into a nursing home is around 83 years (Brown and Finkelstein, 2007).

Figure 2.15: Underpricing



Notes: Black solid line and black dashed line represent the average cost curve and the average revenue curve, respectively. Red solid line represents the average counterfactual claim of the entire population. This is computed by averaging over the smaller of formal care expenses and insurance benefits regardless of insurance holdings. Red dashed line represents the average counterfactual premium payment of the entire population. This is computed by assuming that everyone pays the premium when they are healthy.

computed by averaging over the smaller of formal care expenses and insurance benefits *regardless* of insurance holdings. This curve lies substantially below the correct average cost curve as there is adverse selection and moral hazard in the market.[57] The red dashed line - denoted as the wrong average revenue curve - represents the average counterfactual premium payment of the entire population, which is computed by assuming that everyone pays premiums when they are healthy. The wrong average cost curve and the wrong

[57]The wrong average cost curve is decreasing in premium because as the premium increases, the coverage rate falls, and the wrong average cost is mostly determined by the formal care risk of the uninsured population who are low risk.

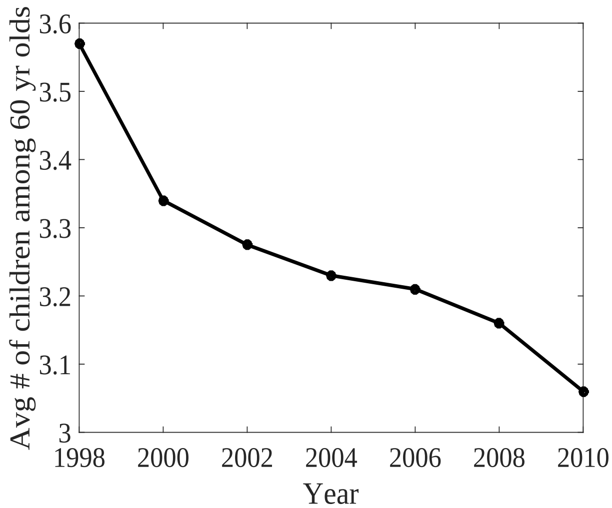
average revenue curve intersect when the premium is $2,991. This is extremely close to the average premium of $3,195 in 2002. This finding suggests that the actuarial model that does not distinguish between the formal care risk of individuals who select into insurance and the formal care risk of individuals who do not substantially underpredicts the break-even premium.

Demographic Changes

The results shown above suggest that a large fraction of recent premium increases are attributable to initial underpricing. I provide another plausible explanation for the premium increases happening around 2010. I draw from the fact that baby boomers, who were born between 1946 and 1964, became major consumers of the long-term care insurance market around that time. Compared to their former cohort (called the silent generation), baby boomers are at higher risk of using formal care as they have fewer children. Figure 2.16 shows that the average number of children among 60-year-olds is monotonically decreasing over time. This suggests that demographic changes may put upward pressure on the equilibrium premium.

To quantify this effect, I analyze how the equilibrium premium changes as the baby boom generation replaces the silent generation as major consumers of the insurance market. The simulation sample used throughout this section consists of 60-year-olds from the HRS 2002 who represent the silent generation. I construct a new simulation sample that represents the baby boom generation by selecting 60-year-olds from the HRS 2010. Figure 2.17 compares the equilibrium premium for the baby boom generation to that for the silent generation. The average cost curve of baby boomers lies above that of the

Figure 2.16: Decreasing Number of Children



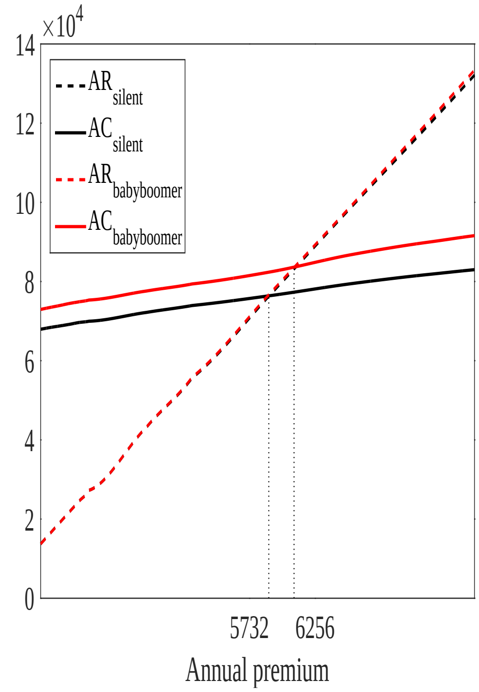
Notes: Figure reports the average number of children among 60-year-olds from HRS 1998-2010.

silent generation, implying overall increases in formal care risk for baby boomers. The equilibrium premium for baby boomers is almost 10 percent higher than the equilibrium premium for the silent generation, and the equilibrium coverage rate falls from 6.1 percent to 4.8 percent.

This finding suggests that insurance companies may be increasing premiums in part because they expect overall increases in formal care risk due to the decreasing availability of informal care. While it is true that insurance companies are still not explicitly pricing on child demographics, that does not imply that they are unaware of the effects of informal care on formal care risk.[58] The results in Figure 2.17 show that without changes in pricing strategies, such as adopting the new risk adjustments suggested in Table 2.13, one

[58]The absence of child demographic-based pricing should not be interpreted as evidence that this pricing is harmful to insurance companies. For example, gender-based pricing only started in 2013, despite the well-known fact that women are at higher risk compared to men.

Figure 2.17: Demographic Changes and Equilibrium Premium Increases



Notes: Black solid line and black dashed line represent the average cost curve and the average revenue curve, respectively, when the policy is sold to the silent generation. The equilibrium coverage rate is 6.1 percent. Red solid line and red dashed line represent the average cost curve and the average revenue curve, respectively, when the policy is sold to the baby boom generation. The equilibrium coverage rate is 4.8 percent.

can expect premium increases in the long-term care insurance market for the foreseeable future.

2.6 Conclusion

This paper provides new empirical explanations for why the long-term care insurance market has not been growing. I develop and structurally estimate a dynamic non-cooperative model of the family in which parents and children interact with altruistic and strategic motives. Counterfactual competitive equilibrium analyses of the market reveal two main mechanisms by which informal care limits the size of the long-term care insurance market. First, the current pricing practices of insurance companies leave consumers with private information about informal care. I show that there is substantial adverse selection based on this dimension of private information. Second, insurance has unintended consequences of discouraging family care by protecting bequests from formal care expenses on behalf of the family. This family moral hazard effect of insurance limits the market size by reducing the value of insurance and increasing the formal care risk of the insured. I demonstrate that the initial neglect of adverse selection and family moral hazard resulted in substantial underpricing. I further show that the decreasing availability of informal care for more recent birth cohorts puts upward pressure on the equilibrium premium. I propose child demographic-based pricing as an alternative risk adjustment that could decrease the average premium, invigorate the market, and create welfare gains.

Challenges in the long-term care sector, such as the aging of the baby boom generation, increasing burdens of informal caregivers, and growing Medicaid spending on formal care, have triggered various policy recommendations. They include the government providing family care subsidies and insurance companies paying cash to informal caregivers. Such recommendations are non-market-based which could lead to even bigger efficiency costs, or involve drastic changes in the structure of the insurance products and raise doubts about the practicality. In contrast, my proposal of using family demographics in pricing is market-based and is already in momentum; the fact that insurance companies have started to price on consumer characteristics makes my proposal well-grounded.

Chapter 3

Partial Rating Area Offering in the ACA Marketplaces

This chapter is co-authored with Hanming Fang.

3.1 Introduction

The Patient Protection and Affordable Care Act of 2010 (ACA) aims at providing affordable health insurance plans through the creation of state-level health insurance marketplaces. The ACA regulates factors based on which insurers set their premiums, and insurers are only allowed to use age, smoking status, and residential area, called "rating area", to adjust premiums for their marketplace plans. The default geographic rating areas for each state was the Metropolitan Statistical Areas (MSAs) plus the remainder of the state that is not included in a MSA. However, states were given a chance to seek approval from the U.S. Department of Health and Humans Services (HHS) for a different division method, provided that the division method was based on counties, three-digit zip codes, or MSAs/non–MSAs. Table B.1 in the Appendix reports the division method and descriptive statistics on rating areas for each state. Seven states use the default "MSAs+1" to define rating areas while the remaining states won approval from the HHS to define their own rating areas based on counties or zip codes. All states, except for Alaska, Idaho, Massachusetts, Nebraska, and California, have rating areas composed of counties.

This paper is about a phenomenon that we label as *partial rating area offering* where marketplace plans are not sold to all counties within a rating area. The ACA regulation mandates uniform pricing for all counties within a rating area, but it does not mandate universal offering. In almost all situations, the HHS disapproves plans covering partial counties, but it has no regulation on plans covering partial rating areas. We use individual qualified health plans sold in 34 federally-facilitated marketplaces in 2016 to show the prevalence of partial rating area coverage. We find that about 57% of plans are not universally offered to all counties within rating area, and about 54% of insurance companies exclude at least one county from their service area while selling plans to other counties in the same rating area. We hypothesize two potential explanations. First, insurers may selectively offer plans to risk screen consumers. This is our risk screening hypothesis. If counties within a rating area are heterogeneous, then insurers may want to offer different plans to better price discriminate consumers. Second, insurers may use partial rating area coverage as a way to avoid competition and divide up a rating area with their competitors. This is our market segmentation hypothesis.

To formalize our hypotheses and derive testable implications, we develop a simple model of insurer competition within a rating area. Each insurer decides which counties to enter, and how to price their plans. We model insurer competition in a county as a form of Bertrand competition with spurious product differentiation. In equilibrium, insurers' entry and pricing decisions are best responding to competitors' entry and pricing decisions. We parametrize the model, and numerically compute the equilibrium for a wide range of parameter values. The equilibrium analysis of the model shows that the partial rating area offering phenomenon is largely explained by insurers' incentive to risk screen consumers. The model shows that market segmentation is hard to be achieved in equilibrium, as the incentive to deviate and enter competitors' counties is too large. The model therefore supports the risk screening hypothesis rather than the market segmentation hypothesis. A testable implication that we obtain is that in equilibrium, insurers' plan offering decisions would be positively correlated, rather than negatively correlated. This is because under risk screening, insurers pool to offering county-specific plans, while under market segmentation, they offer plans only in counties where there are no competitors.

