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DYNAMIC PRICING REGULATION AND WELFARE IN INSURANCE MARKETS

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ABSTRACT

While the traditional role of insurers is to provide protection against individuals' idiosyncratic risks, insurers themselves face substantial uncertainties due to aggregate shocks. To prevent insurers from passing these aggregate risks onto consumers, governments have increasingly adopted dynamic pricing regulations, which limit insurers' ability to change premiums over time. We evaluate dynamic pricing regulation using an equilibrium model of the U.S. long-term care insurance market, featuring insurers' lack of commitment and endogenous market structures. We find that stricter dynamic pricing regulation has a limited impact on improving consumer welfare, while it reduces insurer profits and increases market concentration.

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1 Introduction

Social insurance programs and private insurance markets have grown enormously over the last several decades in many countries (Chetty and Finkelstein, 2013). Most 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 insured risks and pricing contracts accordingly. Even experienced insurers may be challenged when serving a new class of consumers with demographics they have never dealt with before, such as those in the health insurance marketplaces established by the Affordable Care Act. Insurers selling long-term contracts are particularly vulnerable because their financial stability is more exposed to aggregate cost shocks and interest rate fluctuations.

One important concern is that insurers might pass the risks they face onto consumers by adjusting premiums. The resulting premium volatility could exacerbate the financial uncertainties that individuals must manage. To mitigate this issue, the government has increasingly adopted dynamic pricing regulations, which limit insurers' ability to adjust rates. However, little is known about the welfare effects of these regulations. 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 the market or charge higher markups, which could adversely affect consumer welfare.

We study the impact of dynamic pricing regulation on market equilibrium and welfare in the context of U.S. private long-term care insurance (LTCI). LTCI is a long-term contract, with a lag of over 20 years between the purchase and use of the insurance. In addition to being a relatively young insurance product, the dynamic nature of LTCI contracts makes it challenging for insurers to accurately predict future claims costs. Insurers do not commit to a fixed premium schedule over the lifetime of a contract and often revise rates for a given buyer cohort, subject to state regulatory approval. To reduce uncertainty about future rate increases, many states adopted new standards in their oversight of the LTCI industry in the early 2000s, known as the Rate Stability Regulation of 2000 (RSR 2000). These new standards were designed to deter rate increases for existing consumers. This paper examines 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.[1] 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 was one of the factors contributing to insurer exits by lowering their profitability.

We start by providing descriptive evidence for the effect of rate stability regulation on insurers.[2] 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. In the market, risk averse consumers choose from LTCI products supplied by distinct insurers. Risk neutral insurers face various aggregate risks (e.g., uncertainty about future claims costs and interest rates) and decide whether to enter the market and how to price their products over time conditional on entry.

The primary departures from the standard assumptions in long-term insurance markets (e.g., Cochrane, 1995 and Hendel and Lizzeri, 2003) are the consideration of imperfect competition among insurers and their lack of commitment. The LTCI market is highly concentrated, making it essential to accurately account for the market structure to understand the impact of supply-side regulations. Insurers' lack of (or limited) commitment to pricing schedules may reflect various market frictions, including the following major ones considered in the model. First, a significant fraction of consumers face choice frictions, believing that premiums will remain constant over the lifetime of an LTCI contract. In this case, insurers do not commit to future premiums because offering a smooth price schedule does not increase

[1] https://www.kff.org/medicaid/report/medicaid-and-long-term-services-andsupports-a-primer/.
[2] We use dynamic pricing regulation and rate stability regulation interchangeably.

consumers' willingness to pay due to their misbeliefs, while forgoing the opportunity to adjust rates based on realized aggregate shocks. Second, insurers may have limited ability to commit due to financial frictions. Insurers in the LTCI market face high capital requirements relative to other health and life insurance products (NAIC, 2016). The realization of large LTC costs can adversely affect their ability to meet these requirements. Similarly, low interest rates negatively impact insurers' capital reserves by reducing their investment returns. Insurers' weakened financial position due to large claims costs and low interest rates could also heighten their insolvency risks. To manage financial frictions when adverse aggregate shocks occur, insurers may deviate from the initial price and implement rate increases, particularly when existing policyholders are unlikely to terminate their contracts despite the higher rates.

Another important factor contributing to premium hikes in LTCI is that consumers become locked into their current contract as they lose access to other insurers with age. To exploit consumer lock-in, insurers may strategically set a low initial price and then raise the premium over time, especially when consumers are not fully aware of insurers' ability to revise rates. Dynamic pricing regulation, which makes it costly for insurers to revise premiums, serves as a policy tool to force insurers to smooth prices over the lifetime of a contract.

To credibly assess the impact of dynamic pricing regulation, we also account for several important features of the LTCI market. First, the model considers Medicaid as a free public LTCI option for consumers with limited assets (Brown and Finkelstein, 2008). Second, we account for the possibility of both adverse and advantageous selection (Finkelstein and McGarry, 2006). Following Ko (2022), we allow multi-dimensional heterogeneity among consumers, including their access to family care, which affects both the demand for LTCI and the expected claims cost for insurers.[3] As long as the availability of family care is not priced, this heterogeneity leads to adverse selection. Third, in addition to dynamic pricing regulation, we model initial rate regulation, which penalizes insurers for charging an initial rate that is different from the regulator's target level.

We first estimate the demand-side parameters by exploiting plausibly exogenous variations, including states' staggered adoption of RSR 2000. Then, we estimate the supply-side parameters using the estimated demand parameters and claims data. Our estimates suggest that supply-side regulations such as the RSR 2000 indeed made it significantly harder for insurers to revise rates. The estimated model does a good job of replicating the reduced-form effect of the RSR 2000, including the regulation's negative impact on insurer participation.

[3] Although allowing for multidimensional heterogeneity is considered one approach to account for the observed selection in LTCI (e.g., Finkelstein and McGarry, 2006), it can also be rationalized using a single health index by considering insurance rejection (Braun et al., 2019).

Using the estimated model, we conduct several counterfactual experiments. First, we examine the welfare effect of dynamic pricing regulation. We find that stricter regulation generates only a limited gain in consumer welfare, 0.05% at most in terms of the consumption equivalent variation. While the regulation substantially mitigates premium volatility, the small gain is due to the reduction in insurer participation caused by their profit loss. Overall, our finding indicates that the current regulation causes a significant loss in insurer profits and increases market concentration, while generating a negligible gain in consumer welfare.

Next, we consider the value of insurer commitment. Our model incorporates several mechanisms that contribute to insurers' lack of commitment, including the financial frictions they face and consumer myopia. To evaluate the value of insurer commitment, we assume that insurers are required to offer price schedules that smooth consumption across states. This requirement eliminates insurers' inefficient pricing motives arising from consumer myopia but constrains their ability to manage financial frictions. As a result, insurers' profitability decreases, leading to reduced market entry. Despite the improved price stability, the increase in consumer welfare is modest due to reduced varieties and higher initial premiums caused by increased market concentration. These findings highlight the importance of considering the interactions among financial frictions, imperfect competition, and endogenous entry in evaluating the impact of firm commitment.

Finally, we consider how supply-side regulations interact with demand-side policies. When Medicaid benefits double, the share of the elderly with private LTCI decreases by 30%, a crowd-out effect well known in the literature (Brown and Finkelstein, 2008). Interestingly, we find that the generosity of Medicaid depresses the effect of rate stability regulation on consumer welfare and insurer profits. One implication is that the regulation could improve price stability at less cost to insurers when Medicaid benefits are more generous.

