NBER WORKING PAPER SERIES

DYNAMIC PRICING REGULATION AND WELFARE IN INSURANCE MARKETS

Naoki Aizawa
Ami Ko

Working Paper 30952
http://www.nber.org/papers/w30952

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2023

We thank Mariacristina De Nardi, Ying Fan, Sebastian Fleitas, Eric French, Daniel Gottlieb, Gautam Gowrisankaran, Ben Handel, Jean-Francois Houde, You Suk Kim, Karen Kopecky, Dirk Krueger, Martin O'Connell, Ashley Swanson, Motohiro Yogo, as well as participants at the 2022 ASSA meeting, Becker Friedman Institute (University of Chicago), LAEF conference at UCSB, Montreal Ageing Conference, NBER Insurance group meeting, Ridge conference, Stanford Institute of Theoretical Economics (IO of Healthcare and Consumer Finance Markets), Triangle Micro Conference at UNC, University of Nebraska, and USC for helpful comments and discussions. Funding from the Wisconsin Alumni Research Foundation provided by the University of Wisconsin - Madison Office of the Vice Chancellor for Research and Graduate Education is gratefully acknowledged. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Dynamic Pricing Regulation and Welfare in Insurance Markets
Naoki Aizawa and Ami Ko
NBER Working Paper No. 30952
February 2023
JEL No. D14,G22,I13,L11,L51

ABSTRACT

While the traditional role of insurers is to provide protection against idiosyncratic risks of individuals, insurers themselves face substantial uncertainties due to aggregate shocks. To prevent insurers from passing through aggregate risks to consumers, governments have increasingly adopted dynamic pricing regulations that limit insurers' ability to change premiums over time. This paper develops and estimates an equilibrium model with dynamic pricing and firm entry and uses it to evaluate the design of dynamic pricing regulations in the U.S. long-term care insurance (LTCI) market. We find that stricter dynamic pricing regulation lowers social welfare as the benefit from improved premium stability is outweighed by the cost of reduced insurer participation. The welfare loss from stricter dynamic pricing regulation could be mitigated if the government also expands public LTCI through Medicaid.

Naoki Aizawa
Department of Economics
University of Wisconsin-Madison
1180 Observatory Drive
Madison, WI 53706
and NBER
naoki.aizawa@nber.org

Ami Ko
Georgetown University
Department of Economics
3700 O st NW, ICC 557
Washington DC 20007
ami.ko@georgetown.edu

1 Introduction

Social insurance programs and private insurance markets provide protection against a broad range of risks that individuals face. The insurance sector, both private and public, has grown enormously in the last several decades in many countries (Chetty and Finkelstein, 2013). Most existing studies on the insurance sector focus on demand-side issues related to individual-level risks, such as adverse selection and moral hazard. However, insurers themselves also face substantial financial uncertainties in many markets. For example, insurers selling relatively new products confront considerable claims uncertainties because they lack experience in predicting the insured risk and pricing contracts accordingly. Even experienced insurers could be challenged when they serve a new class of consumers with demographics that they never dealt with before, such as those operating in the health insurance marketplaces established by the Affordable Care Act. Insurers selling long-term contracts are particularly challenged because their financial stability is more vulnerable to aggregate cost shocks and interest rate.

One important welfare concern is that insurers might pass through the risks that they face to consumers by adjusting premiums. The resulting premium volatility could aggravate the amount of financial uncertainties that individuals have to deal with. To mitigate the issue, the government has increasingly adopted dynamic pricing regulations, i.e., regulations that limit insurers' ability to adjust rates.[1] However, little is known about their welfare effects. On the one hand, dynamic pricing regulation might improve consumer welfare by decreasing uncertainty about future rate increases. On the other hand, it might induce insurers to exit from the market or charge a higher markup, which will adversely affect consumer welfare.

In this paper, we study the impact of dynamic pricing regulation on the market equilibrium and social welfare in the context of U.S. private long-term care insurance (LTCI). LTCI is a long-term contract in that there is a lag of over 20 years between the purchase and use of insurance. In addition to being a relatively young insurance product, the dynamic feature of LTCI contracts makes it hard for insurers to accurately predict future claims costs.[2] Insurers do not commit to a certain premium schedule over the lifetime of a contract and often revise rates for a given buyer cohort subject to the state regulator's approval. To reduce uncertainty

[1]For example, in health insurance, the Department of Health and Human Services along with state governments establish effective rate review programs such that any health insurance plan (individual or small group plan) with a proposed rate increase of 10% or above is scrutinized by independent experts.

[2]To accurately anticipate claims costs, insurers need to predict not just health and mortality risk, but also formal care costs and lapse rates over the next 20 years as well as the availability of family care that could substitute for formal care services.

about future rate increases, many states adopted new standards in their oversight of the LTCI industry in the early 2000s (Rate Stability Regulation of 2000, henceforth RSR 2000). The new standards were designed to deter rate increases for existing consumers. This paper studies the design of dynamic pricing regulation by developing and estimating an equilibrium model of LTCI.

Understanding the oversight of the LTCI industry is important in its own right. Long-term care is one of the largest uninsured financial risks faced by elderly Americans. Formal long-term care expenses totaled over $310 billion in 2013, which is close to 2% of GDP.[3] Long-term care spending is expected to further increase with population aging. Yet, only 10% of the elderly own private LTCI. Substantial progress has been made to assess several demand-side channels, such as Medicaid's crowd-out effect on the demand for private LTCI, informal care provided by family members, and adverse selection. However, little is known about supply-side incentives and their impact on market outcomes in LTCI. This gap in the literature could be critical as the demand-side channels might not explain the substantial decline of the supply side witnessed in the last two decades: the number of active plans declined by more than 90%, and the number of insurers selling new contracts plunged from over 100 to a dozen (NAIC, 2016). This period overlaps with the time when states implemented new regulation standards to promote rate stability in the LTCI industry. One possibility is that the regulation reduced insurers' profits and triggered their exits. In this paper, we take a first attempt in understanding the effect of supply-side regulations in LTCI.

We start by providing descriptive evidence for the effect of rate stability regulation on insurers.[4] We use regulatory filings submitted by LTCI companies to the National Association of Insurance Commissioners (NAIC) between 2000-2007 and rate increase data obtained from the California Department of Insurance for the years 2007-2017. Using variations in states' adoption of RSR 2000, we find suggestive evidence that the regulation reduced rate increases, reaching its intended goal of improving rate stability. However, we also find evidence that the regulation significantly reduced the number of available plans and insurers.

To quantify the trade-off surrounding dynamic pricing regulation, we develop an equilibrium model of LTCI. There exist risk averse consumers who decide whether to purchase private LTCI. Medicaid is incorporated as free public LTCI for consumers with limited assets. Risk-neutral insurers face uncertainty about future claims costs and decide whether to

[3]Source: Kaiser Family Foundation, https://www.kff.org/medicaid/report/medicaid-and-long-term-services-andsupports- a-primer/.

[4]We use dynamic pricing regulation and rate stability regulation interchangeably.

enter the market and how to price their products conditional on entry. They are subject to two pricing regulations: 1) dynamic pricing regulation which makes it costly for insurers to revise premiums over the lifetime of a contract, and 2) loss ratio regulation which penalizes insurers for charging an initial rate that is different from the regulator's target level. The model incorporates two key assumptions that are empirically grounded. First, insurers exercise market power. Second, similar to Gottlieb and Smetters (2021) and Atal et al. (2022), consumers face choice frictions in the sense that they expect premiums to remain constant over the lifetime of a LTCI contract. With the latter feature, insurers do not commit to future premiums. This is because committing to a smooth price schedule does not increase consumers' value for the product (due to their misbeliefs) while foregoing the opportunity to revise rates based on the realized claims costs. These two features depart from standard models of long-term insurance which assume competitive markets where insurers commit (e.g., Cochrane (1995) and Hendel and Lizzeri (2003)). Due to a lack of commitment, insurers in our model have an incentive to pass through their claims risks to consumers. Dynamic pricing regulation is a policy tool that forces insurers to smooth prices over the lifetime of a contract.

We estimate the demand-side parameters by exploiting plausibly exogenous variations, including states' staggered adoption of RSR 2000. The demand estimates suggest that consumers' preferences are relatively inelastic with respect to initial rates. We then estimate our supply-side parameters using the estimated demand parameters and claims data. Despite the price inelastic demand, our supply estimation finds that insurers do not charge a high markup due to the presence of pricing regulations. We thus find that supply-side regulations are important in explaining observed price dynamics of LTCI contracts.

Using the estimated model, we conduct counterfactual experiments to evaluate alternative policy designs of LTCI. First, we examine the welfare effect of dynamic pricing regulation. On the one hand, stricter dynamic pricing regulation might increase welfare by reducing risk averse consumers' uncertainty about future rate increases. On the other hand, it might decrease welfare by inducing insurers to withdraw from the market or to charge a higher markup. The results reveal that the latter channel dominates the former. Stricter regulation substantially reduces insurer profits. While it increases consumer welfare, the gain is very limited at about 0.05% in terms of the consumption equivalent variation. The small gain is due to the fact that a stricter version of the regulation reduces insurer participation.

Next, we consider the value of firm commitment by correcting consumers' misbeliefs about future rate increases. Once consumers have correct beliefs, insurers no longer pass through their financial uncertainties to consumers as committing to a smooth price schedule maximizes the consumer surplus that they can extract. We find that while insurer commitment increases consumer welfare, the gain is limited due to reduced insurer participation, consistent with our previous counterfactual experiment.

Finally, we consider how supply-side regulations interact with demand-side policies. We find that when Medicaid benefits become more generous, the share with private LTCI decreases from 21% to 15%, a crowd-out effect well known in the literature (Brown and Finkelstein, 2008). Interestingly, we find that the generosity of Medicaid acts to depress the impact of rate stability regulation. When Medicaid is more generous, insurers increase rates by a smaller magnitude over the lifetime of a contract. They also respond less to changes in the strictness of rate stability regulation. Consequently, the negative impact that a stricter version of the regulation has on insurer profits is also mitigated. The result highlights the need to consider the joint design of demand- and supply-side policies.

This research contributes to three strands of literature on social insurance and insurance markets. First, it contributes to the growing literature that evaluates the welfare effects of LTCI. Most studies in this field examine demand-side channels, such as the presence of Medicaid (Brown and Finkelstein, 2008), bequest motives (Lockwood, 2018), preference heterogeneity (Ameriks et al., 2016), and informal care through family (Mommaerts, 2020; Ko, 2022). These studies typically model LTCI as a homogeneous product and focus on aggregate enrollment. A recent paper by Braun et al. (2019) studies insurers' incentive to deny consumers of coverage in a static LTCI market equilibrium with a monopolistic insurer.[5] Our study contributes to the literature by assessing the role of supply-side dynamics and regulatory frictions. Moreover, we provide the first estimate of the demand for LTCI at the insurer level and shed light on the nature of insurer competition in this market.

Second, this study is related to the large literature that investigates policy designs in insurance markets. Most studies in this field focus on demand-side frictions, such as adverse selection or moral hazard (see Einav et al. (2010) for an excellent survey). A few studies investigate supply-side regulations (e.g., capital requirements) and argue that they act as financial frictions to insurers, which significantly affect premiums in life insurance and annuity markets (Koijen and Yogo, 2015, 2016). The most related paper is Koijen and Yogo (2022) which studies how supply-side regulations affect both premium and product quality.

[5] See also Liu and Liu (2020) who provide evidence that political factors such as election cycles affect premium changes, insurers' cash flows, and the decision to sell LTCI.

Our work complements theirs by focusing on how the dynamic nature of insurance contracts is affected by pricing regulations.[6]

Finally, our work adds to the literature on long-term insurance. Cochrane (1995) and Hendel and Lizzeri (2003) study optimal long-term insurance and focus on welfare implications of premium fluctuations which create reclassification risks to consumers. Handel et al. (2015), Handel et al. (2017), and Fleitas et al. (2018) quantitatively assess the welfare cost of reclassification risk. Atal (2019) and Atal et al. (2020) empirically study long-term health insurance in Chile and Germany, respectively. Existing studies assume perfectly competitive insurance markets with insurer commitment and focus on the premium determination. We complement the literature by studying an imperfectly competitive long-term insurance market where price and insurer participation are endogenously determined.[7]

The rest of this paper proceeds as follows. Section 2 provides a simple theoretical model for key economic intuitions. Section 3 presents the institutional background. Section 4 presents the data and descriptive evidence. Section 5 presents the empirical model. Section 6 presents the estimation results. Section 7 presents the counterfactual results. Section 8 concludes.

2 Simple theoretical model for key intuitions

We first introduce a simple model to highlight the key economic forces that we study. The objective is to motivate our empirical analysis and to place our model in the broad literature of social insurance. Consider a continuum of consumers who are ex-ante homogeneous and live for two periods ($t = 1, 2$). Their income in each period is denoted by y_t, and they have risk averse preferences represented by the function $u(\cdot)$. Consumers are subject to financial risks in each period, and the realization of the claims cost is denoted by μ_{ikt}. The claim cost μ_{ikt} is determined by two sources of uncertainties. First, individuals' idiosyncratic expenditure risks (indexed by i) affect the claims. Second, there are aggregate risks in the second period (indexed by k) which affect the cost of providing insurance.

We first consider the optimal long-term contract that the social planner wants to provide.

[6] In the context of static health insurance contracts (Medicare Part D), Fleitas (2017) studies insurers' dynamic pricing behaviors arising from consumers' switching costs.

[7] There is also a growing number of studies that examine why consumers lapse contracts in long-term insurance (e.g., Fang and Kung (2020) and Gottlieb and Smetters (2021)). We take lapses as given and instead explore their implication to insurer behaviors.

The planner's problem can be written as

$$\underset{c_1,\{c_{k2}\}_{k=1}^{K}}{\text{Max}} u(c_1) + \sum_{k=1}^{K} \pi_k u(c_{k2}) \quad \text{s.t.} \quad c_1 + \sum_{k=1}^{K} \pi_k c_{k2} = y_1 + y_2 - \mu_1 - \sum_{k} \pi_k \mu_{k2} \tag{1}$$

where μ_1 is the expected claims cost in period 1 ($\mu_1 = E[\mu_{i1}]$), and μ_{k2} is the expected claims cost in period 2, where we use k to denote the realized state of the aggregate shock. π_k represents the probability that the second-period state is $k = 1, ..., K$. In the socially optimum, the social planner will set that $c := c_1 = c_{k2}$ for all k, which will ensure perfect consumption smoothing with respect to both idiosyncratic and aggregate risks (Cochrane, 1995). The first-best allocation will be implementable in a competitive market if both consumers and insurers credibly commit to insurance contracts over the two periods ex ante.