To test the implication of the model, we develop a non-parametric measure that quantifies correlations between insurers' plan offering decisions within a rating area. Consistent with the model's implication, we find that positive correlations are much more dominant compared to negative correlations. Specifically, among rating areas where there is partial offering, 90 percent have strictly positive correlations among insurers' plan offering decisions. This finding implies that while the ACA regulation allows price discrimination based on rating areas and not on counties, insurers are effectively price discriminating consumers based on counties by endogenously determining their service area within a rating area. Empirical evidence that counties of poorer health measures tend to be underserviced by insurers provides further support for the risk screening hypothesis.

The remainder of the paper is structured as follows. In Section 3.2, we describe the data and provide summary statistics. In Section 3.3, we demonstrate the prevalence of partial rating area coverage using several measures of marketing breadth. In Section 3.4, we present our model of insurer competition. In Section 3.5, we empirically test our hypotheses and discuss the results. Finally, in Section 3.6, we conclude.

3.2 Data

3.2.1 Marketplace Public Use Files (Marketplace PUF)

Our main data come from the Marketplace Public Use Files (Marketplace PUF) provided by the Centers for Medicare and Medicaid Services (CMS). We use the Marketplace PUF for plan year 2016. The Marketplace PUF provides characteristics of plans sold in 38 states with federally-facilitated marketplaces such as premiums, benefit and cost sharing structure, and the set of counties where each plan is sold, i.e., service area.[59] We restrict our analysis to individual health plans. There are 4,125 individual health plans offered in 38 federally-facilitated marketplaces in year 2016. Out of 38 marketplaces, Alaska and Nebraska use zip codes to define rating areas. We drop these two states as our unit of analysis is at the county level. This leaves us with 4,059 plans offered by 235 insurers in 36 states and 405 rating areas. The Marketplace PUF is composed of several files and there exist some inconsistencies detected across different files. Out of 20,569 plan-rating

[59]The degree to which states rely on the HHS varies; 27 states have marketplaces that are entirely operated by the HHS, 7 states perform in-person consumer assistance while delegating all other functions to the HHS, and 4 states are responsible for performing their own marketplace functions, except that they rely on the federal IT platform. In this paper, we refer to the 38 states that rely on the HHS for any support as having federally-facilitated marketplaces.

Table 3.1: 2016 Marketplace PUF Before Excluding Single County RAs

Plans	Insurers	Networks	States	RAs	Non Single County RAs	Counties	Plan-RA
4,059	235	471	36	405	259	2,481	19,991

Notes: Only individual health plans offered in federally-facilitated marketplaces are considered. Alaska and Nebraska are excluded as they use zip codes to define rating areas.

area combinations, we cannot find service area information for 554 combinations, and premium information for 24 combinations. We restrict to plan-rating area combinations for which we have both service area and premium information. The restriction reduces the number of plan-rating area combinations from 20,569 to 19,991. Table 3.1 summarizes our sample after imposing this restriction.

As the goal of this paper is to examine partial rating area coverage, we further exclude rating areas that consist of a single county. Out of 405 rating areas, we drop 146 rating areas that have only one county. Imposing this restriction excludes Florida and South Carolina as their rating areas always consist of a single county. Table 3.2 shows the summary statistics of the final Marketplace PUF. We have 3,442 individual health plans offered by 214 insurers in 34 states. The number of non single county rating areas is 259, and we have a total of 2,335 counties and 13,029 plan-rating area combinations. Table 3.3 shows the average characteristics of plans by their metal class.

3.2.2 County Data

We supplement our analysis with two sets of county level data; the Area Health Resources Files (AHRF) by the HHS and the County Health Rankings by the Robert Wood John-

Table 3.2: 2016 Marketplace PUF After Excluding Single County RAs

Plans	Insurers	Networks	States	RAs	Counties	Plan-RA
3,442	214	423	34	259	2,335	13,029

Notes: Only individual health plans offered in federally-facilitated marketplaces are considered. Rating areas that have only one county are excluded. Alaska and Nebraska are excluded as they use zip codes to define rating areas. Florida and South Carolina are excluded as their rating areas always consist of one county.

Table 3.3: Average Plan Characteristics of the 2016 Marketplace PUF

Metal	No. of Plans	Premium 21	EHB	AV	OOP Max	Deductible
Catastrophic	230	170	53		6,850	6,850
Bronze	1,061	211	53	0.71	5,033	4,471
Silver	1,282	261	53	0.81	3,626	1,824
Gold	767	313	53	0.85	3,336	905
Platinum	102	373	52	0.92	1,703	201

Notes: Premium 21 represents the average monthly rate for a non-smoking 21-year-old. EHB represents the number of essential health benefits covered. AV stands for actuarial value. OOP Max represents the out-of-pocket maximum. For the sample restriction, see Table 3.2 and the text.

son Foundation (CHR). The AHRF provide county level data on health resources and socioeconomic characteristics. The CHR offer data on various health measures such as the percentage of obesity and smokers.

3.3 Prevalence of Partial Rating Area Coverage

In this section, we use the Marketplace PUF to document the prevalence of partial rating area coverage. We develop various measures to assess the pervasiveness of partial rating area coverage both at the plan and insurer levels.

To make our measures easier to understand, we first introduce some notations. We index plan by $p = 1, ..., P$; rating area by $r = 1, ..., R$; and county by $c = 1, ..., C$; and insurer by $i = 1, ..., I$. For each plan $p = 1, ..., P$, we denote by $\mathbb{I}_P(p) \in \{1, ..., I\}$ the insurer for the plan p. For each $r = 1, ..., R$, denote by $\mathcal{C}(r)$ the set of counties in rating area r. Insurance plan p and county c will be our primary focus. From the PUF data, we have:

$$O(p, c) = \begin{cases} 1 \text{ if plan } p \text{ is offered in county } c, \\ 0 \text{ otherwise.} \end{cases} \tag{3.3.1}$$

Using these notations, we can now construct several auxiliary objects of interests.

- The set of plans offered by insurer i is denoted by $\mathcal{P}_I(i)$:

$$\mathcal{P}_I(i) \equiv \{p : \mathbb{I}_P(p) = i\}.$$

- The set of plans offered in county c is denoted by $\mathcal{P}_C(c)$:

$$\mathcal{P}_C(c) \equiv \{p : O(p, c) = 1\}.$$

- The set of plans that are active in rating area r, i.e., offered in at least one county in rating area r, is denoted by $\mathcal{P}_R(r)$:

$$\mathcal{P}_R(r) \equiv \cup_{c \in \mathcal{C}(r)} \mathcal{P}_C(c).$$

- The set of insurers that are active in county c is denoted by $\mathcal{I}_C(c)$:

$$\mathcal{I}_C(c) \equiv \{i : i = \mathbb{I}_P(p) \text{ for } p \in \mathcal{P}_C(c)\}.$$

- The set of insurers that are active in rating area r is denoted by $\mathcal{I}_R(r)$:

$$\mathcal{I}_R(r) \equiv \cup_{c\in\mathcal{C}(r)}\mathcal{I}_C(c) \equiv \{i : i = \mathbb{I}_P(p) \text{ for } p \in \mathcal{P}_R(r)\}.$$

- The set of counties in which plan p is offered is denoted by $\mathcal{C}_P(p)$:

$$\mathcal{C}_P(p) = \{c : O(p,c) = 1\}.$$

- The set of rating areas in which plan p is offered is denoted by $\mathcal{R}_P(p)$:

$$\mathcal{R}_P(p) = \{r : \mathcal{C}(r) \cap \mathcal{C}_P(p) \neq \emptyset\}.$$

3.3.1 Measuring the Marketing Breadth Using Plan Coverage

We first document partial rating area coverage at the plan level. Loosely speaking, we analyze how broadly a plan is sold to counties within a rating area (RA). We define three measures of coverage breadth using plans' service area. First, for each plan and for each of the rating areas where the plan is offered,[60] we define plan-RA level marketing breadth as the fraction of counties in the rating area where the plan is sold. This measure tells us how broadly a plan covers its rating area. This measure can be represented as follows: for every $r \in \{1, ..., R\}$, and every $p \in \mathcal{P}_R(r)$,

$$B_1^P(p,r) = \frac{|\mathcal{C}_P(p) \cap \mathcal{C}(r)|}{|\mathcal{C}(r)|}.$$

[60]We say a plan is offered in a rating area if it is sold in one of the counties in the rating area.

Second, we develop a county level measure to evaluate how completely a county is served by plans in the county's rating area. Specifically, for each county, we compute the fraction of plans offered in its rating area that are sold in the the county:

$$B_2^P(c) = \frac{|\mathcal{P}_C(c)|}{|\mathcal{P}_R(r) : c \in \mathcal{C}(r)|}.$$

Lastly, we develop a rating area level measure to quantify how broadly plans serve counties in a rating area. This measure can be computed either by taking the average of the first measure of the plans offered in the rating area, or by taking the average of the second measure of the counties in the rating area. Both methods yield the same result:[61]

$$\begin{aligned} B_3^P(r) &= \frac{1}{|\mathcal{P}_R(r)|} \sum_{p \in \mathcal{P}_R(r)} B_1^P(p, r) \\ &= \frac{1}{|\mathcal{C}(r)|} \sum_{c \in \mathcal{C}(r)} B_2^P(c). \end{aligned}$$

Table 3.4 reports the summary statistics of the three measures. About one third of the plan-RA combinations have coverage breadth less than one, and on average, a plan is sold to 81% of the counties in a rating area (first row). We find that out of 3,442 unique

[61]To see this, note that, for a given r,

$$\begin{aligned} B_3^P(r) &= \frac{1}{|\mathcal{P}_R(r)|} \sum_{p \in \mathcal{P}_R(r)} B_1^P(p, r) \\ &= \frac{1}{|\mathcal{P}_R(r)|} \sum_{p \in \mathcal{P}_R(r)} \frac{|\mathcal{C}_P(p) \cap \mathcal{C}(r)|}{|\mathcal{C}(r)|} \\ &= \frac{1}{|\mathcal{P}_R(r)| \, |\mathcal{C}(r)|} \sum_{p \in \mathcal{P}_R(r)} |\mathcal{C}_P(p) \cap \mathcal{C}(r)|. \end{aligned}$$

Note that $|\mathcal{C}_P(p) \cap \mathcal{C}(r)|$ is the total number of counties in rating area r where plan p is sold; and thus $\sum_{p \in \mathcal{P}_R(r)} |\mathcal{C}_P(p) \cap \mathcal{C}(r)|$ is the total number of *plan-county combinations* in rating area r. An alternative expression for the toal number of plan-county combinations in rating area r is $\sum_{c \in \mathcal{C}(r)} |\mathcal{P}_C(c)|$.

