# Old, frail, and uninsured: Accounting for features of the U.S. long-term care insurance market *

R. Anton Braun
Federal Reserve Bank of Atlanta
r.anton.braun@gmail.com

Karen A. Kopecky
Federal Reserve Bank of Atlanta
karen.kopecky@atl.frb.org

Tatyana Koreshkova
Concordia University and CIREQ
tatyana.koreshkova@concordia.ca

January 2019

**Abstract**

Half of U.S. 50-year-olds will experience a nursing home stay before they die, and one in ten will incur out-of-pocket long-term care expenses in excess of $200,000. Surprisingly, only about 10% of individuals over age 62 have private long-term care insurance (LTCI) and LTCI takeup rates are low at all wealth levels. We analyze the contributions of Medicaid, administrative costs, and asymmetric information about nursing home entry risk to low LTCI takeup rates in a quantitative equilibrium contracting model. As in practice, the insurer in the model assigns individuals to risk groups based on noisy indicators of their nursing home entry risk. All individuals in frail and/or low income risk groups are denied coverage because the cost of insuring any individual in these groups exceeds that individual's willingness-to-pay. Individuals in insurable risk groups are offered a menu of contracts whose terms vary across risk groups. We find that Medicaid accounts for low LTCI takeup rates of poorer individuals. However, administrative costs and adverse selection are responsible for low takeup rates of the rich. The model reproduces other empirical features of the LTCI market including the fact that owners of LTCI have about the same nursing home entry rates as non-owners.
**Keywords**: Long-Term Care Insurance; Medicaid; Adverse Selection.
**JEL Classification numbers: D82, D91, E62, G22, H30, I13.**

*We thank Taylor Kelley and Jordan Herring for outstanding research assistance. We are grateful for the helpful comments of five referees. We also thank Joseph Briggs, Hector Chade, Martin Eichenbaum, Eric French, John Jones, Robert Shimer and Ariel Zetlin-Jones for helpful feedback. We benefited from comments received at the 2015 workshop on aging in Barcelona, the Canon Institute for Global Studies 2015 Conference, the Keio-GRIPS Macroeconomics and Policy Workshop, the 2016 FRB Atlanta Workshop on Adverse Selection and Aging, the 2016 SED, the 2016 CIREQ MacroMontreal Workshop, the 2017 Utah State University QSPS Workshop, the 2017 GCER/Cemmap Applied Microeconomics Conference, 2018 University of Minnesota HHEI conference, the Michigan Retirement Research Center Workshops, Carlton University, FRB Chicago, FRB Minneapolis, FRB Richmond, FRB St. Louis, ITAM, McGill University,

# 1 Introduction

Nursing home expense risk in the U.S. is significant. Half of U.S. 50-year-olds will experience a nursing home stay before they die, and one in ten will incur out-of-pocket long-term care (LTC) expenses in excess of $200,000. Surprisingly, only about 10% of individuals over age 62 own private long-term care insurance (LTCI). Even though takeup rates increase with wealth, they are low at all levels of the wealth distribution. In our sample of Health and Retirement Study respondents, they are under 2% for individuals in the bottom wealth quintile and 20% for individuals in the top wealth quintile.

Why are LTCI takeup rates so low? Using a quantitative equilibrium contracting model, we analyze the role of three factors. First, LTCI is costly to produce. LTC insurers face significant variable and fixed administrative costs. Commissions to brokers often exceed the first year's premium income. And insurers allocate more resources to underwriting and claims management for LTCI as compared to other life insurance product lines. Second, individuals have private information about their nursing home entry risk.[1] As a result, insurers are exposed to adverse selection. Third, Medicaid offers public assistance for nursing home expenses to individuals who satisfy a means-test.

According to our model, the primary factors leading to low LTCI takeup rates vary across the income distribution. In particular, Medicaid is responsible for low LTCI takeup rates among poor individuals; both Medicaid and administrative costs are important for low takeup rates among the middle class; and adverse selection and administrative costs account for low LTCI takeup rates among affluent individuals. The model also accounts for a range of other empirical features of this market. Notably, owners of LTCI in the model have about the same nursing home entry rates as non-owners.

Our model builds in the following aspects of how underwriting works in practice. U.S. LTC insurers screen individuals in two ways. They collect information about each applicant's health status and finances and use it to assign the applicant to a group of people with similar nursing home entry risk. Some applicants get assigned to an uninsurable risk group and are denied coverage. Applicants who are selected for insurance are offered a specific menu of insurance policies whose terms vary across risk groups.

We consider the problem of a monopolist insurer who incurs fixed and variable costs of providing insurance. Individuals in the model have access to public means-tested nursing home benefits. They also have private information about nursing home entry risk. The insurer in our model assigns each individual to a risk group based on observable indicators of health status and income. As in practice, the insurer screens individuals in two ways. First, the insurer conducts risk-group selection: it decides which risk groups to insure and which ones to deny coverage. Second, it decides the menus of contracts for insurable risk groups. There are two ways that an individual may end up with no insurance. He may be assigned to an uninsurable risk group or he may be assigned to an insurable risk group but decide that none of the policies offered to his risk group are attractive to him.

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Notre Dame University, Purdue University, University of Mannheim, University of Wisconsin-Madison, and Virginia Commonwealth University.

[1] Finkelstein and McGarry (2006) find that self-reported nursing home entry probabilities predict nursing home entry even after controlling for observables.

In the model, all three factors — administrative costs, Medicaid, and variation in the distribution of private information across risk groups — influence both risk-group selection as well as pricing and coverage of contracts offered to insurable risk groups. Variable administrative costs increase the marginal cost of offering insurance. With variable costs, coverage levels are lower and unit prices are higher relative to the optimal contracts in a world where variable costs are zero. If variable costs are sufficiently large, all individuals in some risk groups are denied coverage. Fixed costs may also make it unprofitable to insure any individual in some risk groups, leading the insurer to deny coverage to the entire group.

The insurer also recognizes that low income individuals have low or even no willingness-to-pay for private insurance because they have a high probability of qualifying for Medicaid benefits. As a result, the presence of Medicaid induces the insurer to deny coverage to all individuals in low-income risk groups. Medicaid also lowers the willingness-to-pay of more affluent individuals because it provides free nursing home benefits in the, possibly rare, states of the world where the individual has exhausted his personal resources. Thus, Medicaid also impacts the set of contracts offered to insurable risk groups.

Absent Medicaid and administrative costs, our model is equivalent to the model of Stiglitz (1977). A sharp implication of that model is that all risk groups are insurable. This implication is inconsistent with the fact that LTC insurers deny coverage to all individuals in some risk groups. Our model accounts for this fact because we combine private information with Medicaid and administrative costs. Once either Medicaid or administrative costs are present, the distribution of private information within a risk group impacts whether or not that risk group is insurable. Chade and Schlee (2018) make this point in a theoretical framework with private information and administrative costs. We show that this same point applies when Medicaid is present.

To assess the quantitative significance of Medicaid, administrative costs and private information in accounting for low LTCI takeup rates we parametrize the model as follows. The parameter that governs the scale of Medicaid in the model is set to reproduce U.S. benefit levels. Administrative costs in the model are chosen to reproduce U.S. industry averages of fixed and variable costs. The distribution of nursing home entry risk varies across risk groups in the model. We discipline this variation by targeting the variation in mean nursing home entry and LTCI takeup rates by frailty and income. Finally, the overall dispersion in privately-observed nursing home entry risk is chosen to reproduce the coefficient of variation in self-reported nursing home entry probabilities for Health and Retirement Survey (HRS) respondents. These targets are estimated using HRS data.

The parametrized model reproduces a variety of non-targeted statistics. The dispersion in privately-observed nursing home entry risk in the model is higher in frail and poor risk groups. This pattern is consistent with patterns of dispersion in self-reported nursing home entry probabilities in the HRS data. The average extent of coverage and premia in the model is in good accord with the data, too. Finally, the model reproduces the low correlation between nursing home entry risk and LTCI ownership documented in Finkelstein and McGarry (2006).

Our first step in understanding the role of the three factors in accounting for low LTCI takeup rates is to ascertain the quantitative significance of the two screening devices used by insurers: risk-group selection versus menu design for insurable risk groups. In our model screening is conducted almost exclusively via risk-group selection.

Next, we quantify the relative impacts of Medicaid, administrative costs and private information on the extent of risk-group selection and, hence, average LTCI takeup rates in the model. We find that removing Medicaid increases average takeup rates by 81 percentage points and removing administrative costs increases them by 51 percentage points. Finally, eliminating private information by assuming the insurer can observe individuals' actual nursing home entry probabilities increases takeup rates by 28 percentage points.

Medicaid, administrative costs and private information each play a distinct but essential role in generating the pattern of low takeup rates by income and frailty in the model. Medicaid generates low takeup rates of the poor who can easily meet its means test and, as a result, have very low willingness-to-pay for private insurance. Both Medicaid and administrative costs have a large impact on the takeup rates of middle-income individuals. However, Medicaid's impact on more affluent individuals is small. Their low LTCI takeup rates are, instead, due to the presence of private information and administrative costs.

Our empirical results shed new light on other findings in the literature. Brown and Finkelstein (2008) consider the impact of Medicaid on the demand for LTCI in a setting with exogenously specified insurance contracts. They find that individuals in the bottom two-thirds of the wealth distribution do not purchase a full insurance actuarially-fair product when Medicaid nursing home benefits are available. Our strategy of modeling the insurer's problem creates new interactions between Medicaid and private LTCI. When Medicaid is present, individuals prefer private insurance contracts that feature partial coverage. Since the insurer customizes pricing and coverage to fit the needs of each risk group, the crowding out effect of Medicaid is much smaller in our model.

The ability of our model to generate a low correlation between LTCI ownership and private nursing home entry risk is of independent interest. Standard adverse selection theory predicts a strong positive correlation between insurance ownership and private risk exposure. Empirical evidence of a low or even negative correlation in LTC and other insurance markets has prompted a literature searching for an explanation. Finkelstein and McGarry (2006), for instance, conclude that multiple sources of private information are required to understand the U.S. LTCI market. We obtain this low correlation in a model with a single source of private information. Because the insurer in our model engages in risk-group selection, nearly all risk groups have the property that either both the high and the low risk types in the group are insured or neither are insured. As a result, LTCI ownership rates are uninformative about nursing home entry rates.

Finally Ameriks et al. (2018) find that more affluent individuals are not interested in purchasing the set of LTCI policies available to them in the market but would be interested in purchasing an ideal LTCI product. They refer to their result as the LTCI puzzle. Our results suggest that both private information and administrative costs are important reasons for this puzzle. When both of these mechanisms are present, our parametrized model accounts for the low LTCI takeup rates of affluent individuals in the data. However, when either one of these frictions is removed from the model, most affluent individuals purchase LTCI.

The remainder of the paper is organized as follows. Section 2 provides an overview of the U.S. LTCI market. Section 3 presents the model. Section 4 describes identification and parametrization of the quantitative model. Section 5 assesses the ability of the model to reproduce non-targeted moments. Section 6 contains our main results and robustness analysis, and our concluding remarks are in Section 7.

## 2 The U.S. LTCI market

In the U.S., LTCI is primarily used to insure against lengthy nursing home (NH) stays. For this reason we focus on NH stays that exceed 100 days.[2] We estimate that the lifetime probability of a long-term NH stay is 30% at age 50.[3] On average, those who experience a long-term stay spend about 3 years in a NH. According to the U.S. Department of Health and Human Services, NH costs averaged $225 per day in a semi-private room and $253 per day in a private room in 2016. Thus, it is not unusual for lifetime NH costs to exceed $200,000.

Given the extent of NH risk in the U.S., one would expect that the private LTCI market would be large. But, only 10% of individuals aged 62 and older in the HRS have private LTCI and takeup rates are low at all wealth levels. In particular, they are 4.5% in wealth quintiles 1–3, 14% in wealth quintile 4, and 20% in wealth quintile 5. Moreover, in 2000, private LTCI benefits only accounted for 4% of aggregate NH expenses, while the share of out-of-pocket payments was 37%.[4] Favreault and Dey (2016) estimate that 10.6% of individuals will incur out-of-pocket LTC expenses that exceed $200,000, and Kopecky and Koreshkova (2014) find that the risk of large out-of-pocket NH expenses is the primary driver of wealth accumulation during retirement.

Most LTCI is purchased from agents or brokers by individuals aged 55–66 years, while the average age of NH entry is 83.[5] At the time of applying for LTC coverage, applicants are asked detailed questions about their health status and financial situation. Some common questions include: Do you require human assistance to perform any of your activities of daily living? Are you currently receiving home health care or have you recently been in a NH? Have you ever been diagnosed with or consulted a medical professional for the following: a long list of diseases that includes diabetes, memory loss, cancer, mental illness, and heart disease? Do you currently use or need any of the following: wheelchair, walker, cane, oxygen? Do you currently receive disability benefits, social security disability benefits, or Medicaid?[6] Applicants are also queried about their income and wealth and asked to explain the specific source of resources that will be used to pay premia. Applicants are warned that premia increases are common and queried about their ability to cope with future premia increases. Finally, applicants are informed that, as a rule of thumb, LTCI premia should not exceed 7% of their income.[7]

Underwriting standards are strict and denials are common. About 20% of formal applicants are denied coverage via underwriting according to industry surveys (see Thau et al. (2014)). However, even prior to underwriting, insurance brokers screen out applicants. They discourage individuals from submitting a formal application if their responses indicate that

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[2]Another reason we focus on NH stays is because Medicare offers universal benefits for short-term rehabilitative NH stays of up to 100 days.

[3]In comparison, using HRS data and a similar simulation model, Hurd et al. (2014) estimate that the lifetime probability of having any NH stay for a 50 year old ranges between 53% and 59%.

[4]Source: Federal Interagency Forum on Aging-Related Statistics.

[5]Thau et al. (2014) report that only 10% of sales in 2013 were sold at work-sites.

[6]Source: 2010 Report on the Actuarial Marketing and Legal Analyses of the Class Program.

[7] Source: NAIC Guidance Manual for Rating Aspects of the Long-Term Care Insurance Model Regulation, March 11, 2005.

they have poor health or low financial resources. Using HRS data, we estimate that 36% to 56% of 55–66 year olds would be denied coverage if they applied based on health underwriting guidelines from Genworth and Mutual of Omaha.[8,9] Denials are high even in the top half of the wealth distribution, ranging from 28% to 48%.

For individuals who are offered insurance, coverage is incomplete and premia are high. Insurers cap their losses by offering indemnities instead of service benefits. Brown and Finkelstein (2007) estimate that a "representative" LTCI policy in 2000 only covered about 34% of expected lifetime costs. Brown and Finkelstein (2011) find that coverage has improved in more recent years with a representative policy in 2010 covering 66% of expected lifetime costs.[10] More recently, Thau et al. (2014) report that policies that offer unlimited lifetime benefit periods have largely disappeared from the market. Brown and Finkelstein (2007) and Brown and Finkelstein (2011) also find that individual loads, which are defined as one minus the expected present value of benefits relative to the expected present value of premia, ranged from 0.18 to 0.51 (depending on whether or not adjustments are made for lapses) in 2000 and ranged from 0.32 and 0.50 in 2010. In other words, LTCI policies are sometimes twice as expensive as actuarially-fair insurance. Loads on LTCI are high relative to loads in other insurance markets. For instance, Karaca-Mandic et al. (2011) estimate that loads in the group medical insurance market range from 0.15 for firms with 100 employees to 0.04 for firms with more than 10,000 employees, and Mitchell et al. (1999) estimate that loads for life annuity insurance range between 0.15 and 0.25.