However, regardless of whether insurers offer static or long-term contracts, we observe several empirical patterns that deviate from the socially optimal allocation. First, insurers have substantial market power in most insurance markets. Second, insurers pass through aggregate risk to consumers by adjusting rates. For example, in Germany where long-term health insurance contracts are available, premium adjustments take place based on changes in health care costs (Hofmann and Browne, 2013). Rate adjustments are also frequent in the U.S. LTCI market depending on insurers' claims experience.

In standard models of long-term contracts where insurers commit to a price schedule ex ante, the optimal contract can feature price dependence on aggregate risks if insurers face financial constraints such as capital requirements or bankruptcy constraints.[8] In the context of the U.S. variable annuity market, Koijen and Yogo (2022) show that an adverse aggregate shock that increases the shadow cost of capital requirements results in higher fees. Interestingly, in certain long-term insurance markets, such as the U.S. LTCI market that we study, insurers do not explicitly commit to any future rate schedule. Significant premium increases over the life cycle of plans are quite common for most plans in these markets, even when financial constraints are much less crucial (e.g., periods with stable interest rates and almost no insurer bankruptcy).

We now illustrate an alternative setting that rationalizes the aforementioned empirical facts and provides intuitions about the dependence of social welfare on aggregate risks and government regulations. We consider a monopolistic insurer that sells long-term contracts which provide insurance over the two periods. To rationalize the lack of insurer commitment

[8]For example, long-term health insurance providers in Germany commit to a lifelong premium schedule which is a function of medical inflation (Hofmann and Browne, 2013).

in the context of long-term insurance markets, we consider consumers with misbeliefs that future rates will remain the same as the initial rate over the lifetime of the contract (see Section 5.6.3 for empirical evidence). We will show that the insurer will not only increase rates based on the realized aggregate risk but also choose not to commit.

The insurer's profit over the lifetime of the contract is

$$\Pi = (p_1 - \mu_1)s_1 + \sum_{k=1}^{K} \pi_k (p_{k2} - \mu_{k2}) s_{k2} - C_k^{rs}(p_1, p_{k2}) \tag{2}$$

where s_1 is the insurer's initial market share, and s_{k2} is the updated market share in the second period when the realized aggregate state is k. The function C_k^{rs} represents the cost associated with price adjustments, which may arise from government regulations or from the insurer's opportunity cost of raising rates.[9] If consumers have rational beliefs over price dynamics, then the risk neutral insurer has an incentive to offer a smooth price schedule, i.e., $p_1 = p_{k2}$ for all k. However, if the insurer cannot increase the consumers' value for the contract by committing to a constant price schedule due to their misbeliefs, then the insurer will not specify state-contingent prices and change the rate depending on the realized aggregate risk. For example, the insurer might increase the rate by a higher margin in aggregate states with lower rate adjustment costs. The insurer's optimal contract will feature premium fluctuations, in contrast to the first-best contract chosen by the social planner.

The dynamic dependence of premiums on the buyer-cohort-level aggregate risk is related to "reclassification risk" in the existing literature of long-term insurance (Cochrane, 1995; Hendel and Lizzeri, 2003), where prices are revised based on changes in individual-level risk. In models with reclassification risk, consumers' lack of commitment is the key, as they have an incentive to walk away from the contract when their risk type improves. In our setting, insurers' lack of commitment is the key as they have an incentive to pass through aggregate risk to consumers.

Whenever premium volatility arises due to aggregate risks, the government can mitigate it through dynamic pricing regulation, which can be interpreted as making the rate adjustment

[9] The latter includes reputation costs which are likely to be high when the realized aggregate shock is favorable and the insurer cannot easily justify its rate increases. It may also capture the insurer's cost from dealing with financial frictions. When the insurer is financially constrained due to an adverse aggregate shock, raising rates may be necessary to stay in the market.

cost (C_k^{rs}) higher.[10] Lower premium volatility will be beneficial to risk averse consumers. However, too strict regulation could reduce insurers' expected profit to the point where entry becomes unprofitable. Consumers could be harmed by reduced insurer variety and increased market concentration. In the rest of the paper, we develop and estimate an empirical framework in the context of LTCI and quantify the trade-offs surrounding dynamic pricing regulation.

3 Institutional background

3.1 Long-term care in the U.S.

Long-term care (LTC) is defined as assistance with basic personal tasks of everyday life, called Activities of Daily Living (ADLs) or Instrumental Activities of Daily Living (IADLs).[11] Declines in physical or mental abilities are the main reasons for requiring LTC. In the U.S., over 60% of individuals aged 85 and older require assistance with daily tasks (Ko, 2022). However, not everybody will require LTC in late-life: 26% of healthy 60-year-olds will never need LTC until their death (Ko, 2022). Combined with the very costly nature of LTC services (e.g., the median annual rate for nursing home care was close to $100,000 in 2017), LTC is one of the largest financial risks faced by the elderly.[12] Medicaid is a means-tested public insurance program which covers formal LTC expenses for eligible individuals with limited resources. It is the biggest payer for total LTC payments accounting for 51%, followed by other public insurance programs (21%), out-of-pocket (19%), and private LTCI (8%).[13]

3.2 LTCI market

Private LTCI market is relatively young, and modern insurance products were introduced in the late 1980s (Society of Actuaries, 2014). Typical LTCI contracts cover both facility and paid home care provided by employees of home care agencies. In 2002, 80% of the LTCI contracts sold were individual policies, and group policies which are purchased through employers only accounted for 20% (US Government Accountability Office, 2008). A daily

[10] An alternative policy intervention would be providing reinsurance against aggregate shocks to insurers. We discuss and compare the two policy instruments in Section 5.6.1.

[11] Examples of ADLs include bathing, dressing, using the toilet, and getting in/out of bed. IADLs refer to activities that require more skills than ADLs such as using the telephone and taking medication.

[12] Source: Genworth, https://www.genworth.com/aging-and-you/finances/cost-of-care.html.

[13] Ibid.

benefit cap specifies the maximum amount a LTCI policy will pay on daily basis toward the cost of care. A benefit period specifies the maximum length of time over which the policy will provide coverage. In 2000, the average daily benefit cap was about $100, and benefit periods ranged widely from 1 year to lifetime coverage (Brown and Finkelstein, 2007). The average purchase age is 61 years, but most people do not use insurance until they turn 80 (Broker World, 2009-2015).

Contracts sold on the LTCI market are long-term contracts as there is an average time lag of 20 years between the purchase and use of insurance. Insurers commit to certain contract characteristics. First, contracts are guaranteed renewable in the sense that an insurance company cannot cancel coverage as long as premiums are paid. Second, insurers cannot change a single consumer's premium over the lifetime of the contract based on changes in individual circumstances (e.g., deterioration in health).[14] However, insurers are not required to commit to a certain premium schedule at the buyer cohort level. They can submit rate increase requests to state governments for an entire class of consumers if they can successfully show that the class's premium payments are insufficient to cover expected claims.

Lapses, where policies terminate due to failure of premium payments, result in forfeiture of any future benefits (Brown and Finkelstein, 2007). In practice, lapses are very rare in the industry: the overall lapse rate was 2.7% for years 2005-2007, and 2% for 2008-2011. The lapse rate decreases rapidly in the policy year and converges to 1% after policy year ten.[15]

3.3 Rate Stability Regulation of 2000 (RSR 2000)

Oversight of the LTCI industry is largely the responsibility of states. Many state insurance departments regulate their market based on NAIC's Long-Term Care Insurance Model Regulation (Model #641) which was first adopted in 1987 (NAIC, 2016). This paper focuses on revisions to Model #641 which were adopted in 2000 to improve rate stability. Prior to 2000, states used a minimum loss ratio (ratio of incurred claims to earned premiums) to determine whether initial LTCI rates and subsequent rate increases were adequate (NAIC, 2016).[16] While the loss ratio standard was designed to limit initial rates, it was not effective

[14] At the time of the initial purchase, insurers can charge different rates depending on individual health conditions or deny coverage altogether.

[15] Source: Society of Actuaries, https://www.soa.org/resources/experience-studies/2016/research-ltc-insurance/.

[16] Specifically, Model #641 stated that insurers must demonstrate an expected loss ratio of at least 60% (US Government Accountability Office, 2008).

in preventing insurers from setting initial rates that were too low and imposing large future rate increases.

In 2000, the NAIC adopted a set of new standards to establish more rigorous requirements insurers must satisfy when setting initial premiums and rate increases. First, the RSR 2000 removed the minimum loss ratio test for initial rate filings. Instead, it requires insurers to provide an actuarial certification that an initial premium is adequate to cover expected costs over the life of a policy, even under "moderately adverse conditions," with no future rate increases. Second, the RSR 2000 requires insurers to meet a higher minimum loss ratio of 85% for revenues associated with rate increases (US Government Accountability Office, 2008). Third, the RSR 2000 requires insurers to report data on premiums earned and claims incurred for at least 3 years after implementing a rate increase (US Government Accountability Office, 2008). The RSR 2000 only applies to policies issued after a state incorporates the changes into its laws and regulation (NAIC, 2016).

As with all standards established by the NAIC for the regulation of the LTCI industry, it was up to states to determine whether they adopt the RSR 2000. For each state, Table D.1 in Appendix reports whether and when the state implemented the regulation. Between 2001 and 2012, 41 states adopted the new standards. A total of 23 states adopted them between 2001-2004, and the number of states adopting the regulation reached its peak in 2003. As we will show below, this period overlaps with the time when the LTCI industry experienced a sharp decrease in available plans and active insurers.

4 Data and descriptive evidence

4.1 Data sources

Our main data come from the LTCI Experience Reports submitted annually to the NAIC by the *entire universe* of insurers operating in the LTCI line of business in the U.S. There are multiple forms that the NAIC requires LTC insurers to file, which have different reporting levels. To exploit state variations in the adoption of the RSR 2000, we mainly use Form C reports between 2000 to 2007.[17] Form C are annual reports which provide state-plan-level

[17] After this time period, the NAIC implemented entirely new forms, and reports at the state-plan-level are no longer available.

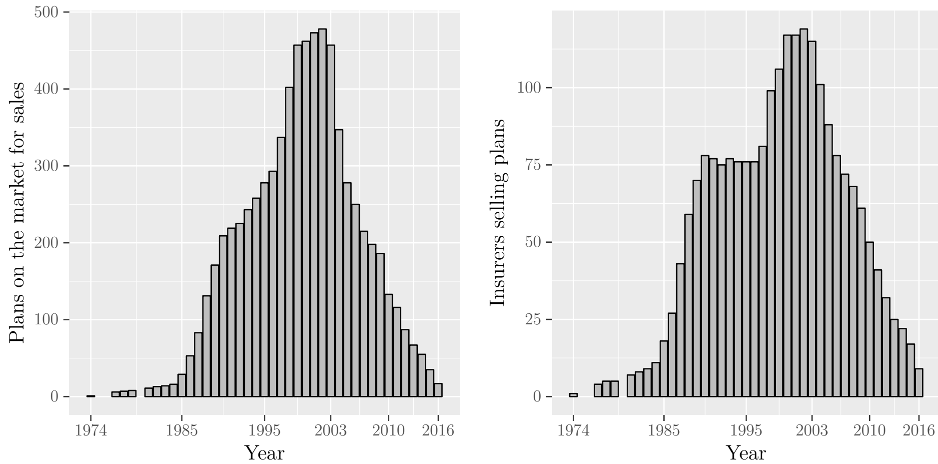


Figure 1: Active plans and insurers by year
Notes: Data = NAIC reports. The figure reports, for each year, the number of active plans and active insurers.

information about enrollment, new sales, premiums collected, and claims incurred.[18]

We complement the NAIC data with rate increase data obtained from the California Department of Insurance for the years 2007-2017. Any insurer who operated in California in the last 10 years is required to submit its rate increase history in all of its active states to the California Department of Insurance. This dataset provides state-plan-level information about rate increase requests and approvals. We link the plans in the NAIC data to the rate increase data using unique plan identifiers found in both datasets.

4.2 Nationwide supply after rate stability regulation

We first use nationwide NAIC reports to document a sharp decrease in the supply size of the LTCI industry in the last two decades.[19] The NAIC data provide information about a plan's first and latest issue year. Based on this information, we can infer the number of active plans on the market for years where we do not have NAIC reports.

Figure 1 reports, for each year between 1974 and 2016, the number of active plans and insurers. We say a plan is active if the plan has strictly positive sales; we say an insurer is

[18]Unfortunately, we do not observe plan features such as benefit amount. While there exist datasets that contain LTCI plan characteristics for a selected *fraction* of insurers, we are not aware of data that carry such information for the universe of insurers in the LTCI industry, which is what we have in the NAIC sample.

[19]Nationwide plan-level information is found in Form A for years 2000-2008, and in Form 2 for years 2009-2016.

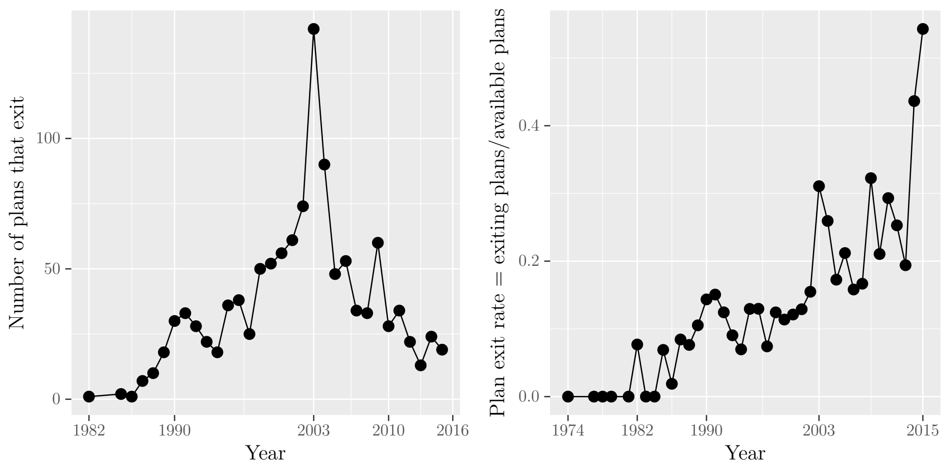


Figure 2: Exiting plans by year
Notes: Data = NAIC reports. The figure reports, for each year, the number of exiting plans (left panel) and exit rate (right panel).

active if it has at least one active plan. The number of active plans and insurers reached its peak in 2002 but experienced a very sharp decrease starting in 2003. As mentioned earlier, the number of states adopting the RSR 2000 reached its peak in 2003.