The findings uncovered in this paper offer novel and robust insights into the design of dynamic pricing regulation. The regulation was originally intended to improve price stability and help policyholders smooth consumption. By accounting for the lack of firm commitment and consumers' limited knowledge about potential rate increases, our study brings to light another critical benefit of the regulation, which is mitigating consumer lock-in. Simultaneously, our exploration of imperfect competition and endogenous entry yields the surprising result that the regulation can, in fact, harm overall welfare by suppressing supply and competition. The inclusion of financial frictions faced by firms highlights another unintended consequence of the regulation: exacerbating firms' difficulties in managing these frictions, including insolvency risks.

Our findings carry significant policy implications for insurance markets. Firm participation in the LTCI market has been shrinking dramatically over the past few decades. The result that dynamic pricing regulation is a contributing factor to this trend provides a novel insight into how the regulation should be designed in light of insurer exits. Moreover, the insights from our study should assist policymakers in designing dynamic pricing regulation in other insurance markets by informing them of new and important margins surrounding the regulation.

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.[4] 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 (Ko, 2022; Mommaerts, 2023). Building on this line of studies, a recent paper by Braun et al. (2019) accounts for insurers' incentive to deny consumers of coverage by specifying a static LTCI market equilibrium with a monopolistic insurer.[5] We contribute to the literature on LTCI by studying the determinants of market structure, imperfect competition, and dynamic contracts, and by evaluating the design of supply-side market regulations.

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; Verani and Yu, 2024). The most closely related paper is Koijen and Yogo (2022), which studies how supply-side regulations affect premiums and product quality. Our work complements theirs by focusing on how the dynamic nature of insurance contracts is affected by pricing regulations.[6]

Third, 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), Fleitas et al. (2018), and Ghili et al. (2023) quantitatively assess the welfare cost of reclassification risk arising from consumers' lack of commitment. Fang and Kung (2021) and Gottlieb

[4]See also Brown and Finkelstein (2009) for an excellent review of prior literature on LTCI.

[5]See also Liu and Liu (2024) who provide evidence that political factors such as election cycles affect premium changes, insurers' cash flows, and the decision to sell LTCI.

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

and Smetters (2021) examine why consumers lapse contracts. Atal (2019) and Atal et al. (2024) empirically study long-term health insurance in Chile and Germany, respectively. Existing studies assume perfectly competitive insurance markets with insurer commitment. We contribute to the literature by studying an economy where the lack of firm commitment is a key friction and analyzing its policy implications in an imperfectly competitive market.

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. 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 claims cost μ_{ikt} is determined by two sources of uncertainties. First, individuals' idiosyncratic expenditure risks (indexed by i) impact the claims. Second, there are aggregate risks in the second period (indexed by k) which determine the cohort-level claims.[7]

We first consider the optimal long-term contract that the social planner wants to provide. The planner's problem can be written as

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

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 state k of 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.

[7] In our empirical model presented in Section 5, we also consider interest rate shocks as an additional source of aggregate risks. The model presented here abstracts from it for expositional simplicity.

In the LTCI market that we study, there are several empirical patterns that deviate from the socially optimal allocation. First, as in most insurance markets, firms have substantial market power. Second, we observe a lack of commitment from the insurers, where rates not only increase over time at the buyer cohort level but also come as a "surprise" in the sense that insurers do not commit to any state-contingent prices ex ante.[8] These observations motivate us to study the implications of insurers' lack of (or limited) commitment in an imperfectly competitive market.

To account for imperfect competition, we start by considering a monopolistic insurer that sells long-term contracts which provide insurance over two periods. The insurer's profit over the lifetime of the contract is

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

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. These market shares may depend on the insurer's price stream, $(p_1, \{p_{k2}\}_{k=1}^{K})$.

For the rest of the analysis in this section, we assume consumers' income remains constant in both periods.[9] Moreover, we assume consumers can commit, meaning that they do not terminate their contract in the second period. This is a reasonable assumption in the LTCI market because (1) consumers cannot purchase a new contract after a certain age due to strict underwriting, and (2) termination of contracts results in forfeiture of all premiums paid. If the monopolistic can also commit, it will offer a smooth price schedule. To see this, recall from our argument in the planner's problem that the utility-maximizing premium stream requires $p_1 = p_{k2}$. Consequently, the insurer will set a smooth price schedule and choose the constant price to maximize its profit.

However, several frictions might lead to a lack of insurer commitment and premium dependence on aggregate shocks, as observed in the LTCI market. First, a lack of commitment may arise from informational friction where consumers wrongly believe rates will remain constant. In this case, insurers will not commit to any price schedule ex-ante as doing so

[8] The rate increases we observe in the LTCI market are different from individual-level rate changes arising from consumers' lack of commitment, which has been extensively studied in the literature on long-term insurance (Cochrane, 1995; Hendel and Lizzeri, 2003). In these models, consumers have an incentive to walk away from the contract when their risk type improves. The optimal contract features reclassification risk where prices are revised based on changes in individual-level risk.

[9] This is a reasonable assumption for consumers in the LTCI market, as the majority of them are retirees whose primary source of income is Social Security.

does not increase consumers' willingness to pay due to their misbeliefs. Instead, insurers will change rates to maximize their second-period payoff depending on the realized state.[10] Second, financial frictions can also lead to limited commitment where rates are revised based on realized aggregate shocks. Insurers are subject to capital reserve requirements, which mandate that they maintain a certain level of capital reserves to continue operating. Failing to meet these requirements can result in a downgrade in credit rating, and in severe cases, can lead to insolvency. These requirements, therefore, act as a participation constraint for insurers, which may bind when adverse aggregate shocks occur, such as low interest rates or significant cost shocks. In such situations, insurers may raise rates for existing customers, particularly because limited outside options make it unlikely for these customers to let their policies lapse despite the increases.

To account for lack of insurer commitment, we revise the insurer's problem as

$$\begin{aligned} \max_{p_1} \quad & (p_1 - \mu_1)s_1 + \sum_{k=1}^{K} \pi_k \Pi_{k2}^* \quad \text{where} \\ \Pi_{k2}^* \quad & = \max_{p_{k2}} \quad (p_{k2} - \mu_{k2})s_{k2} - C_k^{rs}(p_1, p_{k2}). \end{aligned} \tag{3}$$

In the absence of commitment, the insurer will choose the revised rate to maximize its second period payoff and choose the initial rate to maximize its lifetime profit. The function C_k^{rs}, which increases with the rate increase $p_{k2} - p_1$, is added to the second-period payoff to capture the cost of breaking the initial commitment and revising the rate.[11] For example, when the insurer revises the rate, the regulator can impose additional scrutiny and regulatory challenges. We allow this cost to vary by aggregate state k because the likelihood of the insurer's financial constraint binding might depend on k. For instance, in adverse aggregate states, increasing rates might be necessary to meet capital reserve requirements or avoid insolvency. In such cases, insurers can more easily justify premium hikes, which would be reflected in a low rate adjustment cost. Moreover, if C_k^{rs} is sufficiently high for any rate increases in all k, indicating a significant cost for deviating from the initial commitment, the monopolistic insurer will opt for constant pricing. In our empirical model, we will use the approach in (3) to incorporate the lack of insurer commitment in an imperfectly competitive LTCI market.

[10]Such incomplete contracting may also be observed when it is costly for insurers to determine all profit-relevant aggregate states and specify state-contingent prices accordingly.

[11]In Online Appendix A, we show how the rate adjustment cost function can be interpreted as an alternative optimization problem where insurers need to satisfy various constraints including financial constraints. Similar to Koijen and Yogo (2015, 2016), we choose the "soft" constraint approach because it provides tractability when empirically mapping the model.

The extent to which insurers' lack of commitment results in rate increases depends on how "locked-in" consumers are. If consumers can easily switch their contracts, firms' incentives to increase rates will be tamed. However, if the lock-in issue is severe, as in the LTCI market where consumers after a certain age are denied coverage, lack of insurer commitment can result in large efficiency costs. For instance, firms have an incentive to exploit consumers with misbeliefs by setting a low initial rate and subsequently imposing large rate increases.