Table 3.4: Plan Coverage Measures

Measure	Unit	Obs.	Share of Obs. < 1	Mean	Std
$B_1^P(p,r)$	Plan-RA	13,029	0.33	0.81	0.30
$B_2^P(c)$	County	2,335	0.57	0.79	0.25
$B_3^P(r)$	RA	259	0.63	0.87	0.15

Notes: Table reports summary statistics on the three measures of plan coverage. See the text for details.

plans in our sample, 1,957 plans (about 57%) are partially offered in at least one rating area. More than half of the counties are excluded by at least one plan in their rating area, and on average, a county is served by 79% of plans in its rating area (second row). About 63% of rating areas have at least one plan that is not universally offered across counties (third row).

3.3.2 Measuring the Marketing Breadth Using Insurer Coverage

While the previous measures are informative of the marketing breadth at the plan level, they ignore the fact that insurers may offer multiple plans in a rating area. For example, suppose insurers offer different plans to each and every county in a rating area. In this case, insurers are selling plans in all counties within a rating area, and no county is left out by any insurer. However, the previous measures would imply that the marketing breadth is very narrow, and they would miss the fact that the marketing breadth is actually comprehensive at the insurer level. To mitigate these potential issues, we use insurer coverage to define analogous measures of marketing breadth. First, for each insurer and for each of the rating areas where the insurer is active, we compute the share of counties where the insurer offers at least one plan:

$$B_1^I(i,r) = \frac{|\mathcal{C}_I(i) \cap \mathcal{C}(r)|}{|\mathcal{C}(r)|}.$$

This measure tells us how broadly an insurer sells to counties in a rating area. Second, for each county, we compute the fraction of insurers who sell at least one plan in the county:

$$B_2^I(c) = \frac{|\mathcal{I}_C(c)|}{|\mathcal{I}_R(r) : c \in \mathcal{C}(r)|}.$$

This measure tells us how completely a county is served by participating insurers in the rating area. Third, for each rating area, we compute the average of the first measure or the second measure to quantify how broadly insurers serve counties in a rating area:

$$\begin{aligned} B_3^I(r) &= \frac{1}{|\mathcal{I}_R(r)|} \sum_{i \in \mathcal{I}_R(r)} B_1^I(i,r) \\ &= \frac{1}{|\mathcal{C}(r)|} \sum_{c \in \mathcal{C}(r)} B_2^I(c). \end{aligned}$$

Table 3.5 reports the summary statistics of the three measures. About one third of the insurer-RA combinations have breadth measure that is less than one, and on average, an insurer does not offer any plans in 15% of counties in a rating area where it participates (first row). We find that out of 214 insurers in our sample, 116 insurers (about 54%) engage in partial rating area marketing by not offering any plans to at least one county that is in a rating area where they participate. Over 40% of counties are excluded by some insurers participating in their rating areas, and on average, a county is excluded by 17% of insurers (second row). More than half of the rating areas have some insurers

Table 3.5: Insurer Coverage Measures

Measure	Unit	Obs.	Share of Obs. < 1	Mean	Std
$B_1^I(i,r)$	Insurer-RA	1,236	0.29	0.85	0.28
$B_2^I(c)$	County	2,335	0.41	0.83	0.26
$B_3^I(r)$	RA	259	0.52	0.89	0.14

Notes: Table reports summary statistics on the three measures of insurer coverage. See the text for details.

selectively serving counties, and on average, a rating area has a insurer participation rate of 89%. (third row).

3.3.3 County and Plan Characteristics

To examine how insurers' plan offering decisions are correlated with county characteristics, we categorize counties based on $B_2^P(c)$, the plan participation rate in a county. We consider five groups of counties; Least Favored if $B_2^P(c)$ is less than 20%, Less Favored if between 20-40%, Favored if 40-60%, More Favored if 60-80%, and Most Favored if higher than 80%.

Table 3.6 shows the average county characteristics for each county group. Counties with lower plan participation rates tend to be much less populated and have a smaller share of urban population. They have higher uninsured rates, fewer people with high school diploma or more, and much fewer health providers. Counties belonging to the Least Favored or Less Favored groups tend to have poorer health measures such as higher share of smokers. They also have higher per capita Medicare expenditures.

We now examine the characteristics of plans sold in each county category. The first five rows of Table 3.7 report the share of each metal class. In Least Favored and Less Favored counties, Bronze plans are dominant and have the biggest share. On the other

Table 3.6: County Characteristics by Plan Participation Rates

	Least Favored	Less Favored	Favored	More Favored	Most Favored
Population	16,881	26,888	56,319	69,836	87,126
	(18,961)	(32,002)	(87,903)	(231,528)	(201,676)
Urban Share (%)	36	36	38	39	41
	(30)	(33)	(27)	(29)	(31)
Household Income	42,454	44,229	46,570	47,007	44,583
	(8,732)	(10,606)	(11,265)	(12,921)	(10,725)
Uninsured Share (%)	27	20	16	17	17
	(4.5)	(6.2)	(5.5)	(4.8)	(4.4)
Uninsured & $\leq$ 400% Poverty (%)	32	25	20	21	21
	(4.4)	(6.9)	(6.1)	(4.9)	(4.5)
HS Diploma or More (%)	76	80	85	85	85
	(8.2)	(7.5)	(6.1)	(6.4)	(6.1)
Physicially Unhealthy Days	4.5	3.9	3.5	3.8	3.9
	(1.3)	(1.4)	(1.1)	(1.1)	(1.1)
Smoker Share (%)	25	23	21	21	22
	(7.5)	(5.9)	(6.0)	(5.8)	(6.2)
Access to Exercise (%)	54	55	63	61	61
	(23)	(25)	(21)	(22)	(23)
Per Capita Medicare Exp.	9,838	8,875	8,472	8,571	8,448
	(1,617)	(1,575)	(1,033)	(1,142)	(1,220)
MDs	13	26	133	142	237
	(25)	(54)	(359)	(717)	(789)
Hospitals	0.90	0.85	1.34	1.62	1.97
	(0.77)	(0.84)	(1.48)	(3.90)	(3.39)
Observations	131	132	199	442	1,431

Notes: Table reports county characteristics based on $B_2^P(c)$, the plan participation rates. A county is Least Favored if $B_2^P(c)$ is less than 20%, Less Favored if between 20-40%, Favored if 40-60%, More Favored if 60-80%, and Most Favored if higher than 80%. For each county category, the table reports the mean across counties. Observations are at county level. Standard deviation is reported in parentheses.

hand, in counties with higher plan participation rates (Favored, More Favored and Most Favored counties), Silver plans have the biggest share. No Platinum plan is offered in Least Favored counties. Premiums tend to be lower in counties with lower plan participation rates across all metal classes.

3.3.4 Possible Explanations

Various measures of marketing breadth developed above show that partial rating area coverage is quite common in the marketplaces. We now describe potential explanations for this phenomenon.

Risk Screening Hypothesis. The first potential explanation is that insurers target counties with different plans in order to better risk screen consumers. This explanation is what we label as *risk screening hypothesis*. If counties within a rating area are heterogeneous, then offering a single plan would hurt insurers' profit maximization problem as the ACA rules mandate that premiums be the same for all counties. Instead, insurers can offer county-specific plans (by differentiating plans) and charge different premiums. For example, in the extreme case, each insurer could offer a county-specific plan to every county within a rating area. In this case, the marketing breadth measures based on plan coverage would be smaller than those based on insurer coverage. This is because while insurers enter all counties within a rating area, plans are very selectively offered to counties. Figure 3.1 plots the RA-level marketing breadth based on insurer coverage, $B_3^I(r)$, against that based on plan coverage, $B_3^P(r)$, along with a 45-degree line. The figure shows that it is common to observe rating areas where the plan coverage is substantially smaller than the insurer coverage. Furthermore, Tables 3.6 and 3.7 suggest that insurers tend

Table 3.7: Plan Characteristics

	Least Favored	Less Favored	Favored	More Favored	Most Favored
Share of Catastrophic	0.062	0.060	0.061	0.061	0.058
Share of Bronze	0.42	0.38	0.30	0.31	0.31
Share of Silver	0.28	0.34	0.39	0.40	0.39
Share of Gold	0.24	0.21	0.22	0.21	0.22
Share of Platinum	0.0000	0.0058	0.0253	0.0137	0.0210
Catstrophic Premium	158	174	175	181	184
	(4.4)	(24.7)	(26.1)	(30.9)	(32.6)
Bronze Premium	183	217	226	226	225
	(12)	(30)	(35)	(37)	(38)
Silver Premium	237	259	273	273	274
	(15)	(31)	(42)	(43)	(45)
Gold Premium	296	317	330	331	335
	(20)	(35)	(50)	(49)	(59)
Platinum Premium	NaN	391	386	412	437
	(NA)	(42)	(45)	(73)	(87)
Observations	2,209	3,807	7,283	16,782	51,986

Notes: Table reports the characteristics of plans offered in each county category. Counties are categorized based on $B_2^P(c)$, the plan participation rates (see the text for details). The first five rows report the share of each metal class. The remaining rows report the mean and standard deviation of premiums (standard deviation is reported in parentheses). Premiums represent the average monthly rate for a non-smoking 21-year-old. Observations are at plan-county level.

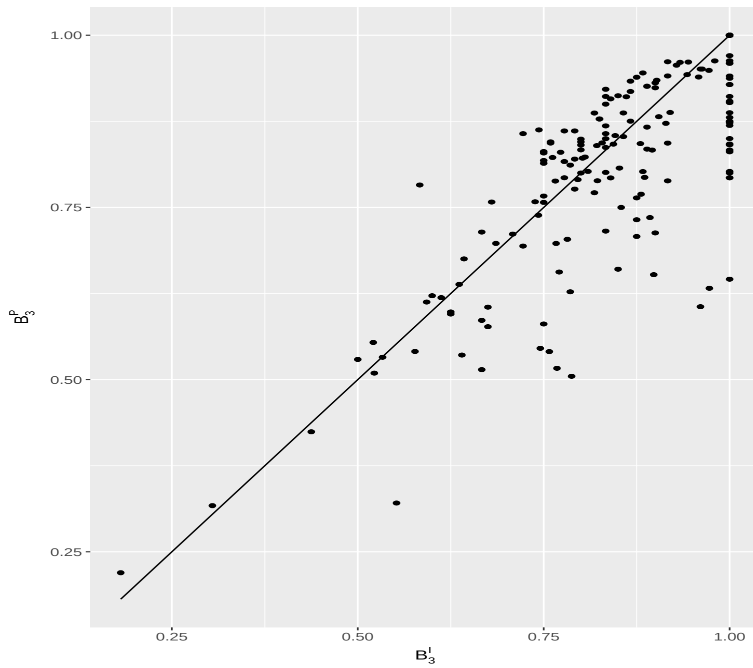
to avoid counties of smaller population and higher risk. When insurers do enter these counties, they tend to offer less comprehensive plans. As not offering any plans is an extreme form of price discrimination, and insurers tend to target high risk consumers with less comprehensive plans, these statistics also support the risk screening hypothesis.