The left panel in Figure 2 shows the number of exiting plans by year. We say a plan exits if it no longer has positive sales.[20] The panel shows that there is a spike in the number of exiting plans in 2003. The right panel shows the exit rate by year, which is the ratio of exiting plans to active plans. The exit rate increased sharply in 2003 and has remained high since then.

4.3 Descriptive evidence on effect of RSR 2000

4.3.1 Insurer participation and initial rates

We use variations in states' adoption of RSR 2000 to provide descriptive evidence on the effect of the regulation on insurer participation and initial rates. We use an event study framework to report changes in LTCI market outcomes at the state level. We estimate

$$y_{st} = \alpha + \sum_{k=-2}^{2} \beta_k I_{stk} + \tau_t + \eta_s + \varepsilon_{st}. \tag{3}$$

[20]Insurers still have to file regulatory forms to the NAIC for plans that have exited the market as long as they have existing consumers.

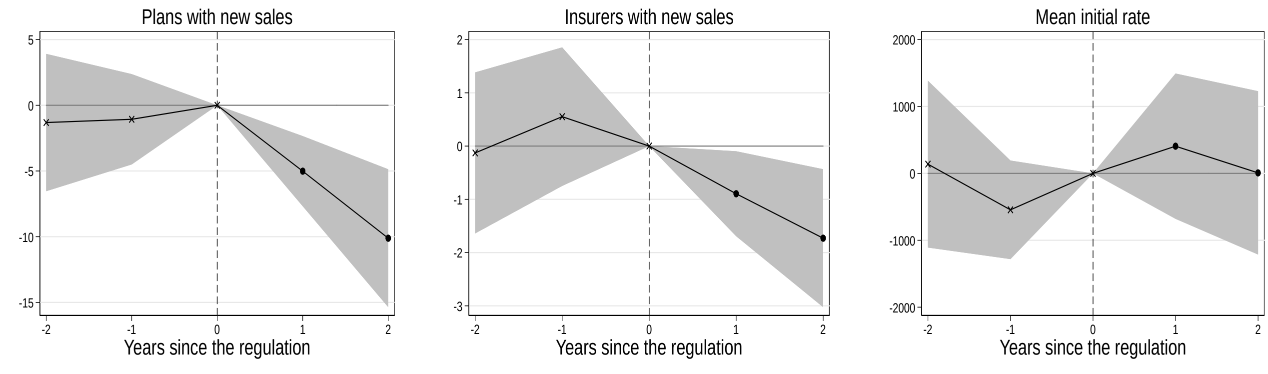


Figure 3: Impact of the rate stability regulation on market outcomes
Notes: Data = Form C NAIC reports 2000-2007. The sample consists of plans sold in 24 states that implemented the RSR 2000 between 2002-2005. The figure reports the estimates of β_k's in equation (3). The gray area indicates 95% confidence intervals. Standard errors are clustered by state.

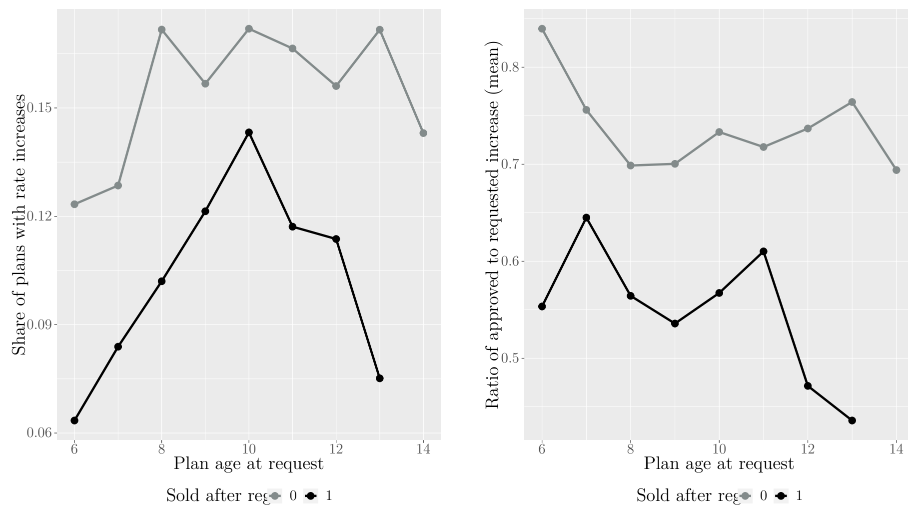
For the dependent variable, we use (i) the number of active plans, (ii) the number of active insurers, and (iii) the median initial rate in each state s in year t. I_{stk} is an indicator for being k years since the state's implementation of the RSR 2000.

The regression sample comes from 24 states that implemented the regulation between 2002-2005. This is because we control for 2 years before and after the adoption of the regulation, and the state-level NAIC reports are available for the years 2000-2007.

Figure 3 reports the estimated β_k's in equation (3). The adoption of the regulation has a negative impact on product variety and insurer participation in a state. In two years since the adoption, the number of plans decreased by 10, and the number of insurers went down by two. The negative impact of the regulation on insurers' participation is consistent with anecdotal evidence. Department of Health and Human Services (2005) surveyed executives from LTCI companies who exited the market in the 2000s. Over 60% of the executives reported "concerns about ability to get rate increases if necessary" as one of the reasons why their company left the market.

We find that most of the negative impact comes from the fringe.[21] Figure D.1 in Appendix shows that while the regulation significantly increased fringe firms' exit probability and reduced their plan offerings, its impact on major firms is not statistically different from zero.

[21]We classify a firm as a major insurer if its sales account for at least 5% of the total sales in the market; otherwise, we classify the firm as a fringe.



Extensive margin

Intensive margin

Figure 4: Rate increases of plans sold before and after the rate stability regulation
Notes: Data = Rate increase data and NAIC reports. Conditional on plan age and whether the plan was sold before or after the state's enactment of the RSR 2000, the figure reports the share of available plan-state combinations obtaining rate increase approvals (left) and the mean approved increase relative to the requested increase (right).

Despite the fact that rate stability regulation makes it harder for insurers to increase rates ex post, the last graph in Figure 3 shows that they do not start with a higher initial rate. We suspect the tight regulation around initial rates might have to do with the seemingly inelastic response.

To sum, we have descriptive evidence which suggests that the regulation had a negative impact on consumers by reducing product variety and insurer competition. However, its overall impact on consumer welfare depends on by how much the regulation reduced premium volatility. In what follows, we provide suggestive evidence for the positive effect of the regulation in improving rate stability.

4.3.2 Rate increases

We use the rate increase data obtained from the California Department of Insurance for the years 2007-2017 to examine how the RSR 2000 might have affected rate increases.[22] Figure 4 compares, conditional on plan age, rate increases of plans sold before and after states' adoption of the RSR 2000 both on the extensive and the intensive margin. Note that the

[22]We report the sample construction and basic summary statistics of the rate increase data in Appendix.

regulation applies only to plans that are issued after the implementation of the regulation. Most rate increases are requested when plans are aged 6-14 years since the initial issue, and the horizontal axes in the figure represent plan ages. The left graph shows that plans sold after the adoption of the regulation have a lower chance of having a rate increase at about 10%, while the chance is substantially higher at 15% for plans sold before the regulation. The right graph shows that for plans where the regulation is binding, the mean ratio of approved to requested rate increase is about 55%, while the mean ratio is much higher at 75% for plans sold before the regulation.

We thus find suggestive evidence that the RSR 2000 might have achieved its intended goal of stabilizing future rate increases. However, this benefit should be weighed against the possible cost of the regulation documented in Figure 3, a reduction in insurer variety.

4.4 Major and fringe firms

Our model presented in the next section has two types of firms: major and fringe. This is because the descriptive analysis presented earlier shows that rate stability regulation had substantially varying impacts on insurers by their type. We conclude this section by providing summary statistics on major and fringe firms.

Table 1 is constructed from the Form C NAIC reports 2000-2007. Fringe firms on average sell plans that cost less and have lower per-enrollee claims. Their plans are relatively younger, and they are less likely to experience higher than anticipated claims. Fringe firms on average sell fewer plans, and they tend to operate in fewer markets compared to major firms. We find that the price dispersion among fringe firms is lower than that of major firms.

While we do not observe non-financial characteristics of fringe firms in the NAIC data, our understanding is that they tend to focus more on small towns where insurance agents tend to be local. For example, Washington National sold LTCI policies just in three states during our sample period and usually accounted for less than 1% of the total market sales. The company emphasizes the shared value that their local agents operating in small towns have with their clients.[23] As the access to the Internet was not as common during our sample period, we conjecture that potential buyers of LTCI who were mostly retirees had a value for purchasing insurance from local agents.

[23]https://washingtonnational.com/.

	(1) Major firms		(2) Fringe firms	
Annual premium	2981.1	(3241.0)	2461.2	(1953.1)
Plan age	8.852	(3.640)	6.505	(3.786)
Have higher than anticipated claims	0.145	(0.191)	0.130	(0.251)
Per-enrollee annual claims	3001.8	(4615.5)	2350.0	(3542.6)
Plans offered	2.278	(1.603)	1.405	(0.824)
Insurer share of total sales	0.176	(0.126)	0.0163	(0.0140)
States where the insurer is active	39.89	(16.59)	29.72	(15.74)
Observations	1765		5994	

Table 1: Major vs. fringe firms
Notes: Data = Form C NAIC reports 2000-2007. The sample is at the insurer-state-year level. The sample consists of insurers that have strictly positive sales in a given state-year combination. We classify a firm as major if its sales account for at least 5% of the total market sales; otherwise, the firm is classified as a fringe. The table reports the means with standard deviations in parentheses.

5 Model

5.1 Environment

There are M LTCI markets that are defined by a geographical state and calendar year. In each market, there exists a unit mass of potential consumers and many potential insurers. There are three stages in the model (see Figure 5). In stage 0, insurers decide whether to enter the market based on the entry cost and the expected profit. In stage 1, insurers set an initial price for their LTCI contract.[24] Consumers observe the menu of insurance options available and make their insurance purchase decision. Consumers who choose the outside option are not necessarily uninsured, as those with limited assets can qualify for means-tested public LTCI, Medicaid. In stage 2, the uncertainty about aggregate risk is resolved, and insurers revise their price determined in the first stage. Consumers with private LTCI might lapse their contract, and LTC utilization takes place in the end.

During our sample period, no insurer offered LTCI that specified state-contingent prices, such as future rates indexed to inflation. As described in Section 2, we rationalize no insurer commitment by incorporating consumers that do not expect prices to increase (see also Section 5.6.3).

To make the analysis empirically tractable, we assume insurers consist of a finite number

[24]Each insurer in our model offers just one plan in a given market. This is a plausible assumption as over 60% of insurers offer just one plan in the data, and the mean number of plans offered is around 1.6.

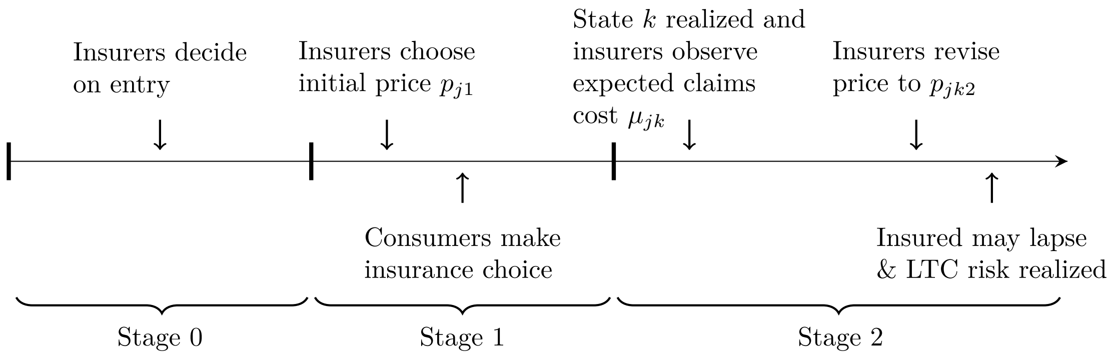


Figure 5: Timing of events

of major firms and many fringe firms. There are two differences between major and fringe firms. First, fringe firms make an entry decision, while major firms do not. This is based on the empirical evidence that pricing regulations have no effect on major firms' entry and exit, while they have a significant impact on the fringe (Figure D.1 in Appendix). Second, after entry, there is a representative fringe in each market that chooses a price schedule that all fringe entrants follow.[25] We impose this simplifying assumption to avoid endogenizing pricing decisions of every fringe observed in the data, which would render solving and estimating the model infeasible.

5.2 Fringe firms' entry decision

There is a continuum of fringe insurers that decide whether to enter the market. They know that once they enter, there will be a representative fringe that will decide on prices that all fringe entrants will follow. Fringe firms will enter the market if their expected profit is equal to or greater than their entry cost c^e, which follows the CDF denoted by G. Once fringe firms enter, they will respectively earn the profit of

$$\max\{\frac{1}{n_J}\Pi_J^* - c^e, 0\} \tag{4}$$

where Π_J^* denotes the profit of the representative fringe, and n_J is the measure of fringe firms that enter the market.

[25]A shown in Table 1, the price dispersion among fringe firms in the data is indeed smaller than that of major firms.