The government can mitigate inefficiencies arising from insurers' lack of commitment through dynamic pricing regulation, which can be interpreted as increasing the rate adjustment cost (C_k^{rs}). The regulation may not only improve premium volatility but also prevent insurers from exploiting locked-in consumers. However, too strict regulation could reduce insurers' expected profit to the point where entry becomes unprofitable. In the case of oligopoly, consumers could be harmed by reduced insurer varieties and increased market concentration. The overall welfare may also decrease if financial friction is the primary cause of rate increases. 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).[12] 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.[13] 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%).[14]

[12]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.

[13]`https://www.genworth.com/aging-and-you/finances/cost-of-care.html`.

[14]Ibid.

3.2 LTCI Market

The 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. They typically do not reimburse informal LTC provided by family or friends. 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 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, 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).[15] 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.

3.3 Insurers' Risks in LTCI

While the role of LTCI is to protect consumers from financial risks arising from LTC needs, insurers themselves are confronted with various risks (Cutler, 1996; NAIC, 2016). First, LTC insurers face uncertainty about aggregate claims costs. In addition to the market being relatively young, formal LTC costs including nursing home costs are hard to forecast as they are impacted by technological changes applied to medical treatments. Furthermore, given the long time lag between the purchase and use of insurance, insurers' ability to forecast future costs is limited. Second, LTC insurers are especially vulnerable to interest rate risks due to the long-term nature of contracts and capital requirements. Interest rate risks may

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

be important for LTC insurers as they affect returns on investments and their ability to comply with regulatory capital reserve requirements. Low interest rates may critically affect insurers' behaviors, such as pricing or entry into the markets.[16]

3.4 Consumer-side Frictions

There are several demand-side frictions that affect the workings of the LTCI market. First, the market may possibly suffer from asymmetric information. Finkelstein and McGarry (2006) find evidence that both adverse and advantageous selection coexist in the LTCI market. More recently, Ko (2022) argues the availability of family care as a source of selection in this market. Consumers who are unlikely to receive family care are more likely to resort to formal LTC services in case of disability. As the availability of family care is not priced by insurers, consumers with limited access to family care are more likely to purchase insurance, resulting in adverse selection.

Second, informational frictions about possible rate increases seem to exist. 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 another survey conducted by Brown et al. (2012) in 2011, only 58% of the survey participants were concerned about possible rate increases.[17]

Third, consumer lock-in might be a severe issue in the LTCI market. Lapses are very rare in this industry, especially as the contracts age. The overall lapse rate was 2.7% for the years 2005-2007 and 2% for 2008-2011. The lapse rate decreases rapidly over the policy years and converges to 1% after the tenth policy year.[18] The low lapse rate might be attributable to the fact that lapses result in the forfeiture of any premiums paid, unlike life insurance which provides some cash value. Furthermore, due to strict underwriting, it becomes very difficult to find an insurer willing to sell new coverage to consumers over 75, and insurers almost always reject consumers over 80 (Broker World, 2015).[19,20] Together with the low lapse rate,

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[16]As discussed in NAIC (2016), interest rate risk is especially relevant since the Great Recession.

[17]Evidence for such informational friction is found in other insurance markets as well. Atal et al. (2022) provide evidence that about one half of retirees do not consider possible changes in future premiums when they decide to purchase health insurance. In the context of life insurance, Gottlieb and Smetters (2021) provide evidence that consumers understate the likelihood of needing money in the future.

[18]https://www.soa.org/resources/experience-studies/2016/research-ltc-insurance/.

[19]Sales to consumers aged 75 and plus accounted for 2-3% during years 2008-2011 (Broker World, 2015).

[20]Hendren (2013) argues that the amount of private information held by consumers in this age group is too much, such that if insurers were to serve them, the adverse selection problem would be too severe.

such limited outside options imply that consumers are likely to be locked into their current LTCI contract.

3.5 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).[21] While the loss ratio standard was designed to limit initial rates, it was not effective 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 with the goal of increasing rate stability (US Government Accountability Office, 2008). First, the RSR 2000 requires insurers to meet a higher minimum loss ratio of 85% for revenues associated with rate increases. Second, for at least 3 years after implementing a rate increase, the RSR 2000 requires insurers to report data on premiums earned and claims incurred. Third, the RSR 2000 removes 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. 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 A.1 in the Online 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.

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

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 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.[22] Form C are annual reports which provide state-plan-level information about enrollment, new sales, premiums collected, and claims incurred.[23]

We complement the NAIC data with rate increase data obtained from the California Department of Insurance for the years 2007-2017. Any insurer that 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. 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 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. 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

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

[23] 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.

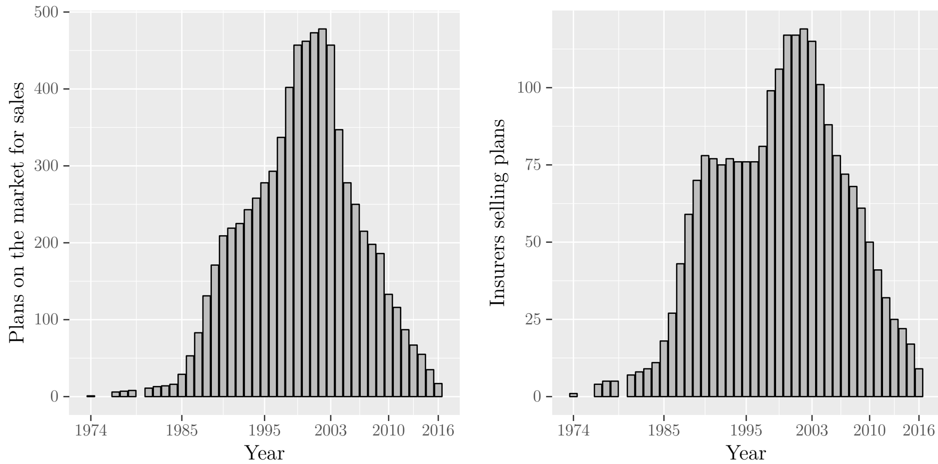


Figure 1: Active plans and insurers by year
Notes: Data = NAIC reports. The figure reports, for each year, the number of active plans and active insurers.

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 Rate Stability Regulation

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

$$y_{st} = \alpha + \sum_{k=-2}^{2} \beta_k I_{stk} + \tau_t + \eta_s + \varepsilon_{st}. \tag{4}$$

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 in the main specification 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.[24]

[24] In Online Appendix C.1, we show the robustness of our findings under the specification that utilizes all states and explicitly allows heterogeneity in treatment effects across the timing of policy adoption.

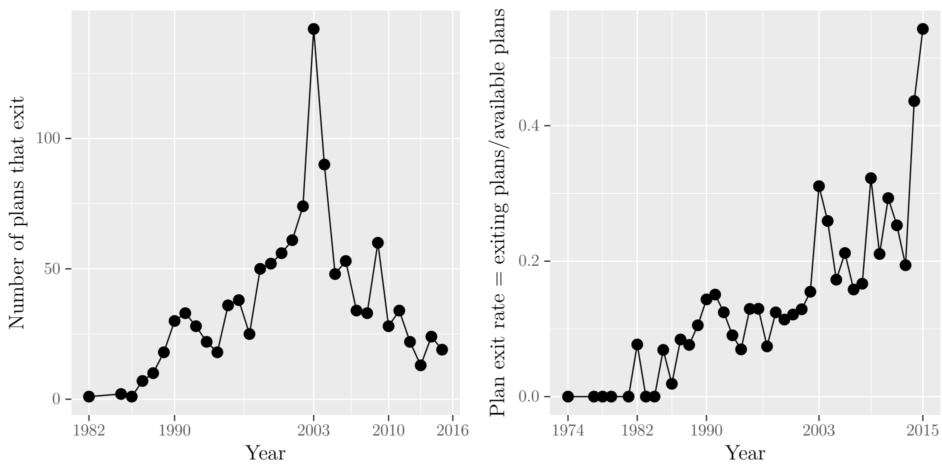


Figure 2: Exiting plans by year
Notes: Data = NAIC reports. The figure reports, for each year, the number of exiting plans (left panel) and exit rate (right panel).