Market Segmentation. One other potential reason for partial offering is that insurers do not wish to engage in fierce premium competition. If all insurers are active in all counties within a rating area, they will face competition in every county which will put downward pressure on premiums. Insurers can avoid competition by dividing up a rating area, and serving a mutually exclusive subset of counties. This is what we label as *market segmentation hypothesis*. For example, in the extreme case, insurers could be a monopoly in counties where they sell plans. In this case, the marketing breadth measure based on insurer coverage would be very small. Table 3.5 reports that on average, an insurer enters 85% of counties within a rating area. While suggestive, such statistics imply that market segmentation may be hard to be achieved in equilibrium, as incentives to deviate and enter other counties may be too large.

3.4 Model

We now develop a model of insurer competition to formalize our hypotheses and derive testable implications. To simplify the analysis, we examine two insurers' plan offering decisions in a rating area with two counties.

Figure 3.1: Insurer Coverage and Plan Coverage



Notes: Figure compares the values of $B_3^I(r)$, the rating area level marketing breadth based on insurer coverage, to those of $B_3^P(r)$, the rating area level marketing breadth based on plan coverage. The black line is a 45-degree line.

3.4.1 Model Description

Market Environment. Consider a rating area that consists of two counties, county A and B. We index counties by $i \in \{A, B\}$. The distribution of health expenditure θ in county i is given by CDF $H_i(\theta)$ with corresponding PDF $h_i(\theta)$. The willingness to pay for a type-θ consumer is given by $v(\theta)$. We assume that $v(\theta) > \theta$. The population size in county i is given by $\lambda_i \in (0, 1)$. Let

$$H_R(\theta) = \sum_{i=A,B} \lambda_i H_i(\theta)$$

denote the CDF of the risk of the consumers in the rating area.

There are two insurance companies, insurer 1 and 2. We index insurers by $j \in \{1, 2\}$. The two insurers are completely symmetric. Let p_j^i denote the price of a health plan sold to county i by insurer j. Each insurer chooses a vector of prices, $p_j = (p_j^A, p_j^B) \geq 0$, to maximize its profit given its competitor's vector of prices, $p_{j'} = (p_{j'}^A, p_{j'}^B)$. If insurer j's price in county i is infinite, i.e., $p_j^i = +\infty$, it implies that insurer j is inactive in county i. On the other hand, a finite price, $p_j^i < +\infty$, implies that insurer j is active in county i. If an insurer were to offer an identical plan to both county A and county B, the regulation requires that the prices be the same, i.e., $p_j^A = p_j^B$.

There is a fixed cost, C, associated with offering a distinctive health plan. The total fixed cost function is defined as

$$TC(p_j) = \begin{cases} C & \text{if } j \text{ is active in only one county or } p_j^A = p_j^B < \infty, \\ \\ 2C & \text{if } p_j^A \neq p_j^B,\ p_j^A < \infty, \text{ and } p_j^B < \infty. \end{cases} \tag{3.4.1}$$

If an insurer is active in only one county, his total fixed cost would be C. If an insurer offers an identical plan to both counties, his total fixed cost would also be C. On the other hand, if an insurer offers two distinctive plans, say, by marketing the two plans under different names, then his total fixed cost would be $2C$.[62]

Imperfect Competition. Following Fang and Wu (2016), we model the competition between the two insurers in a particular county as a form of modified "Bertrand competition." Different from the standard Bertrand competition in which the insurer who posts the lower price will get the entire market, we assume that consumers cannot compare price perfectly.[63] Instead, a consumer receives a noisy signal about which of the two firms has a lower price. The consumer inspects the actual price of the firm indicated by the noisy signal, and decides whether to buy the product accordingly. The noisy signal creates spurious product differentiation and induces imperfect competition.

Specifically, given the vector of prices posted by the two insurers in county i, (p_1^i, p_2^i),

[62] We assume that insurers can make two plans with the same benefit structures look different by incurring fixed costs. So even when two plans have the same benefits such as deductibles, copays, and coinsurance, insurers can market them under different labels and charge different premiums by incurring fixed costs. This is a simplifying assumption that we impose to abstract away from endogenizing plan design decisions.

[63] This is a modeling device to introduce imperfect competition in a tractable way, and not to be taken literally.

the noisy signal, s, is determined by:

$$s = \begin{cases} 1 & \text{if } p_1^i - p_2^i + \epsilon \leq 0, \\ 2 & \text{otherwise,} \end{cases}$$

where $\epsilon \sim \mathcal{N}(0, \sigma_s^2)$. It is clear that a consumer always follows the signal: if $s = j$, the consumer will find out the actual price p_j^i and decide between purchasing insurance at price p_j^i and staying uninsured. Hence, conditional on price vector (p_1^i, p_2^i), the probability that a consumer considers purchasing from firm j is $\Phi\left(\frac{p_{j'}^i - p_j^i}{\sigma_s}\right)$, where Φ is the normal CDF. Conditional on observing firm j's price p_j^i, the purchase decision of type-θ consumer is very simple: purchase at price p_j^i if and only if $v(\theta) \geq p_j^i$. [64]

Game between the Insurers. We denote an insurer's monopoly profit function in county i as $\Pi_M^i(p)$ where p is the insurer's monopoly price. The monopoly profit function is defined as

$$\Pi_M^i(p) = \lambda_i \int_{v(\theta) \geq p} (p - \theta)\, dH_i. \tag{3.4.2}$$

We assume that the fixed cost, C, is less than the optimal monopoly profit from each county:

$$C < \Pi_M^i(p_M^{i*}) \quad \text{where} \quad p_M^{i*} = \underset{p \geq 0}{\operatorname{argmax}}\, \Pi_M^i(p) \tag{3.4.3}$$

for $i = A, B$. We define insurer j's profit function as

$$\Pi_j(p_j, p_{j'}) = \Phi\left(\frac{p_{j'}^A - p_j^A}{\sigma_s}\right) \Pi_M^A(p_j^A) + \Phi\left(\frac{p_{j'}^B - p_j^B}{\sigma_s}\right) \Pi_M^B(p_j^B) - TC(p_j). \tag{3.4.4}$$

[64] Under the ACA regulation, insurers can vary premiums not only by rating areas, but also by age and smoking status. The implicit assumption that we maintain throughout this section is that PDF h_i represents the health expenditure distribution conditional on age and smoking status.

The profit function is the sum of any profits from county A and county B minus the total fixed costs. If insurer j is inactive in county i by charging an infinite price, the profit from county i will be zero.

Definition. Strategy profile (p_1^*, p_2^*) is a Nash equilibrium of the model described above if for $j \neq j'$,

$$\Pi_j(p_j^*, p_{j'}^*) \geq \Pi_j(p_j, p_{j'}^*) \quad \text{for all } p_j \geq 0 \text{ and } j = 1, 2. \tag{3.4.5}$$

In equilibrium, each insurer's prices are optimally set in response to its competitor. The model cannot be analytically solved, so we numerically solve the model.

Risk Screening vs. Market Segmentation. Before we present numerical results, we first want to discuss how the model captures insurers' incentive to risk screen consumers based on counties, and their incentive to avoid competition by segmenting the rating area. We first discuss the risk screening incentive. As the risk distributions of the two counties are allowed to differ, insurers may find it profitable to offer two separate plans to better price discriminate consumers. So if we observe insurers pooling to two separate plans in equilibrium, it suggests that insurers selectively offer plans to price discriminate consumers. This risk screening incentive increases in risk heterogeneity between the two counties, while it decreases in fixed costs.

On the other hand, insurers may wish to avoid competition and be a monopoly in one of the two counties. So if we observe insurers each being a monopoly in equilibrium, it suggests that insurers selectively offer plans to avoid premium competition. This market segmentation incentive increases in the accuracy of the price signal, i.e., the inverse of σ_s, because when the price signal is accurate, insurers have to engage in fierce premium competition. In this case, they may wish to give up one county entirely, and earn the optimal monopoly profit from the other county.

3.4.2 Parameterization

To numerically solve the model, we make several parametric assumptions. We parameterize the health expenditure distribution in county i as log normal with location parameter μ_i and scale parameter σ_i. We parameterize type-θ's willingness to pay for a health plan as $v(\theta) = (1+\rho)\theta$ where ρ can be interpreted as the degree of risk aversion. The parameters of the model are therefore (C, σ_s, ρ), and $(\mu_i, \sigma_i, \lambda_i)$ for $i = A, B$.

Key parameters of interest are C, σ_B, and σ_s. The fixed cost, C, is of interest because it affects insurers' incentive to offer county-specific plans. The scale parameter of the health expenditure distribution in county B, σ_B, is of interest because it determines the risk heterogeneity between the two counties. The standard deviation of the pricing signal, σ_s, is of interest because it determines the degree of premium competition between the two insurers.

We compute the equilibrium of the model for various values of (C, σ_B, σ_s), while fixing the values of the remaining parameters. We fix the values of the remaining parameters as follows; the risk aversion parameter, ρ, is set to 1; the health expenditure parameters of county A, μ_A and σ_A, are set such that the mean monthly health expenditure is \$550, and the standard deviation is one fourth of its mean; μ_B is identical to μ_A; county B is of higher risk compared to county A with $\sigma_B \geq \sigma_A$; and finally, both counties are of equal size with $\lambda_A = \lambda_B = 0.5$.

3.4.3 Equilibrium Analysis

Before we present results from our equilibrium analysis, it is useful to categorize an insurer's pricing decision, $p_j = (p_j^A, p_j^B)$, into four groups: 1) charge different and finite prices to county A and county B (two separate plans), 2) charge the same finite price to both county A and county B (RA plan), 3) charge a finite price to county A only (A only plan), and 4) charge a finite price to county B only (B only plan). The reason why we categorize insurers' pricing decisions in this manner is because it would be easier to present equilibria of the game in terms of the resulting market structures, rather than in terms of equilibrium prices.