5.3 Firms' initial pricing and consumers' insurance choice

At the beginning of stage 1, the market consists of $J-1$ major firms and one representative fringe which is the collection of fringe entrants. Let $j \in \{1, 2, ..., J\}$ index insurers where $j = J$ means the representative fringe. Insurer j's profit in stage 1 is

$$\Pi_{j1} = p_{j1}s_{j1} - C_j^l(p_{j1} - \tilde{\mu}_j). \tag{5}$$

s_{j1} is the number of enrollees for insurer j in stage 1. C_j^l is the regulatory cost of setting an initial price that is different from the target level $\tilde{\mu}_j$ set by the government. The government sets $\tilde{\mu}_j$ based on the insurer's anticipated claims to ensure a certain level of loss ratio. We allow the regulatory cost C_j^l to be insurer-specific, capturing the idea that the enforcement of the regulatory standards set by the NAIC often depends on the regulator's taste (Liu and Liu, 2020). LTC utilization takes place at the end of the second stage, and insurers do not incur any claims cost in stage 1.[26]

Consumer i's flow utility from contracting with insurer j in stage 1 is

$$\tilde{u}_{ij1} \quad = \quad \alpha u(y_i - p_{j1}) + \gamma I(j = J)\ln(n_J) + \xi_j + \varepsilon_{ij}. \tag{6}$$

The function u represents consumers' utility over income and exhibits risk aversion. The individual consumes her income y_i minus the price she pays to insurer j. ξ_j is insurer j's unobserved characteristics that consumers might value, such as brand fixed effects. ε_{ij} represents choice-specific taste shocks. When the consumer chooses to buy insurance from the representative fringe $j = J$, the consumer's utility depends on the measure of fringe firms that have entered the market, n_J. This is to incorporate the possibility that consumers might value having insurer variety.[27]

If consumer i does not purchase any private LTCI, then her utility in stage 1 is given by

$$\tilde{u}_{i01} \quad = \quad \alpha u(y_i) + \varepsilon_{i0} \tag{7}$$

where ε_{i0} represents the consumer's taste shock associated with choosing the outside option.

[26] We assume there is no administrative cost of offering LTCI. While Braun et al. (2019) find that the administrative cost is important in explaining the low take-up rate of LTCI, we abstract from it as we do not have data on administrative cost at the insurer level.

[27] Consider a consumer's expected value when choosing from J fringe firms that generate the same utility to the consumer except for *i.i.d.* choice-specific logit shocks. Then, the consumer's expected value is equal to $\ln(n_J)$.

5.4 Firms' revised pricing

There are K possible aggregate states of the world in stage 2, and each state happens with probability π_k where $k = 1, ..., K$. When state k is realized, insurers learn that the expected claims cost from their existing cohort of consumers is equal to μ_{jk}.[28] Insurers then decide whether to increase the initial premium, and if so, by how much. Insurers are subject to the rate adjustment cost $C^{rs}_{jk}(p_{j1}, p_{jk2})$, which represents the cost associated with revising the premium from p_{j1} to p_{jk2} when the realized state is k in stage 2.

Insurer j's profit from the second stage when the realized state is k is

$$\Pi_{jk2} = (p_{jk2} - \mu_{jk})s_{jk2} - C^{rs}_{jk}(p_{j1}, p_{jk2}). \tag{8}$$

s_{jk2} is the insurer's market share in stage 2 which could be different from its first stage market share due to possible lapses by consumers. μ_{jk} is the expected claims cost given the realized state of the world. $C^{rs}_{jk}(p_{j1}, p_{jk2})$ is the cost associated with revising rates. It depends on the realized aggregate state (k) and the insurer (j), which means that it implicitly depends on the insurer's realized claims as well. The rate adjustment cost captures various frictions that insurers might face. First, it depends on government policies such as rate stability regulation. The government can make it costlier for insurers to increase rates by implementing stricter rate stability regulation. Second, $C^{rs}_{jk}(p_{j1}, p_{jk2})$ might also reflect the opportunity cost of adjusting prices. Implementing very large rate increases might lead to a negative reputation among regulators which could be costly to insurers. The reputation cost might be lower if insurers can better justify their rate increases, such as experiencing a severely adverse aggregate shock or being financially constrained.[29] When insurers set p_{jk2}, they also recognize that a higher price could potentially make consumers terminate their contract, the point we will further elaborate below.

After observing the second period premium, consumers terminate their contract with prob-

[28] Although we are not explicit about how insurers learn the realized state, one can consider that insurers update their beliefs based on realized claims from recent and older cohorts, in addition to changes in expected claims from the current cohort.

[29] In principle, it is more desirable to explicitly model mechanisms determining the opportunity cost of rate increases and disentangle it from rate stability regulation. We do not pursue this route because it requires much more financial information about insurers than we currently have in our data. Furthermore, it requires modeling complex interactions among consumers in different cohorts, the government, and insurers. Instead, in Section 6.4, we empirically show that the adjustment cost is higher in markets with stricter rate stability regulation. In counterfactual experiments, we focus on the short-run effects of policies to alleviate concerns about endogenous responses arising from mechanisms that we abstract from, such as changes in reputation costs.

ability δ_k. The lapse probability is modeled as exogenous and might be driven by reasons such as forgetting to pay premiums. We also model endogenous lapses in a simple way by assuming that consumers terminate their contract if they cannot afford the premium, i.e., $p_{jk2} > y_i$.[30] If consumers let their policies lapse, they have to use their own assets to pay for LTC, unless they qualify for Medicaid by having sufficiently low resources. Switching to a different insurer in the second stage is not a feasible option for consumers.[31]

When the realized state is k, consumer i's expected utility from holding the contract sold by insurer j is

$$\tilde{u}_{ijk} = (1 - \delta_k) u_{ijk,stay} + \delta_k u_{ik,lapse} \tag{9}$$

where $u_{ijk,stay}$ is consumer i's utility from keeping the existing contract, and $u_{ik,lapse}$ is the utility from lapsing the contract. The utility from retaining the current contract is given by

$$u_{ijk,stay} = \alpha u(y_i - p_{jk2}) + \gamma I(j = J) \ln(n_J) + \xi_j. \tag{10}$$

If consumers expect prices to remain unchanged in stage 2, they will use $p_{jk2} = p_{j1}$ when they evaluate their value from contracting with insurer j ex ante. As we assume full coverage LTCI contracts, consumers do not face any LTC spending risk when they keep their contract. The utility from terminating the contract is given by

$$u_{ik,lapse} = \int_{\lambda} \alpha u(y_i - oop(\lambda, y_i)) f_k(\lambda) d\lambda \tag{11}$$

λ is a random variable which represents the consumer's LTC expenses. It is distributed according to the PDF $f_k(\lambda)$ where k represents the aggregate state of stage 2. In the first stage, neither firms nor consumers know the exact distribution of λ. What they know is that (1) there are $K < \infty$ candidate distributions of λ, and (2) the probability that λ follows the PDF $f_k(\cdot)$ is $\pi_k \in [0, 1]$. We assume the distribution of λ is realized and observed by firms

[30] We do not explicitly consider the case where consumers endogenously terminate their contract based on changes in their preference for LTCI. In the previous version of the paper, we endogenized lapses by adding some (dis)tastes associated with terminating LTCI contracts in the second stage. As lapses are very rare when LTCI contracts are mature, the model predicted that consumers are not sensitive to rate increases. Consequently, insurers' incentive to raise rates was just as strong as the case with exogenous lapses, and the rate adjustment cost was again the key determinant of price dynamics. The insensitivity of lapses with respect to revised rates is also consistent with previous research. For example, Gottlieb and Smetters (2021) find that forgetting to pay premiums is the most important reason behind lapses in life insurance. Friedberg et al. (2017) similarly find that unintentional lapses are the most prevalent in the LTCI market.

[31] This is empirically grounded as most insurers do not sell contracts to individuals older than 70: sales made to individuals aged 70 or older account for less than 5% (Broker World, 2009-2015).

and consumers at the beginning of the second period. This implies that there is symmetric learning. The function *oop* represents consumers' out-of-pocket LTC costs which depend on their income y_i. This is to capture possible benefits from means-tested Medicaid. If consumer i did not purchase any LTCI contract in stage 1, then the consumer's utility in stage 2 is also equal to $u_{ik,lapse}$.

5.5 Equilibrium

Consumers in the first period make insurance purchase decisions to maximize their lifetime utility. Consumer i's expected lifetime utility from contracting with insurer $j \in \{1, ..., J\}$ is

$$\tilde{v}_{ij} = \underbrace{\alpha u(y_i - p_{j1}) + \gamma I(j = J) \ln(n_J) + \xi_j + \beta_c \sum_k \pi_k \left((1 - \delta_k) u_{ijk,stay} + \delta_k u_{ik,lapse}\right)}_{=v_{ij}} + \varepsilon_{ij} \tag{12}$$

where β_c is the consumer's discount factor. As described above, when consumers expect prices to remain unchanged from stage 1 to stage 2, they will use the initial price p_{j1} in evaluating their value from retaining the contract in stage 2, $u_{ijk,stay}$. The consumer's expected lifetime utility from not purchasing any insurance is

$$\tilde{v}_{i0} = \underbrace{\alpha u(y_i) + \beta_c \sum_k \pi_k u_{ik,lapse}}_{=v_{i0}} + \varepsilon_{i0}. \tag{13}$$

If j^* is the chosen option by consumer i, then $j^* = \underset{j=0,1,...,J}{\text{argmax}}\ \tilde{v}_{ij}$.

Insurers' problem can be solved backwards. In stage 2, given the realized state k, each insurer j chooses the revised premium by maximizing its state-specific profit:

$$\Pi^*_{jk2} = \underset{p_{jk2}}{\text{Max}}\ (p_{jk2} - \mu_{jk}) s_{jk2} - C^{rs}_{jk}(p_{j1}, p_{jk2}) \tag{14}$$

where s_{jk2} is the market share in stage 2, which depends on the lapse rate and the initial market size, i.e., $s_{jk2} = (1 - \delta_k) s_{j1}$. We allow for a possible corner solution, $p_{jk2} = p_{j1}$, where insurers decide not to increase the premium in the second stage. This may happen if the adjustment cost contains a fixed cost of revising the premium.

Given the optimal sequence of $\{p_{jk2}\}_{k=1}^K$ which is a function of the initial premium p_{j1}, insurer j in stage 1 chooses p_{j1} to maximize its profit over the lifetime of LTCI contracts:

$$\Pi_j^* = \operatorname*{Max}_{p_{j1}} p_{j1}s_{j1} - C_j^l(p_{j1} - \tilde{\mu}_j) + \beta_f \sum_k \pi_k \Pi_{jk2}^* \tag{15}$$

where β_f is the firm's discount factor.

In stage 0, a fringe firm with entry cost c^e will enter the market if

$$c^e \leq \frac{1}{n_J}\Pi_J^* \tag{16}$$

where n_J is the measure of fringe entrants, and Π_J^* is the representative fringe's lifetime profit given in equation (15).

We characterize a Nash equilibrium in each market that consists of the vector of premiums $(p_{j1}, \{p_{jk2}\}_{k=1}^K)$ for each insurer j and the number of fringe insurers n_J that solve equations (14), (15), and (16).

5.6 Model discussion

5.6.1 Price dynamics

In our model, insurers pass through aggregate risk to consumers by setting premiums that depend on the realized state of the world, $k = 1, ..., K$. The dependence arises because the adjustment cost C_{jk}^{rs} varies by k.[32] For example, in states where the reputation cost is small due to the realization of adverse claims costs, insurers have a strong incentive to raise their premium. The rate increase incentive is strengthened by the fact that there is no competition among insurers in the second stage.

Government policies related to C_{jk}^{rs} can crucially affect premium volatility in the market. For example, the government can improve premium stability by increasing the adjustment cost through a stricter version of rate stability regulation. However, the regulation might negatively impact the number of fringe insurers by lowering their expected profit from entry. The welfare consequence of dynamic pricing regulation depends on this trade-off.

[32]The price dependence on k might also arise if consumers' value for the outside option depends on k, and consumers' lapses are very responsive to the revised premium. We do not pursue this route because the lapse rate at older contract ages is negligible in the LTCI market.

The government can alternatively impact the price dynamics by offering reinsurance to insurers, i.e., providing state-dependent subsidies.[33] Reinsurance can potentially reduce the price dependence on aggregate risks. However, it cannot prevent insurers from exploiting locked-in consumers and charging a high mark-up in the second stage. In contrast, dynamic pricing regulation tames insurers' exercise of market power by directly affecting the cost of rate increases.

5.6.2 Aggregate risk

Insurers in our model face aggregate risk about their future claims costs.[34] The sources of the risk include uncertainty over formal LTC costs, which are hard to forecast as they are impacted by technological changes applied to medical treatments (Cutler, 1996). This is in contrast to life insurance where the dollar value of a payout is fixed. Furthermore, given the long time lag between the purchase and use of insurance, insurers' ability to forecast future costs is limited. Cutler (1996) discusses the quantitative importance of average cost uncertainty faced by LTC insurers and how it might prevent them from offering insurance.

5.6.3 Lack of insurer commitment

The key assumption we use to rationalize the lack of insurer commitment is consumers' misbeliefs that prices will remain constant, as described in Section 2. According to a survey by LifePlans (2017), in 2015, less than 20% of LTCI policyholders knew that their insurer had raised premiums on other policyholders. In health insurance, Atal et al. (2022) also provide evidence that about one half of retirees do not consider possible changes in future premiums when they decide to purchase insurance. In the context of life insurance, Gottlieb and Smetters (2021) provide evidence that consumers understate the likelihood of needing money in the future. Admittedly, our assumption that all consumers have misbeliefs might be too restrictive, which could inflate the welfare benefit of providing consumers with correct beliefs over future rates. In Section 7.1.2, we show that consumers' benefit from correct information

[33] While there are policy discussions about state-based reinsurance in the LTCI market, it currently does not exist (NAIC, 2016). Instead, each state has State Guaranty Association that pays out claims up to certain limits when an insurer becomes insolvent.

[34] In practice, insurers also face other types of risks, including interest rate risk. Together with high capital requirements in the industry, such risks are also considered to be important in accounting for insurer exits especially since the great recession (NAIC, 2016). We abstract from this channel because we focus on the years before the great recession when the interest rates were more stable.

is relatively small, suggesting that the quantitative bias generated by our assumption is limited.

5.6.4 Assumptions on demand-side channels

While our model is richer in the treatment of the market structure, dynamic contracts, and supply-side regulations than existing studies on LTCI, there are a few limitations. First, although we explicitly model Medicaid as a mean-tested public LTCI, we do not consider alternative modes of insurance through savings or family care, which interact with the demand for private LTCI (Lockwood, 2018; Mommaerts, 2020; Ko, 2022). As long as the impact of supply-side regulations on these alternative channels is limited, our quantitative analysis will still be valid.[35] Second, we do not model the possibility of adverse selection. Papers like Braun et al. (2019) and Ko (2022) show that private information limits the size of the LTCI market to a certain degree.[36] As the pricing regulations we focus on affect the entire cohort of buyers, we conjecture that the omission of adverse selection does not substantially bias our quantitative findings.