## 2.1 Administrative costs and profitability

Even though prices are high and coverage is incomplete, insurers have found that LTCI products are costly products to offer and profits have been low. In order to promote sales, brokers are given a substantial commission in the year that the policy is written and smaller commissions in subsequent years. In 2000, initial commissions averaged 70% of the first year's premium and, in 2014, they averaged 105%. However, total commissions over the life of a policy have been reasonably stable. They were about 12.6% of present-value premium for policies written in 2000 and 12.3% of present-value premium for policies written in 2014. Administrative expenses associated with underwriting and claims processing are also significant. These expenses averaged 20% of present-value premium in 2000 and 16% of present-value premium in 2014.[11] Finally, as pointed out in Cutler (1996), LTCI products are subject to intertemporal risk. These policies pay out, on average, about 20 years after they are written and, if interest rates, retention rates or claims duration vary from an insurer's forecast, the costs of the entire pool of policies changes. Insurers are under increasing pressure by regulators to provision for this risk by including a markup on the

[8] All HRS data work is done using our HRS sample. Details on our sample selection criteria are reported in Section 2 of the appendix.

[9] The denial rate is 56% if we assume that all individuals who stated that they had ever been diagnosed with any of the diseases asked about are denied coverage and 36% if we assume that none of them are denied coverage.

[10] Most of this increase in coverage is due to the fact that the representative policy in 2010 includes an escalation clause that partially insures against inflation risk.

[11] These figures on costs are from the Society of Actuaries as reported in Eaton (2016).

initial premium. The additional proceeds are held as reserves to provision against adverse future developments in claims.

Insurers have not been able to fully pass higher costs through to consumers. According to Cohen et al. (2013), most insurers have exited the market since 2003 and many insurers are experiencing losses on their LTCI product lines. New sales of LTCI in 2009 were below 1990 levels and, according to Thau et al. (2014), over 66% of all new policies issued in 2013 were written by the largest three companies.[12]

## 2.2 Asymmetric information and adverse selection

One contributing factor to low LTCI takeup rates pursued in this analysis is that individuals have private information about their nursing home entry risk. As a result, insurers are exposed to adverse selection. Actuaries are keenly aware that the high costs of offering LTCI translate into high premia. This negatively impacts the risk composition of the pool of applicants, further raising the LTCI premia (see, for instance, Eaton (2016)). Academic research has also documented evidence of asymmetric information in the LTCI market. Finkelstein and McGarry (2006) provide direct evidence that individuals have private information about their NH entry risk and act on it. Specifically, they find that individuals' self-assessed NH entry risk is positively correlated with both actual NH entry and LTCI ownership even after controlling for characteristics observable by insurers.

Interestingly, even though Finkelstein and McGarry (2006) find evidence of private information in the LTCI market, they fail to find evidence that the market is adversely selected based on the positive correlation test proposed by Chiappori and Salanie (2000). When they do not control for the insurer's information set, they find that the correlation between LTCI ownership and NH entry is negative and significant. Individuals who purchased LTCI are less likely to enter a NH as compared to those who did not purchase LTCI. When they include controls for the insurer's information set, they also find a negative, although no longer statistically significant, correlation. Finally, when they use a restricted sample of individuals who are in the highest wealth and income quartile and are unlikely to be rejected by insurers due to poor health, they again find a statistically significant negative correlation.

Hendren (2013) raises the possibility that Finkelstein's and McGarry's findings are driven by individuals in high risk groups. Specifically, he finds that self-assessed NH entry risk is predictive of a NH event for individuals who would likely be denied coverage by insurers. One objective of our analysis is to assess the quantitative significance of denials. Hendren's measure of a NH event is independent of the length of stay. Since we focus on stays that are at least 100 days, we have repeated the logit analysis of Hendren (2013) using our definition of a NH stay and our HRS sample. We get qualitatively similar results. In particular, we find evidence of private information at the 10-year horizon in a sample of individuals who would likely be denied coverage by insurers.[13]

[12]The top three insurers are Genworth, Northwest and Mutual of Omaha. For information about losses on this business line see, e.g., *The Insurance Journal*, February 15, 2016, `http://www.insurancejournal.com/news /national/2016/02/15/398645.htm` or Pennsylvania Insurance Department MUTA-130415826.

[13]See Section 2.3 of the appendix for more details.

## 2.3 Public LTCI

Public insurance is known to have important interactions with the demand for private insurance.[14] The primary public LTC insurer is Medicaid. It is means-tested and only available to individuals who have either low wealth and retirement income (categorically needy) or low wealth and very high medical expenses (medically needy). Medicaid is also a secondary payer that only offers benefits after any private LTCI benefits have been exhausted. Brown and Finkelstein (2008) find pronounced crowding-out effects of Medicaid on the demand for private LTCI. Specifically, they find that in the presence of Medicaid about two-thirds of individuals would not purchase an actuarially-fair, full-coverage, private LTCI policy.

# 3 Modeling the market for LTCI

In this section we start by describing a simple model. The heart of which is a variant of the model in Rothschild and Stiglitz (1976). The model consists of a single risk group comprised of risk-adverse individuals and a single monopolist insurer as in Stiglitz (1977). The assumption of a single insurer is a parsimonious way to capture the concentration we documented above in this market.[15] We extend the model by adding administrative costs on the insurer and Medicaid. Our modeling of administrative costs is inspired by Chade and Schlee (2018) who conduct a theoretical analysis of administrative costs and coverage denials in an adverse selection model with a continuum of private types. We are unaware of other work that incorporates a public means-tested insurer into an optimal contracting framework.

We use the simple model to illustrate two distinct ways to generate low LTCI takeup rates. The first way is an optimal menu in which all individuals in a risk group are denied coverage. The second way is an optimal menu in which some individuals in an insurable risk group prefer not to purchase insurance. We describe conditions under which administrative costs, Medicaid and the distribution of private information induce coverage denials to all individuals in a risk group. We also describe conditions under which these factors affect the pricing and extent of coverage offered to an insurable risk group. Having made these points we then explain the additional details that are needed to make the model suitable for quantitative analysis.

## 3.1 Optimal contracts with adverse selection and administrative costs

Suppose that there is a continuum of individuals and that each individual has a type $i \in \{g, b\}$. They each receive endowment $\omega$ but face the risk of entering a NH and incurring costs $m$. The probability that an individual with type $i$ enters a NH is $\theta^i \in (0, 1)$. A fraction

[14]For instance, Mahoney (2015), finds that U.S. bankruptcy laws provide implicit insurance against large health expense, and Fang et al. (2008) document evidence of advantageous selection in the the U.S. Medigap market.

[15]Lester et al. (2017) propose a framework with adverse selection that allows one to investigate how optimal contracts vary with the extent of market power. However, for reasons of tractability they assume risk neutrality and their optimal contracts are different from ours.

$\psi \in (0,1)$ of individuals are good risks who face a low probability $\theta^g$ of a NH stay. The remaining $1-\psi$ individuals are bad risks whose NH entry probability is $\theta^b > \theta^g$. Let $\eta$ denote the fraction of individuals who enter a NH then $\eta \equiv \psi\theta^g + (1-\psi)\theta^b$. Each individual observes his true NH risk exposure but the insurer only knows the structure of uncertainty. A contract consists of a premium $\pi^i$ that the individual pays to the insurer and an indemnity $\iota^i$ that the insurer pays to the individual if he incurs NH costs $m$. A menu consists of a pair of contracts $(\pi^i, \iota^i)$, one for each private type $i \in \{g, b\}$.

The optimal menu of contracts offered by the insurer maximizes his profits subject to participation and incentive compatibility constraints. Our specification of the insurer's profits includes two administrative costs. The first cost is a variable cost of paying claims with constant of proportion $\lambda - 1 \geq 0$ and the second cost is a fixed cost $\gamma \geq 0$ of paying claims. Thus, profits are

$$\psi\Big\{\pi^g - \theta^g\big[\lambda\iota^g + \gamma I(\iota^g > 0)\big]\Big\} + (1-\psi)\Big\{\pi^b - \theta^b\big[\lambda\iota^b + \gamma I(\iota^b > 0)\big]\Big\}.$$

This formulation is general enough to handle the various costs incurred by insurers that we described in Section 2.[16] The participation and incentive compatibility constraints for each type are

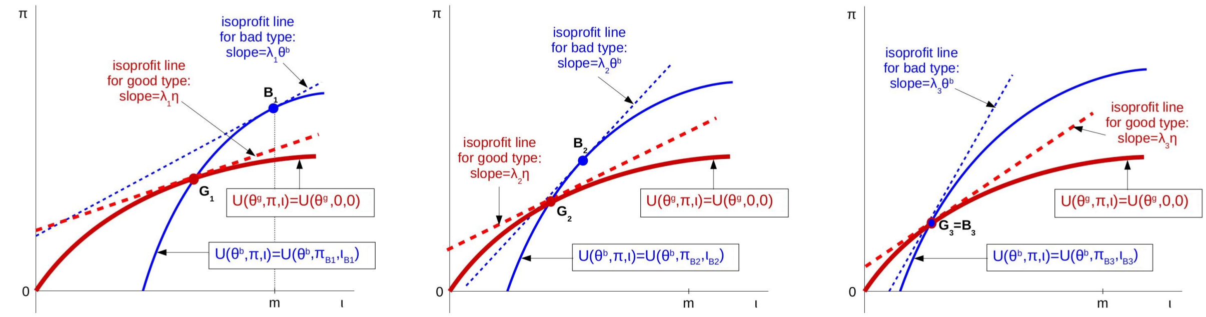
$$\begin{aligned} (PC_i) \quad & U(\theta^i, \pi^i, \iota^i) - U(\theta^i, 0, 0) \geq 0, \quad i \in \{g, b\}, \\ (IC_i) \quad & U(\theta^i, \pi^i, \iota^i) - U(\theta^i, \pi^j, \iota^j) \geq 0, \quad i, j \in \{g, b\},\ i \neq j, \end{aligned}$$

where $U(\theta^i, \pi^i, \iota^i) = (1-\theta^i)u(\omega - \pi^i) + \theta^i u(\omega - \pi^i - m + \iota^i)$ is the utility of an individual with NH entry probability $\theta^i$ who chooses contract $(\pi^i, \iota^i)$. Individuals choose the contract from the menu that maximizes their utility. The participation constraints ensure that each type of individual prefers the contract designed for his type over no insurance, and the incentive compatibility constraints ensure that each type prefers his own contract over the other types contract.

Under the optimal contracts, the participation constraint binds for the good types and the incentive compatibility constraint binds for the bad types. Figure 1 shows various types of optimal menus that can arise. In each case, the curve which passes through the origin (the red curve) is the binding participation constraint of the good types. The other (blue) curve, which passes through the good type's contract, is the binding incentive compatibility constraint of the bad types. Each curve traces out a locus of contracts that individuals of the corresponding type are indifferent over taking. At each indemnity level, the slope of the indifference curve is that type's willingness to pay for a marginal increase in coverage. Hence the good type's indifference curves are flatter than those for the bad type.

Figure 1a illustrates a typical optimal menu under the standard case: $\lambda = 1$ and $\gamma = 0$. The menu exhibits the classic properties of an optimal menu under adverse selection. Specifically, the menu features two distinct contracts. The bad types prefer the contract at point $B_1$ that features full coverage against the loss and the good types prefer the contract at point $G_1$ which exhibits partial coverage, $0 \leq \iota^g < m$, but a smaller premium, $\pi^g < \pi^b$. Note that pooling contracts cannot be equilibria in this setting because, starting from a pooling

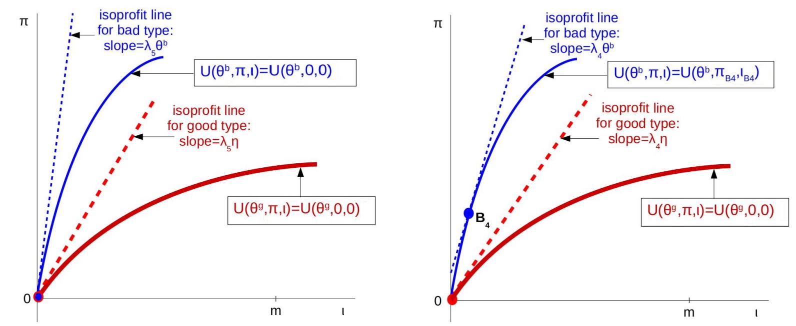
[16] In Section 1.4 of the appendix, we show that costs that are proportional to premia such as brokerage




(a) Separating equilibrium with $\lambda = 1$

(b) Separating equilibrium with $\lambda > 1$

(c) Pooling equilibrium with $\lambda > 1$




(d) Equilibrium with no insurance and $\lambda > 1$

(e) Equilibrium with only bad types insured and $\lambda > 1$

Figure 1. An illustration of the effects of increasing the insurer's proportional administrative costs factor ($\lambda$) on the optimal menu. The blue (red) lines are the indifference curves of bad (good) types. The dashed blue lines are isoprofits from contracts for bad types and the red dashed lines are isoprofits from a pooling contract.

contact at a point such as $G_1$, the insurer can always increase total profits by offering the bad types a more comprehensive contract.

In the standard case, the optimal contracts generally feature cross-subsidization from good to bad types. However, a separating equilibrium where the good types have a $(0, 0)$ contract can occur if the fraction of good types, $\psi$, is sufficiently low and the dispersion in the $\theta$'s is sufficiently high. This particular type of optimal menu is important because it is the only way for the standard model to produce a LTCI takeup that is less than one. We will refer to it as a choice menu. This term is used because all individuals are offered positive insurance, but the good-risk types choose the $(0, 0)$ contract.

We want to emphasize that a risk group is always insurable in the standard case. Regardless of the distribution of private information, willingness-to-pay always weakly exceeds the cost of insurance for the bad types. This property of the standard model is inconsistent with the fact that LTC insurers deny coverage to some risk groups. We now turn to discuss two distinct ways to produce coverage denials for all individuals in the risk group.

The first way is by assuming that the insurer incurs administrative costs. With non-zero

fees and pricing margins can be mapped into the variable cost term.

variable administrative costs, $\lambda > 1$, the optimal menu exhibits less than full insurance for both risk types. Pooling contracts can arise and, when the costs are sufficiently large, all individuals in the risk group may be denied coverage. The various types of optimal menus that can arise are displayed in Figure 1. Start by by comparing Figure 1a with Figure 1b which shows an optimal separating menu when $\lambda$ is above 1.[17] Increasing $\lambda$ increases the slopes of the insurer's isoprofit lines. The insurer responds by reducing indemnities and premia of both types, and the optimal contracts move southwestward along the individuals' indifference curves. Thus, if $\lambda > 1$, the property of the standard model — that bad types get full insurance — no longer holds as both types are now offered contracts where indemnities only partially cover NH costs.[18]

Since the marginal costs of paying out claims to the bad type are higher than to the good type, when $\lambda$ increases, the contracts also get closer together and a single (pooling) contract may arise. Figure 1c depicts such a case where both types get the same nonzero contract. Once a pooling contract occurs, the equilibrium under any larger values of $\lambda$ will also involve pooling. However, the pooling contract will be lower down on the good types' indifference curve and feature less coverage, lower premia, and lower profits. If $\lambda$ is sufficiently large then no profitable nonzero pooling contract will exist. Figure 1d illustrates this case of an uninsurable risk group. The optimal menu consists of a pooling $(0, 0)$ contract, and the LTCI takeup rate is zero.[19] Note that, as in the standard case, choice menus where only the bad-risk types have positive insurance, such as the one depicted in Figure 1e, can also occur when $\lambda > 1$. Thus, with administrative costs, a risk group's LTCI takeup rate can be less than one for two reasons: the entire risk group is uninsurable, or the risk group is insurable but the good types prefer to remain uninsured.

Fixed administrative costs, $\gamma$, are per capita, and can produce low LTCI takeup rates in the same two ways. However, they cannot produce partial coverage for bad-risk types. Specifically, if only fixed administrative costs are present and the risk group is insurable, then the optimal menu will always feature full coverage of the bad-risk types.