Depending on insurers' pricing decisions, various market structures could be observed in equilibrium, from duopoly in every county to monopoly in every county. Furthermore, if a specific market structure is observed in equilibrium, then the corresponding equilibrium premiums satisfy inequality (3.4.5) when each insurer's choice set is restricted to prices that yield the specific market structure. For example, if we observe insurer 1 offering an A only plan and insurer 2 offering a B only plan in equilibrium, then insurer 1's equilibrium pricing strategy is $p_1 = (p_M^{A*}, +\infty)$, and insurer 2's equilibrium pricing strategy is $p_2 = (+\infty, p_M^{B*})$ where p_M^{i*} is the optimal monopoly premium as in equation (3.4.3).

We now present market structures observed in equilibrium as functions of the key parameters, (C, σ_B, σ_s). The results are reported in Figure 3.2. Each panel uses a constant value of C and indicates the equilibrium market structures in the $\sigma_B - \sigma_s$ plane. Values of σ_B range from σ_A to $2\sigma_A$. Values of σ_s range from 27.5 to 550, which represent 5% and 100% of the mean health expenditure in county A, respectively. We set values of C

such that for all values of (σ_B, σ_s), the duopoly profit in county B is higher than C.

According to Figure 3.2, only two market structures are observed in equilibrium (excluding the case of $\sigma_B = \sigma_A$); pooling to an RA plan or pooling to two separate plans. This suggests that in equilibrium, insurers' plan offering decisions are *positively correlated*. Pooling to an RA plan is more likely when the fixed costs are large, the risk heterogeneity is small, and consumers receive rather inaccurate information about prices. Pooling to an RA plan implies that there is no partial rating area offering, and all plans are offered in all counties within a rating area. In this case, both $B_3^P(r)$ and $B_3^I(r)$ would be 1. According to Table 3.4, about 37% of the rating areas in our sample fall into this category.

The model implies insurers engage in risk screening, i.e., they pool to offering two separate plans, when the fixed costs are small, the risk heterogeneity is large, and consumers are very price sensitive. Under this market structure, $B_3^P(r)$ would be 0.5 while $B_3^I(r)$ would be 1. Figure 3.1 shows that in our data, it is quite common to observe rating areas where $B_3^I(r)$ is much higher than $B_3^P(r)$.[65]

Figure 3.2 also implies that market segmentation is hard to be observed in equilibrium. For all parameter values considered in the figure, we cannot observe (A only plan, B only plan) as an equilibrium market structure. This is because in our model, the incentive to deviate from (A only plan, B only plan) and enter the other county is too large. For example, suppose insurer 1 is a monopoly in county A and insurer 2 is a monopoly in county B. In this case, insurer 1 cannot do worse by expanding the plan coverage, and making its A only plan an RA plan. This result suggests that without other mechanisms to

[65] While there are many rating areas with $B_3^P(r) > B_3^I(r)$, for these rating areas, the difference $|B_3^P(r) - B_3^I(r)|$ is small. On the other hand, for rating areas with $B_3^P(r) < B_3^I(r)$, the difference is fairly large.

penalize deviating behaviors, market segmentation is hard to be achieved in equilibrium.

To sum, the model supports the risk screening hypothesis, rather than the market segmentation hypothesis. A testable implication that we obtain from the model is that in equilibrium, insurers' plan offering decisions would be *positively correlated* rather than *negatively correlated*. We now turn to the data to empirically test this implication.

3.5 Empirical Results

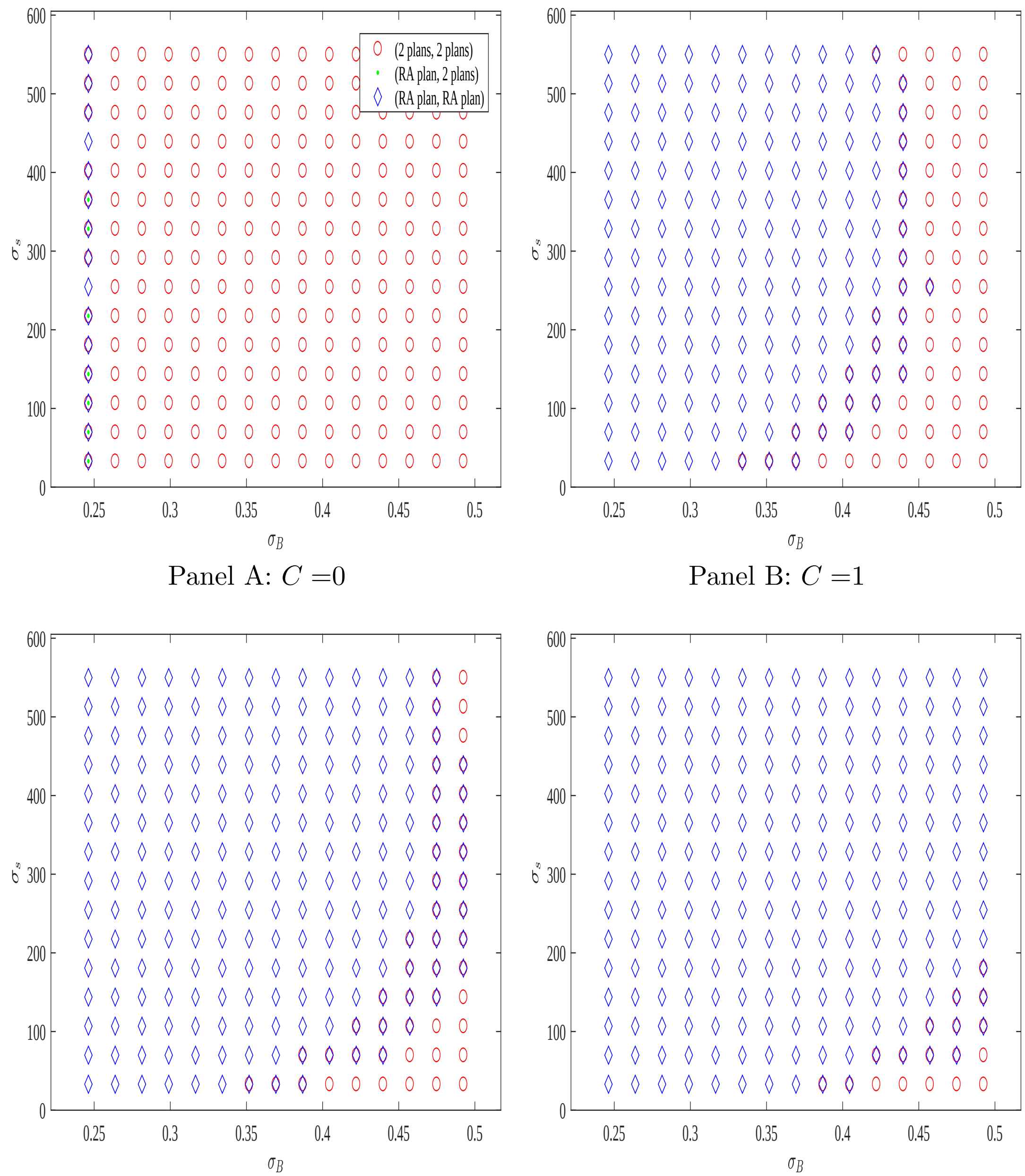
The equilibrium analysis of the model suggests that partial rating area offerings are largely explained by the risk screening hypothesis, and as a result, we can expect to observe a positive correlation among insurers' plan offering decisions. To test the model's implication, we now develop statistics that could measure correlations among insurers' plan offering decisions.

3.5.1 Correlation Construction

Using the notations introduced in Section 3.3, we construct a non-parametric measure of correlations between insurers' plan offering decisions. Recall that the set of plans offered by insurer i is denoted by $\mathcal{P}_I(i)$, and the set of plans offered in rating area r is denoted by $\mathcal{P}_R(r)$. Then, for each insurer i who is active in rating area r, i.e., $i \in \mathcal{I}_R(r)$, we can define the set of plans insurer i offers in rating area r as:

$$\mathcal{P}_{I,R}(i,r) = \mathcal{P}_I(i) \cap \mathcal{P}_R(r).$$

Figure 3.2: Nash Equilibrium and (C, σ_B, σ_s)



Panel A: C =0

Panel B: C =1

Panel C: C =2

Panel D: C =4

Notes: Figure reports the equilibrium market structure for various values of (C, σ_B, σ_s). Each panel uses a constant value of C, and reports the equilibrium market structure for different values of (σ_B, σ_s). The distribution of health expenditure in county A is held constant at μ_A =6.2796 and σ_A =0.246. The mean health expenditure in county A is therefore $E(\theta_A)$ = \$550 and the standard deviation is \$137.5. To examine how risk heterogeneity affects insurers' plan offering choices, the model assumes county B is of higher risk compared to county A. Specifically, we assume $\mu_B = \mu_A$ and $\sigma_B \geq \sigma_A$. The figure holds constant the rest of the parameter values at $\lambda_A = 0.5$, $\lambda_B = 0.5$, and $\rho = 1$. For all configurations of the parameter values considered in the figure, the fixed cost, C, is always less than or equal to the monopoly profit from each county, i.e., $C \leq \Pi^i_M(p^{i*}_M)$ for $i = A, B$.