Figure 3 reports the estimated β_k's in equation (4). 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 almost all of the negative impact on insurer participation comes from fringe firms, which we show in Figure A.1 in Online Appendix.[25] The adoption of RSR 2000 had no impact on major firms' exit decisions while it significantly reduced the number of fringe firms by 6.6%.

Despite the fact that rate stability regulation makes it harder for insurers to increase rates ex post, we do not find a significant impact of the regulation on the initial rate, as shown in the last graph of Figure 3. This result might be influenced by heterogeneous responses from insurers and compositional effects associated with changes in the mix of insurers. For example, we show in Online Appendix C.1 that brand-new plans entering the market for the

[25]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. In Table A.2 of the Online Appendix, we provide summary statistics on major and fringe firms. Among other things, the table shows that fringe insurers operate more locally by being present in fewer states compared to major insurers.

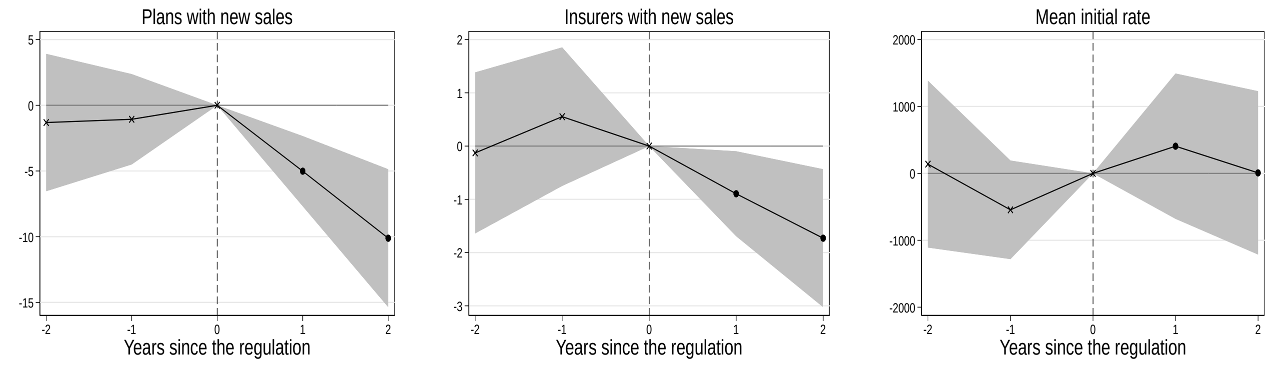


Figure 3: Impact of the rate stability regulation on market outcomes
Notes: Data = Form C NAIC reports 2000-2007. The sample consists of plans sold in 24 states that implemented the RSR 2000 between 2002-2005. The figure reports the estimates of β_k's in equation (4). The shaded area indicates 90% confidence intervals. Standard errors are clustered by state.

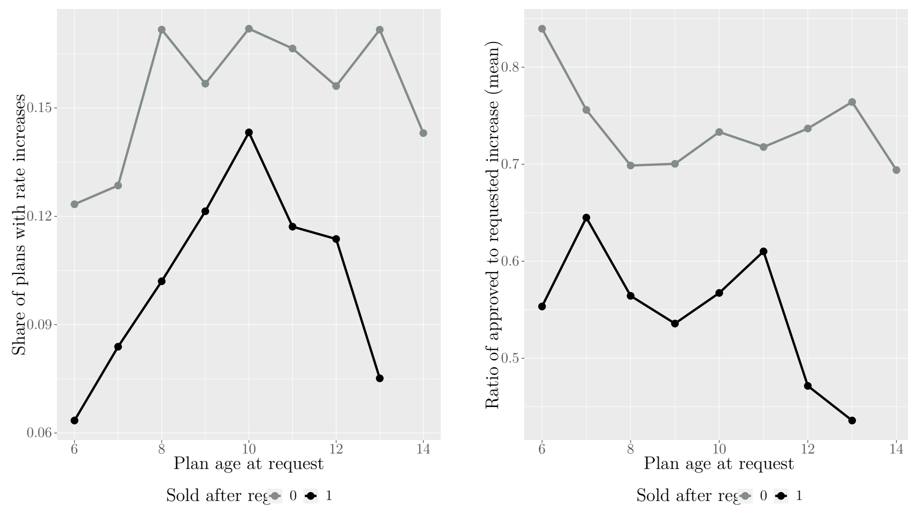
first time tend to experience premium increases after the adoption of RSR 2000.

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.[26] Figure 4 compares, conditional on plan age (the horizontal axis), 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 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. 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

[26] We report the sample construction and basic summary statistics of the rate increase data in Section B of the Online Appendix.



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).

55%, while the mean ratio is much higher at 75% for plans sold before the regulation. In Online Appendix C.2, we also provide suggestive evidence that these effects are not due to a composition effect, where plans that survived differ in terms of how much they rely on rate increases.

To sum, we 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 participation.

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 consumers and many potential insurers. As shown in Figure 5, there are three stages in the model. In stage 0, insurers decide whether to enter the market based on the entry cost and the expected profit. In stage 1, insurers set

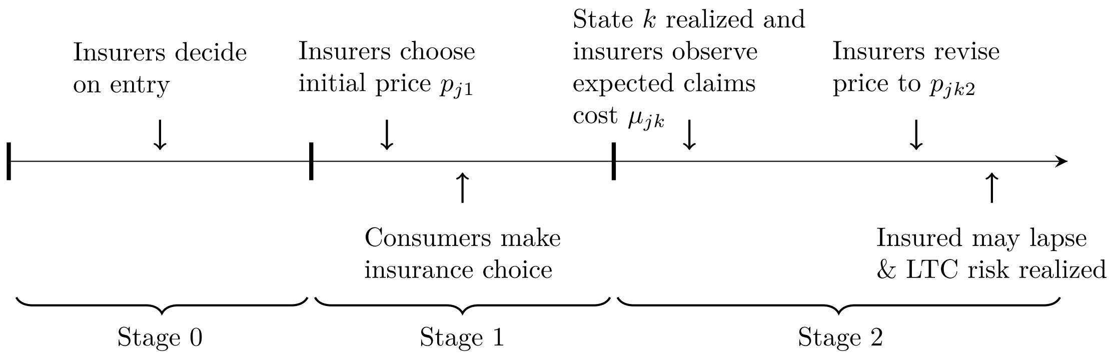


Figure 5: Timing of events

an initial price for their LTCI contract.[27] Consumers observe the menu of insurance options available and make their insurance purchase decisions. 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, uncertainty surrounding *multiple* dimensions of aggregate risk is resolved, including interest rate risk, formal long-term care price shocks, and other claims-relevant risks. Upon observing the realized aggregate states, insurers revise their prices determined in the first stage. Consumers with private LTCI might lapse their contract, and LTC utilization takes place in the end.