6 Estimation

6.1 Estimation sample

As explained in Section 4.1, we build our estimation sample by linking Form C NAIC reports to the rate increase data based on plan identifiers.[37] The rate increase data contain state-specific rate increase history of insurers who had business in California between 2007-2017. For plans observed in the NAIC data that were sold by insurers who did not operate in California between 2007-2017, we do not know how their premiums changed afterwards. To deal with this issue, we only use plans in the NAIC data that were sold by insurers who had strictly positive lives covered in California between 2007-2017. Imposing this restriction reduces the total nationwide sales observed in the NAIC sample by about 9% and insurer-state-year pairs by 14%.

[35] For example, existing studies find that family caregivers' opportunity cost and guilt are important determinants of informal LTC (Ko, 2022).

[36] Kong et al. (2022) show that adverse selection may also affect insurers' participation.

[37] It is not uncommon to observe insurers not using exactly the same plan identifier across the two datasets. We identify such inconsistencies based on information available in both datasets such as lives covered and the first issue year. We manually correct for mistakes to increase the match rate between the two datasets.

We define a market at the state-year level. We observe 50 states for 8 years, resulting in 400 markets. Our model assumes insurers offer just one plan, which is largely consistent with the data: insurers typically sell just one or two plans in a given market. When insurers offer multiple plans, we select the "dominant" plan which has the largest sales. After the dominant plan selection, each insurer is matched to one plan in our sample. We classify an insurer as a major firm if its sales account for at least 5% of the total sales in the market; otherwise, we classify the firm as a fringe. We aggregate all fringes' sales to compute the representative fringe's sales in a given market. We take the mean of all fringes' prices to compute the representative fringe's price.[38]

To compute market shares, we divide each insurer's sales by the total number of potential enrollees in a given market. We use the population aged 60 multiplied by the "non-reject" scale as the denominator. Braun et al. (2019) estimate that about 46% of 55-66 year olds would be denied LTCI coverage based on health underwriting practices. We, therefore, assume only 54% of the population aged 60 are able to purchase insurance. The overall coverage rate is computed as 20%.

6.2 Empirical specification

6.2.1 Time horizon

At the beginning of the first stage, consumers make an once-and-for-all private LTCI choice. Then, they pay the annual premium for n_1 years during the first stage. The second stage lasts n_2 years, during which those with private LTCI pay the revised premium and those without pay for LTC either using their own resources or Medicaid benefits. We set $n_1 = 8$ years and $n_2 = 4$ years. We assume both consumers and insurers have the same annual discount factor ($\beta = \beta_c = \beta_f$) and set $\beta = 0.97$. For notational simplicity in what follows, we define the following time horizon scales: $B_1 = \frac{1-\beta^{n_1}}{1-\beta}$ and $B_2 = \frac{1-\beta^{n_2}}{1-\beta}$.

6.2.2 Consumer income and assets

For information about consumer income and assets, we turn to the Health and Retirement Study (HRS) which has surveyed a representative sample of elderly Americans every two years since 1992. Our measure of income includes social security retirement income, employer

[38]Table D.2 in Appendix reports how the summary statistics of the fringes change after the aggregation.

pension, annuity income, and other income. We consider three consumer groups whose resources correspond to the 20th, 50th, and 80th percentiles of the sample distribution.

6.2.3 LTC risk and Medicaid

We calibrate the costs of LTC such that the mean lifetime LTC expenses are \$60,000, and the mean lifetime LTC expenses conditional on using LTC throughout the second stage are \$100,000 (Kemper et al., 2005/2006).[39] For consumers whose net resources become negative after paying for LTC costs, Medicaid provides transfers such that their resources become zero (Lockwood, 2018).[40]

6.2.4 Cost function

We assume the following functional forms for firms' costs:

$$C_{jk}^{rs}(p_{j1}, p_{jk2}) = \begin{cases} c^0 + \frac{c_{jk}^1}{2}(p_{j1} - p_{jk2})^2 & \text{if } p_{jk2} > p_{j1} \\ 0 & \text{if } p_{jk2} = p_{j1} \end{cases} \tag{17}$$

$$C_j^l(p_{j1} - \tilde{\mu}_j) = \frac{c_j^l}{2}(p_{j1} - \tilde{\mu}_j)^2 \tag{18}$$

The premium adjustment cost C_{jk}^{rs} incorporates a fixed cost component (c^0). This is to rationalize the share of insurers that do not increase rates in the data.

We specify the initial rate regulation such that costs are incurred whenever the firm's initial premium p_{j1} deviates from its target price set by the government $\tilde{\mu}_j$. We assume the government sets $\tilde{\mu}_j$ such that the loss ratio reaches a certain target level, lr_{target}. For the purpose of determining $\tilde{\mu}_j$, the government assumes there are zero lapses and the premium remains constant. Then, the target loss ratio will be achieved if p_{j1} is equal to

$$\tilde{\mu}_j = \frac{\beta^{n_1} B_2 \sum \pi_k \mu_{jk}}{lr_{target}(B_1 + \beta^{n_1} B_2)} \tag{19}$$

where the numerator is the expected present discounted value of claims. We set $lr_{target} = 0.8$, which falls in the range of the targeted loss ratio during our sample period. We allow c_j^l to

[39] Specifically, we assume that in each year of the second stage, consumers use formal LTC services with a probability 0.6 which results in annual LTC costs of $\$100,000/n_2$.

[40] The implicit assumption is that the type of formal care services used is nursing home care which already provides basic food and housing.

vary across insurers and markets. The parameter will therefore capture policy changes to loss ratio regulation during our sample period.

6.2.5 Other parameters

We assume consumers' utility over income follows a log function, $u(y) = \ln(y)$. A joint study by LIMRA and Society of Actuaries reports that the annualized lapse rate was around 3% between 2008-2011. As our second stage lasts four years ($n_2 = 4$), we calibrate the lapse probability at $\delta_k = 4 \times 3\% = 12\%$ for all k.

6.3 Estimation strategy

6.3.1 Demand estimation

Prediction of second-stage premium increases

One empirical challenge we face is that we only observe revised premiums for the realized state of the world. That is, we do not observe p_{jk2} for all $k = 1, ..., K$. We address the challenge by estimating the distribution of rate increases using a finite mixture model, which we detail in Appendix B.

Estimation of demand-side parameters

We follow the estimation strategy in Berry et al. (1995) to recover demand parameters. The demand parameters that we estimate is (α, γ), which comprises consumption utility scale and preference for fringe variety. We specify the unobserved characteristics of insurer j as

$$\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}. \tag{20}$$

We explicitly control for insurer and time fixed effects, and the remaining variation in unobserved characteristics is $\Delta\xi_{jt}$, changes in consumers' unobserved taste for insurer j. The key challenge in our demand estimation is the endogeneity issue of premiums and fringe variety, which could reflect unobserved demand changes.

We use various plausibly exogenous variations to address the issue. First, we exploit cross-market variations in the spirit of Hausman (1996) and Nevo (2001) and instrument prices using insurers' own prices in other markets.[41] Our identification assumption is that there may be common supply shocks across geographic areas that affect prices, which are uncorrelated with demand. For example, insurers may update their beliefs about future claims cost based on the realized claims costs from their existing buyer cohorts. As long as insurers' updated beliefs are uncorrelated with unobserved demand from potential buyers, we have a valid instrument. Second, we exploit variations in states' adoption of the RSR 2000. We assume the implementation of supply-side regulations is orthogonal to changes in consumers' unobserved demand. Specifically, we use the change in the number of fringe entrants in the year the RSR 2000 was adopted to instrument for endogenous fringe variety.[42]

The estimation is implemented by the standard Generalized Method of Moment. We use a contraction mapping to recover ξ_{jt} as in Berry et al. (1995). Given other demand parameter estimates, we solve for ξ_{jt} that rationalizes the observed market share of each insurer. We then calculate $\Delta\xi_{jt}$ and evaluate the moment conditions.

6.3.2 Supply estimation

Prediction of second-stage claims

To estimate the supply side, we need demand estimates and data on premiums and claims. As we did for the demand estimation, we use observed initial prices p_{j1} and estimated state-contingent prices p_{jk2}. Moreover, we only observe claim costs for the realized state of the world. Using a procedure similar to the one used in the estimation of p_{jk2}, we estimate state-contingent claims μ_{jk} outside the model. Appendix B provides details.

Estimation of premium adjustment cost

We first estimate the parameters that enter the premium adjustment cost function which include the fixed cost component c^0 and the coefficient c^1_{jk}. Note that we cannot separately identify c^0 and c^1_{jk} without imposing further functional form assumptions. We assume $c^1_{jk} \sim \ln N(\mu_c, \sigma_c)$. As we detail in Appendix B, we estimate (c^0, μ_c, σ_c) by the maximum likelihood estimator. The resulting estimates do not point-identify c^1_{jk} in states where insurer j does not increase its premium. However, we need an estimate of c^1_{jk} to estimate the rest of the

[41]We use this instrument only for major firms' prices.

[42]Another implicit assumption is that such policy change does not inform consumers that insurers often change the second stage premium. We believe this assumption is plausible in our context as consumers' lack of knowledge about future rate increases was common even in 2015 (see Section 5.6.3).

cost parameters and to do counterfactuals. Therefore, for observations with $p_{jk2} = p_{j1}$, we predict c^1_{jk} using the estimated distribution of c^1_{jk} and firms' optimality condition. Define the threshold c^{1*}_{jk} which makes insurer j indifferent between increasing and not increasing its premium:

$$c^{1*}_{jk} = \frac{(s_{jk2})^2}{2c^0} \tag{21}$$

We set c^1_{jk} as

$$c^1_{jk} = \begin{cases} E[c|c > c^{1*}_{jk}] & \text{if } p_{jk2} = p_{j1} \\ \frac{s_{jk2}}{p_{jk2}-p_{j1}} & \text{if } p_{jk2} > p_{j1} \end{cases} \tag{22}$$

Estimation of initial rate regulation cost

We estimate the parameter that enters the cost function associated with initial rate regulation, c^l_j, using the first-order condition with respect to p_{j1}:

$$c^l_j(p_{j1} - \tilde{\mu}_j) = B_1 \left(s_{j1} + p_{j1} \frac{\partial s_{j1}}{\partial p_{j1}} \right) + \beta^{n_1} B_2 \sum_k \pi_k \left((p_{jk2} - \mu_{jk}) \frac{\partial s_{jk2}}{\partial p_{j1}} - 1(p_{j1} \neq p_{jk2}) c^1_{jk} (p_{jk2} - p_{j1}) \right) \tag{23}$$

Estimation of entry cost

The entry cost cutoff c^{e*} faced by the fringe in each market is

$$c^{e*} = \frac{\Pi_J}{n_J} \tag{24}$$

n_J is the measure of fringe entrants which is directly observed in the data. Once we have the demand and regulatory cost estimates, we can calculate insurer profits and hence the cutoff c^{e*}. We assume that the CDF of the entry cost is log-normal, i.e., $c^e \sim \ln N(\mu_e, \sigma_e)$, and that the measure of the potential fringe is N_J. We then have

$$G(c^{e*}; \mu_e, \sigma_e) = \frac{n_J}{N_J} \tag{25}$$

where G is the CDF of the entry cost. We set $N_J = 100$ and $\sigma_e = 1$ and estimate μ_e for each market using the equation above.

Parameter	Notation	Estimate
Consumption utility scale	α	0.0816 (0.0289)
Fringe variety utility scale	γ	0.0146 (0.0115)
Demand elasticity		
With respect to initial premium	$\frac{\partial \ln s_{j1}}{\partial \ln p_{j1}}$	-0.0745
With respect to fringe variety	$\frac{\partial \ln s_{J1}}{\partial \ln n_J}$	0.1555

Table 2: Demand parameter estimates
Notes: The table reports the demand parameter estimates. Standard errors are reported in parentheses.

6.4 Estimation results

Table 2 reports the results from our demand estimation. The consumption utility scale (α) has an estimate of 0.0816. Consumers' preference for fringe variety (γ) is estimated at 0.0146, which implies that consumers value having access to more fringe firms. To better interpret the estimates, we report the associated demand elasticity with respect to the initial rate (p_{j1}) and with respect to fringe variety (n_J).[43] We find that the mean elasticity with respect to the initial premium is -0.0745, which is quite small. There are very few studies that have estimated the price elasticity of LTCI. The small elasticity that we find is broadly consistent with Cramer and Jensen (2006) who also find that the demand for LTCI is price inelastic, with elasticities as small as -0.23.[44] Regarding demand elasticity with respect to fringe variety, we find that when fringe variety is reduced by 10%, the demand for fringe firms in the market decreases by 1.56%. To the best of our knowledge, we are not aware of other papers that have estimated insurer variety elasticity in the LTCI market.

Our demand estimates suggest that consumers are relatively insensitive to premium and insurer variety. The result suggests that premium subsidies may not be effective in increasing the demand for LTCI. This is consistent with existing studies (e.g., Brown and Finkelstein (2008)) which argue that the level of premiums is not sufficient to explain the low take-up rate of LTCI. They find other factors such as Medicaid as a more relevant explanation. Our conclusion is drawn from a different identification strategy which accounts for insurer-level demand and price variations across insurers. Moreover, it suggests that insurers can exercise significant market power.

[43]In calculating the elasticities, we assume consumers stay with the same insurer and are subject to changes in premiums and insurer variety in both periods.

[44]Goda (2011), in contrast, finds a higher price elasticity of -3.3. She uses variation in state tax subsidies for private LTCI to estimate individuals' probability of purchasing any private LTCI contract. Our approach differs from hers as we estimate the demand for each LTCI insurer, explicitly allowing for preference heterogeneity for different providers.

Parameter	Notation	Mean	S.d.
Premium adjustment cost			
: Fixed cost	c^0	0.7451	-
: Mean of $\ln(c^1_{jk})$	μ_c	-9.5213	-
: S.d. of $\ln(c^1_{jk})$	σ_c	2.6700	-
: Cost	C^{rs}_{jk}	8.51	15.65
Initial rate regulation cost			
: Coefficient (10^{-2})	c^l_j	0.0005	0.6128
: Cost	C^l_j	52.44	165.55
Fringe firms' entry cost			
: Mean of $\ln(c^e)$	μ_e	4.3629	0.7187
: Mean entry cost	$E(c_e)$	162.22	116.70

Table 3: Supply parameter estimates

Notes: The table reports summary statistics of the supply parameter estimates. Standard deviation (S.d.) of C^{rs}_{jk} represents the standard deviation across market-insurer-state combinations. S.d. of c^l_j and C^l_j represents the dispersion across insurer-market pairs. S.d. of μ_e and $E(c_e)$ represents across-market dispersion.