## 3.2 Optimal contracts in the presence of Medicaid

Medicaid can also induce optimal menus that exhibit partial coverage for both types (under certain conditions) and denial of coverage to all individuals in a risk group. To establish how and when these situations occur, assume for the time being that there are no administrative costs ($\lambda = 1$, $\gamma = 0$). Suppose, instead, that individuals who experience a NH event receive means-tested Medicaid transfers according to

$$TR(\omega, \pi, \iota) \equiv \max\left\{0, \underline{c}_{NH} - [\omega - \pi - m + \iota]\right\}, \tag{1}$$

where $\underline{c}_{NH}$ is the consumption floor. Then consumption in the NH state is

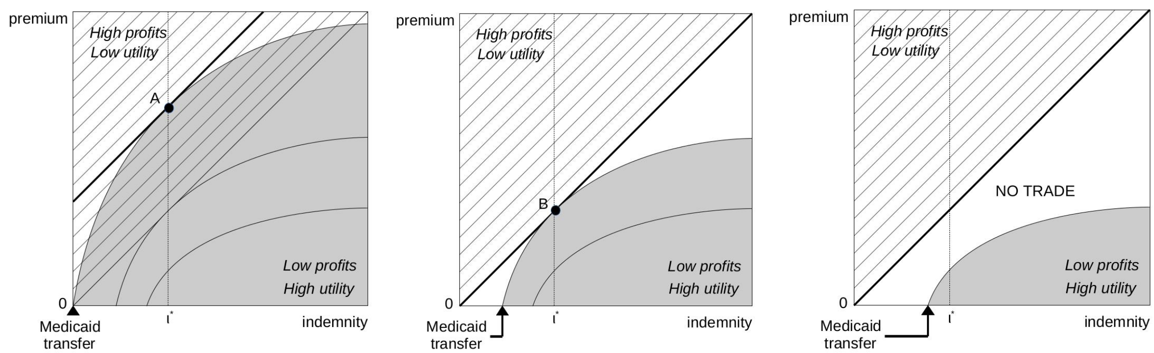
$$c^i_{NH} = \omega + TR(\omega, \pi^i, \iota^i) - \pi^i - m + \iota^i.$$

[17] Note that the good types' contract in the figure is illustrated as the optimal pooling contract. Conditions under which this holds, as well as, conditions characterizing the optimal contracts in the general case are provided in Section 1.1 of the appendix.

[18] See Proposition 1 in Section 1.1 of the appendix for a formal proof of this claim.

[19] Proposition 2 in Section 1.1 of the appendix provides a set of necessary and sufficient conditions for the

By providing NH residents with a guaranteed consumption floor, Medicaid increases utility in the absence of private insurance thus reducing demand for such insurance. Moreover, Medicaid is a secondary payer. When $\underline{c}_{NH} > \omega - \pi - m + \iota$, marginal increases in the amount of the private LTCI indemnity $\iota$ are exactly offset by a reduction in Medicaid transfers, and individual utility remains constant at $u(c_{NH}) = u(\underline{c}_{NH})$. It follows that the marginal utility of the insurance indemnity is zero for individuals who meet the means-test, and only non-zero LTCI contracts that satisfy $\iota - \pi > \underline{c}_{NH} + m - \omega$ are potentially attractive to them.




(a) Non-binding consumption floor (b) Low consumption floor (c) High consumption floor

Figure 2. Illustrates the effects of Medicaid on the trading space. The straight lines are the insurer's isoprofit lines and the curved lines are the individual's indifference curves.

Medicaid reduces profits for the insurer but does not impact the extent of coverage offered to insured individuals within the risk group. In particular, when the risk group is insurable, the bad types always receive full coverage against the NH event. To see this, suppose that without Medicaid, the optimal contract of one of the types is given by point A in Figure 2a with indemnity $\iota^*$. Figure 2b illustrates the impact of introducing Medicaid with a small value of $\underline{c}_{NH}$. Notice that the optimal indemnity is unchanged. However, the individual's outside option has improved, and to satisfy the participation constraint, the premium is reduced. Because the insurer gives the individual the same coverage at a lower price, his profits decline.

As $\underline{c}_{NH}$ increases, an equilibrium, such as the one depicted in Figure 2c, will eventually occur. In this case, $\underline{c}_{NH}$ is so large that the insurer cannot give the agent an attractive enough positive contract and still make positive profits. As a result, the individual is denied coverage. The same logic obtains when there are two private information types. It follows that Medicaid can also induce the insurer to deny coverage to the entire risk group. This occurs when the Medicaid consumption floor is large relative to the individual's endowment net of the cost of NH care.

In practice, at the time of LTCI purchase, most individuals do not know how much wealth they will have at the time a NH event occurs and are, thus, uncertain about whether and to what extent Medicaid will cover their costs if they experience a NH stay. As we now illustrate, modeling this uncertainty affects the amount of coverage that individuals demand.

optimal menu to consist of a pooling $(0, 0)$ contract.

Suppose that when individuals are choosing their LTCI contract, they face uncertainty about the size of their endowment. Specifically, let $\omega$ be distributed with cumulative distribution function $H(\cdot)$ over the bounded interval $\Omega \equiv [\underline{\omega}, \overline{\omega}] \subset \mathbb{R}_+$ with $\underline{\omega} \geq m$ so that LTCI is always affordable. Then an individual's utility function is given by

$$U(\theta^i, \pi^i, \iota^i) = \int_{\underline{\omega}}^{\overline{\omega}} \left[ \theta^i u(c^i_{NH}(\omega)) + (1 - \theta^i) u(c^i_o(\omega)) \right] dH(\omega),$$

where

$$\begin{aligned} c^i_o(\omega) &= \omega - \pi^i, \\ c^i_{NH}(\omega) &= \omega + TR(\omega, \pi^i, \iota^i) - \pi^i - m + \iota^i, \end{aligned}$$

and the Medicaid transfer is defined by (1).

When endowments are random, NH entrants may only be eligible for Medicaid under smaller realizations of the endowment. A private LTCI product is thus potentially valuable because it provides insurance in the states of nature where the endowment is too large to satisfy the means-test. However, the individual will not want full private LTCI coverage because, due to Medicaid, he is already partially insured against NH risk in expectation.[20]

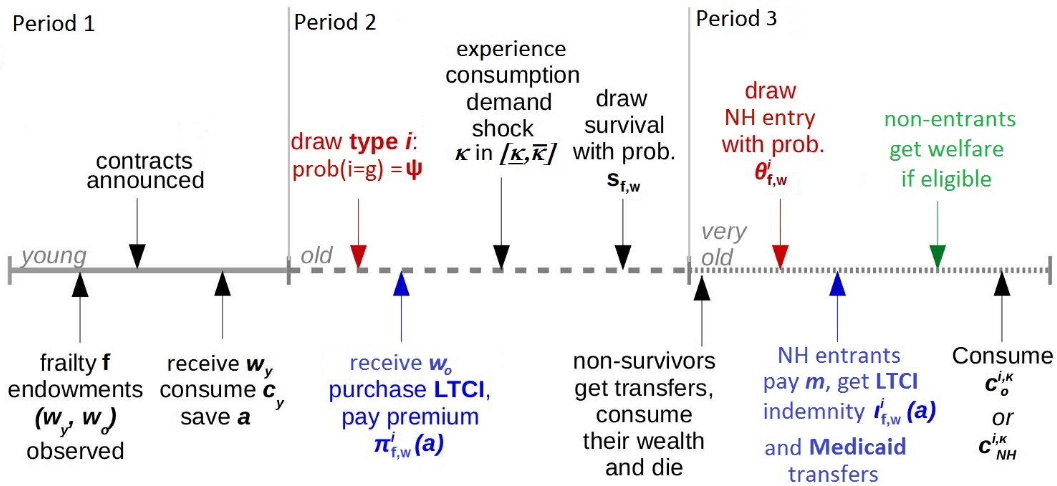
We have explained that a risk group is always insurable when administrative costs and Medicaid are absent. However, when either is present, it may be optimal for the insurer to deny coverage to the entire group. Whether a risk group is denied coverage depends on the size of administrative costs and the scale of the Medicaid program. It also depends on the distribution of private information within the risk group. In particular, either an increase in $\theta^b$ or a mean-preserving increase in the dispersion of private information raises the possibility that the entire risk group will be denied coverage.[21] A larger dispersion in private information makes cross-subsidization more difficult and reduces the profitability of menus offering positive insurance to both types. At the same time increasing $\theta^b$ makes choice menus less profitable.

The quantitative model that follows features administrative costs, Medicaid, and asymmetric information. In addition, it features multiple risk groups that vary both in observable characteristics of their members and in the distribution of private information within the group. The insurer screens individuals in two ways. First, it conducts risk-group selection. In other words, it decides which risk groups to insure and which ones to deny coverage. Second, it chooses the menu of contracts to offer to insurable risk groups. The variation in the distribution of private information across groups impacts risk-group selection. It also impacts the contracts offered to insurable risk groups.

[20] See Section 1.2 of the appendix for a detailed discussion of this version of the model, and Propositions 3 and 4 which provide a sufficient condition for partial coverage contracts and a set of necessary conditions for coverage denials.

[21] Proposition 6 in the appendix describes conditions under which this can occur when administrative costs are present. We do not have a formal proof for Medicaid due to the non-convexities it creates. Still, our numerical results indicate that varying the distribution of private information can also result in the entire risk group being denied coverage if only Medicaid is present instead.

Figure 3. Timeline of events in the baseline model.




## 3.3 The quantitative model

Our goal is to conduct a quantitative analysis of the LTCI market. In particular, we want to analyze how asymmetric information, administrative costs, and Medicaid influence LTCI takeup rates, comprehensiveness of coverage, and pricing for groups of individuals who differ along two dimensions that are observable to insurers: frailty and wealth. We now describe the model we use to achieve this objective.

### 3.3.1 Individual's problem

In the U.S. most individuals purchase private LTCI around the time of retirement. Their saving decisions up to this point in time have been influenced not only by their assessment of NH entry risk, but also by their assessment of the amount of public and private insurance they can obtain to help them cope with this risk. The distribution of wealth in turn influences the optimal contracting problem of the insurer. Those with high wealth have the outside option of self-insuring, and those with low wealth have the outside option of relying on Medicaid if they experience a NH event. We capture the fact that wealth is a choice in a parsimonious way by dividing an individual's life into three periods. In period 1, he works and decides how much of his income to save for retirement.[22] In period 2, he retires, decides whether to purchase LTCI, and then experiences realizations of consumption demand and survival shocks. Finally, in period 3, he experiences a realization of the NH entry shock.

Figure 3 shows the timing of events in the model.[23] At birth, an individual draws his frailty status $f$ and lifetime endowment of the consumption good $\mathbf{w} = [w_y, w_o]$ which are jointly distributed with density $h(f, \mathbf{w})$. Frailty status and endowments are noisy indicators of NH risk. He also observes his probability of surviving from period 2 to period 3, $s_{f,\mathbf{w}}$, which varies with $f$ and $\mathbf{w}$, and the menus of LTCI contracts that will be available in period 2. A

[22]In Section 1.5 of the appendix we show how our 3 period model could be easily mapped into a model that allows for more periods during individuals' working-age before LTCI purchase occurs.

[23]See Section 1.6 of the appendix for a table summarizing the model parameters.

working-aged individual then decides how to divide his earnings, $w_y$, between consumption $c_y$ and savings $a$. This decision is influenced by Medicaid and also by the structure of LTCI contracts. Medicaid benefits are means-tested which creates an incentive to save less so that the individual can qualify for Medicaid. LTCI contracts vary with assets, and this may induce individuals to save more if risk groups with higher assets face lower premia and/or more comprehensive coverage.

In period 2, the individual receives a pension $w_o$ and observes his true risk of entering a NH conditional on surviving to period 3: $\theta^i_{f,\mathbf{w}}$, $i \in \{g, b\}$ with $\theta^g_{f,\mathbf{w}} < \theta^b_{f,\mathbf{w}}$. With probability $\psi$ the individual realizes a low (good) NH entry probability, $i = g$, and with probability $1-\psi$ he realizes a high (bad) NH entry probability, $i = b$. The individual's true type $i \in \{g, b\}$ is private information. We assume that NH entry probabilities also depend on $f$ and $\mathbf{w}$. The individual then chooses a LTCI contract from the menu offered to him by the private insurer.[24] The insurer observes and conditions the menu of contracts offered to each individual on their frailty status, endowments, and assets. We assume that the insurer observes assets because, as we discussed above, LTC insurers are required by regulators in many states to ascertain that the LTCI product sold to an individual is suitable (affordable).[25] Each menu contains two incentive-compatible contracts: one for the good types and one for the bad types. A contract consists of a premium $\pi^i_{f,\mathbf{w}}(a)$ that the individual pays to the insurer and an indemnity $\iota^i_{f,\mathbf{w}}(a)$ that the insurer pays to the individual if the NH event occurs.

After purchasing LTCI, individuals experience a demand shock that induces them to consume a fraction $\kappa$ of their young endowment where $\kappa \in [\underline{\kappa}, \overline{\kappa}] \subseteq [0, 1]$ has density $q(\kappa)$. The demand shock creates uncertainty about the size of wealth at the time of NH entry and thus is important if the model is to attribute partial coverage to Medicaid as we explained above. More generally, it allows the model to capture the following features of NH events in a parsimonious way. On average, individuals have 18 years of consumption between their date of LTCI purchase and their date of NH entry, during which they are exposed to medical expense and spousal death risks, among other risks. In addition, the timing of a NH event is uncertain, and individuals who experience a NH event at older ages are likely to have consumed a larger fraction of their lifetime endowment beforehand.

Period 2 ends with the death event. With probability $s_{f,w}$ individuals survive until period 3, and with probability $1 - s_{f,w}$ they consume their wealth and die.[26] We model mortality risk because it is correlated with frailty and wealth, and it impacts the likelihood of NH entry.

Finally, in period 3 the NH shock is realized, and those who enter a NH pay cost $m$

[24]We assume the insurer does not offer insurance to working-age individuals in period 1 because LTCI takeup rates are low among younger individuals. For example, only 9% of LTCI buyers were less than 50 years old in 2015 according to LifePlans, Inc. "Who Buys Long-Term Care Insurance? Twenty-Five Years of Study of Buyers and Non-Buyers in 2015–2016" (2017).

[25]The reference in footnote 7 contains a model worksheet for reporting financial assets that is used to determine suitability. Lewis et al. (2003) reports that 31 States had adopted some form of suitability guidelines by 2002 and Chapter 5 of " Wall Street Instructors Long-term Care Partnerships online training course" https://www.wallstreetinstructors.com/ce/continuing_education/ltc8/id32.htm explains how suitability is assessed in the state of Florida.

[26]There is evidence that individuals anticipate their death. Poterba et al. (2011) have found that most retirees die with very little wealth, and Hendricks (2001) finds that most households receive very small or no inheritances. This assumption eliminates any desire for agents to use LTCI to insure survival risk.

and receive the private LTCI indemnity. NH entrants may also receive benefits from the public means-tested LTCI program (Medicaid). Medicaid is a secondary insurer in that it guarantees a consumption floor of $\underline{c}_{NH}$ to those who experience a NH shock and have low wealth and low levels of private insurance.