For each insurer $i \in \mathcal{I}_R(r)$, and for each county $c \in \mathcal{C}(r)$, define an indicator $O(i,c)$ as follows:

$$O(i,c) = \begin{cases} 1 \text{ if } i \in \mathcal{I}_C(c), \\ 0 \text{ if } i \notin \mathcal{I}_C(c). \end{cases}$$

where $\mathcal{I}_C(c)$ is the set of insurers who are active in county c. Define, for each $i \in \mathcal{I}_R(r), i' \in \mathcal{I}_R(r) \backslash i$, and for each $c \in C(r)$, $c' \in C(r) \setminus \{c\}$:

$$\hat{1}\left(i, i'; c, c'\right) = \begin{cases} 1 \text{ if } O(i,c) = O(i',c) \ \& \ O(i,c') = O(i',c'), \\ -1 \text{ if } O(i,c) \neq O(i',c) \ \& \ O(i,c') \neq O(i',c'), \\ 0 \text{ otherwise.} \end{cases}$$

In words, $\hat{1}(i,i';c,c')$ takes value 1 if insurers i and i' are completely aligned regarding their entry decisions in the two counties; -1 if they are completely opposed; and 0 for any other cases. Our measure of correlation is based on this indicator, $\hat{1}(i,i';c,c')$:

$$CORR^I(r) \equiv \frac{\sum_{i\in\mathcal{I}_R(r)} \sum_{i'\in\mathcal{I}_R(r)\backslash\{i\}} \sum_{c\in C(r)} \sum_{c'\in C(r)\backslash\{c\}} \hat{1}(i,i';c,c')}{\sum_{i\in\mathcal{I}_R(r)} \sum_{i'\in\mathcal{I}_R(r)\backslash\{i\}} \sum_{c\in C(r)} \sum_{c'\in C(r)\backslash\{c\}} 1}. \tag{3.5.1}$$

The denominator can be simplified. Let $n_C(r) = |C(r)|$ be the number of counties in rating area r; and let $n_I(r) = |\mathcal{I}_R(r)|$ be the number of active insurers in rating area r. Then

$$\sum_{i\in\mathcal{I}_R(r)} \sum_{i'\in\mathcal{I}_R(r)\backslash\{i\}} \sum_{c\in C(r)} \sum_{c'\in C(r)\backslash\{c\}} 1 = n_I(r)\, n_C(r)\, [n_I(r) - 1]\, [n_C(r) - 1].$$

Hence,

$$CORR^{I}(r) = \frac{\sum_{i \in \mathcal{I}_R(r)} \sum_{i' \in \mathcal{I}_R(r) \setminus \{i\}} \sum_{c \in C(r)} \sum_{c' \in C(r) \setminus \{c\}} \hat{1}(i, i'; c, c')}{n_I(r)\, n_C(r)\, [n_I(r) - 1]\, [n_C(r) - 1]}. \tag{3.5.2}$$

3.5.2 Illustrative Examples

Example 1. We first compute correlations for market structures implied by the model in Section 3.4. First, suppose there is a pooling to an RA plan. In this case, $CORR^{I}(r)$ would be 1. Second, suppose there is a pooling to two separate plans. Then, $CORR^{I}(r)$ would also be 1. Finally, suppose insurer 1 offers an A only plan, while insurer 2 offers a B only plan. Then, $CORR^{I}(r)$ would be -1. This exercise suggests that our correlation measure is well suited to test the implication that insurers' offering decisions are positively correlated under the risk screening hypothesis, while they are negatively correlated under the market segmentation hypothesis.

Example 2. Consider a rating area r with two counties, c_1 and c_2. There are two insurance companies, insurer 1 and insurer 2, and a total of 5 plans, $\{a, b, d, e, f\}$. Suppose that $\mathcal{P}_{I,R}(1, r) = \{a, b\}$, and $\mathcal{P}_{I,R}(2, r) = \{d, e, f\}$. Suppose further that $\mathcal{P}_C(c_1) = \{a, d, e\}$, and $\mathcal{P}_C(c_2) = \{b, e, f\}$. In words, insurer 1 offers plan a in county c_1 and plan b in county c_2; insurer 2 offers plans d and e in county c_1 and plans e and f in county c_2.

The numerator of the correlation measure is

$$\sum_{i' \in \mathcal{I}_R(r)\backslash\{1\}} \sum_{\substack{c \in C(r) \\ c' \in C(r)\backslash\{c\}}} \hat{1}\left(1, i'; c, c'\right) + \sum_{i' \in \mathcal{I}_R(r)\backslash\{2\}} \sum_{\substack{c \in C(r) \\ c' \in C(r)\backslash\{c\}}} \hat{1}\left(2, i'; c, c'\right)$$
$$= \hat{1}\left(1, 2; c_1, c_2\right) + \hat{1}\left(1, 2; c_2, c_1\right) + \hat{1}\left(2, 1; c_1, c_2\right) + \hat{1}\left(2, 1; c_2, c_1\right) = 4.$$

The denominator is $2 \times 2 = 4$. The correlation measure is therefore 1, suggesting that the two firms are perfectly aligned in their county entry decisions.

Example 3. Consider a rating area r with two counties, c_1 and c_2. There are two insurance companies, insurer 1 and insurer 2, and a total of 5 plans, $\{a, b, d, e, f\}$. Suppose that $\mathcal{P}_{I,R}(1, r) = \{a, b\}$, and $\mathcal{P}_{I,R}(2, r) = \{d, e, f\}$. Suppose further that $\mathcal{P}_C(c_1) = \{a, b\}$, and $\mathcal{P}_C(c_2) = \{d, e, f\}$. In words, insurer 1 offers plans a and b in county c_1, and insurer 2 offers plans d, e and f in county c_2. The numerator of the correlation measure is

$$\sum_{i' \in \mathcal{I}_R(r)\backslash\{1\}} \sum_{\substack{c \in C(r) \\ c' \in C(r)\backslash\{c\}}} \hat{1}\left(1, i'; c, c'\right) + \sum_{i' \in \mathcal{I}_R(r)\backslash\{2\}} \sum_{\substack{c \in C(r) \\ c' \in C(r)\backslash\{c\}}} \hat{1}\left(2, i'; c, c'\right)$$
$$= \hat{1}\left(1, 2; c_1, c_2\right) + \hat{1}\left(1, 2; c_2, c_1\right) + \hat{1}\left(2, 1; c_1, c_2\right) + \hat{1}\left(2, 1; c_2, c_1\right) = -4.$$

The denominator is $2 \times 2 = 4$. The correlation measure is therefore -1, suggesting that the two insurance companies are perfectly misaligned in their county entry decisions.

Example 4. Consider a rating area r with two counties, c_1 and c_2. There are *three* insurance companies, insurer 1,2, and 3, and a total of 7 plans, $\{a, b, d, e, f, g, h\}$. Suppose that $\mathcal{P}_{I,R}(1, r) = \{a, b, d\}$, $\mathcal{P}_{I,R}(2, r) = \{e, f\}$, and $\mathcal{P}_{I,R}(3, r) = \{g, h\}$. Suppose further that $\mathcal{P}_C(c_1) = \{a, b, d, e\}$, and $\mathcal{P}_C(c_2) = \{e, f, g, h\}$. In words, insurer 1 offers plans a, b and d in county c_1; insurer 2 offers plan e in both counties and plan f in county c_2; and insurer 3 offers plans g and h in county c_2. The numerator of the correlation measure is

$$\begin{aligned}
& \sum_{i' \in \mathcal{I}_R(r) \backslash \{1\}} \sum_{\substack{c \in C(r) \\ c' \in C(r) \backslash \{c\}}} \hat{1}\left(1, i'; c, c'\right) + \sum_{i' \in \mathcal{I}_R(r) \backslash \{2\}} \sum_{\substack{c \in C(r) \\ c' \in C(r) \backslash \{c\}}} \hat{1}\left(2, i'; c, c'\right) \\
& + \sum_{i' \in \mathcal{I}_R(r) \backslash \{3\}} \sum_{\substack{c \in C(r) \\ c' \in C(r) \backslash \{c\}}} \hat{1}\left(3, i'; c, c'\right) \\
= \;& \hat{1}(1, 2; c_1, c_2) + \hat{1}(1, 2; c_2, c_1) + \hat{1}(1, 3; c_1, c_2) + \hat{1}(1, 3; c_2, c_1) \\
& + \hat{1}(2, 1; c_1, c_2) + \hat{1}(2, 1; c_2, c_1) + \hat{1}(2, 3; c_1, c_2) + \hat{1}(2, 3; c_2, c_1) \\
& + \hat{1}(3, 1; c_1, c_2) + \hat{1}(3, 1; c_2, c_1) + \hat{1}(3, 2; c_1, c_2) + \hat{1}(3, 2; c_2, c_1) \\
= \;& 0 + 0 + (-1) + (-1) + 0 + 0 + 0 + 0 + (-1) + (-1) + 0 + 0 \\
= \;& -4.
\end{aligned}$$

The denominator is $n_I(r) \, n_C(r) \, [n_I(r) - 1] \, [n_C(r) - 1] = 3 \times 2 \times 2 \times 1 = 12$. The correlation measure is therefore $-\frac{1}{3}$. This suggests that overall, the insurers in the rating area are negatively correlated in their county entry decisions.

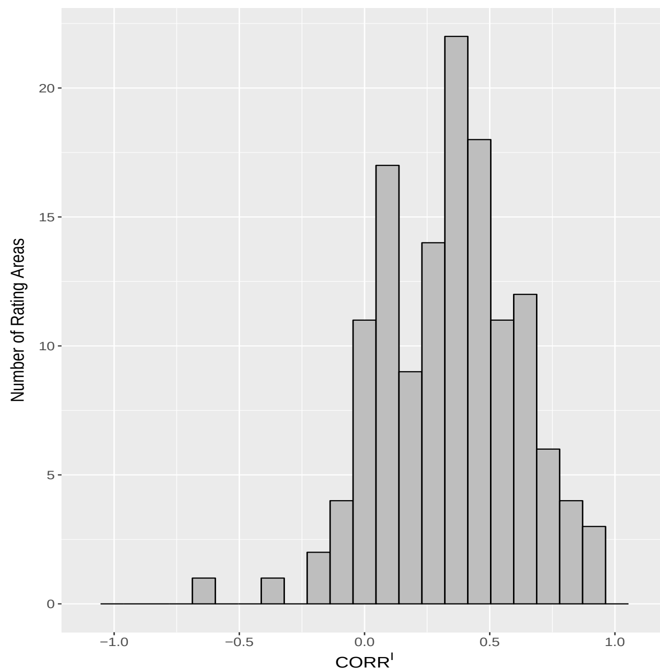
3.5.3 Empirical Correlations

We now compute correlations for rating areas in our sample. The goal is to see if positive correlations are much more likely to be observed, as implied by the model. We exclude rating areas where there is a single insurer, because our correlation measure can only be computed for rating areas with at least two insurers. This restriction reduces our sample size from 259 rating areas to 247 rating areas.

Table 3.8 reports the results. For rating areas where all insurers offer at least one plan in every county, the correlation measure is one. About 45% of the sample (112 rating areas) fall into this category. The remaining 55% of the sample (135 rating areas) have at least one insurer who selectively enters counties. Our focus is on these rating areas as we are interested in explaining the partial offering decisions. From the fourth row, the table reports correlation measures of these rating areas. Of the 135 rating areas with some partial entry, 121 rating areas have correlations that are strictly positive, while only 12 rating areas have correlations that are strictly negative. The mean correlation is positive at 0.34. Figure 3.3 reports the histogram of the correlations for rating areas with some partial entry. It has a very thin left tail as rating areas with negative correlations are very rare.