Table 3 shows the cost parameter estimates. On average, insurers pay 8.51 for adjusting rates. As the average market share is about 0.03, we can express the per enrollee cost associated with rate adjustment as \$284 (8.51/0.03). We analyze whether our cost estimates increase with the adoption of RSR 2000. We compute the point estimates of the cost coefficient c^1_{jk} as defined in equation (22) and examine how they change after the regulation adoption. Table D.3 in Appendix reports the results. We find that across all possible states of the world (k), the mean cost estimate increases after the regulation adoption. On average, the regulatory cost coefficient increases by 40%, consistent with the fact that RSR 2000 made it harder for insurers to revise rates. The finding suggests that rate stability regulation directly affects premium adjustment costs. For initial rate regulation, insurers pay 52.44, which translates into the per enrollee cost of \$1748 (52.44/0.03). Such large regulatory costs are needed to rationalize relatively low premiums in the data, despite the small price elasticity that we find.

7 Counterfactual policy experiments

In this section, we use our estimated model to examine the effect of supply-side regulations on the market equilibrium and welfare. For each counterfactual, we numerically solve for a new equilibrium. To calculate the impact on welfare, we calculate consumers' expected utility and use it to obtain the consumption equivalent variation (see Appendix for details). While consumers in our model believe prices remain constant, in calculating consumer welfare, we use *actual* prices charged by firms. By doing so, we account for how premium volatility affects consumer welfare in the market.

7.1 Dynamic pricing regulation

7.1.1 Welfare effect of rate stability regulation

First, we examine the effect of rate stability regulation. Theoretically, the welfare impact is ambiguous. The direct effect of the policy is to reduce premium volatility. This will benefit risk averse consumers. However, it also implies that insurers face a higher cost of revising rates, lowering their expected profit in the second stage. If this profit loss is large, fringe insurers will have an incentive to stay out of the market. As we find that consumers value having fringe variety, this margin will negatively impact their welfare.

We vary the estimated cost associated with premium adjustment, c^1_{jk} in equation (22).[45] Specifically, we consider values of c^1_{jk} from 50% to 200% of its baseline estimate. The first row of Figure 6 reports the resulting changes in equilibrium prices and fringe variety relative to the benchmark equilibrium. According to Panel A, the initial rate shows almost no response to the changes in the adjustment cost.[46] This is because as reported in Table 3, we find substantial costs associated with deviating from the initial target price set by the regulator. As such, for the range of c^1_{jk} that we consider in our counterfactual, we see almost no change in the initial rate set by insurers. This is consistent with our descriptive finding that the RSR 2000 had no impact on initial rates (see Figure 3 in Section 4).

Panel B shows the mean change in the revised price in the second stage. The second-stage premium decreases in the strictness of the regulation. Specifically, when the regulatory cost is reduced by a half, the second-stage price increases by 15% on average relative to the baseline equilibrium. In contrast, when the regulatory cost doubles, the second-stage price decreases by about 7%. Consistent with our descriptive finding, we find that rate stability regulation in our model acts to depress rate increases. Panel C shows that the measure of

[45] Although we consider that C^{rs}_{jk} captures both regulatory and non-regulatory components, in the rest of analysis, we assume that the government can directly change the rate adjustment cost that insurers face. As reported in Section 6.4, we find that the adoption of RSR 2000 increases c^1_{jk} by about 40%.

[46] For example, when the regulatory cost doubles, the mean initial rate increases by 4.33e-04% relative to the baseline.

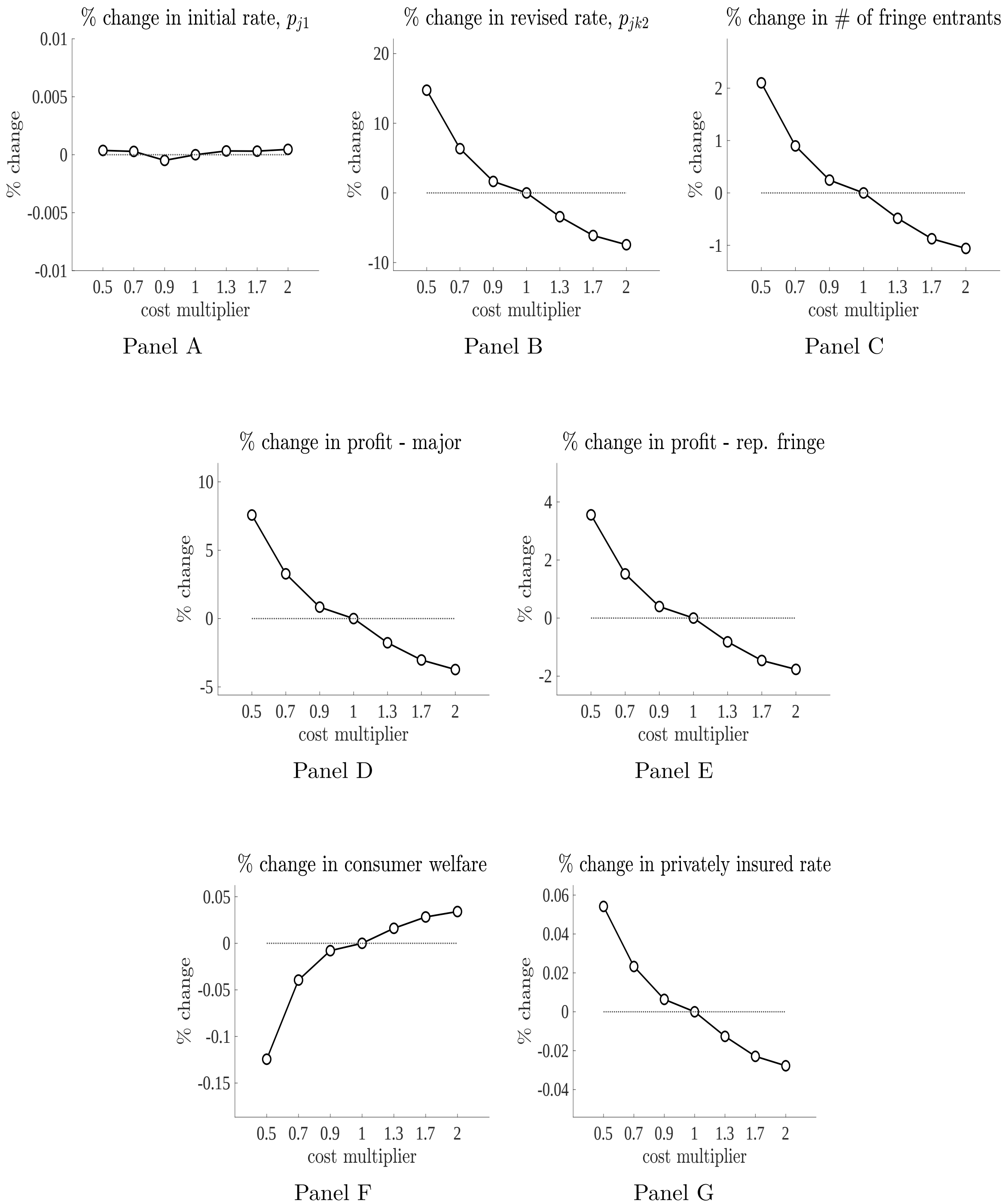


Figure 6: Counterfactual rate stability regulation
Notes: All panels report the % change in the market outcome relative to the baseline estimate. We consider values of c^1_{jk} from 50% to 200% of its baseline estimate.

fringe entrants decreases in the regulatory cost. For example, when the regulatory cost is halved, the fringe variety measure increases by about 2%. In contrast, when the regulatory cost doubles, the fringe variety decreases by about 1%. Panel C therefore represents the cost of the rate stability regulation to consumers, while Panel B illustrates the benefit of the regulation.

Panels D and E show that profits decrease in the rate stability regulatory cost for both major and fringe firms. For example, when the rate stability regulatory cost is reduced by a half, major firms' profits increase by about 8%, and representative fringes' profits increase by about 4%.

Panel F shows the impact on consumer welfare. We find that consumer welfare increases in the regulatory cost, but the impact is very modest. For example, when the regulatory cost doubles, consumer welfare increases just by 0.03% relative to the baseline. The result implies that the benefit of improved premium stability is almost washed out by the cost of reduced fringe variety.[47] Finally, Panel G reports the impact on the LTCI coverage rate. A stricter version of the regulation improves premium stability at the cost of reduced insurer variety. As consumers in our model believe there are no rate increases, only the latter channel affects their insurance choice. As a result, the demand for LTCI decreases in the strictness of the rate stability regulation, although the magnitude is very modest.

To sum, stricter rate stability regulation has a very limited impact on improving consumer welfare, while substantially lowering insurer profits and participation on the market. The negligible impact on consumer welfare stems from the fact that the benefit of enhanced premium stability is almost washed out by the reduction in insurer variety. The result highlights the importance of quantifying the dynamic consequences of pricing regulations.

7.1.2 Value of commitment

We now consider the welfare impact of insurer commitment. As discussed in Section 2, the key feature in our model resulting in a lack of insurer commitment is consumers' misbeliefs about the distribution of future premiums. Once consumers have correct beliefs, risk-neutral insurers will have an incentive to offer a smooth premium schedule, which will positively impact consumers' insurance choice.

To explore the value of insurer commitment, we conduct a counterfactual experiment where consumers have correct beliefs over the distribution of rate increases which results in

[47] When we drastically decrease the rate stability regulatory cost to 10% of the baseline, consumer welfare decreases substantially by about 5%. In this case, the second-stage price increases by 132% relative to the baseline, and the fringe variety increases by 18%.

Panel A. Changes in equilibrium outcomes (%)	
Initial rate	0.17
Revised rate	-13.12
Fringe entrants	-1.76
Total enrollment	-0.06
Panel B. Changes in welfare (%)	
Consumer welfare	0.05
Major insurer profits	-2.03
Representative fringe profits	-3.00

Table 4: Impact of insurer commitment
Notes: The table reports the effect of correcting consumers' beliefs about future rates, which results in insurer commitment to a constant price schedule.

insurers' commitment to a constant premium schedule. Table 4 reports how the equilibrium outcomes change relative to the benchmark economy where consumers do not expect rate increases. First, the new equilibrium has a slightly higher initial rate while it achieves a substantially lower revised premium. Interestingly, consumer welfare increases while total enrollment decreases slightly. The decline in enrollment is mainly due to the reduction in the number of fringe entrants. We find that insurers' profitability decreases, suggesting that they exploit consumers' lack of knowledge about future rate increases in the benchmark economy.

The findings suggest that policies such as better informing consumers about product characteristics have nontrivial welfare implications. On the one hand, price stability could be improved as a result of firm commitment. On the other hand, the welfare gain could be limited due to a reduction in product variety. We conjecture that policies such as entry subsidies could mitigate the latter impact and sustain firm participation.

7.2 Interaction between rate stability regulation and Medicaid

Many existing studies have identified Medicaid as an important demand-side policy that explains the low take-up rate in the LTCI market. We now examine whether the effectiveness of supply-side policies interacts with the generosity of Medicaid.

To do this, we first simulate an economy with a more generous Medicaid program which provides a higher consumption floor.[48] Table 5 reports the equilibrium outcomes under baseline Medicaid (Column 1) and under generous Medicaid (Column 2). When Medicaid

[48]The baseline Medicaid program ensures assets do not become negative. This is what Medicaid does in reality for people in a nursing home who already receive basic food and housing provided by nursing home care. To consider a more generous Medicaid program, we increase the annual consumption floor to $5,000.

	(1) Baseline Medicaid	(2) Generous Medicaid
Initial rate	1945.82	1945.81
Revised rate	2444.83	2281.07
Fringe entrants	17.30	12.19
Major insurer profits	341.25	224.08
Each fringe insurer profits	33.08	26.92
Private LTCI coverage rate	0.21	0.15

Table 5: Medicaid generosity and market outcomes
Notes: Column (1) reports the market equilibrium outcomes under the baseline Medicaid program. Column (2) reports the market equilibrium outcomes when Medicaid benefits become more generous. Specifically, we increase the annual consumption floor from zero to $5,000.

benefits become larger, consumers' value for the outside option increases, which reduces the demand for LTCI. Note that the marginal revenue from rate increases is proportional to the demand. As the marginal revenue from rate increases is smaller when Medicaid is more generous, insurers increase rates by a smaller magnitude to reduce the marginal cost of rate adjustment accordingly. We find that the mean annual premium in the second stage decreases by about 7%.[49] Insurers' mean profits decrease by about a third due to the lower demand. The reduction in insurer profits leads to less entry, and the measure of fringe variety is reduced by 30%. As a result of a better outside option and reduced fringe variety, the equilibrium LTCI coverage rate decreases from 21% to 15%.[50]

To examine the effect of rate stability regulation when Medicaid is more generous, we again vary the regulatory cost. We then compare the resulting outcome to the equilibrium reported in Column (2) of Table 5. In Figure 7, dashed lines with cross markers represent the percent change in market outcomes relative to Column (2) of Table 5. We find that the generosity of Medicaid acts to depress the impact of rate stability regulation on rate increases, fringe variety, insurer profits, and consumer welfare. The result is generated by the fact that there is a larger crowd-out effect of public insurance, which acts to dampen the impact of the regulation on the private insurance market. One policy implication is that the regulation could improve price stability at a smaller negative impact on insurers when

[49]We find that increasing Medicaid benefits has almost no impact on the initial rate. On the one hand, insurers might reduce the initial rate in response to a better outside option that consumers have. On the other hand, consumers that still remain in the market after Medicaid expansion are wealthier individuals who are less price sensitive, which might put upward pressure on the initial rate. The two forces seem to cancel out each other, resulting in close to zero impact on the initial rate.

[50]While premium stability is improved when Medicaid benefits increase, it does not affect consumers' insurance choices as they believe rates are always constant.