An individual of type $(f, \mathbf{w})$ solves the following maximization problem, where the dependence of choices and contracts on $f$ and $w$ is omitted to conserve notation,

$$U_1(f, \mathbf{w}) = \max_{a \geq 0, c_y, \mathbf{c}_{NH}, \mathbf{c}_o} u(c_y) + \beta U_2(a),$$

with

$$U_2(a) = \left[\psi u_2(a, \theta^g_{f,\mathbf{w}}, \pi^g, \iota^g) + (1-\psi) u_2(a, \theta^b_{f,\mathbf{w}}, \pi^b, \iota^b)\right],$$

and

$$u_2(a, \theta^i, \pi^i, \iota^i) = \int_{\underline{\kappa}}^{\overline{\kappa}} \Big\{ u(\kappa w_y) + \alpha \Big[ s_{f,\mathbf{w}} \big(\theta^i u(c^{i,\kappa}_{NH}) + (1-\theta^i) u(c^{i,\kappa}_o)\big) + (1 - s_{f,\mathbf{w}}) u(c^{i,\kappa}_o) \Big] \Big\} q(\kappa) d\kappa,$$

subject to

$$\begin{aligned}
&c_y = w_y - a, \\
&c^{i,\kappa}_o + \kappa w_y = w_o + (1+r)a - \pi^i(a), \\
&c^{i,\kappa}_{NH} + \kappa w_y = w_o + (1+r)a + TR(a, \pi^i(a), \iota^i(a), m, \kappa) - \pi^i(a) - m + \iota^i(a)
\end{aligned}$$

where $i \in \{g, b\}$, and $\alpha$ and $\beta$ are subjective discount factors. The parameter $\beta$ captures discounting between the time individuals enter the working-age and the time of retirement, and the parameter $\alpha$ captures discounting between the time of retirement and the time of NH entry. The Medicaid transfer is

$$TR(a, \pi, \iota, m, \kappa) = \max\left\{0, \underline{c}_{NH} - \left[w_o + (1+r)a - \kappa w_y - \pi - m + \iota\right]\right\},$$

and $r$ denotes the real interest rate.

In the U.S. retirees with low means also receive welfare through programs such as the Supplemental Security Income program. We capture these programs in a simple way. After solving the agent's problem above, which assumes that there is only a consumption floor in the NH state, we check whether they would prefer, instead, to save nothing and consume the following consumption floors: $\underline{c}_{NH}$ in the NH state and $\underline{c}_o$ in the non-NH state. If they do, we allow them to do so and assume that they do not purchase LTCI.[27]

[27] Modeling the Supplemental Security Income program in this way helps us to generate the low levels of savings of individuals in the bottom wealth quintile without introducing additional nonconvexities into the insurer's maximization problem.

### 3.3.2 Insurer's problem

The insurer observes each individual's endowments $\mathbf{w}$, frailty status $f$, and assets $a$. He does not observe an individual's true NH entry probability, $\theta^i_{f,\mathbf{w}}$, but knows the distribution of NH risk in the population and the individual's survival risk $s_{f,\mathbf{w}}$. We assume that the insurer does not recognize that asset holdings depend on $\mathbf{w}$ and $f$ via household optimization. We believe that this is realistic because most individuals purchase private LTCI relatively late in life. Note that the demand shock, $\kappa$, is realized after LTCI is contracted.

The insurer creates a menu of contracts $\left(\pi^i_{f,\mathbf{w}}(a), \iota^i_{f,\mathbf{w}}(a)\right)$, $i \in \{g, b\}$ for each group of observable types that maximizes expected revenues taking into account that individual's face survival risk after insurance purchase. His maximization problem is

$$\Pi(h, \mathbf{w}, a) = \max_{(\pi^i_{f,\mathbf{w}}(a), \iota^i_{f,\mathbf{w}}(a))_{i\in\{g,b\}}} \psi\Big\{\pi^g_{f,\mathbf{w}}(a) - s_{f,\mathbf{w}}\theta^g_{f,\mathbf{w}}\left[\lambda\iota^g_{f,\mathbf{w}}(a) + \gamma I(\iota^g_{f,\mathbf{w}}(a) > 0)\right]\Big\}$$

$$+ (1-\psi)\Big\{\pi^b_{f,\mathbf{w}}(a) - s_{f,\mathbf{w}}\theta^b_{f,\mathbf{w}}\left[\lambda\iota^b_{f,\mathbf{w}}(a) + \gamma I(\iota^b_{f,\mathbf{w}}(a) > 0)\right]\Big\}$$

subject to the incentive compatibility and participation constraints

$$(IC_i) \quad u_2(a, \theta^i_{f,\mathbf{w}}, \pi^i_{f,\mathbf{w}}(a), \iota^i_{f,\mathbf{w}}(a)) \geq u_2(a, \theta^i_{f,\mathbf{w}}, \pi^j_{f,\mathbf{w}}(a), \iota^j_{f,\mathbf{w}}(a)), \quad \forall i, j \in \{g, b\}, i \neq j$$

$$(PC_i) \quad u_2(a, \theta^i_{f,\mathbf{w}}, \pi^i_{f,\mathbf{w}}(a), \iota^i_{f,\mathbf{w}}(a)) \geq u_2(a, \theta^i_{f,\mathbf{w}}, 0, 0), \quad \forall i \in \{g, b\}.$$

Let $\tilde{h}(f, \mathbf{w}, a)$ denote the measure of agents with frailty status $f$, endowment $\mathbf{w}$, and asset holdings $a$. Then total profits for the insurer are given by

$$\Pi = \sum_{\mathbf{w}} \sum_{f} \sum_{a} \Pi(f, \mathbf{w}, a)\tilde{h}(f, \mathbf{w}, a).$$

# 4 Parametrization

Parametrizing the model proceeds in two stages. In the first stage we calibrate parameters that can be assigned to values using data without computing the model equilibrium. In the second stage we set the remaining parameters by minimizing the distance between target moments calculated using data and their model counterparts.[28] We do not formally estimate the model due to its computational intensity. To capture cross-sectional variation in income and frailty in the data, we allow for 150 different income levels and 5 different frailty levels or a total of 750 risk groups. Thus, 750 distinct optimal menus need to be computed, and solving for an optimal menu often requires computing several candidate solutions due to non-convexities.[29]

[28]In Section 6.5 we summarize the results from a series of robustness exercises that explore the implications of alternative parametrizations.

[29]See Section 3 and 4 of the appendix for more details on the computation and a table that summarizes the model parametrization.

## 4.1 Highlights of our parametrization strategy

Our main objective is to understand the relative contributions of administrative costs, Medicaid, and asymmetric information in producing low LTCI takeup rates. We can use direct estimates based on data to pin down the scale of administrative costs and Medicaid in our model. However, our direct measure of private information, self-reported NH entry risk, is noisy. We deal with this issue by parameterizing the model in the following way. First, we assume that administrative costs are identical in all risk groups. Second, we fix the parameters that govern the scale of administrative costs and Medicaid to reproduce the scale of these two factors in the U.S. LTCI market. Third, we fix the overall dispersion in actual NH entry probabilities to reproduce the overall dispersion in self-reported NH entry risk. Finally, we vary the dispersion of private information across risk groups to match the cross sectional pattern of LTCI takeup rates and NH entry rates in our data.

The parameters that govern the scale of Medicaid and administrative costs use data targets from multiple sources. The scale of Medicaid is determined by the consumption floor provided to recipients and also the distribution of wealth at the point of NH entry because Medicaid benefits are means tested. We set the Medicaid NH consumption floor to the value used by Brown and Finkelstein (2008) which is based on the dollar value of transfers to Medicaid NH residents. Recall that the $\kappa$ shock determines the distribution of wealth at the point of NH entry. We choose the mean of the $\kappa$ shock distribution to reproduce the ratio of average wealth at NH entry to average wealth at the time of private insurance purchase, and the variance to reproduce the same ratio for quintile 5. We use the ratio of quintile 5's wealth to pin-down the variance because the extent to which higher wealth individuals have access to Medicaid is key to the relative importance of Medicaid versus the two supply-side frictions in accounting for the extent of private insurance. Individuals with low wealth at the time of insurance purchase are already very likely to get Medicaid benefits in the event of NH entry regardless of the size of their $\kappa$ shock.

We set the administrative costs using industry-level data provided by the Society of Actuaries. The fixed cost $\gamma$ and variable cost parameter $\lambda$ are chosen so that the model reproduces industry-level average fixed and variable costs faced by insurers.

Having fixed the scale of Medicaid and administrative costs, the next step is to parametrize the distribution of private information. We set the fraction of good types, $\psi$, such that the overall dispersion in private information in the model is consistent with estimates based on the data. The only direct measure of private information in HRS data is respondents' self-reported probabilities of entering a NH within the next 5 years. We set $\psi$ such that the coefficient of variation of NH entry probabilities in the model matches the coefficient of variation of self-reported NH entry probabilities in the HRS data.[30]

The NH entry probabilities conditional on survival within each risk group, $\{\theta^b_{f,\mathbf{w}}, \theta^g_{f,\mathbf{w}}\}$, are pinned-down using data on NH entry by frailty and permanent earnings (PE) and data

[30]Ideally, we would like to use data on dispersion in self-reported NH entry risk by frailty and wealth to pin down the variation in dispersion across risk groups. However, this measure of private information is noisy, especially as sample sizes decline, and does not measure individuals' lifetime NH entry risk. For these reasons, we do not use it to parametrize $\{\theta^b_{f,\mathbf{w}}, \theta^g_{f,\mathbf{w}}\}$. Instead, in Section 5, we use this data to assess our parametrization.

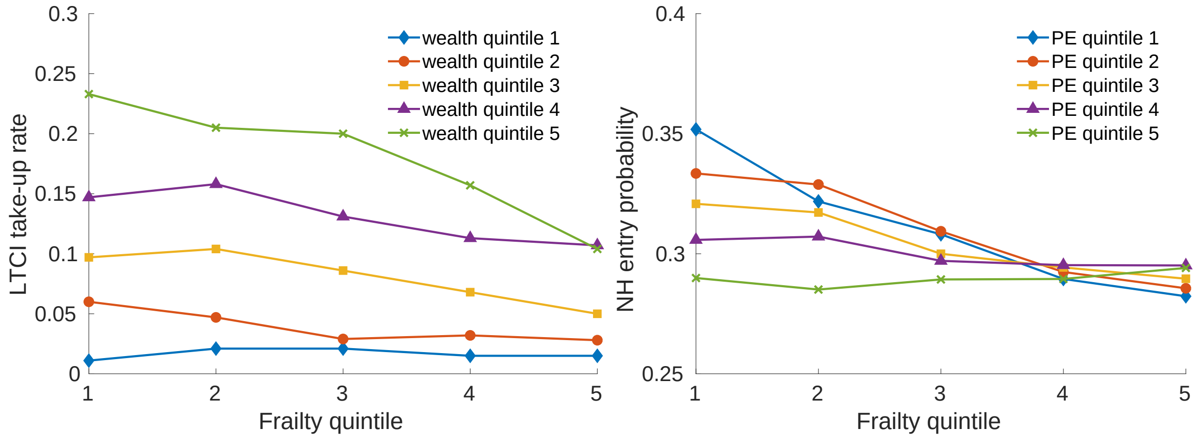



Figure 4. LTCI takeup rates by wealth and frailty quintiles (left panel) and the probability that a 65-year old will ever enter a NH by frailty and PE quintiles (right panel). LTCI takeup rates are for 62–72 year-olds in our HRS sample. NH entry probabilities are for a NH stay of at least 100 days and are based on our auxiliary simulation model which is estimated using HRS data. Frailty, wealth, and PE all increase from quintile 1 to quintile 5. The wealth quintiles reported here are marginal and not conditional on the frailty quintile, so for example only around 7% of people in frailty quintile 1 are in wealth quintile 1, while 33% are in wealth quintile 5.

on LTCI takeup rates by frailty and wealth.[31] The left panel of Figure 4 shows the LTCI takeup rates of HRS respondents by frailty and wealth quintiles. LTCI takeup rates are low, 9.4% on average, decline with frailty and increase with wealth.[32] The right panel of Figure 4 shows how the lifetime NH entry probability of a 65 year-old varies across frailty and PE quintiles.[33] Notice that NH entry risk does not vary much with frailty within each PE quintile. It is essentially flat in PE quintiles 4 and 5, and decreases slightly in quintiles 1–3. Also notice that NH entry does not vary much by PE within frailty quintiles. It is slightly decreasing in PE in frailty quintiles 1–3, and there is essentially no variation in frailty quintiles 4 and 5. These patterns occur because frailty and PE are good indicators of both NH entry risk and mortality risk.

To illustrate how the model adjusts $\{\theta^b_{f,\mathbf{w}}, \theta^g_{f,\mathbf{w}}\}$ to simultaneously account for the patterns of NH entry and LTCI takeup, consider PE/wealth quintiles 4 and 5. LTCI takeup rates decline with frailty in these two quintiles but the mean probability of NH entry does not vary. The only way to generate both of these patterns in the model is if the dispersion in private information, and thus the severity of the adverse selection problem, increases

[31]We use annuitized income to proxy for PE and assign individuals the annuitized income of their household head. See Section 2 of the appendix for details.

[32]The pattern of LTCI takeup rates by frailty and wealth is robust to controlling for marital status and whether or not individuals have any children. See Section 2.4 of the appendix for details.

[33] Lifetime NH entry probabilities by frailty and PE quintile groups were obtained using an auxiliary simulation model similar to that in Hurd et al. (2014) and our HRS data. All NH entry probabilities are probabilities of experiencing a long-term (at least 100 day) NH stay. We focus on long-term NH stays because stays of less than 100 days are heavily subsidized by Medicare.

with frailty within these two PE/wealth quintiles. In other words, the dispersion in NH entry probabilities conditional on surviving, $\{\theta^g_{f,\mathbf{w}}, \theta^b_{f,\mathbf{w}}\}$, must go up. To provide a second example, observe that, in frailty quintiles 4 and 5, LTCI takeup rates increase with wealth but mean NH entry probabilities do not vary with PE. To account simultaneously for these two observations, the dispersion in $\{\theta^g_{f,\mathbf{w}}, \theta^b_{f,\mathbf{w}}\}$ must decline with PE/wealth in these frailty quintiles.

Our strategy for parametrizing $\psi$ and $\{\theta^g_{f,\mathbf{w}}, \theta^b_{f,\mathbf{w}}\}$ allows us to determine the extent to which low LTCI takeup rates are due to choice menus offered to insurable risk groups versus risk-group selection. To see this, consider two alternative schemes for matching the pattern of takeup rates in the data. The first scheme is to have a large differential in NH entry between good and bad types (large $\theta^b$ to $\theta^g$ ratios within each risk group), but few bad types (a high $\psi$). The second scheme is to have many bad types (a low $\psi$), but a smaller differential in NH entry between good and bad types (small $\theta^b$ to $\theta^g$ ratios within each risk group). In our model, coverage denials play a relatively larger role in generating low takeup rates under the first scheme, while choice menus play a relatively larger role under the second. Risk group denials play a larger role under the first scheme because the large differential between $\theta^b$ and $\theta^g$ makes cross-subsidizing menus unprofitable but large $\theta^b$ also makes choice menus unprofitable. Choice menus in insurable risk groups play a larger role under the second scheme because the large fraction of bad types makes cross-subsidizing menus unprofitable, but lower $\theta^b$ means the insurer can still make profits by insuring bad types on their own. Thus, choice menus are still profitable.

Consistently, in Section 6.5, we document that lowering $\psi$ and then reparametrizing $\{\theta^g_{f,\mathbf{w}}, \theta^b_{f,\mathbf{w}}\}$ to match the LTCI takeup rates results in a higher fraction of individuals being offered choice menus. However, this second scheme also produces too little overall dispersion in private information. In practice, the reduction in dispersion due to reducing the ratios of $\theta^b$ to $\theta^g$ within risk groups dominates the increase in dispersion due to reducing $\psi$. Thus, by reproducing the overall dispersion in private information in the data we are able to identify the relative role of risk-group selection versus choice menus in generating low LTCI takeup rates.

## 4.2 Functional forms and first stage calibration

We assume constant-relative-risk-aversion utility such that

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}.$$

Individuals cover a substantial fraction of NH expenses using their own resources. Given the size of these expenses, it makes sense to assume that households are risk averse and thus willing to pay a premium to avoid this risk. A common choice of the risk aversion coefficient in the macroeconomics incomplete markets literature is $\sigma = 2$. We use this value.