We index consumers by i, and they differ by characteristics z_i, which consists of three dimensions: (i) income, (ii) access to family care, and (iii) whether they believe rates do not increase in the second stage or they hold a rational expectation about rate increases. First, we incorporate income heterogeneity to capture the potential crowd-out effect of means-tested public insurance on the demand for private insurance (Brown and Finkelstein, 2008). As higher-income consumers tend to be healthier, this heterogeneity creates a scope for advantageous selection, as found in Finkelstein and McGarry (2006). Second, the availability of family care is considered as it is found be an important source of adverse selection (Ko, 2022): individuals with limited access to family care are more likely to resort to formal care and submit LTCI claims. Third, we incorporate the possibility that consumers mistakenly believe rates will remain constant, as found in Brown et al. (2012) and LifePlans (2017), which could be important in firms' dynamic pricing decisions.

To render the analysis empirically tractable, we assume insurers consist of a small number of major firms and many fringe firms. In the model, fringe firms make an entry decision,

[27] In our model, each insurer offers only one plan per market. This assumption is plausible, given that over 60% of insurers in the data offer just one plan.

while major firms do not. This is based on the empirical finding that pricing regulations had no effect on major firms' entry and exit, while they significantly impacted fringe insurers (see Figure A.1 in the Online Appendix). We formulate entry decisions following the standard static entry models (e.g., Mankiw and Whinston, 1986, Bresnahan and Reiss, 1991 and Berry and Waldfogel, 1999). Similar to these studies, we consider symmetric fringe firms to maintain tractability.[28]

5.2 Decision Problems in Each Stage

5.2.1 Stage 0

There are potentially many fringe insurers that decide whether to enter the market. Fringe firm j will enter the market if its expected profit Π_j^* is equal to or greater than its entry cost c_j^e, which follows the CDF denoted by G. Following Seim (2006), we assume each fringe does not observe the realization of other fringe firms' entry cost.[29]

5.2.2 Stage 1

At the beginning of stage 1, the market consists of J firms that include major and fringe firms. Let $j \in \{1, 2, ..., J\}$ index insurers. 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

[28]As extensively discussed in the literature, entry models with heterogeneous firms can quickly become computationally intractable and may suffer from multiple equilibria. One way to avoid the issue of multiplicity is to impose an order on the entry decisions. We refrain from adopting this strategy as our data do not provide a credible way of identifying the sequence of the moves. Another option is to adopt a random sequential move game. However, solving and estimating such a model would be computationally infeasible, especially due to the large number of fringes observed in the data.

[29]Note that the ex-post profit will be the same among fringe firms in each market. Allowing entry cost heterogeneity generates more flexibility in accounting for the data.

Liu, 2024). LTC utilization takes place at the end of the second stage, and insurers do not incur any claims cost in stage 1.[30]

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

$$\tilde{u}_{ij1} \quad = \quad \alpha u(y_{z_i} - p_{j1}) + \xi_j + \varepsilon_{ij}. \tag{6}$$

The function u represents consumers' utility over income and exhibits risk aversion. An individual consumes her retirement income y_{z_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. Given our assumption of symmetric fringes, the unobserved demand component for all fringe insurers is the same, i.e., $\xi_j = \xi_F$ for all j that are fringe insurers. ε_{ij} represents the match value shock, which follows an *i.i.d.* Type I Extreme Value distribution with scale one. These choice-specific taste shocks are drawn for each and every firm and are allowed to differ across fringe firms as well. Conditional on prices, the presence of more fringe entrants implies more match value draws, which is precisely why a greater number of fringe varieties is beneficial to consumers.[31]

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

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

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

5.2.3 Stage 2

At the beginning of stage 2, the aggregate state vector k is realized, comprising aggregate state variables relevant to insurers' claims and profits. In the empirical specification, we set $k = (l, m, n)$, where the first element l denotes the interest rate. The interest rate is a relevant aggregate shock to insurers as it affects their returns on investments. The second

[30] We abstract from administrative cost as we lack such data at the insurer level. This choice may impact our estimates of C_j^l, but it is unlikely to change our main findings because we will treat C_j^l as fixed in our main counterfactual analysis.

[31] See Berry and Waldfogel (1999) for a similar specification. Such match values may arise from consumers' preference for brands. According to a survey of LTCI buyers by LifePlans (2017), insurer reputation (brand) was the most commonly cited reason for choosing a particular company in 2005. Additionally, fringe insurers often operate locally and do business in fewer states compared to major insurers, as shown in Table A.2 of the Online Appendix.

element m represents the nursing home price, and the third element n captures all other claims-relevant aggregate risks.[32]

We assume the number of values that k can take is K, and the aggregate state vector k happens with probability π_k. When state k is realized, insurers learn that the expected claims cost from their existing cohort of type-z consumers equals μ_{zjk}. 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 follows

$$\Pi_{jk2} = \sum_z (p_{jk2} - \mu_{zjk}) g_z s_{zjk2} - C^{rs}_{jk}(p_{j1}, p_{jk2}). \tag{8}$$

g_z is the proportion of consumers with type z, and s_{zjk2} is insurer j's market share of type-z consumers in stage 2 when the realized state is k. Note that s_{zjk2} could be different from its first-stage market share due to possible lapses by consumers. The function C^{rs}_{jk} is the cost associated with revising rates. While we index the claims cost μ_{zjk} by $k = (l, m, n)$, it only depends on two aggregate states, nursing home price m and other claims-relevant shocks n. The cost function C^{rs}_{jk} depends on all of the three aggregate states contained in k, including interest rate l.

As discussed in Section 2, the rate adjustment cost function C^{rs}_{jk} captures the cost of breaking the initial commitment, which could trigger reputation costs. This cost depends on state k to account for the possible impact of financial frictions and insolvency risks, a channel studied in other insurance industries by Koijen and Yogo (2015, 2016). In states with large claims costs or low interest rates, insurers' capital reserves would be low, making it difficult to meet the high capital requirements imposed on LTC insurers (NAIC, 2016). This could also heighten insurers' insolvency risks, as failing to meet capital requirements can lead to insolvency in severe cases. Consequently, increasing rates might become necessary, which would be reflected in a lower rate adjustment cost.[33] The rate adjustment cost also depends on the stringency of rate stability regulation, which changed during our sample period due to the adoption of RSR 2000. Note that we do not explicitly model how insurers' balance sheets or the regulations affect the rate adjustment cost, as the empirical implementation

[32] For example, n might capture the average longevity of the insured, policyholders' overall taste for using nursing home services etc. As the LTCI market is relatively new, it is plausible that there is a good amount of uncertainties beyond interest rate risks (l) and nursing home price shocks (m).

[33] We report in Online Appendix D that in the data, low interest rates and high nursing home prices are indeed associated with larger rate increases.

would require detailed financial information from insurers, which we do not have. Instead, in Section 6.4, we empirically demonstrate that the estimated adjustment costs align with the effects of financial frictions and pricing regulations.

After observing the second stage premium, consumers may terminate their contract with some probability. In the benchmark specification, we assume lapses occur either exogenously with probability δ_k (e.g., due to reasons such as forgetting to pay premiums) or if consumers cannot afford the premium, i.e., if $p_{jk2} > y_{z_i}$.[34] In Section 5.4, we formally endogenize consumer lapses and examine the robustness of our analysis. 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. Based on underwriting practices, switching to a different insurer in the second stage is not a feasible option for consumers.

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

$$\tilde{u}_{z_i jk} = (1 - \delta_k) u^{stay}_{z_i jk} + \delta_k u^{lapse}_{z_i k}, \tag{9}$$

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

$$u^{stay}_{z_i jk} \quad = \quad \alpha u(y_{z_i} - p_{jk2}) + \xi_j. \tag{10}$$

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

$$u^{lapse}_{z_i k} \quad = \quad \int_\lambda \alpha u(y_{z_i} - oop(\lambda, y_{z_i})) f_{z_i k}(\lambda) d\lambda. \tag{11}$$

λ is a random variable that represents the consumer's LTC expenses. It is distributed according to the PDF $f_{z_i k}(\lambda)$. It varies by consumer type (indexed by z_i) because we allow for heterogeneity in income and access to family care, which can affect the risk of using formal LTC services. It also depends on k as the aggregate state vector includes nursing home costs. We assume the distribution of λ is realized and observed by firms and consumers

[34] 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. (2023) similarly find that unintentional lapses are the most prevalent in the LTCI market.