The empirical findings reported in Table 3.8 and Figure 3.3 agree with the model's implication that insurers' plan offering decisions would be positively correlated in equilibrium. This result suggests that the partial rating area offering phenomenon is better explained by the risk screening hypothesis rather than the market segmentation hypothesis. The risk screening hypothesis is further supported by Table 3.6 which reports the average county characteristics based on insurers' plan offering decisions. As described earlier, counties with poorer heath measures tend to be excluded by insurers. These findings imply that while the ACA regulation allows price discrimination based on rating areas and not on counties, insurers are effectively price discriminating consumers based on counties by endogenously determining their service area within a rating area.

Figure 3.3: Histogram for Correlation Measure $CORR^I(r)$



Notes: Figure reports the histogram of the correlation measure $CORR^I(r)$ defined in Equation 3.5.1. The sample is restricted to rating areas that have at least two counties and two participating insurers, where there is some partial entry.

Table 3.8: Descriptive Statistics of the Correlation Measure $CORR^I(r)$

Number of RAs	247
Number of RAs with No Partial Entry	112
Number of RAs with Some Partial Entry	135
: Number of RAs with $CORR > 0$	121
: Number of RAs with $CORR == 0$	2
: Number of RAs with $CORR < 0$	12
: Mean	0.34
: Median	0.34
: Standard deviation	0.27

Notes: Table reports descriptive statistics of the correlation measure $CORR^I(r)$ defined in Equation 3.5.1. The sample is restricted to rating areas with at least two counties and two participating insurers, and the first row reports the number of such rating areas. The second row reports the number of rating areas where all insurers offer at least one plan in every county. These rating areas have a correlation measure of 1 by construction. The third row reports the number of rating areas where some insurers do not offer any plan in some county. From the fourth row, the sample is restricted to the rating areas included in the third row; the rating areas where there is some partial entry.

3.6 Conclusion

This paper documents the pervasiveness of partial rating area coverage in the ACA marketplaces. Using both theoretical and empirical approaches, we argue that insurers in the marketplaces price discriminate consumers based on county, which is a much narrower definition of residential area than rating areas. As the regulation mandates uniform pricing, but not universal offering within a rating area, insurers endogenously determine their service area to price discriminate consumers based on county. We find evidence that price discrimination takes a form of offering county-specific plans or completely excluding high risk counties from their service area.

Appendices

Appendix A

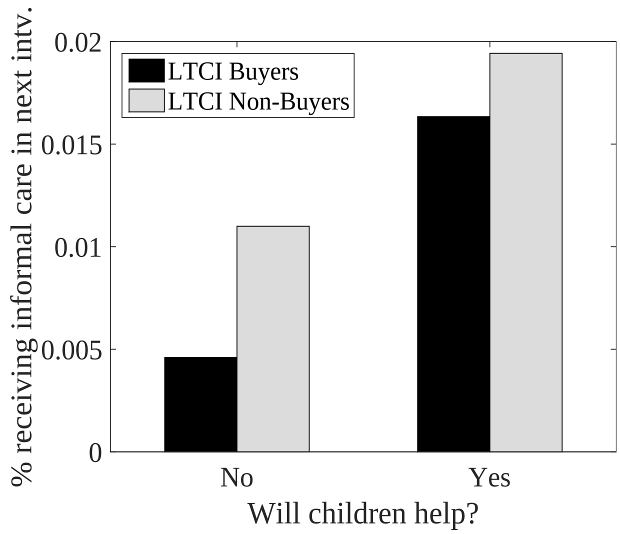
Appendix to Chapter 2

A.1 Descriptive Evidence on Family Moral Hazard

I provide descriptive evidence that parents' decision to buy long-term care insurance undermines children's informal care incentives. Children's informal care behaviors may be affected not only by parents' long-term care insurance coverage but also by other important factors such as the opportunity costs of providing care. To better control for the determinants of informal care other than long-term care insurance coverage, I again take advantage of the subjective beliefs about informal care reported in the HRS (B^{IC}).[66] Using healthy respondents who do not yet own long-term care insurance in the current interview, I split the sample by their beliefs about informal care in the current interview and long-term care insurance purchase choices in the next interview. For each of the four subsamples, I compute the share of respondents who receive informal care from children in the next interview. The goal is to see if respondents who buy long-term care insurance

[66] See Section 2.2.2 for the description of these beliefs.

Figure A.1: Long-Term Care Insurance Purchase and Informal Care



Notes: Sample is limited to healthy individuals who do not yet own long-term care insurance in the current interview. I split the sample by their current beliefs about the availability of informal care and long-term care insurance purchase choices in the next interview. For each of the four subsamples, the figure reports the share receiving informal care from children in the next interview.

receive less informal care conditional on beliefs about informal care before the insurance purchase. Figure A.1 shows that, conditional on beliefs about informal care, parents who buy long-term care insurance are less likely to receive care from children. To the extent that beliefs about informal care are reasonable measures of informal care before the insurance purchase, this finding serves as suggestive evidence that long-term care insurance undermines children's informal care incentives.

A.2 Child Inheritance Value

The child's value from an inheritance is determined by assuming that the child optimally consumes her share of bequests, $B := 0.5w_a^P$, over the next T_0 periods.[67] Given that the child is risk-averse, she will allocate B equally over the next T_0 periods. Let x denote the equally allocated amount. Using $\beta = \frac{1}{1+r}$, I obtain $x = B\frac{1-\beta}{1-\beta^{T_0}}$. As the child's income is likely to affect the consumption value of bequests, I assume that the child receives a constant income, y, over the next T_0 periods. This constant income depends on whether or not the child has some college education. I use the average child family income conditional on college education to calibrate y. In each of the next T_0 periods, the child consumes $y + x$. The child's value from inheritance, Π_d^K, is given as the discounted sum of the consumption utilities over the next T_0 periods:

$$\Pi_d^K = \frac{1-\beta^{T_0}}{1-\beta} \log(y + x). \tag{A.2.1}$$

A.3 Child Family Income Estimation

The HRS reports the annual family income of the respondents' children as bracketed values: below $10K, between $10K-35K, between $35K-70K, above $35K, and above $70K. I put children in the "above $35K" bracket into the "$35K-70K" bracket. As each period is two years in my model, I double the threshold values and define $\hat{y}_i^K$ by the

[67] I use $T_0 = 5$.

following:

$$\hat{y}_i^K = \begin{cases} 1 & \text{if below \$20K,} \\ 2 & \text{if between \$20K-70K,} \\ 3 & \text{if between \$70K-140K,} \\ 4 & \text{and if above \$140K.} \end{cases}$$

I assume there is an underlying continuous family income, $\tilde{y}_i^K$, which is defined by the following equation

$$\log(\tilde{y}_i^K) = x_i^K \gamma + \eta_i \tag{A.3.1}$$

where

$$\begin{aligned} x_i^K \gamma = {} & \gamma_{1,1} + \gamma_{1,2} age_i^K + \gamma_{1,3}(age_i^K)^2 + \gamma_{1,4} home_i^K + \gamma_{1,5} edu_i^K + \gamma_{1,6} female_i^K \\ & + \gamma_{1,7} female_i^K * married_i^K + \gamma_{1,8}(1 - female_i^K) * married_i^K \\ & + e_i^K * \Big\{ \gamma_{2,1} + \gamma_{2,2} age_i^K + \gamma_{2,3}(age_i^K)^2 + \gamma_{2,4} female_i^K + \gamma_{2,5} edu_i^K \\ & + \gamma_{2,6} female_i^K * (e_{i,-1}^K) + \gamma_{2,7}(1 - female_i^K) * (e_{i,-1}^K) \Big\} \end{aligned}$$

and η_i follows an *i.i.d.* normal distribution with mean zero and variance σ_η^2. The log likelihood function is given by

$$\log L(\gamma, \sigma_\eta | \hat{y}^K, x^K) = \sum_{i=1}^{N} \log P(\hat{y}_i^K | x_i^K; \gamma, \sigma_\eta) \tag{A.3.2}$$

where

$$\begin{aligned}
P(\hat{y}_i^K = 1 | x_i^K) &= \Phi_{\sigma_\eta}(\log(20K) - x_i^K \gamma | x_i^K), \\
P(\hat{y}_i^K = 2 | x_i^K) &= \Phi_{\sigma_\eta}(\log(70K) - x_i^K \gamma) - \Phi_{\sigma}(\log(20K) - x_i^K \gamma), \\
P(\hat{y}_i^K = 3 | x_i^K) &= \Phi_{\sigma_\eta}(\log(140K) - x_i^K \gamma) - \Phi_{\sigma}(\log(70K) - x_i^K \gamma), \quad \text{and} \\
P(\hat{y}_i^K = 4 | x_i^K) &= 1 - \Phi_{\sigma_\eta}(\log(140K) - x_i^K \gamma | x_i^K).
\end{aligned}$$

Φ_{σ_η} is the cumulative distribution function of η_i. To estimate Equation (A.3.2), I use data on respondents' children from the HRS 1998-2010. I use children aged between 21 and 60. The results of the estimation are reported in Table A.1. I use these estimates, $\hat{\gamma}$, to construct the deterministic family income function in Equation (2.3.12).

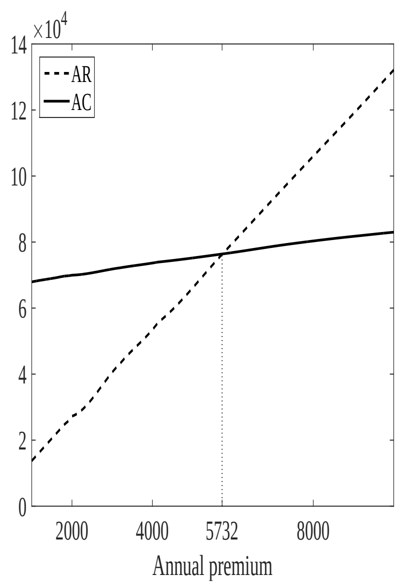
A.4 Additional Tables and Figures

Table A.1: Child Family Income Estimates

	Estimate
Constant	8.3439
Age	0.0607
Age^2	-0.0006
Home	0.4090
Female	0.3114
Female$\times$Married	0.5835
Male$\times$Married	0.3451
Work	0.8525
Work$\times$Age	-0.0112
Work$\times$Age^2	0.0000
Work$\times$Female	-0.3655
Work$\times$College	0.3393
Work$\times$Female$\times$Work$_{-1}$	0.2306
Work$\times$Male$\times$Work$_{-1}$	0.3667
σ_η	0.5002

Notes: Table reports estimated coefficients for the two-year child family income process.