The distribution of frailty in the model is calibrated to replicate the distribution of frailty of individuals aged 62–72 in our HRS sample. We focus on 62–72 year-old individuals because frailty is observed by the insurer at the time of LTCI purchase. In our HRS sample, the frailty of 62–72 year-old individuals is negatively correlated with their PE. To capture this feature of the data we assume that the joint distribution of frailty and the endowment stream,

TABLE I. Mean frailty by PE quintile in the data and the model.

| | PE Quintile 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Data | 0.23 | 0.22 | 0.19 | 0.17 | 0.15 |
| Model | 0.23 | 0.20 | 0.19 | 0.17 | 0.15 |

Data source: Authors' calculations using our HRS sample.

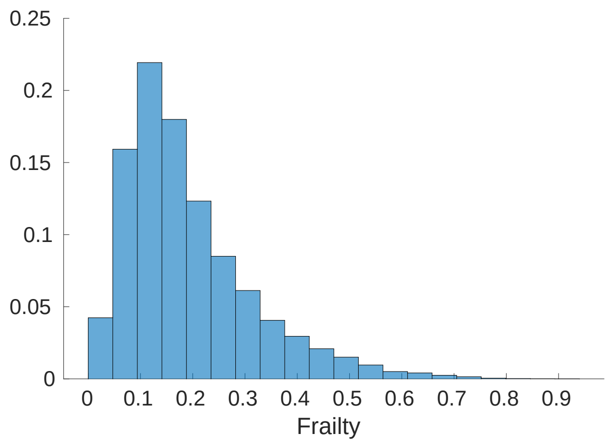



Figure 5. Distribution of frailty for 62–72 year-olds in our HRS sample. Severity of frailty is increasing with the index value and the maximum is normalized to one.

$h(f, \mathbf{w})$, is a Gaussian copula. This distribution has two attractive features: the marginal distributions do not need to be Gaussian and the dependence between the two marginal distributions can be summarized by a single parameter $\rho_{f,\mathbf{w}}$. The value of this parameter is set to $-0.29$ so that the variation in mean frailty by PE quintile in the model is as observed in the data. Table I shows the data values and model counterparts.

Figure 5 shows the empirical frailty distribution. We approximate it using a beta distribution with $a = 1.54$ and $b = 6.30$. The parameters of the distribution are chosen such that mean frailty in the model is 0.19 and the Gini coefficient of the frailty distribution is 0.34, consistent with their counterparts in the data. When computing the model, we discretize frailty into a 5-point grid. We use the mean frailty of each quintile of the distribution as grid values.

The marginal distribution of endowments is assumed to be log-normal. We equate endowments to the young with permanent earnings and normalize the mean young endowment to 1. This is equivalent to a mean permanent earnings of \$1,049,461 in year 2000 which is approximated as average earnings per adult aged 18–64 in year 2000 multiplied by 40 years.[34] The standard deviation of the log of endowments to the young is set to 0.8 because it implies that the Gini coefficient for the young endowment distribution is 0.43. This value

[34]To derive average earnings per adult aged 18-64 in year 2000 we divide aggregate wages in 2000 taken from the Social Security Administration by number of adults aged 18-64 in 2000 taken from the U.S. Census.

is consistent with the Gini coefficient of the permanent earnings distribution for individuals 65 and older in our HRS sample.

Endowments to the old are a stand in for retirement income which is comprised primarily of income from social security and private pension benefits. We assume that the income replacement ratio (retirement income relative to pre-retirement income) is linear in logs. Purcell (2012) calculates income replacement ratios for HRS respondents. Using his calculations, we set the level and slope of the replacement rate function such that the median replacement rate of retirees in the bottom pre-retirement income quartile is 64% and the median rate for retirees in the top quartile is 50%.[35] The resulting average replacement rate in the baseline economy is 57%.

The consumption demand shock, $\kappa$, captures the uncertainty individuals face at the time of LTCI purchase about their resources later in life when a NH event may occur. This uncertainty is, in part, due to uncertainty about the date of NH entry itself. Since the distribution of NH entry ages is left-skewed, we assume that the distribution of the $\kappa$ shock, $q(\kappa)$, is also left-skewed.[36] This is achieved by setting $q(\kappa)$ such that $1-\kappa$ has a truncated log-normal distribution over $[0.2, 0.8]$.[37] The mean and variance of $\kappa$, $\mu_\kappa$ and $\sigma_\kappa^2$, are determined in the second stage.

We estimate the risk of a long-term stay in a NH using HRS data and the questions in that survey do not distinguish between stays in skilled nursing facilities (SNF) and stays in assisted living communities or residential care centers (RCC). Thus, when estimating the average cost of a NH stay we take a weighted average of SNF and RCC expenses. In practice residential LTC expenses have two components. The first component is nursing and medical care and the second component is room and board. We interpret the room and board component as being part of consumption and thus a choice and not an expense shock. Using data from a variety of sources, we estimate that the average medical and nursing expense component of residential LTC costs was $32,844 per annum in 2000 and the average benefit period was 2.976 years. Multiplying the annual medical and nursing cost by the average benefit period yields total medical expenses of $97,743 or a value of $m$ of 0.0931 when scaled by mean permanent earnings.[38]

We set the consumption floor provided by Medicaid, $\underline{c}_{NH}$, and the consumption floor for those who do not enter a NH, $\underline{c}_o$, to the same value: $6,540 a year. As mentioned above, this value is taken from Brown and Finkelstein (2008) and consists of a consumption allowance of $30 per month and housing and food expenses of $515 per month. The former number is based on Medicaid administrative rules and the latter figure was the monthly amount that SSI paid a single elderly individual in 2000. We assume that the third period of the model has the same length as the average duration of long-term NH stays. Thus, we multiply the annual consumption floor by 2.976 years to come up with the total size of the consumption floor. The resulting value of $c_{nh}$ is 1.855% of mean permanent earnings.

Having calibrated the joint distribution of frailty and the endowment stream, $h(f, \mathbf{w})$, we use it to assign individuals in the model to frailty and PE quintiles, and thereby partition

[35] These estimates are the median replacement rates of retirees who have been retired for at least 6 years. See Purcell (2012), Table 4.

[36] Murtaugh et al. (1997) estimate the distribution of NH entry ages.

[37] The baseline parametrization is robust to expanding the range of $\kappa$ values within $[0, 1]$.

[38] See Section 4 of the appendix for details and data sources.

the population into 25 groups, one for each frailty/PE quintile combination. To reduce the number of parameters, we assume that individuals within the same group have the same survival probability $s_{f,\mathbf{w}}$ and the same set of NH entry probabilities $\{\theta^b_{f,\mathbf{w}}, \theta^g_{f,\mathbf{w}}\}$.[39]

The 25 survival probabilities are set to the probability that a 65 year-old will survive to either age 80 or until a NH event occurs.[40] We use survival until age 80 *or* a NH event because this way, regardless of which one we target, our parametrized model will match both the unconditional NH entry probabilities reported in Figure 4 and NH entry probabilities conditional on survival which we report in Section 4 of the appendix. The resulting survival probabilities of each frailty and PE quintile are also reported in the appendix. Not surprisingly, the relationship between frailty and survival is negative in all PE quintiles.

Finally, the risk-free real return, $r$, is not separately identified from the preference discount factor $\beta$. We normalize it to 0% per annum.[41]

### 4.3 Second stage: simulated moment matching strategy

The set of parameters left to pin down are the preference discount factors $(\beta, \alpha)$, the consumption shock distribution parameters $(\mu_\kappa, \sigma_\kappa)$, the administrative cost parameters $(\lambda, \gamma)$, the fraction of good types $\psi$, and the 25 NH entry probability pairs: $\{\theta^b_{f,\mathbf{w}}, \theta^g_{f,\mathbf{w}}\}$ for each frailty/PE quintile combination. These parameters are chosen to minimize the distance between equilibrium moments of the model and their data counterparts. Even though all of these parameters are chosen simultaneously through the minimization procedure, each parameter has a specific targeted moment.

The preference discount factor, $\beta$, in conjunction with the interest rate and $\sigma$ determines how much people save for retirement. It is chosen such that the model reproduces the average wealth of 62–72 year olds in our HRS sample relative to average lifetime earnings. This value is 0.222 in the data and 0.229 in the model. The resulting annualized value of $\beta$ is 0.94.[42]

On average individuals in our dataset enter a NH at age 83 or about 18 years after they retire. The parameter $\alpha$ captures the discounting between the age of retirement and LTCI purchase, and the age when a NH event is likely to occur. The more that individuals discount the NH entry period, the larger the fraction of NH residents who will be on Medicaid. Thus our choice of $\alpha$ targets the Medicaid recipiency rate of NH residents in our HRS sample. The target rate is 46%, the model rate is 48%, and the value of $\alpha$ is 0.20.[43] Eighteen years between age 65 and NH entry implies that the annualized value of $\alpha$ is 0.91.

We set the consumption shock distribution parameters, $(\mu_\kappa, \sigma_\kappa)$, to target two data facts. The first data target is the average wealth of NH entrants immediately before entering the

[39] We wish to emphasize that these groups are not risk groups because individuals in a given group are not identical to the insurer. The insurer observes 150 distinct levels of permanent earnings and thus will offer different menus to individuals in a given group.

[40] Survival probabilities by frailty and PE quintiles are estimated using HRS data and our auxiliary simulation model. See footnote 33.

[41] This normalization only impacts the value of $\beta$ and for our analysis, which does not involve any welfare calculations, is innocuous.

[42] Our choice of this age group is based on two considerations. First, if we limit attention to those aged 65 we would only have a small number of observations. Second, the average age when individuals purchase LTCI in our sample is 67 and this is the midpoint of the interval we have chosen.

[43] Our Medicaid recipiency rate target is lower than other estimates. But, this reflects the fact that in

TABLE II. LTCI takeup rates by wealth and frailty: data and model

| Frailty Quintile | Data | | | Model | | |
|---|---|---|---|---|---|---|
| | Wealth Quintile | | | Wealth Quintile | | |
| | 1–3 | 4 | 5 | 1–3 | 4 | 5 |
| 1 | 0.071 | 0.147 | 0.233 | 0.073 | 0.145 | 0.245 |
| 2 | 0.065 | 0.158 | 0.205 | 0.069 | 0.165 | 0.202 |
| 3 | 0.049 | 0.131 | 0.200 | 0.048 | 0.128 | 0.245 |
| 4 | 0.037 | 0.113 | 0.157 | 0.032 | 0.122 | 0.151 |
| 5 | 0.025 | 0.107 | 0.104 | 0.029 | 0.102 | 0.118 |

Frailty quintile 5 has the highest frailty and wealth quintile 5 has the highest wealth. We merge wealth quintiles 1–3 because takeup rates are very low for these individuals. Data source: 62–72 year olds in our HRS sample.

NH relative to the average wealth of 62–72 year olds. This ratio is 0.62 in our dataset and 0.68 in our model.[44] The second data target is the ratio of average wealth in quintile 5 of NH entrants immediately before entering the NH relative to the average wealth in quintile 5 at age 62–72. The ratio is 0.70 in our dataset and 0.66 in the model. The resulting mean and standard deviation of the the distribution of $\kappa$ are respectively 0.60 and 0.071.

As discussed in Section 2, LTC insurers incur large administrative costs because they conduct extensive medical underwriting and pay large commissions to the brokers who sell their products. We divide administrative costs into a fixed and variable cost component. Eaton (2016) reports that fixed administrative costs, which include underwriting costs and costs of paying claims, were 20% of present-value premium on average in 2000. Variable costs consist of commissions paid to agents and brokers. They amounted to 12.6% of present-value premium on average in 2000. We choose $\gamma$ and $\lambda$ to reproduce these targets. The resulting values of $\gamma$ and $\lambda$ are 0.019 and 1.195, respectively.

The coefficient of variation of self-reported 5-year NH entry probabilities is 0.94 in the HRS data.[45] We choose the fraction of good types, $\psi$, such that the coefficient of variation of NH entry probabilities in the Baseline economy replicates this value. The resulting value of $\psi$ is 0.709.

As we explained above, we assume that individuals within the same frailty and PE quintiles have the same set of NH entry probabilities, $\{\theta^b_{f,\mathbf{w}}, \theta^g_{f,\mathbf{w}}\}$. We pin down these 25 NH entry probability pairs using two sets of targets. The first set of targets are the 25

our HRS sample a NH stay includes a stay in an RCC and Medicaid takeup rates are much lower in RCC facilities. For instance, data from the CDC national survey of LTC providers (see Harris-Kojetin et al. (2016)) reports that 63% of individuals in skilled nursing facilities receive Medicaid benefits but only 15% of individuals in RCC facilities receive Medicaid benefits. According to Spillman and Black (2005), 36% of NH residents are in RCC facilities. These numbers imply a similar Medicaid takeup rate of 48%.

[44] To calculate this number in the data, we average the wealth of NH entrants in the wave that precedes their NH entry wave.

[45] This is the value when we do not count reports of 0, 50% or 100%. Including these additional observations in any combination slightly increases the coefficient of variation. In Section 6.5, we discuss the robustness of our results to this choice of data target.

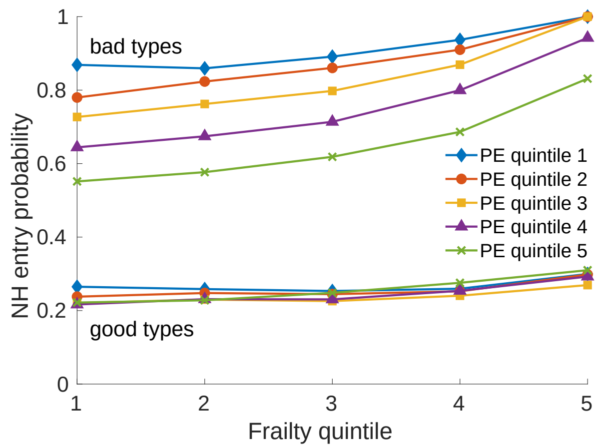



Figure 6. Nursing home entry probabilities conditional on surviving for good and bad types by frailty and PE quintile in the Baseline economy.

probabilities of entering a NH for a lifetime stay by frailty/PE quintile combination reported in the right panel of Figure 4. By targeting these probabilities we are ensuring that the average NH entry probability in each frailty/PE quintile group replicates its estimated value based on the HRS data. The second set of targets are the 15 LTCI takeup rates of individuals in all combinations of quintiles 1–3, 4, and 5 of the wealth distribution and quintiles 1 through 5 of the frailty distribution reported in the lower panel of Table II. In order to identify these 50 parameters using only 40 moments, we assume that the ratio of NH entry probabilities within a risk group is constant across wealth quintiles 1–3 within each frailty quintile.[46] Our decision to restrict the parameters in this way is based on two considerations. First, recall from Figure 4 that only a very small number of individuals in quintiles 1 and 2 have LTCI in our dataset. Second, in the model, no individuals in these quintiles buy LTCI because they are guaranteed to get Medicaid if they incur a NH event.[47] The resulting NH entry probability pairs are displayed in Figure 6. Observe that the dispersion in the $\theta's$ increases with frailty but declines with PE. From this we see that the model is indeed assigning a bigger role to private information in frail and poor risk groups as we suggested in Section 4.1.

Table II reports the 15 LTCI takeup rates in the Baseline economy. The fit of the model is not perfect due to the fact that we discretize the state space to compute the model. Note, however, that the takeup rates generated by the model increase with wealth and decline with frailty for both the rich and poor. The model also does a good job of reproducing the average LTCI takeup rate. In our HRS sample, 9.4% of retirees aged 62–72 have LTCI and in the model 9.7% of 65 year-olds have a nonzero LTCI contract. The fact that we are able

[46]Specifically, we assume that $\theta^b_{f,\mathbf{w}}/\theta^g_{f,\mathbf{w}}$ is constant across wealth quintiles 1–3 within each frailty quintile. This produces 10 restrictions such that, together with the 40 other moments, the 50 parameters are exactly identified.