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_{z_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 equal to $u_{z_ik}^{lapse}$.

5.3 Equilibrium

Consumers in the first period make insurance purchase decisions to maximize their lifetime utility. When insurer j's price schedule is $(p_{j1}, \{p_{jk2}\}_k)$, consumer i's expected lifetime utility from contracting with insurer j is

$$\tilde{v}_{ij}(p_{j1}, \{p_{jk2}\}_k) = \underbrace{\alpha u(y_{z_i} - p_{j1}) + \xi_j + \beta_c \sum_k \pi_k \tilde{u}_{z_ijk}}_{=v_{z_ij}(p_{j1},\{p_{jk2}\}_k)} + \varepsilon_{ij}, \tag{12}$$

where β_c is the consumer's discount factor, and v_{z_ij} is the deterministic component of choice-specific utility, which depends on consumer type z_i. The consumer's expected lifetime utility from not purchasing any insurance is

$$\tilde{v}_{i0} \quad = \quad \underbrace{\alpha u(y_{z_i}) + \beta_c \sum_k \pi_k u_{z_ik}^{lapse}}_{=v_{z_i0}} + \varepsilon_{i0}. \tag{13}$$

When consumer i has correct beliefs about price dynamics of LTCI contracts, then her choice j^* satisfies $j^* = \underset{j=0,1,\ldots,J}{\operatorname{argmax}}\, \tilde{v}_{ij}(p_{j1}, \{p_{jk2}\}_k)$. If the consumer believes the second-stage rates will be the same as the initial price, then her choice will satisfy $j^* = \underset{j=0,1,\ldots,J}{\operatorname{argmax}}\, \tilde{v}_{ij}(p_{j1}, \{p_{j1}\}_k)$, where p_{j1} is used for all states of the second stage. By integrating idiosyncratic taste shocks across individuals, one can obtain the demand for insurer j conditional on consumer type z:

$$s_{zj1} = \begin{cases} \frac{\exp(v_{zj}(p_{j1},\{p_{j1}\}_k))}{\sum_{j'} \exp(v_{zj'}(p_{j'1},\{p_{j'1}\}_k))} & \text{if type-}z\text{ consumers have biased beliefs} \\ \frac{\exp(v_{zj}(p_{j1},\{p_{jk2}\}_k)}{\sum_{j'} \exp(v_{zj}(p_{j'1},\{p_{j'k2}\}_k)} & \text{if type-}z\text{ consumers have correct beliefs.} \end{cases} \tag{14}$$

The initial market share for insurer j is given as $s_{j1} = \sum_z s_{zj1} g(z)$.

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

$$\Pi^*_{jk2} = \max_{p_{jk2}} \sum_z (p_{jk2} - \mu_{zjk}) g_z s_{zjk2} - C^{rs}_{jk}(p_{j1}, p_{jk2}), \tag{15}$$

where s_{zjk2} is the market share of consumers with type z in stage 2, which depends on the lapse rate and the initial market size, i.e., $s_{zjk2} = (1 - \delta_k)s_{zj1}$. 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 $\{p_{jk2}\}_k$ 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,

$$\Pi_j^* = \max_{p_{j1}} p_{j1}s_{j1} - C_j^l(p_{j1} - \tilde{\mu}_j) + \beta_f \sum_k \pi_k \Pi_{jk2}^*, \tag{16}$$

where β_f is the firm's discount factor.[35]

In stage 0, fringe firm j with entry cost c_j^e will enter the market if and only if

$$c_j^e \leq \Pi_j^*. \tag{17}$$

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 entry choices of fringe firms that solve (15), (16), and (25).

5.4 Discussion

5.4.1 Endogenous Lapses

The model essentially has exogenous lapses based on the low lapse rate of the industry, as described in Section 3.4. As this specification might give too strong incentives for insurers to raise rates, we also consider an alternative model where we fully endogenize lapses and allow consumers to decide based on rate increases. Details are provided in Section F of the Online Appendix. We find that, compared to the predictions under our benchmark specification, changes in second-period premiums become slightly smaller when the strictness of rate stability regulations is adjusted. However, the overall predictions remain largely consistent with the baseline model.

[35] For simplicity, we assume that the realization of interest rate shocks does not affect insurers' discount factor. As the second-period premium is not *directly* influenced by β_f, this simplification will not have a large impact in our model. Instead, we capture the effect of interest rate shocks through the rate adjustment function.

5.4.2 Dynamic Pricing Regulation vs Reinsurance Subsidies

Our main policy analysis focuses on dynamic pricing regulation, which impacts the rate adjustment cost, C^{rs}_{jk}. The government can alternatively impact the price dynamics by offering reinsurance to insurers, i.e., providing state-dependent subsidies.[36] 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.

5.4.3 Other Modeling Assumptions

While our model provides a more comprehensive treatment of market structure, dynamic contracts, and supply-side regulations compared to existing studies on LTCI, it still omits some relevant mechanisms. On the consumer side, we do not allow for savings, as doing so would make our analysis intractable. Without self-insurance, the welfare benefit from rate stability regulation could be overpredicted. Our model, therefore, provides an upper bound on consumers' benefit from the regulation. As we discuss later in Section 7, we find that stricter rate stability regulation generates a limited consumer welfare gain and a much larger insurer profit loss. As adding savings would further lower consumers' benefit, we suspect it will strengthen our quantitative result about the overall impact of the regulation.

We also assume that the fraction of consumers with biased beliefs does not change in response to the strictness of rate stability regulation, which we believe is not a critical concern in our context for the following reasons. First, as the regulation applies only to insurers and is complex, consumers may not fully recognize the changes. Specifically, the adoption of RSR 2000 reduced the frequency of premium increases, suggesting that it is unlikely that more consumers became aware of potential rate increases during our analysis period. Second, we conjecture that our long-run qualitative conclusions from counterfactual regulation analysis will hold even when consumer awareness shifts in response to regulation changes. If rate stability regulations are relaxed, consumer awareness of premium increases is likely to grow over time. This heightened awareness could reduce insurers' ability to exploit consumer lock-in, thereby mitigating inefficiencies.

[36] 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.

On the supply side, there are some complex issues that we abstract from. While we account for insolvency *risks* arising from aggregate risks and financial frictions, we do not explicitly model the occurrence of bankruptcy. This is based on the fact that only two relatively small insurers went bankrupt during our analysis period.[37],[38] When insurers do go bankrupt, state governments provide benefits up to a cap through state guaranty funds, which are funded by taxes levied on all health insurers. This could admittedly create agency problems and induce insurers to take excessive risks. We abstract from such agency issues as it would require a complex model of the government budget and portfolio decisions of insurers. We also abstract from any externality that one insurer's decision to increase rates might have on other firms' reputations.[39]

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. 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%.

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

[37] https://www.nolhga.com/factsandfigures/main.cfm/location/insolvencies.

[38] Allowing for insolvency is likely to strengthen our quantitative conclusion, which is that stricter rate stability regulation has an overall negative impact. When the regulation becomes more stringent, insolvency risks increase, which will hurt consumers as they only have access to state guaranty funds that pay out capped benefits when their insurer goes bankrupt.

[39] We conjecture that this omission is likely to have a limited impact in our counterfactual analysis of rate stability regulation. This is because our counterfactual considers uniformly increasing or decreasing the regulatory cost, which would either reduce or strengthen all insurers' incentives to change rates.