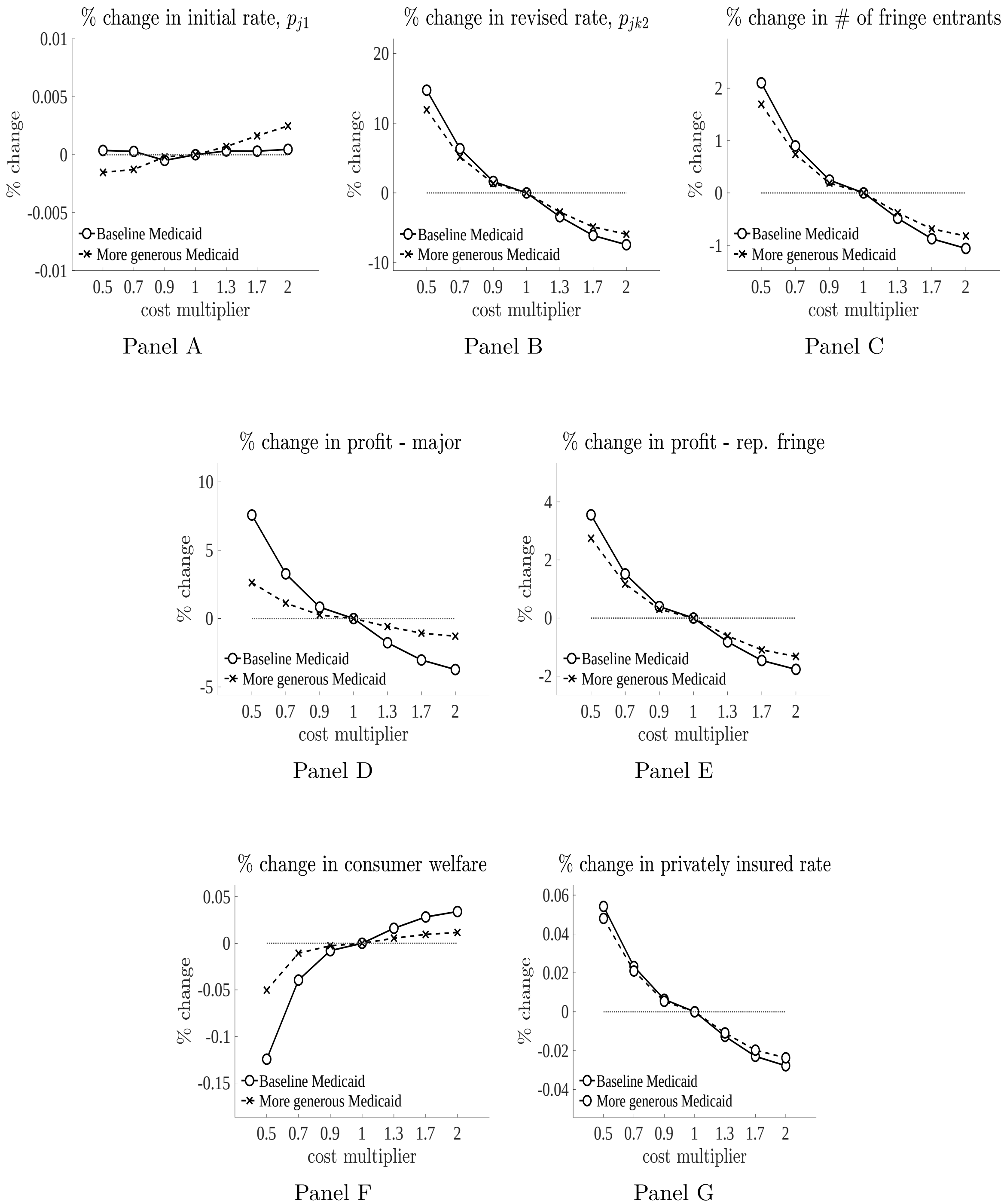


Figure 7: Counterfactual rate stability regulation under more generous Medicaid
Notes: Dashed lines with cross markers represent the change in the market outcome as we vary the regulatory cost under a more generous Medicaid program. Solid lines with circle markers are the same lines reported in Figure 6, which represent the change in market outcomes when we vary the regulatory cost under the baseline Medicaid program.

Medicaid benefits are more generous.

8 Conclusion

In this paper, we examine the effects of dynamic pricing regulation on market outcomes and welfare in the LTCI industry. We start by documenting descriptive evidence that the introduction of rate stability regulation reduced premium volatility faced by policyholders at the expense of lower insurer participation. To assess the welfare impact of dynamic pricing regulation, we develop and estimate a dynamic equilibrium model of LTCI with endogenous entry where insurers face uncertainty about future claims costs. The model incorporates various frictions, including imperfect competition, regulatory costs, and consumers' misbeliefs about future rates. We find that very strict rate stability regulation reduces social welfare. This is mainly because the benefit of improved rate stability is outweighed by the cost of insurer participation. We show that the magnitude of the welfare impact depends on the generosity of demand-side policies, such as Medicaid.

Our paper takes a first step to address market design problems in insurance markets where dynamic contracting and imperfect competition are relevant. In doing so, we have made several simplifying assumptions that could be relaxed in future research. First, we do not explicitly model a possibility of adverse selection. It would be interesting to explore how adverse selection affects the efficiency of supply-side regulations. Second, there are other supply-side frictions that the paper does not incorporate. For example, it would be interesting to examine the effect of capital requirements or bankruptcy constraints faced by insurers on their dynamic pricing and plan offering decisions.

References

Ameriks, John, Joseph Briggs, Andrew Caplin, Matthew D Shapiro, and Christopher Tonetti, "The Long-Term-Care Insurance Puzzle: Modeling and Measurement," Working Paper 22726, National Bureau of Economic Research October 2016.

Atal, Juan Pablo, "Lock-in in Dynamic Health Insurance Contracts: Evidence from Chile," Technical Report 19-020, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania November 2019.

_ , Eduardo M. Azevedo, and Sebastian Fleitas, "Static and Dynamic Incentives in Selection Markets," Working Paper, 2022.

— , **Hanming Fang, Martin Karlsson, and Nicolas R Ziebarth**, "Long-Term Health Insurance: Theory Meets Evidence," Working Paper 26870, National Bureau of Economic Research March 2020.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, pp. 841–890.

Braun, R. Anton, Karen A. Kopecky, and Tatyana Koreshkova, "Old, Frail, and Uninsured: Accounting for Features of the U.S. Long-Term Care Insurance Market," *Econometrica*, 2019, *87* (3), 981–1019.

Broker World, "Long Term Care Survey," 2009-2015. Broker World.

Brown, J. R. and A. Finkelstein, "Why Is the Market for Long-Term Care Insurance So Small?," *Journal of Public Economics*, 2007, *91(10)*, 1967–1991.

Brown, Jeffrey R. and Amy Finkelstein, "The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market," *American Economic Review*, June 2008, *98* (3), 1083–1102.

Chetty, Raj and Amy Finkelstein, "Social Insurance: Connecting Theory to Data," in "handbook of public economics," Vol. 5 of *Handbook of Public Economics*, Elsevier, 2013, pp. 111 – 193.

Cochrane, John, "Time-Consistent Health Insurance," *Journal of Political Economy*, 1995, *103* (3), 445–73.

Cramer, A.T. and G.A. Jensen, "Why don't people buy long-term-care insurance?," *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 2006, *61* (4).

Cutler, David M., "Why Don't Markets Insure Long-Term Risk?," *Working paper*, 1996.

Department of Health and Human Services, "Exiting the Market: Understanding the Factors Behind Carriers' Decision to Leave the Long-Term Care Insurance Market," April 2005.

Einav, Liran, Amy Finkelstein, and Jonathan Levin, "Beyond Testing: Empirical Models of Insurance Markets," *Annual Review of Economics*, 2010, *2* (1), 311–336.

Fang, Hanming and Edward Kung, "Why do life insurance policyholders lapse? The roles of income, health, and bequest motive shocks," *forthcoming, Journal of Risk and Insurnace*, 2020.

Fleitas, Sebastian, "Dynamic Competition and Price Regulation When Consumers Have Inertia: Evidence from Medicare Part D," Working Paper, 2017.

— , **Gautam Gowrisankaran, and Anthony Lo Sasso**, "Reclassification Risk in the Small Group Health Insurance Market," Working Paper 24663, National Bureau of Economic Research 2018.

Friedberg, Leora, Wenliang Hou, Wei Sun, and Anthony Webb, "Lapses in Long-Term Care Insurance," *Working paper*, 2017.

Goda, G.S., "The impact of state tax subsidies for private long-term care insurance on coverageand Medicaid expenditures," *Journal of Public Economics*, 2011, *95*, 744–757.

Gottlieb, Daniel and Kent Smetters, "Lapse-Based Insurance," *American Economic Review*, 2021, *111* (8), 2377–2416.

Handel, Ben, Igal Hendel, and Michael D. Whinston, "Equilibria in Health Exchanges: Adverse Selection versus Reclassification Risk," *Econometrica*, 2015, *83* (4), 1261–1313.

Handel, Benjamin R, Igal Hendel, and Michael D Whinston, "The Welfare Effects of Long-Term Health Insurance Contracts," Working Paper 23624, National Bureau of Economic Research July 2017.

Hausman, Jerry A, "Valuation of new goods under perfect and imperfect competition," in "The economics of new goods," University of Chicago Press, 1996, pp. 207–248.

Hendel, Igal and Alessandro Lizzeri, "The Role of Commitment in Dynamic Contracts: Evidence from Life Insurance*," *The Quarterly Journal of Economics*, 02 2003, *118* (1), 299–328.

Hofmann, Annette and Mark Browne, "One-sided commitment in dynamic insurance contracts: Evidence from private health insurance in Germany," *Journal of Risk and Uncertainty*, 2013, *46*, 81–112.

Kemper, P., H. Komisar, and L. Alecxih, "Long-Term Care Over an Uncertain Future: What Can Current Retirees Expect?," *Inquiry*, 2005/2006, *42* (4), 335–350.

Ko, Ami, "An Equilibrium Analysis of the Long-Term Care Insurance Market," *Review of Economic Studies*, 2022, *89*, 1993–2025.

Koijen, Ralph S. J. and Motohiro Yogo, "The Cost of Financial Frictions for Life Insurers," *American Economic Review*, January 2015, *105* (1), 445–75.

_ **and** _ , "Shadow Insurance," *Econometrica*, 2016, *84* (3), 1265–1287.

_ **and** _ , "The Fragility of Market Risk Insurance," *The Journal of Finance*, 2022, *77* (2), 815–862.

Kong, Edward, Timothy Layton, and Mark Shepard, "Adverse Selection Pricing and Unraveling of Competition in Insurance Markets," Working Paper, 2022.

LifePlans, "Who Buys Long-Term Care Insurance? Twenty-Five Years of Study of Buyers and Non-Buyers in 2015–2016," Technical Report Prepared for America's Health Insurance Plans by LifePlans, Inc. , 2017.

Liu, Jessica and Weiling Liu, "The Effect of Political Frictions on Long-term Care Insurance," Working paper, Northeastern University and ConerStone Research, 2020.

Lockwood, L., "Incidental Bequests and the Choice to Self-Insure Late-Life Risks," *American Economic Review*, 2018, *108* (9), 2513–2550.

Mommaerts, Corina, "Long-Term Care Insurance and the Family," Working paper, University of Wisconsin-Madison, 2020.

NAIC, "The State of Long-Term Care Insurance: The Market, Challenges and Future Innovations," Working paper, National Association of Insurance Commissioners, 2016.

Nevo, Aviv, "Measuring market power in the ready-to-eat cereal industry," *Econometrica*, 2001, *69* (2), 307–342.

Society of Actuaries, "An Overview of the U.S. LTC Insurance Market (Past and Present): The Economic Need for LTC Insurance, the History of LTC Regulation & Taxation and the Development of LTC Product Design Features," 2014.

US Government Accountability Office, "Long-Term Care Insurance: Oversight of Rate Setting and Claims Settlement Practices," June 2008. Report to Congressional Requesters.

Online Appendix (Not for Publication)

A Sample construction from the rate increase data

From the rate increase data obtained from the California Department of Insurance for years 2007-2017, we exclude observations where policy identifier is missing; state identifier is missing; rate increase request year is missing; first issue date of the policy is missing or takes incredible values; requested rate increase amount is missing; or approved rate increase amount is missing. Table A.1 provides basic summary statistics of the rate increase sample. The sample includes all 50 states plus D.C. Insurers request a rate increase of 37-42% and are approved of 21-24%. About 89% of the requests are approved of a strictly positive rate increase.

# of insurers	59.00
# of policies	6005.00
# of states	51.00
Share of requests that are approved	0.89
Mean requested lower bound (%)	37.22
Mean requested upper bound (%)	42.29
Mean approved lower bound (%)	21.44
Mean approved upper bound (%)	24.21
Number of requests (at policy-state-year level)	35326.00

Table A.1: Summary statistics of the rate increase data
Notes: Some insurers specify a range of the rate increase, e.g., 10-30%. In this case, we refer to 10% (30%) as the lower (upper) bound of the rate request. We say a rate request was approved if the approved upper bound is strictly positive.

B Estimation details

B.1 Prediction of state-contingent rate increases

One empirical challenge we face is that we only observe revised premiums for the realized state of the world. That is, we do not observe p_{jk2} for all $k = 1, ..., K$. We address the challenge by estimating the distribution of rate increases using a finite mixture model. Let r_{ijs} denote the cumulative rate increase for plan j sold by insurer i in geographical state s

observed during the sample period. Define $y_{ijs} = \ln(r_{ijs} + 1)$ which is a monotonic transformation of r_{ijs}. We represent the density of y_{ijs} by the following finite mixture model:

$$f(y_{ijs}) = \sum_{g=1}^{G} \pi_{gs} f_g(y_{ijs}|x'_{ij}\beta_g) \tag{26}$$

Specifically, we set $G = 2$. For $g = 1$, we assume the price increase is degenerate and is equal to zero with probability one. This is because in our data, about 55% of observations report zero rate increases over the sample period. For $g = 2$, we assume the price increase follows a normal distribution.