[47]This difference between the model and the data is present for a variety of reasons including measurement error, our parsimonious specification of the Medicaid transfer function, and the fact that we have not modeled all shocks faced by retirees such as spousal death.

TABLE III. Standard deviation of self-reported (private) NH entry probabilities by frailty and permanent-earnings quintiles: data and model

| | Frailty Quintile | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Data | 1.00 | 1.00 | 1.03 | 1.27 | 1.47 |
| Model | 1.00 | 1.08 | 1.20 | 1.31 | 1.47 |
| | Permanent Earnings Quintile | | | | |
| | 1 | 2 | 3 | 4 | 5 |
| Data | 1.00 | 0.92 | 0.85 | 0.79 | 0.76 |
| Model | 1.00 | 0.96 | 0.91 | 0.78 | 0.59 |

The standard deviations (SDs) are normalized such that the SD of frailty quintile 1 is 1. Data values are SDs of self-reported probabilities of entering a NH in the next 5 years for individuals aged 65–72 excluding observations where the probability is 0, 100% or 50%. The pattern in the data is robust to variations in the way we construct the SDs including how we handle those reporting a probability of 0, 100% or 50%. Data source: Authors' calculations using our HRS sample.

to reproduce the average LTCI takeup rate suggests that the restrictions we have imposed on the $\theta^b_{f,\mathbf{w}}$'s for wealth quintiles 1-3 are broadly consistent with our data.

# 5 Assessing the model parametrization

**Dispersion of private information by frailty and permanent earnings.** One way to assess this aspect of our model is to provide independent evidence that dispersion in private NH entry probabilities, and thus the severity of the private information friction, increases with frailty and decreases with PE. The first and third rows of Table III report normalized standard deviations of self-reported NH entry probabilities for 65–72 year-old HRS respondents by frailty and PE quintile. These probabilities are not exactly comparable to the private NH entry probabilities in the model for two reasons. First, they are self-reported probabilities of NH entry in the next 5 years whereas the model values are lifetime NH entry probabilities. Second, the self-reported probabilities are noisy and in some instances sensitive to how one cleans the data. For instance, 1/3 of respondents report 0.5 and another third report either 0 or 1 in the raw data. We choose to omit these responses. The second and fourth rows of the table report the distribution of private NH entry probabilities by frailty and PE quintile that emerge from the model. Despite the noise, the dispersion of private information is increasing in frailty and decreasing in PE in both the data and the model. This pattern of dispersion is consistent with Hendren (2013)'s findings, discussed in Section 2.2, that adverse selection is more severe among individuals that are more likely to denied coverage by LTC insurers. Notice finally that the magnitudes of the normalized standard deviations in the model are reasonably close to their corresponding values in the data.

TABLE IV. Distribution of insurance across NH residents: data and model

| | LTCI | Medicaid | Both | Neither |
|---|---|---|---|---|
| Data | 8.1 | 45.6 | 1.4 | 44.2 |
| Model | 9.5 | 47.6 | 0.3 | 42.6 |

Percent of NH residents covered by LTCI only, Medicaid only, both, or neither in the data and the model. Data source: Authors' calculations using our HRS sample.

**Distribution of insurance.** Table IV shows the distribution of insurance across NH residents in the model and the HRS data. None of these moments were explicitly targeted when parametrizing the model. Yet, the fit between the model and data is very good. The model even predicts that some NH residents receive both private LTCI and Medicaid benefits. In the model, these are individuals who, ex-ante, bought LTCI because they would not be covered by Medicaid for all realizations of the demand shock but, ex-post, drew a realization of $\kappa$ that resulted in Medicaid eligibility.

**Pricing and coverage of LTCI.** Pricing and coverage statistics were not targeted when parametrizing the model. It is thus noteworthy that the average pricing and coverage levels of LTCI in our model are consistent with observations from the U.S. LTCI market. Recall that Brown and Finkelstein (2007) and Brown and Finkelstein (2011) find that the average load in the LTCI market is in the range 0.18 and 0.5, depending on whether or not the loads are adjusted for policy lapses in the sample period. The average load in our model at 0.41 falls in middle of this range. In Section 2 we explained that typical coverage levels for LTCI products range between one-third and two-thirds of expected lifetime NH expenses. Insurance contracts in our model offer indemnities that cover on average 58% of NH medical costs.

Brown and Finkelstein (2007) also find that the relationship between loads and comprehensiveness is non-monotonic and that for some individuals loads are negative. Table V, shows that average loads and coverage do not vary systematically with wealth. However, average loads are increasing in frailty and coverage levels are declining in frailty. Thus, frail individuals pay more for LTCI and receive less coverage according to the model.

Table V also reports coverage and loads by private information type. It is immediately clear from these results that, as in Stiglitz (1977), the insurer offers bad-risk types in insurable risk groups more coverage at a lower unit price. In virtually all wealth and frailty quintiles, bad types have negative loads indicating that they are getting a good deal relative to the actuarially fair benchmark. Good types, in contrast, have large and positive loads at all wealth and frailty quintiles. The combination of negative loads for bad types and positive loads for good types highlights the fact that the optimal contracts feature cross-subsidization. Revenues from good types are used by the insurer to subsidize contracts to bad types within a given risk group.

In the model, the insurer is free to create a separate menu for each risk group and, in equilibrium, offers hundreds of risk-group-specific menus. Table V indicates that, on the one

TABLE V. Comprehensiveness and individual loads by private type and frailty and wealth quintiles in the Baseline economy.

| | Wealth Quintile | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Average | | | | | |
| Fraction of NH costs covered | NA | NA | 0.552 | 0.607 | 0.581 |
| Load | NA | NA | 0.408 | 0.389 | 0.406 |
| Good risks ($\theta^g$) | | | | | |
| Fraction of NH costs covered | NA | NA | 0.507 | 0.507 | 0.514 |
| Load | NA | NA | 0.631 | 0.605 | 0.558 |
| Bad risks ($\theta^b$) | | | | | |
| Fraction of NH costs covered | NA | NA | 0.711 | 0.711 | 0.816 |
| Load | NA | NA | -0.082 | -0.046 | 0.056 |
| | Frailty Quintile | | | | |
| | 1 | 2 | 3 | 4 | 5 |
| Average | | | | | |
| Fraction of NH costs covered | 0.578 | 0.592 | 0.578 | 0.572 | 0.564 |
| Load | 0.400 | 0.394 | 0.405 | 0.409 | 0.414 |
| Good risks ($\theta^g$) | | | | | |
| Fraction of NH costs covered | 0.514 | 0.517 | 0.518 | 0.492 | 0.487 |
| Average load | 0.581 | 0.589 | 0.591 | 0.607 | 0.620 |
| Bad risks ($\theta^b$) | | | | | |
| Fraction of NH costs covered | 0.763 | 0.753 | 0.774 | 0.739 | 0.736 |
| Load | -0.004 | -0.005 | -0.017 | -0.020 | -0.031 |

The fraction of NH costs covered is the average indemnity divided by the medical and nursing expense cost of a nursing-home stay or $(\iota/m)$ for individuals with a positive amount of insurance. NA denotes cases where LTCI takeup rates are zero.

hand, these menus feature very different contracts for good versus bad private information types. On the other hand, the optimal contracts are quite similar across alternative wealth and frailty levels for a given private information type. For instance, coverage levels and loads for good types only vary by about 7 percentage points across wealth quintiles. It is consequently conceivable that modeling a small fixed cost for writing each distinct menu could result in a much smaller set of menus. We do not pursue this strategy here because introducing this type of fixed cost significantly complicates the insurer's problem.[48] Still, the results in Table V suggest that the incremental return associated with offering a custom menu to each risk group may be small.

[48]Finding the optimal set of menus with fixed menu costs is a challenging combinatorics problem because there are a very large number of risk groups and thus combinations of menus that have to be considered. For each posited set of menus one has to verify that each risk group's incentive-compatibility and participation constraints hold.

# 6 Results

## 6.1 LTCI takeup rates and denials

There are two different ways that low LTCI takeup can arise in the model. One way is through choice menus. Recall that a choice menu consists of two contracts: a non-zero contract and a $(0,0)$ contract. As we explained above, under these types of menus, good-risk types choose the no-insurance $(0,0)$ contract. The other way is via risk-group selection. Recall that risk-group selection will occur when all individuals in some risk groups are uninsurable and, hence, denied coverage by the insurer. It turns out that only 0.11% of individuals choose not to purchase LTCI. Thus, in the model, low LTCI takeup rates are primarily due to risk-group selection. Consistently, as the first column of Table VI shows, the denial rate in our Baseline economy is 90.1%. It is 100% for individuals in PE quintiles 1 and 2 and declines with permanent earnings in quintiles 3–5. However, the denial rates are non-monotonic among the highest PE individuals. Denial rates are only 58.8% among individuals in the top 5% of PE but then rise to 100% for those in the top 1%. Individuals with the highest PE prefer to self-insure NH risk.

The pattern of denials reported in the first column of Table VI is consistent with the estimates of denial rates that we reported in Section 2. Denial rates decline with wealth in both the model and the data. Denial rates in the model are much larger than our estimated denial rates reported in Section 2 which range from 36% to 56% for 55–66 year old HRS respondents. Our estimated denial rates only capture denials that arise as a result of information revealed during medical underwriting. However, there are other reasons why a risk group may be uninsurable. For instance, all individuals in healthy, but poor, risk-groups may be uninsurable because they know they will qualify for Medicaid. Similarly, all individuals in healthy, high- income risk-groups may be uninsurable because they prefer to self-insure since LTCI is costly to produce. Survey results in Ameriks et al. (2018) suggest that the high cost of LTCI is also an important reason for low takeup rates. In general, a risk group is uninsurable if no profitable positive insurance contract exists that at least one individual in the risk group is willing to take.

## 6.2 Insurance ownership and NH entry

Our finding on the quantitative significance of denials raises the possibility that empirical tests for adverse selection based on estimated correlations between insurance ownership and loss occurrence may have weak power. These tests are based on the standard theory of adverse selection with a single source of private information which predicts that, if adverse selection is present in the market, LTCI owners should have higher NH entry rates than non-owners (see Chiappori and Salanie (2000)). As we discussed in Section 2.2, Finkelstein and McGarry (2006) use these empirical tests to test for adverse selection in the U.S. LTCI market. They find that LTCI owners, if anything, have lower NH entry rates than non-owners. Their result is striking because they also find that individuals have private information about their NH risk and that they act on this risk by purchasing LTCI.

Finkelstein and McGarry (2006) conclude that, to reconcile their conflicting set of findings, there must be multiple sources of private information present in the U.S. LTCI market.

TABLE VI. Denial rates in the Baseline, the No Administrative Costs, the No Medicaid, and the Full Information Economies

| Scenario Description | Baseline | No Admin. Costs $\lambda = 1$, $\gamma = 0$ | No Medicaid $\underline{c}_{nh} = 0.001$ | Full Information $\theta^i_{f,\mathbf{w}}$ public |
|---|---|---|---|---|
| Average | 90.1 | 38.7 | 9.4 | 62.5 |
| By PE Quintile | | | | |
| 1 | 100 | 100 | 27.4 | 100 |
| 2 | 100 | 93.4 | 0.0 | 99.6 |
| 3 | 85.7 | 0.0 | 0.0 | 54.1 |
| 4 | 83.9 | 0.0 | 0.0 | 29.1 |
| 5 | 81.2 | 0.0 | 19.8 | 29.7 |
| High PE | | | | |
| top 10 | 75.1 | 0.0 | 39.5 | 30.4 |
| top 5 | 58.8 | 0.0 | 76.2 | 31.7 |
| top 1 | 100 | 0.0 | 100 | 100 |
| By receiving Medicaid NH benefits conditional on surviving | | | | |
| Would | 47.6 | 37.0 | 5.5 | 43.9 |
| Would not | 42.5 | 1.6 | 4.0 | 18.6 |

Denial rates are percentage of individuals who are only offered a single contract of $(0, 0)$ by the insurer. Note that, in the first nine rows, the figures are the percentage of individuals in that group. However, the bottom two rows of the table are a decomposition of the average denial rate for that economy.

Interestingly, our model with a single source of private information and an active extensive contracting margin generates each of their empirical results. First, Finkelstein and McGarry (2006) find a positive correlation between self-assessed NH entry risk and NH entry, even after controlling for observable health, and interpret this as evidence of private information. We have explicitly modeled private information and adverse selection and, as Figure 6 shows, our model delivers this correlation by construction. Second, they find that individuals act on their private information by documenting a positive correlation between self-assessed NH entry risk and LTCI ownership. The baseline economy has this property too. The LTCI ownership rate of bad types is 10.6% while the ownership rate of good types is 10.2%. Moreover, bad types have a higher LTCI ownership rate than good types no matter whether or how we control for the information set of the insurer, or whether or not we condition on survival. Third, the correlations between LTCI ownership and NH entry rates in the Baseline economy are small and can be negative. Table VII reports NH entry rates conditional on survival of LTCI owners and non-owners. Only 36.9% of LTCI owners in the Baseline economy enter a

[49] We believe that the NH entry rates conditional on survival are the most comparable to Finkelstein and McGarry (2006)'s findings given that they only look at NH entry within 5 years of observed LTCI ownership. That said, with no controls, our model still generates a negative, albeit smaller, correlation even if we do not condition on survival. The reason conditioning on survival matters is because it impacts the correlation between average NH entry and LTCI takeup rates across risk groups (see Figure 4).

TABLE VII. NH entry rates of LTCI owners and non-owners in the Baseline economy

| | | Frailty Quintile | | | | |
|---|---|---|---|---|---|---|
| | Average | 1 | 2 | 3 | 4 | 5 |
| LTCI owners | 36.9 | 33.4 | 36.0 | 37.2 | 41.2 | 47.5 |
| Non-owners | 40.7 | 35.9 | 37.9 | 40.1 | 43.0 | 49.1 |

Numbers are percent of survivors to the very old stage of life who enter a NH.

NH whereas 40.7% of non-owners enter, consistent with the negative correlation Finkelstein and McGarry (2006) find when they do not control for the insurer's information set.[49]

Chiappori and Salanie (2000) ascertain that to properly test for the presence of private information one must fully control for the information set of the insurer. Finkelstein and McGarry (2006) consider two different sets of controls. The first set only controls for observable variation in health. The second set controls for both observable health variables and individuals' wealth and income quartiles. In both cases, they find a small negative but not statistically significant correlation. Only when they consider a special sample of individuals who are in the fourth quartile of the wealth and income distributions and have no health issues that would likely lead them to be denied coverage by insurers do they find a statistically significant negative correlation.

Consistent with their findings, as Table VII shows, if we only control for frailty, we continue to find a negative correlation but the sizes of the differentials between the entry rates of non-owners and owners is smaller.[50,51] If, in addition to frailty, we also control for wealth and income quartile, the differences in the entry rates between non-owners and owners becomes even smaller.[52] In addition, the correlation is negative for precisely half of the groups and positive for the other half, and the average differential is essentially zero.[53] Finally, like Finkelstein and McGarry (2006), if we focus on individuals in the top wealth and income quartile and the lowest frailty quintile, we find a negative correlation between LTCI ownership rates and NH entry. The NH entry rate of LTCI owners in this group is 31.8% while the entry rate of non-owners is 32.2%.[54]

The intuition for our findings is as follows. First, to understand how the model produces small positive correlations between LTCI ownership and NH entry it is useful to return to

[50]We check for conditional independence of NH entry and LTCI ownership because Chiappori and Salanie (2000) point out that this strategy, which is the basis of their $\chi^2$ statistic, is more robust to nonlinearities.

[51]If we do not condition on survival, some of the differentials in the upper frailty quintiles flip sign but the absolute value of the difference in NH entry rates between owners and non-owners becomes even smaller.