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. Due to the symmetry assumption, the model predicts that all fringes choose the same price, which we set to be the mean price of fringes in a given market.[40]

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 65 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 65 are able to purchase insurance. The overall coverage rate is computed as 20%.

We incorporate the distribution of consumer type z_i using various data sources. For income and the availability of family care, we use the Health and Retirement Study (HRS), which has surveyed a representative sample of elderly Americans every two years since 1992. We use social security retirement income, employer pension, annuity income, and other income to obtain the income information. We consider three income levels based on the income terciles of the sample distribution. To measure the availability of family care, we use the question in the HRS that directly asks whether individuals have kids who will provide LTC in the future. If the answer is yes, we treat the individual as having access to family care; otherwise, the individual is regarded as having no access to family care. Regarding consumers' expectation about rate increases, we use the study by Brown et al. (2012) who find that 58% of their survey participants believed premiums might go up. Based on their finding, we set the fraction of consumers with correct beliefs about price dynamics as 58% and the share with misbeliefs as 42%.

6.2 Empirical Specification

6.2.1 Time Horizon

We assume consumers are aged 65 years old at the beginning of the first stage, at which point they make a once-and-for-all private LTCI choice. We abstract from insurance rejections and assume consumers are healthy enough to purchase. Throughout the first stage, consumers remain relatively healthy and do not require long-term care. Those who opt for private LTCI pay the annual premium for n_1 years. The second stage lasts n_2 years, during which long-term care shocks are realized. Those with private LTCI are fully insured and pay the revised

[40] As shown in Table A.2 in Online Appendix, the price dispersion among fringe firms in the data is indeed smaller than that of major firms.

premium, while those without pay for LTC either using their own resources or Medicaid benefits. We set $n_1 = 8$ years and $n_2 = 4$ years.[41] Both consumers and insurers have the same annual discount factor ($\beta = \beta_c = \beta_f$), and we 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 LTC Risk

To model individual-level LTC risk, we use the data from the HRS and compute the likelihood of using formal LTC conditional on income and availability of family care. In Online Appendix Table A.4, we report the estimated formal care risk for each consumer type. The risk decreases with both income and availability of family care, and the risks vary significantly across consumer types. For example, low-income consumers without access to family care have a 53% chance of using formal LTC services, while high-income consumers with access to family care have only a 27% chance of using formal LTC services. The pattern suggests that the selection of high-income people into LTCI is advantageous, while the selection of consumers without the family care option is adverse. We set the cost of formal care such that the mean lifetime LTC expenses are $60,000 as in Kemper et al. (2006).

6.2.3 Cost Function

We assume the following functional forms for firms' costs:

$$C^{rs}_{jk}(p_{j1}, p_{jk2}) = \begin{cases} c^0 + \frac{c^1_{jk}}{2}(p_{j1} - p_{jk2})^2 & \text{if } p_{jk2} > p_{j1} \\ 0 & \text{if } p_{jk2} = p_{j1} \end{cases} \tag{18}$$

$$C^l_j(p_{j1} - \tilde{\mu}_j) = \frac{c^l_j}{2}(p_{j1} - \tilde{\mu}_j)^2. \tag{19}$$

The premium adjustment cost, C^{rs}_{jk}, includes a fixed cost component, c^0, to account for the administrative costs associated with submitting a rate increase request.[42] We allow c^0 to vary by market as the application process differs across states and the adoption of RSR 2000 might have impacted the fixed cost.

[41] Our model allows rate increases to happen in the second stage, and in our data, most rate increases happen at contract ages 8-12. Furthermore, using this time horizon, consumers in the model enter their mid 70s when the second stage starts, which is usually when LTC risks become substantial (Ko, 2022).

[42] To obtain rate increases, insurers have to submit detailed documentation that provides justifications for proposed rate increases, including historical evidence of higher-than-expected claims experience. In some cases, state regulators hold public hearings which would require participation from insurers and even further documentation.

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

$$\tilde{\mu}_j = \frac{\beta^{n_1} B_2 \sum \pi_k \mu_{jk}}{lr_{target}(B_1 + \beta^{n_1} B_2)}, \tag{20}$$

where the numerator is the expected present discounted value of claims, and μ_{jk} is insurer j's claims cost in aggregate state k (see Section 6.3.2 for its calculation). 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 vary across insurers and markets. The parameter will therefore capture policy changes to loss ratio regulation during our sample period.

6.2.4 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.[43] As our second stage lasts four years ($n_2 = 4$), we calibrate the lapse probability at $\delta_k = 1 - 0.97^4$ for all k. Means-tested Medicaid is modeled as a consumption floor. We set it at \$10,000 per year, a value close to the estimate by Mommaerts (2023) (\$11,691) and the benefit from Supplemental Security Income (\$7,800).

6.3 Estimation Strategy

6.3.1 Demand Estimation

Distribution of Aggregate Risk and State-contingent Premium Increases. We define the aggregate state vector k as $k = (l, m, n)$ where l is the interest rate, m is the nursing home price, and n represents other claims-relevant aggregate shocks. We first use plan-level rate increase data and utilize time and geographical variations of premium increases across plans to identify the distribution of n and predict n-contingent rate increases. Then, we use cross-time variations to identify the distribution of interest rate (l) and nursing home price shocks (m), and adjust the predicted rate increases to account for their dependence on l and m. We provide details in Online Appendix D.

[43] https://www.soa.org/resources/experience-studies/2016/research-ltc-insurance/.

Estimation of Demand-side Parameters. We follow the estimation strategy in Berry et al. (1995) for demand estimation. A key demand parameter that determines the magnitude of the price elasticity of demand is the consumption utility scale α. To estimate this parameter, we specify the unobserved characteristics of insurer j as

$$\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}. \tag{21}$$

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. To identify and estimate α, we require variations in premiums that are independent of unobserved demand shocks $\Delta\xi_{jt}$. However, the key challenge is that, in practice, insurers may adjust premiums in response to these unobserved changes in demand.

We use several plausibly exogenous variations to address the issue. First, we leverage cross-market variations in the spirit of Hausman (1996) and Nevo (2001), instrumenting initial premiums, p_{j1}, using insurers' own initial premiums in neighboring states. Our identification assumption is that there may be common supply shocks across geographic areas that affect initial premiums, but these shocks are uncorrelated with demand. For example, insurers may update their beliefs about future claims costs 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. In Table A.3 of the Online Appendix, we show that this instrument has a statistically significant and positive effect on the insurer's own initial premium. Second, we exploit variations in states' adoption of the RSR 2000, which affects rate increases. These changes in rate increases can affect the demand of consumers with correct beliefs. We assume the implementation of supply-side regulations is orthogonal to changes in consumers' unobserved demand. Specifically, we use changes in rate increases in the year the RSR 2000 was adopted. As shown in Section 4.3.2, this policy change significantly reduced the rate increases.

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

6.3.2 Supply Estimation

Distribution of Second-stage Claims. To estimate the supply side, we need the demand estimate and data on premiums and claims. As in demand estimation, we use observed initial prices p_{j1} and estimated state-contingent prices p_{jk2}. For claims costs, we assume $\mu_{zjk} = \omega_z \mu_{jk}$, where ω_z is the consumer type-specific weight on LTC usage. We calibrate this parameter using the HRS to reflect differences in LTC utilization across consumer types. Using a procedure similar to the one used in predicting p_{jk2}, we estimate state-contingent claims μ_{jk} outside the model. Online Appendix D provides details.