We estimate $\{\pi_{gs}, \beta_g\}_{g,s}$ by a maximum likelihood estimator. Then, we obtain the predicted premium increase for each state of world by using quantile values of the estimated distribution. Specifically, we express the expected price increase as

$$E[y_{ijs}] = \pi_{g=1,s} E_1[y_{ijs}] + \pi_{g=2,s} E_2[y_{ijs}] \tag{27}$$

where E_1 and E_2 are expectation operators using densities $f_{g=1}$ and $f_{g=2}$, respectively. Alternatively, we can express the expected increase as:

$$E[y_{ijs}] = \pi_{g=1,s} E_1[y_{ijs}] + \pi_{g=2,s} \left(\sum_{k=2}^{K} Pr(q_{k-1} < y_{ijs} \leq q_k) E_2[y_{ijs}|q_{k-1} < y_{ijs} \leq q_k] \right) \tag{28}$$

where q_k represents the k^{th} quantile value of the second class distribution. Define the probability that the second-period state is $k \in \{1, ..., K\}$ as the following:

$$\pi_{ks} = \begin{cases} \pi_{g=1,s} \text{ if } k = 1 \\ \pi_{g=2,s} Pr(q_{k-1} < y_{ijs} \leq q_k) \text{ if } k = 2, ..., K \end{cases} \tag{29}$$

Then we can rewrite the expected price increase as:

$$E[y_{ijs}] = \pi_{k=1,s} E_1[y_{ijs}] + \sum_{k=2}^{K} \pi_{ks} E_2[y_{ijs}|q_{k-1} < y_{ijs} \leq q_k] \tag{30}$$

We predict a plan's price increase when the second-period state is k as the following:

$$E[y_{ijs}|\pi_{ks} = 1] = \begin{cases} 0 \text{ if } k = 1 \\ E_2[y_{ijs}|q_{k-1} < y_{ijs} \leq q_k] \text{ if } k = 2, ..., K \end{cases} \tag{31}$$

Panel A: Second-stage premium (p_{jk2})	
p_{jk2} for $k = 1$	1,955 (1,027)
p_{jk2} for $k = 2$	2,275 (1,155)
p_{jk2} for $k = 3$	2,500 (1,307)
p_{jk2} for $k = 4$	2,739 (1,505)
p_{jk2} for $k = 5$	3,283 (2,030)
Panel B: State probabilities (π_{ks})	
π_{ks} for $k = 1$	0.36 (0.11)
π_{ks} for $k = 2, ..., 5$	0.16 (0.03)
Panel C: State-contingent claims (μ_{jk})	
μ_{jk2} for $k = 1$	1,479 (789)
μ_{jk2} for $k = 2$	2,472 (1,351)
μ_{jk2} for $k = 3$	3,116 (1,657)
μ_{jk2} for $k = 4$	4,039 (2,115)
μ_{jk2} for $k = 5$	6,365 (3,296)

Table B.1: Second-stage premium, aggregate state probability, and claims estimates
Notes: Means are reported with standard deviations in parentheses. Panel A reports the predicted second-stage annual premium estimates. $k = 1$ represents the state when there are no rate increases. Panel B reports the estimated second-stage state probabilities which are allowed to vary by geographical state. We set the values of $\{q_k\}_k$ in equation (28) such that we have quartile values of the second class distribution. Panel C reports the estimated annual claims.

Combined with the NAIC data on initial rates, we recover premiums for all possible states of the second stage. We set $K = 5$ and choose $\{q_k\}_k$ such that we have quartile values of the second class distribution. Panel A and Panel B in Table B.1 report the summary statistics on the estimated second-stage premiums and state probabilities, respectively.

B.2 Prediction of state-contingent claims

To estimate the supply side, we need demand estimates and data on premiums and claims. As we did for demand estimation, we use observed initial prices p_{j1} and estimated state-contingent prices p_{jk2}. We estimate state-contingent claims μ_{jk} outside the model based on a procedure similar to the one used in the estimation of p_{jk2}. Specifically, for a given geographic state s, we define quantiles of the claims distribution based on the probability of the state of the world $\{\pi_{ks}\}_{k=1}^{K}$ estimated in equation (29). We then compute the mean claims for each quantile conditional on insurer characteristics, which we use as μ_{jk}. Using estimated claims and premiums, the model predicts a mean loss ratio of 60% which is reasonable. Panel C in Table B.1 reports the summary statistics on the estimated claims.

B.3 Premium adjustment cost estimation

Let F denote the CDF of c^1_{jk}, and let f denote its PDF. Suppose $p_{jk2} > p_{j1}$. The first-order condition of the firm's second-stage optimization problem implies

$$c^1_{jk}(p_{jk2} - p_{j1}) = s_{jk2} \tag{32}$$

The individual likelihood contribution is

$$\begin{aligned} Pr(p_{jk2}) &= Pr\left(c^0 < (p_{jk2} - p_{j1})s_{jk2} - \frac{c^1_{jk}}{2}(p_{j1} - p_{jk2})^2\right) \times \ln N\left(c^1_{jk} = \frac{s_{jk2}}{p_{jk2} - p_{j1}}\right) && (33) \\ &= F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right) \times f\left(\frac{s_{jk2}}{p_{jk2} - p_{j1}}; \mu_c, \sigma_c\right) && (34) \end{aligned}$$

Suppose instead $p_{jk2} = p_{j1}$. Let p^*_{jk2} be the interior solution that satisfies

$$c^1_{jk}(p^*_{jk2} - p_{j1}) = s_{jk2} \tag{35}$$

Then, the likelihood contribution is

$$\begin{aligned} Pr(p_{jk2} = p_{j1}) &= Pr\left(c^0 > (p^*_{jk2} - p_{j1})s_{jk2} - \frac{c^1_{jk}}{2}(p_{j1} - p^*_{jk2})^2\right) && (36) \\ &= 1 - F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right) && (37) \end{aligned}$$

Combining the two cases, we obtain the following likelihood function which we maximize to estimate (c^0, μ_c, σ_c):

$$\begin{aligned} \max_{c^0, \mu_c, \sigma_c} \quad & \sum_{j,k} 1(p_{jk2} = p_{j1}) \log\left(1 - F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right)\right) \\ & + 1(p_{jk2} > p_{j1}) \log\left(F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right) f\left(\frac{s_{jk2}}{p_{jk2} - p_{j1}}; \mu_c, \sigma_c\right)\right) \end{aligned} \tag{38}$$

C Consumer welfare

We calculate changes in the consumer welfare in conterfactual policy experiments by deriving the consumption equivalent variation. To do so, we first calculate consumer's expected utility. It is given by

$$EV_i = \log(\sum_{j=1}^{J} \exp(v_{ij})) \tag{39}$$

$$= \log(\sum_{j=1}^{J} \exp(\alpha \sum_t B_t u(c_{ijt}) + \overline{v}_{ij})) \tag{40}$$

where $\overline{v}_{ij} = v_{ij} - \alpha \sum_t B_t u(c_{ijt})$. Denote the welfare in a new counterfactual equilibrium by EV_i^{new}. Then, we solve for Δ such that

$$EV_i^{new} = \log(\sum_{j=1}^{J} \exp(\alpha \sum_t B_t u((1+\Delta)c_{ijt}) + \overline{v}_{ij})) \tag{41}$$

Using $u(c) = \log(c)$, this is equivalent to

$$\exp(EV_i^{new}) = \sum_{j=1}^{J} \exp(\alpha \sum_t B_t u((1+\Delta)c_{ijt}) + \overline{v}_{ij}) \tag{42}$$

$$= \sum_{j=1}^{J} \exp(\alpha \sum_t B_t u(c_{ijt}) + \overline{v}_{ij}) \exp \alpha \sum_t B_t \log((1+\Delta))) \tag{43}$$

$$= \exp(EV_i) \exp(\alpha \sum_t B_t \log((1+\Delta))) \tag{44}$$

Then, after some algebra, we have

$$\log\left(\frac{\exp(EV_i^{new})}{\exp(EV_i)}\right) = \alpha \sum_t B_t \log((1+\Delta))) \tag{45}$$

and we can therefore characterize Δ as

$$1 + \Delta = \exp\left(\frac{EV_i^{new} - EV_i}{\alpha \sum_t B_t}\right) \tag{46}$$

D Additional tables and figures

State	Has Adopted Regulation	Implementation Year
Alabama	1	2006
Alaska	0	
Arizona	1	2005
Arkansas	1	2006
California	1	2002
Colorado	1	2007
Connecticut	0	
Delaware	1	2005
District of Columbia	0	
Florida	1	2003
Georgia	1	2008
Hawaii	1	2008
Idaho	1	2001
Illinois	1	2003
Indiana	0	
Iowa	1	2003
Kansas	1	2003
Kentucky	1	2003
Louisiana	1	2005
Maine	1	2004
Maryland	1	2002
Massachusetts	0	
Michigan	1	2007
Minnesota	1	2002
Mississippi	0	
Missouri	1	2004
Montana	1	2009
Nebraska	0	
Nevada	0	
New Hampshire	1	2012
New Jersey	1	2006
New Mexico	1	2004
New York	0	
North Carolina	1	2003
North Dakota	1	2004
Ohio	1	2003
Oklahoma	1	2001
Oregon	1	2006
Pennsylvania	1	2002
Rhode Island	1	2008
South Carolina	1	2010
South Dakota	1	2002
Tennessee	1	2004
Texas	1	2002
Utah	1	2003
Vermont	1	2010

Virginia	1	2003
Washington	1	2009
West Virginia	1	2009
Wisconsin	1	2002
Wyoming	0	
Total	41	

Table D.1: States' adoption of the RSR 2000
Notes: The table reports whether each state (plus District of Columbia) has implemented the RSR 2000, and if so, what year the regulation was adopted.

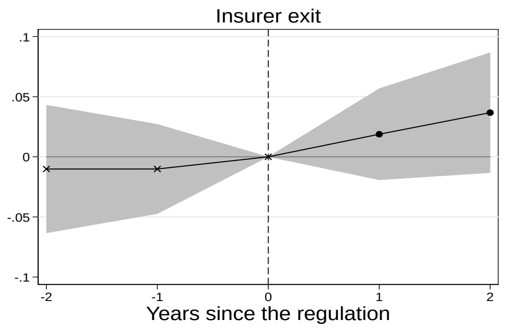
	(1) Fringe firms	(2) Representative fringe
Initial premium	2275 (1370)	2306 (508)
Rate increases	20% (121%)	20% (42%)
Sold after Rate Stability Reg.	0.10 (0.30)	0.09 (0.19)
Observations	6060	400

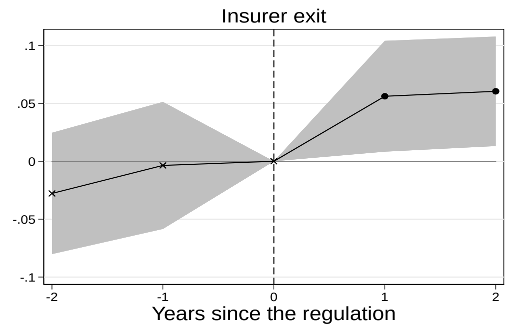
Table D.2: Estimation sample
Notes: Form C NAIC reports 2000-2007 merged with rate increase data. Means are reported with standard deviations in parentheses. Column (1) uses fringe firms whose sales account for less than 5%. Column (3) uses representative fringes.

Premium adjustment cost	(1) Before adoption of RSR 2000	(2) After adoption of RSR 2000
c^1_{jk} for $k = 1$	0.0129	0.0131
c^1_{jk} for $k = 2$	0.0043	0.0059
c^1_{jk} for $k = 3$	0.0043	0.0058
c^1_{jk} for $k = 4$	0.0048	0.0080
c^1_{jk} for $k = 5$	0.0009	0.0016

Table D.3: Premium adjustment cost estimates

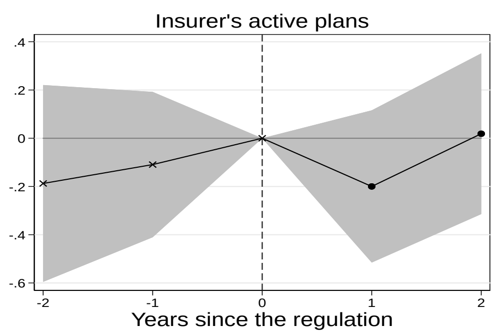
Notes: The table reports the mean value of c^1_{jk} estimates as defined in equation (22). Column (1) reports the mean only using markets where the RSR 2000 was not yet implemented. Column (2) reports the mean after states adopted the RSR 2000.

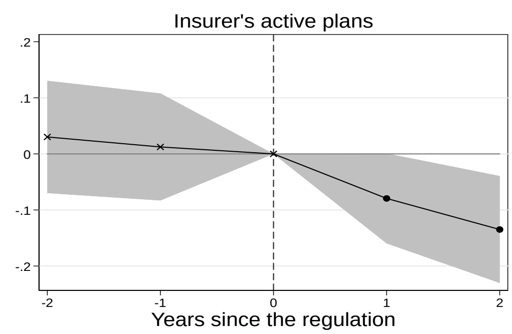




Major firms
Mean exit rate = 3%

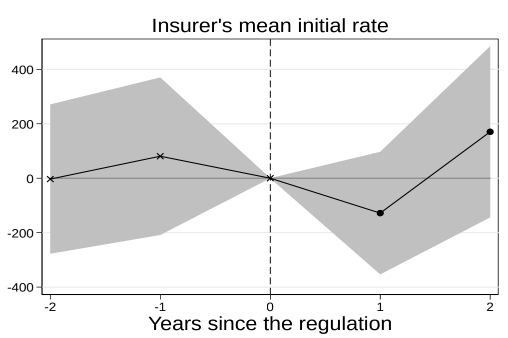
Fringe firms
Mean exit rate = 21%

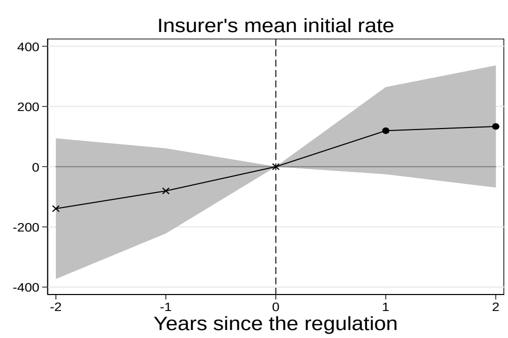




Major firms
Mean plans offered = 2.6

Fringe firms
Mean plans offered = 1.5





Major firms
Mean initial rate = $2212

Fringe firms
Mean initial rate = $2125

Figure D.1: Impact of the rate stability regulation on insurers by type
Notes: Data = Form C NAIC reports 2000-2007. The figure reports the impact of a state's adoption of the rate stability regulation on insurers' market outcomes conditional on type. In a given market, we classify an insurer as a major firm if its sales account for at least 5% of the total sales; otherwise, we classify the firm as a fringe. Controls include the number of years the insurer has been active in the market, and insurer, state, and year fixed effects. The gray area indicates 95% confidence intervals. Standard errors are clustered by state.