[52]These results are not reported in the table because the number of groups is so large.

[53]Equally weighting each group, the average NH entry rate of LTCI owners is 0.07 percentage points higher than the entry rate of non-owners.

[54]One difference between the moments generated by our model and the statistics reported in Finkelstein and McGarry (2006) is that they compute correlations between LTCI ownership and NH entry within the 5 years after observing ownership. NH entry rates in our model are the lifetime rates. Alternatively, one could construct an empirical measure of lifetime NH entry risk to compare to our model results. However, this is not straightforward because lifetime NH risk of HRS respondents is not directly observable and would have to be estimated using an auxiliary model. This creates an additional source of noise and specification error. In our view it is best to compare our model results with the empirical findings of Finkelstein and McGarry (2006).

Figure 1 which shows the various types of optimal menus that can occur. Observe that only one of these types, the one displayed in Figure 1e, will generate a non-zero (positive) correlation between LTCI ownership and NH entry within a risk group. This menu features no insurance for good risks and positive insurance for bad risks. Under all the other optimal menus the correlation is zero because either both risk-types are insured or neither risk-type is insured. In other words, only optimal menus of the type illustrated in Figure 1e will provide identification of adverse selection using using an empirical test that relies on the correlation between LTCI ownership and NH entry. Now recall that only 0.11% of individuals are offered this type of menu in the Baseline economy. The fact that this type of menu is so infrequent means that the correlation test of adverse selection has low power in our model.

Second, to understand how the model produces negative correlations between LTCI ownership and NH entry recall that adverse selection is more pronounced in poor and frail risk groups and, consequently, denial rates, like NH entry rates, decrease in permanent earnings and increase in frailty. These facts create the possibility of finding a negative correlation if the information set of the insurer and econometrician are different such that the econometrician bunches two or more risk groups together. In this scenario, the negative correlation between LTCI ownership and NH entry across risk groups may dominate the positive correlations within risk groups. Given that very few risk groups in the Baseline economy feature a non-zero positive correlation, it is not surprising that when risk groups are bunched together a negative correlation is found.

A more effective way to test for adverse selection in our model would be to look at the correlation between NH entry and the comprehensiveness of LTCI coverage. All optimal menus with positive amounts of insurance have the property that bad-risk types have more coverage than good risk types. Unfortunately, the HRS data, which is the data used by both Finkelstein and McGarry (2006) and us, only has information on LTCI ownership, not on the comprehensiveness of coverage. However, even if data on comprehensiveness was available, the bunching effect would still be operative.

### 6.3 Why are LTCI takeup rates low?

We now turn to analyze the relative contributions of administrative costs, Medicaid and asymmetric information in producing low LTCI takeup rates. To help distinguish between them, we will compare the Baseline economy with three other economies. In each economy, endowments and the interest rate are held fixed at their baseline values. In the No Administrative Costs economy, we remove the insurer's variable and fixed costs by setting $\lambda = 1$ and $\gamma = 0$. In the No Medicaid economy, the NH consumption floor $\underline{c}_{NH}$ is reduced to 0.001.[55] Finally, in the Full Information economy, which is designed to understand the effects of private information, the insurer can directly observe each individual's true NH risk exposure, $\theta^i_{f,\mathbf{w}}$.

Column 2 of Table VI reports denial rates in the No Administrative Costs economy. When administrative costs are absent, the insurer no longer denies coverage to risk groups consisting of more affluent individuals. The average denial rate drops by 51.4 percentage

[55]We do not reduce $\underline{c}_{NH}$ to zero because then some individuals would experience negative consumption. Also note that the non-NH consumption floor, $\underline{c}_o$, does not vary across economies.

TABLE VIII. LTCI takeup rates by wealth and frailty: Baseline and Full Information economies

| | Baseline | | | Full Information | | |
|---|---|---|---|---|---|---|
| Frailty | Wealth Quintiles | | | Wealth Quintiles | | |
| Quintile | 3 | 4 | 5 | 3 | 4 | 5 |
| 1 | 0.183 | 0.145 | 0.245 | 0.565 | 0.709 | 0.694 |
| 2 | 0.175 | 0.165 | 0.202 | 0.512 | 0.709 | 0.709 |
| 3 | 0.142 | 0.128 | 0.245 | 0.418 | 0.709 | 0.708 |
| 4 | 0.111 | 0.122 | 0.151 | 0.409 | 0.709 | 0.711 |
| 5 | 0.111 | 0.102 | 0.118 | 0.413 | 0.709 | 0.699 |

The LTCI takeup rates in wealth quintiles 1 and 2 are zero in both economies.

points. Consistent with our result that the fraction of choice menus is small, LTCI takeup rates increase by about the same amount to 61%. All individuals in PE quintiles 3–5 now purchase LTCI. However, denial rates remain high in the two lowest PE quintiles.

Removing Medicaid, has the biggest overall impact on LTCI takeup rates. Denials fall by 80.7 percentage points and 90.6% of individuals purchase private insurance. Absent Medicaid, LTCI takeup rates are high among the poor as shown in column 3 of Table VI. The reason why denials still occur in PE quintile 1 stems from the fact that some individuals in that quintile are so poor that they cannot afford NH care and must rely on Medicaid even though the Medicaid consumption floor is extremely low. Interestingly, denial rates also decline among higher PE individuals when Medicaid is removed. Denials fall in PE quintiles 3–5 and also in the top decile. Removing Medicaid increases these individuals willingness-to-pay for private insurance because there are fewer states of nature where they qualify for Medicaid benefits. This result is consistent with previous findings by Braun et al. (2017) and De Nardi et al. (2016) who find that even high PE individuals value Medicaid. Finally, observe that denial rates actually increase in the top 5% PE group. Removing Medicaid increases saving and thus wealth at the time that individuals contract for LTCI. For individuals in the top 5% PE group, this effect is very pronounced. They have more wealth and thus are in a better position to self-insure.

Finally, consider the role of private information by comparing column 1 with the final column of Table VI. Absent private information, denial rates fall by 27.6 percentage points and LTCI takeup rates are now about 38%.[56] This increase in LTCI takeup rates is primarily due to higher takeup rates of more affluent individuals. The fraction of individuals denied coverage declines in PE quintiles 3–5 and also in the top 10% and top 5% PE groups. Removing private information increases profitability for the insurer because it can now price discriminate on the basis of true-risk exposure. This has a larger effect on takeup rates of higher income individuals because the option value of Medicaid is relatively small for them.

Administrative costs and private information have similar effects in that they both pri-

[56]Note that choice menus do not exist in the Full Information economy because each risk group is only offered one contract. Thus the denial rate in this economy is one minus the LTCI takeup rate.

marily impact the denial rates of higher PE individuals. This raises the following question. Is private information essential to generate the extent and pattern of denials, and hence LTCI takeup, observed in the data or could the model do just as well if we abstracted from it? Table VIII reports LTCI takeup rates in the Baseline and Full Information economies. The table shows that, not only does the presence of private information reduce the extent of LTCI takeup, but it also plays an important and unique role in allowing the model to account for the empirical pattern of LTCI takeup among affluent individuals. Notice that, in wealth quintiles 4 and 5 of the Full Information economy, the LTCI takeup rates exhibit the wrong pattern by frailty (see also Table II). LTCI takeup rates in these two wealth quintiles are declining in frailty in the data and the Baseline economy. However, in the Full Information economy, they are constant in frailty in wealth quintile 4 and hump-shaped in frailty in quintile 5. As we discuss in Section 6.5, even if we reparametrize the Full Information economy, it is unable to match both the level and pattern of LTCI takeup in the data. These findings show that the extent and pattern of private information in the market documented by Finkelstein and McGarry (2006) and Hendren (2013) is an important driver of low LTCI takeup rates and their correlation with frailty.

In the Baseline economy, like in the U.S., a substantial fraction of NH costs are paid for out-of-pocket. There are two reasons for this. First, as we explained in Section 4, very few NH residents have both LTCI and Medicaid, and LTCI contracts only provide partial coverage. Second, many individuals who do not purchase LTCI are too affluent to quality for Medicaid NH benefits and have no recourse but to pay for their NH care out-of-pocket. The bottom two rows of Table VI report statistics related to this second source of out-of-pocket payments. In these two rows, individuals in the model who are denied coverage by the insurer are divided into two groups: those who, if they survive to the very old age and enter a NH, would qualify for Medicaid NH benefits and those who would not. In the baseline economy, 42.5% of individuals denied coverage would be completely uninsured, if they enter a NH, because they would be too affluent to satisfy the Medicaid means test. This group pays all of their NH expenses out-of-pocket. Notice that the insurance coverage gap decreases substantially if either administrative costs or private information is absent. In the No Administrative Cost economy, only 1.6% of those who are denied coverage would end up paying for all their care out-of-pocket and, in the Full Information economy, only 18.6% of individuals would find themselves in this situation. The reason the coverage gap is so small in these two economies is because denial rates are much lower among high PE individuals. Thus most high PE individuals are covered by private LTCI, while less affluent individuals continue to receive extensive Medicaid coverage. These findings indicate that policies aimed at correcting supply-side distortions in the U.S. LTCI market could lead to large reductions in the fraction of individuals paying out-of-pocket for NH care.

## 6.4 Coverage, loads and profits

We now turn to consider the individual roles of Medicaid, administrative costs and private information in determining the pricing and comprehensiveness of coverage in insurable risk groups.

Table IX reports the LTCI takeup rates, fractions of NH costs covered, and loads on good and bad-risk types in the Baseline economy and the other three economies. The table reports the average value of each statistic and and a break down by private information type. Removing administrative costs produces savings to the insurer that get passed through to consumers in the form of higher comprehensiveness of coverage and lower loads. Allowing the insurer to directly observe private information type also increases comprehensiveness but average loads increase. Under full information, the insurer is able to extract the entire surplus, and both good and bad risks have binding participation constraints. Note that the load on bad risks increases substantially from -0.012 to 0.316 and this group's LTCI takeup rate falls. The intuition for this finding can be found in Arrow (1963) who demonstrates that the amount of insurance available to those with high risk exposures declines if insurance markets open after their risk exposure is observed.

Medicaid acts like a competitor to private insurance and removing it also allows the private insurer to extract more rents from individuals. This is reflected in higher loads on average and for each private information type in the No Medicaid economy. The pricing distortion is particularly large for good types who face a load of 0.717 in the No Medicaid economy versus 0.593 in the Baseline economy. However, they are compensated somewhat by higher comprehensiveness of coverage which increases by 9 percentage points. Takeup rates are very high in the No Medicaid economy. Lacking the outside option of Medicaid, 90.6% of good-risk and bad-risk types purchase LTCI. Finally, note that bad-risk types get a relatively good deal in this economy because the insurer is constrained in the amount of rents he can extract from them by the incentive compatibility constraint. The loads for bad risks are only 0.167 and their contracts cover 82.5% of NH expenses on average.

Brown and Finkelstein (2008) and Ameriks et al. (2018) use a different strategy to assess the roles of high loads, incomplete coverage and Medicaid in accounting for low LTCI takeup rates. Both of these papers specify contracts exogenously and consider counterfactuals in which individuals are offered full insurance against NH risk at an actuarially-fair price. Brown and Finkelstein (2008) find that only the top one-third of individuals, when ranked by wealth, purchase a full-coverage actuarially-fair LTCI policy when Medicaid is present. In other words, in their model Medicaid crowds-out the demand for LTCI by individuals in the bottom two-thirds of the wealth distribution. In our model contracts are endogenous and the insurer responds to Medicaid not only by adjusting the fraction of individuals who it insures but also by adjusting the comprehensiveness and pricing of the contracts.

As we now show, the crowding-out effect of Medicaid is much smaller when the insurer's optimal contracting problem is modeled. To illustrate this point, consider a version of our Baseline economy in which the two supply-side frictions — private information and administrative costs — are removed. Medicaid is present with the consumption floor set at the baseline level. Insurance is not actuarially fair in this scenario, the average load is 0.36, due to the fact that the insurer is a monopolist. Nevertheless, 61% of individuals purchase LTCI. Table X reports LTCI takeup rates, comprehensiveness of coverage and average loads by wealth and frailty quintiles in this alternative economy. LTCI takeup rates are 100% in wealth quintiles 3–5. Medicaid crowds out most private insurance in wealth quintile 2 and all private insurance in quintile 1. Wealth quintile 2 is particularly interesting because the load on insurance for this group is only 0.16 and thus reasonably close to the actuarially-fair benchmark. Yet, LTCI only covers half of the loss. These individuals are not interested in

[57] Recall that the optimal contracts have this same partial coverage property in the simple model.

TABLE IX. LTCI takeup rates, comprehensiveness and individual loads by private type in the Baseline, the No Administrative Costs, the No Medicaid, and the Full Information economies

| Scenario | Baseline | No Admin. Costs | No Medicaid | Full Information |
|---|---|---|---|---|
| Description | | $\lambda = 1$, $\gamma = 0$ | $\underline{c}_{nh} = 0.001$ | $\theta^i_{f,\mathbf{w}}$ public |
| Average | | | | |
| LTCI takeup rate | 0.097 | 0.610 | 0.906 | 0.375 |
| Fraction of NH costs covered | 0.582 | 0.629 | 0.662 | 0.839 |
| Load | 0.415 | 0.333 | 0.557 | 0.483 |
| Good risks ($\theta^g$) | | | | |
| LTCI takeup rate | 0.097 | 0.609 | 0.906 | 0.524 |
| Fraction of NH costs covered | 0.506 | 0.547 | 0.596 | 0.839 |
| Load | 0.593 | 0.538 | 0.717 | 0.484 |
| Bad risks ($\theta^b$) | | | | |
| LTCI takeup rate | 0.099 | 0.613 | 0.906 | 0.012 |
| Fraction of NH costs covered | 0.753 | 0.816 | 0.825 | 0.848 |
| Load | -0.012 | -0.162 | 0.167 | 0.316 |

The fraction of NH costs covered is the average indemnity divided by the medical expense cost of a nursing-home stay or $(\iota/m)$ for individuals with a positive amount of insurance.

a full-coverage private LTCI product because for some values of the demand shock they will qualify for Medicaid NH benefits.[57] Indeed, 96% of individuals in wealth quintile 2 prefer to rely exclusively on Medicaid.

Coverage levels are higher in the top two wealth quintiles. Individuals in quintile 4 receive extensive coverage (88% of the loss) and those in quintile 5 receive nearly full coverage with insurance covering 97% of the loss. For the latter group, the chance of receiving Medicaid NH benefits is particularly low and full coverage is attractive to them. This final property of the model is related to Ameriks et al. (2018). They find that 59% of individuals in a sample of affluent individuals with median wealth of $546,935 have demand for an ideal state-contingent LTCI product that is priced in an actuarially-fair manner. However, only 22% of their respondents hold LTCI and they refer to this as a "LTCI puzzle." For purposes of comparison, in our baseline model, average wealth in wealth quintile 5 is $695,000 and average wealth in quintile 4 is $304,000.[58] In our baseline economy, individuals in wealth quintiles 4–5 have LTCI takeup rates of 14% and 21%, respectively. Thus, we find that the LTCI puzzle that Ameriks et al. (2018) document for wealthy individuals can be attributed to supply-side distortions induced by private information and administrative costs.

We have focused on these two examples because they are the most relevant to our analysis. However, it is common practice in the literature to abstract from the contract design problem

[58]Both figures are expressed in terms of year 2000 dollars.