Figure A.2: Competitive Equilibrium



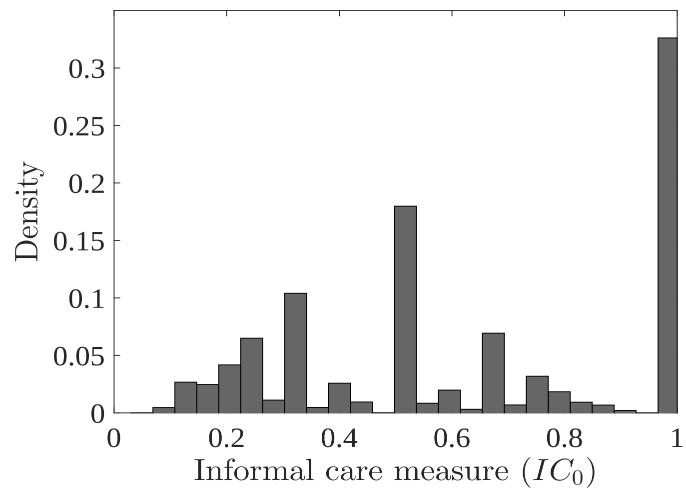
Notes: Figure reports the simulated average cost curve (AC) and the simulated average revenue curve (AR) for the standard policy under default pricing (all healthy 60-year-olds pay the same premium). The simulation sample consists of healthy 60-year-old parents and their children from the HRS 2002. The equilibrium premium is $5,732 and the equilibrium coverage rate is 6.1 percent.

Table A.2: Moments Generated with First-Stage Policy Functions

	Data	First-Stage Policy Functions
LTCI purchase rate	0.14	0.14
Among parents w/ light LTC needs		
Light informal care rate	0.37	0.35
Intensive informal care rate	0.18	0.13
Paid home care rate	0.50	0.51
Nursing home rate	0.07	0.04
Among parents w/ severe LTC needs		
Light informal care rate	0.09	0.05
Intensive informal care rate	0.29	0.26
Paid home care rate	0.30	0.35
Nursing home rate	0.36	0.30
Child employment rate	0.63	0.65
Parent mean consumption		
Age 60s	40956	40421
Age 70s	38065	40031
Age 80s	36517	37151
Age 90s	35114	32582

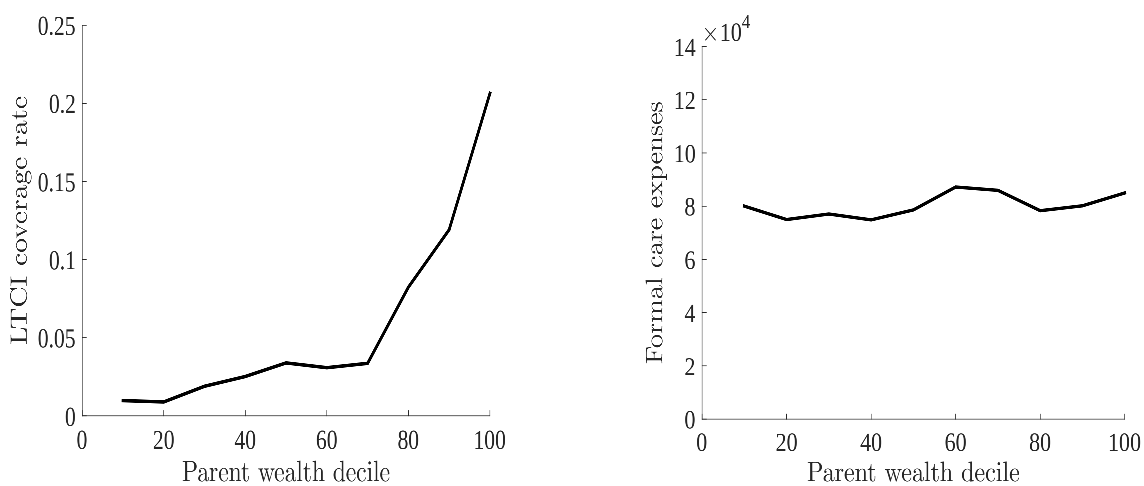
Notes: Table reports empirical moments and simulated moments. Simulated moments are generated using the first-stage empirical policy functions of the CCP estimation. Formal care rates are among parents who have specified health statuses and do not receive informal care from children. Empirical consumption moments are based on the CAMS data.

Figure A.3: Density of Informal Care Measure (IC_0)



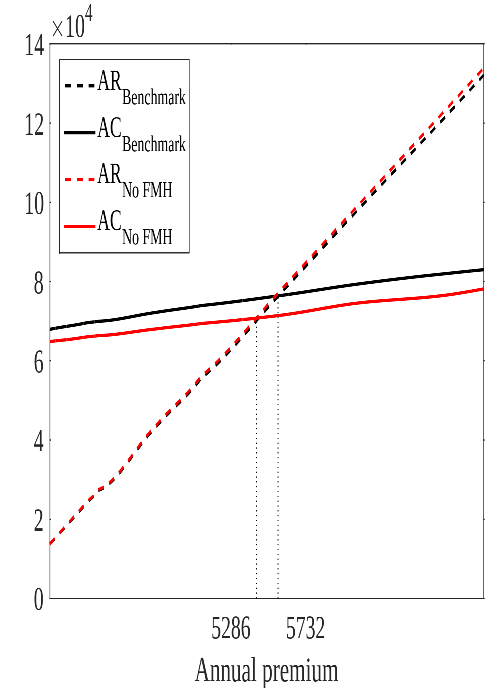
Notes: Figure reports the density of IC_0 conditional on $IC_0 > 0$. For each family in the simulation sample, IC_0 is defined as the number of total informal care periods divided by the number of total bad health periods when there is no private long-term care insurance. About 55 percent of families have $IC_0 = 0$. This is consistent with the data patterns; Table 2.3 shows that among parents with long-term care needs, 55 percent do not receive any informal care from children.

Figure A.4: Wealth and Insurance Selection



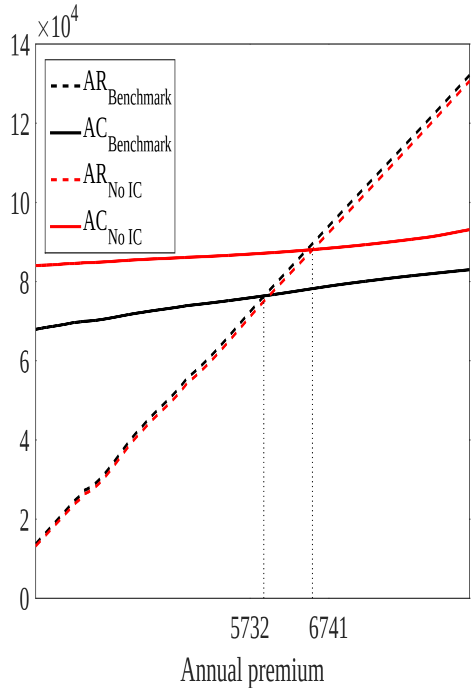
Notes: Left panel reports the share of parents who buy long-term care insurance at the equilibrium premium (\$5,732), by parent wealth decile (wealth is measured at parent age 60). Right panel reports the average present-discounted value of the lifetime formal care expenses when parents own long-term care insurance.

Figure A.5: Equilibrium without Family Moral Hazard



Notes: Black solid line and black dashed line represent the average cost curve and the average revenue curve, respectively, of the benchmark model where children can react to parents' insurance coverage. The equilibrium coverage rate is 6.1 percent. Red solid line and red dashed line represent the average cost curve and the average revenue curve, respectively, when there is no family moral hazard. The equilibrium coverage rate is 8.6 percent.

Figure A.6: Equilibrium without Informal Care



Notes: Black solid line and black dashed line represent the average cost curve and the average revenue curve, respectively, of the benchmark model where children can provide informal care. The equilibrium coverage rate is 6.1 percent. Red solid line and red dashed line represent the average cost curve and the average revenue curve, respectively, when there is no informal care. The equilibrium coverage rate is 9.5 percent.

Appendix B

Appendix to Chapter 3

Table B.1: Rating Area by State

State	Units of RAs	RAs	Non Single County RAs	Counties	FFM
Alabama	MSAs+1	13	8	67	1
Alaska	3-Digit Zip Codes	3		29	1
Arizona	Counties	7	5	15	1
Arkansas	Counties	7	7	75	1
California	Counties/3-Digit Zip Codes	19		58	0
Colorado	Counties	9	4	64	0
Connecticut	Counties	8	0	8	0
Delaware	Counties	1	1	3	1
DC	Counties	1	0	1	0
Florida	Counties	67	0	67	1

Georgia	Counties	16	16	159	1
Hawaii	Counties	1	1	5	1
Idaho	3-Digit Zip Codes	7		44	0
Illinois	Counties	13	12	102	1
Indiana	Counties	17	16	92	1
Iowa	Counties	7	7	99	1
Kansas	Counties	7	7	105	1
Kentucky	Counties	8	8	120	0
Louisiana	Counties	8	8	64	1
Maine	Counties	4	4	16	1
Maryland	Counties	4	4	24	0
Massachusetts	3-Digit Zip Codes	7		14	0
Michigan	Counties	16	15	83	1
Minnesota	Counties	9	9	87	0
Mississippi	Counties	6	6	82	1
Missouri	Counties	10	10	115	1
Montana	Counties	4	4	56	1
Nebraska	3-Digit Zip Codes	4		93	1
Nevada	Counties	4	3	17	1
New Hampshire	Counties	1	1	10	1
New Jersey	Counties	1	1	21	1
New Mexico	MSAs+1	5	2	33	1

New York	Counties	8	8	62	0
North Carolina	Counties	16	16	100	1
North Dakota	MSAs+1	4	2	53	1
Ohio	Counties	17	17	88	1
Oklahoma	MSAs+1	5	4	77	1
Oregon	Counties	7	7	36	1
Pennsylvania	Counties	9	9	67	1
Rhode Island	Counties	1	1	5	0
South Carolina	Counties	46	0	46	1
South Dakota	Counties	4	4	66	1
Tennessee	Counties	8	8	95	1
Texas	MSAs+1	26	16	254	1
Utah	Counties	6	5	29	1
Vermont	Counties	1	1	14	0
Virginia	MSAs+1	12	12	134	1
Washington	Counties	5	4	39	0
West Virginia	Counties	11	10	55	1
Wisconsin	Counties	16	14	72	1
Wyoming	MSAs+1	3	1	23	1

Notes: FFM is an indicator for having a federally-facilitated marketplace.

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