TABLE X. LTCI takeup rates, comprehensiveness, and individual loads in the economy with no private information and no administrative costs.

| | Wealth Quintile | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| LTCI takeup rates | 0.00 | 0.04 | 1.00 | 1.00 | 1.00 |
| Fraction of loss covered | NA | 0.50 | 0.61 | 0.88 | 0.97 |
| Average load | NA | 0.16 | 0.30 | 0.41 | 0.38 |
| | Frailty Quintile | | | | |
| | 1 | 2 | 3 | 4 | 5 |
| LTCI takeup rates | 0.75 | 0.67 | 0.62 | 0.57 | 0.44 |
| Fraction of loss covered | 0.85 | 0.83 | 0.80 | 0.77 | 0.80 |
| Average load | 0.42 | 0.42 | 0.41 | 0.40 | 0.43 |

NA denotes cases where the denominator is zero.

of the insurer when modeling the LTCI market. Some recent examples include Lockwood (2018) who analyzes optimal saving and bequests in a setting with exogenously specified LTCI and Mommaerts (2016) and Ko (2018) who analyze the informal care market under the assumption that an alternative option is an exogenously specified LTCI contract. It is conceivable that modeling the supply-side of the LTCI market would also provide new insights into saving decisions of the old in the presence of bequest motives and demand for informal care.

#### 6.4.1 Profits

In Section 2 we documented that profits in the U.S. private LTCI market are low. Profits are also low in our Baseline economy. They are 2.3% of revenues. The left panel of Figure 7, which reports the distribution of profits by frailty and PE quintiles in the Baseline economy, reveals that most profits come from insuring healthy rich individuals as most of the other risk groups are denied coverage and profits are thus zero. Medicaid, administrative costs and private information all work to reduce profits. Medicaid, however, has the largest impact. When it is removed profits rise to 28.5% of revenues.[59] The right panel of Figure 7 shows the distribution of profits by frailty and PE quintiles in the No Medicaid economy. In this economy, in contrast to the Baseline, the insurer generates most of his profits from the poor. Profits fall monotonically with permanent earnings and do not vary as much with frailty. Medicaid has a large effect on profits for two reasons. First, Medicaid's presence dramatically reduces the fraction of insurable risk groups. When Medicaid is removed the fraction of insurable risk groups increases sharply. Second, as we explained above in the discussion of loads, Medicaid also substantially lowers profit margins in insurable risk groups.

[59]Profits are 15.2% of revenues in the No Administrative Costs economy and 9.8% of revenues in the Full Information economy.

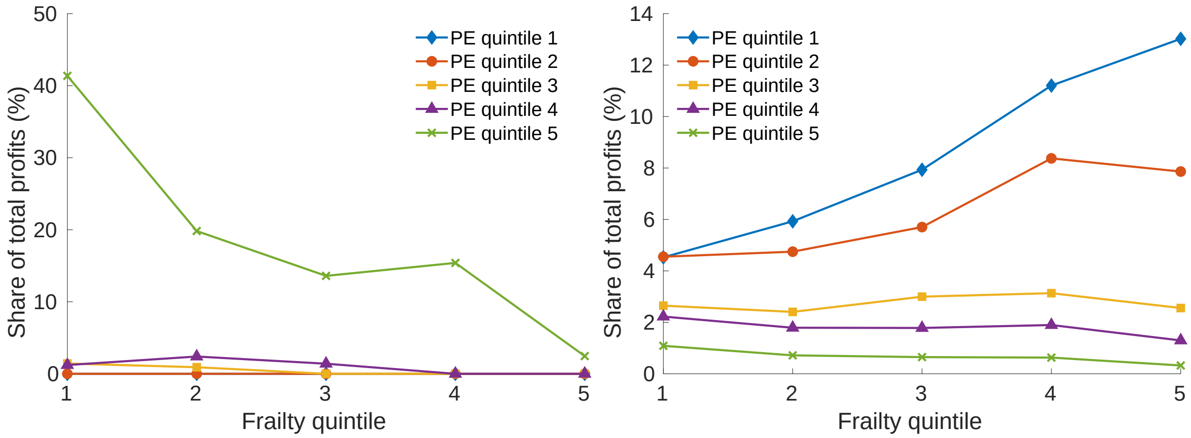



Figure 7. Profits Baseline and No Medicaid Specifications.
The left (right) panel reports the distribution of profits by frailty and PE quintiles in the Baseline (No Medicaid) economy. Note the difference in scale of the two plots.

## 6.5 Robustness

We start by considering the robustness of our finding that optimal menus that feature choice are rare. The parameter $\psi$ plays a central role in determining the costs of cross-subsidization from good to bad-risk types and ultimately the fraction of risk groups that are offered an optimal menu that provides them with the choice of either positive insurance or no insurance. In our setting with a monopoly insurer, premia from good types are used to cross-subsidize premia for bad types. If $\psi$ is reduced a smaller fraction of good types is available to provide the subsidies and it becomes more likely that the optimal menus in insurable risk groups include a $(0, 0)$ contract. To explore the quantitative significance of this effect, we reparametrized the model with $\psi$ reduced from its baseline value of 0.709 to 0.609. When $\psi$ is 0.609 the fraction of individuals that are offered the choice of a $(0, 0)$ contract and opt for it increases from 0.11% to 6.3% and the number of denials falls to 82%. Even though choice becomes relatively more important, risk-group selection is still the main reason why LTCI takeup rates are low. One important difference between this scenario and the baseline parametrization is that it is much easier to detect adverse selection by comparing NH entry frequencies of LTCI holders and non-holders in this scenario. For instance, the fraction of LTCI holders who enter a NH (conditional on survival) is now larger, at 0.44, than the fraction of non-holders who enter a NH (0.40). Thus, the model with a lower value of $\psi$ no longer accounts for the adverse selection correlation puzzle.

Another important difference is that the model with the lower value of $\psi$ exhibits too little dispersion in private information as compared to our data. The coefficient of variation of private information produced by the model falls from 0.94 in the baseline to 0.86 when $\psi = 0.609$. Recall, that the target for our baseline value of $\psi$ is the coefficient of variation of self-reported NH entrance probabilities. Our data measure omits responses of 0, 1/2 and 1. If some/all of these responses are included, the coefficient of variation for self-reported NH risk is even larger than 0.94. In this sense, our strategy for setting $\psi$ in the baseline parametrization is conservative. Apart from these two differences, the performance of the model with a lower $\psi$ is similar to our baseline parametrization. In particular, this version of the model is able to match the pattern of LTCI takeup rates and NH entry rates by frailty and wealth.

Our strategy for parametrizing the model used particular data facts to pin down the scale of Medicaid NH benefits and administrative costs. We have explored how the results change if we assign a more prominent role to each of these factors. One experiment we have performed is to increase the scale of the Medicaid consumption floor by a factor of 1.76. This value lies at the upper end of values used in previous studies.[60] Private information and administrative costs continue to have a large impact on LTCI takeup rates of affluent individuals even with the higher consumption floor. For instance, LTCI takeup rates increase by 50% or more if the private information distortion is removed.

Recall that LTCI takeup rates are very high in the Full Information economy. We have also investigated whether it is possible to reparametrize this version of the model to reproduce the LTCI takeup rates in the data. We need significantly higher administrative costs (49% of premia instead of 33%) to get the average takeup rate to match the data. However, this parametrization cannot generate the empirical pattern of LTCI takeup rates at alternative frailty quintiles among more affluent individuals no matter how we adjust the NH entry probability distribution.

In addition, we have considered how well the model performs if it is reparametrized under the assumption that administrative costs are absent. This version of the model fails to produce low LTCI takeup rates among affluent risk-groups with high frailty levels. For instance, the model predicts that LTCI takeup rates of individuals in wealth and frailty quintile 5 are nearly 1 while they are only 0.1 in our data. More complete details about these robustness checks can be found in Section 5.2 of the appendix.

Finally, our finding that adverse selection is an important factor is robust to the level of risk aversion. We set $\sigma$ to 2 but there is not a consensus in the profession on its value and larger values have been used by others in the insurance literature. For instance, Ameriks et al. (2011) use a value of 3. Under our parameterization scheme, if we used a higher value of $\sigma$, adverse selection would play a bigger role in accounting for low LTCI takeup rates. The easiest way to see this is to consider the simple model described in Section 3. For given choices of the parameters that determine the administrative costs and the scale of Medicaid ( $\lambda$ ,$\gamma$, and $\underline{c}_{NH}$), a higher value of risk aversion requires more dispersion in private information or a higher fraction of bad-types to produce the same level of takeup rates.

Our model has abstracted from several features of the U.S. LTCI market. Most notably in recent years regulators in this industry have required that insurers add markups, called "pricing margins", to the price of their initial premia to reduce the probability of future premium increases due to intertemporal risk. We do not model pricing margins. In the model neither individuals nor the insurer face aggregate uncertainty about interest rates, mortality rates or LTCI takeup rates and there is no reason to provision for it. Pricing margins could compound the problem of adverse selection.

We have also abstracted from moral hazard. In the 1980s and early 1990s LTC insurers were not concerned about moral hazard because they felt that individuals given the choice would prefer not to be institutionalized. However, as coverage has been expanded to provide home care benefits, insurers have had to allocate more resources to claims management

[60] See Kopecky and Koreshkova (2014) for a summary of previous studies.

to ascertain that individuals have an ongoing need for LTC services. In this sense, high administrative costs in this market may partially reflect moral hazard.

# 7 Concluding Remarks

We have found that Medicaid, administrative costs and adverse selection all play important but distinct roles in accounting for the observation that LTCI takeup rates are low at all wealth levels and decline with health status. Modeling these three factors also allowed us to account for a broad range of other empirical features of this market including coverage levels and pricing of insurance, low profitability, and the low empirical correlation between LTCI ownership and nursing home entry.

Our result that risk-group selection is a quantitatively important screening device may be relevant in other insurance markets. For instance, the U.S. individual health insurance market prior to the Affordable Care Act (ACA) shared many features with the U.S. LTCI market: takeup rates were low, denials were common, and loads were high for insured individuals. Underwriting is also used as a screening device in life and disability insurance markets.

# References


Ameriks, J., J. Briggs, A. Caplin, M. Shapiro, and C. Tonetti (2018): "The Long-Term-Care Insurance Puzzle: Modeling and Measurement," Unpublished Manuscript, Stanford University.

Ameriks, J., A. Caplin, S. Laufer, and S. Van Nieuwerburgh (2011): "The Joy of Giving or Assisted Living? Using Strategic Surveys to Separate Bequest and Precautionary Motives," *Journal of Finance*, 66, 519–561.

Arrow, K. (1963): "Uncertainty and the Welfare Economics of Medical Care," *American Economic Review*, 53, 941–973.

Braun, R. A., K. Kopecky, and T. Koreshkova (2017): "Old, Sick, Alone and Poor: A Welfare Analysis of Old-Age Social Insurance Programs," *Review of Economic Studies*, 84, 580–612.

Brown, J. R. and A. Finkelstein (2007): "Why is the Market for Long-Term Care Insurance So Small?" *Journal of Public Economics*, 91, 1967–1991.

——— (2008): "The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market," *American Economic Review*, 98, 1083–1102.

——— (2011): "Insuring Long-Term Care in the United States," *Journal of Economic Perspectives*, 25, 119–42.

Chade, H. and E. Schlee (2018): "Insurance as a Lemons Market: Coverage Denials and Pooling," Unpublished Manuscript, Arizona State University.

Chiappori, P.-A. and B. Salanie (2000): "Testing for Asymmetric Information in Insurance Markets," *Journal of Political Economy*, 108, 56–78.

Cohen, M., R. Kaur, and D. B. (2013): "Exiting the Market: Understanding the factors behind carriers' decision to leave the long-term care insurance market," Office of Disability, Aging and Long-Term Care Policy, U.S. Department of Health and Human Services.

Cutler, D. (1996): "Why Don't Markets Insure Long-term Risk?" Unpublished Manuscript, Harvard University.

De Nardi, M., E. French, and J. B. Jones (2016): "Medicaid Insurance in Old Age," *American Economic Review*, 106, 3480–3520.

Eaton, R. (2016): "Long-Term Care Insurance: The SOA Pricing Project," Society of Actuaries.

Fang, H., M. A. Keane, and D. Silverman (2008): "Sources of Advantageous Selection: Evidence from the Medigap Insurance Market," *Journal of Political Economy*, 116, 303–350.

Favreault, M. and J. Dey (2016): "Long-Term Services and Supports for Older Americans: Risks and Financing," Office of Disability, Aging and Long-Term Care Policy, U.S. Department of Health and Human Services.

Finkelstein, A. and K. McGarry (2006): "Multiple Dimensions of Private Information: Evidence from the Long-Term Care Insurance Market," *American Economic Review*, 96, 938–958.

Harris-Kojetin, L., E. Park-Lee, et al. (2016): "Long-term Care Providers and Services Users in the United States: Data from the National Study of Long-Term Care Providers, 2013–2014," *National Center for Health Statistics. Vital Health Stat*, 3.

Hendren, N. (2013): "Private Information and Insurance Rejections," *Econometrica*, 81, 1713–1762.

Hendricks, L. (2001): "Bequests and Retirement Wealth in the United States," Unpublished Manuscript, Arizona State University.

Hurd, M., P. Michaud, and S. Rohwedder (2014): "The Lifetime Risk of Nursing Home Use," in *Discoveries in the the Economics of Aging*, ed. by D. Wise, Chicago and London: University of Chicago Press, 81–109.

Karaca-Mandic, P., J. Abraham, and C. Phelps (2011): "How do Health Insurance Loading Fees Vary by Group Size?: Implications for Healthcare Reform," *International Journal of Health Care Finance and Economics*, 11, 181–207.

Ko, A. (2018): "An Equilibrium Analysis of the Long-Term Care Insurance Market," Unpublished Manuscript, Georgetown University.

Kopecky, K. and T. Koreshkova (2014): "The Impact of Medical and Nursing Home Expenses on Savings," *American Economic Journal: Macroeconomics*, 6, 29–72.

Lester, B., A. Shourideh, V. Venkateswaran, and A. Zetlin-Jones (2017): "Screening and Adverse Selection in Frictional Markets," *Journal of Political Economy*, forthcoming.

Lewis, S., J. Wilkin, and M. Merlis (2003): "Regulation of Private Long-Term Care Insurance: Implementation Experience and Key Issues," The Henry J. Kaiser Family Foundation.

Lockwood, L. (2018): "Incidental Bequests and the Choice to Self-Insure Late-Life Risks," *American Economic Review*, 108, 2513–2550.

Mahoney, N. (2015): "Bankruptcy as Implicit Health Insurance," *American Economic Review*, 105, 710–46.

Mitchell, O. S., J. M. Poterba, M. J. Warshawsky, and J. R. Brown (1999): "New Evidence on the Money's Worth of Individual Annuities," *American Economic Review*, 89, 1299–1318.

Mommaerts, C. (2016): "Long-term Care Insurance and the Family," Unpublished Manuscript, University of Wisconsin-Madison.

Murtaugh, C. M., P. Kemper, B. C. Spillman, and B. L. Carlson (1997): "The Amount, Distribution, and Timing of Lifetime Nursing Home Use," *Medical Care*, 35, 204–218.

Poterba, J. M., S. F. Venti, and D. A. Wise (2011): "Family Status Transitions, Latent Health, and the Post-Retirement Evolution of Assets," in *Explorations in the Economics of Aging*, ed. by D. Wise, Chicago: University of Chicago Press.

Purcell, P. J. (2012): "Income replacement ratios in the Health and Retirement Study," *Social Security Bulletin*, 72, 37.

Rothschild, M. and J. Stiglitz (1976): "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information," *The Quarterly Journal of Economics*, 90, 629–649.

Spillman, B. and K. Black (2005): "The Size of the Long-Term Care Population in Residential Care: A Review of Estimates and Methodology," Office of Disability, Aging and Long-Term Care Policy, U.S. Department of Health and Human Services.

Stiglitz, J. (1977): "Non-Linear Pricing and Imperfect Information: The Insurance Market," *The Review of Economic Studies*, 44, 407–430.

Thau, C., D. Helwig, and A. Schmitz (2014): "2014 Long Term Care Insurance Survey," *Broker World*.