Estimation of Second-stage Parameters. We first estimate the parameters that enter the premium adjustment cost function, which includes the fixed cost component c^0 and the coefficient c^1_{jk}. 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 Online Appendix D, 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 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 as

$$c^{1*}_{jk} = \frac{(s_{jk2})^2}{2c^0}. \tag{22}$$

We set c^1_{jk} as

$$c^1_{jk} = \begin{cases} E[c|c > c^{1*}_{jk}] & \text{if } p_{jk2} = p_{j1} \\ \frac{s_{jk2}}{p_{jk2} - p_{j1}} & \text{if } p_{jk2} > p_{j1}. \end{cases} \tag{23}$$

Estimation of First-stage Parameters. 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}:

$$\begin{aligned} c^l_j(p_{j1} - \tilde{\mu}_j) \quad &= \quad B_1 \left(s_{j1} + p_{j1} \frac{\partial s_{j1}}{\partial p_{j1}} \right) \\ &+ \quad \beta^{n_1} B_2 \sum_k \pi_k \left((p_{jk2} - \mu_{jk}) \frac{\partial s_{jk2}}{\partial p_{j1}} + 1(p_{jk2} > p_{j1}) c^1_{jk} (p_{jk2} - p_{j1}) \right). \end{aligned} \tag{24}$$

Estimation of Entry Cost. The entry cost cutoff c^{e*} satisfies $c^{e*} = \Pi_j^*$ where Π_j^* is the equilibrium profit that is the same for all j considered as a fringe. This value can be computed once we have the demand and regulatory cost estimates. 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_F. We then have

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

where n_F is the number of fringe entrants observed in the data, and G is the CDF of the entry cost. We set $N_F = 145$ which is the number of unique insurers observed in the NAIC data.[44] We calibrate σ_e to 0.6 to match the reduced-form impact of the RSR 2000 on the number of insurers documented in Section 4. We estimate μ_e for each market using the equation above.

6.4 Estimation Results

Table 1 reports the results from our demand estimation. The consumption utility scale (α) has an estimate of 0.44. The associated demand elasticity with respect to the initial rate (p_{j1}) is about -0.60.[45] The estimated elasticity falls in the range of existing estimates of price elasticity (between -1 and -0.5) for health insurance (Goda, 2011). There are very few studies that have estimated the price elasticity for LTCI and have reported divergent estimates. For example, using variations in tax incentives for LTCI, Courtemanche and He (2009) and Goda (2011) find substantially larger price elasticities, which are between -4 and -3. Ameriks et al. (2016) exploit a strategic survey design and find a significantly smaller elasticity, e.g., -0.5 for the median elasticity. Thus, while we take a very different identification strategy, our estimates are slightly above the lower end of the existing estimates.[46]

In Table A.5 of the Online Appendix, we show that our model can fit well the private insurance coverage rates across different consumer types. The data show that, compared to the population average (Table A.4 in the Online Appendix), a higher proportion of the insured

[44]Because the number of potential fringe entrants is very large in our setting, we assume that the entry condition in equation (25) is satisfied with equality. It does not guarantee that the number of fringe entrants n_F is a strictly positive integer in counterfactual analysis, which is what we need as the model assumes a discrete number of insurers. In counterfactual analysis, we round it up to the nearest integer.

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

[46]In Section E.3 of the Online Appendix, we show that using a higher demand elasticity with respect to price would not change the main qualitative conclusion from our counterfactual experiments.

	Estimate
Consumption utility scale (α)	0.4414
	(0.0135)
Mean demand elasticity	-0.5983

Table 1: Demand parameter estimates
Notes: The table reports the estimated coefficient of consumption utility scale and the estimated demand elasticity with respect to the premium. Standard errors are reported in parentheses.

consumers lack family care availability, indicating adverse selection. Additionally, a higher proportion of the insured consumers belong to high-income groups, indicating advantageous selection. Our model effectively captures both types of selection.

Our demand estimates suggest that consumers are relatively insensitive to premiums. 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.

Table 2 shows the cost parameter estimates. We first discuss the estimates that enter the rate adjustment cost function. The fixed cost of revising the rate (c^0) in the second stage is allowed to vary by market and has a mean estimate of 0.18. The variable cost efficient (c^1_{jk}) has a mean estimate of 0.0026. The implied per-enrollee annual cost associated with rate adjustment is \$221 on average.

We analyze whether rate adjustment cost estimates increase with the adoption of RSR 2000. To do so, we perform a difference-in-difference (DID) analysis where we regress the cost estimates on the dummy which is one if the state has RSR 2000 in place, controlling for year and state fixed effects. We find that c^0 increases by 24% as a result of the RSR 2000 adoption, while c^1_{jk} increases by a greater magnitude of 194%. The result is consistent with the fact that RSR 2000 made it harder for insurers to revise rates. It also demonstrates that rate stability regulation directly affects premium adjustment costs.

We also examine the relative importance of different aggregate risks in determining rate adjustment costs. The cost coefficient c^1_{jk} depends on the vector $k = (l, m, n)$, consisting of the interest rate l, nursing home cost m, and residual claims-relevant aggregate risk n. The

Parameter	Notation	Mean	S.d.
Rate adjustment cost			
: Fixed cost	c^0	0.1776	0.2197
: Variable cost coefficient	c^1_{jk}	0.0026	0.0246
: Per-enrollee annual cost		221	201
Initial rate regulation cost			
: Coefficient (10^{-1})	c^l_j	0.0009	0.0565
: Per-enrollee annual cost		445	247
Mean entry cost	$E[c^e]$	76	47

Table 2: Supply parameter estimates
Notes: The table reports summary statistics of the supply parameter estimates. The parameter c^1_{jk} is estimated at the market-insurer-aggregate state level; c^l_j at the market-insurer level; and c^0 and $E[c^e]$ at the market level. We report "Mean" and "Standard deviation (S.d.)" of these parameters.

mean estimate of c^1_{jk}, conditional on being in a high-interest state (favorable for insurers), is 7% larger compared to the mean estimate conditional on being in a low-interest state. The larger rate adjustment cost for high-interest states is needed to rationalize the data pattern that rate increases are smaller when interest rates are favorable (see Online Appendix D). Similarly, the mean estimate of c^1_{jk} is 8% higher when the nursing home growth rate is low relative to when it is high. These findings suggest the importance of financial frictions as determinants of rate adjustment costs. When firms' financial constraints are likely to bind due to adverse aggregate shocks, they can better justify their rate increases, resulting in lower rate adjustment costs. Regarding residual aggregate risks captured by n, we find that the conditional mean of c^1_{jk} increases by almost 270% when moving from the top half to the bottom half of the distribution. The results suggest that during our sample period, insurer-level claims risks were more significant in determining price adjustments than aggregate risks arising from interest rates and nursing home costs. This finding may be due to the market still being relatively young, with insurers lacking sufficient experience in predicting claims.

For initial rate regulation, insurers incur an average per-enrollee annual cost of $445. Such large regulatory costs are needed to rationalize relatively low premiums in the data, despite the small price elasticity that we find. We also examine whether the RSR 2000 had a significant effect on the cost estimates of initial rate regulation. Unlike rate stability regulation, we find that the effect is small and noisy.

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 Online Appendix E.1). While a certain fraction of 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 Welfare Effect of Dynamic Pricing Regulation

Theoretically, the welfare impact of rate stability regulation 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. The reduced number of fringe entrants can have a negative impact on consumer welfare by diminishing the option value and by dampening price competition.

We vary the estimated cost associated with premium adjustment, c^1_{jk} in equation (23).[47] 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 entrants relative to the benchmark equilibrium. According to Panel A, the initial rate shows almost no response to the changes in the adjustment cost, c^1_{jk}. This is because when c^1_{jk} changes, the revised rate p_{jk2} is adjusted sufficiently to absorb most of the impact. The little response of the initial rate aligns with our descriptive finding that the RSR 2000 had no significant impact on initial rates (see Figure 3 in Section 4).[48]

From a supplementary exercise reported in Table A.6 of the Online Appendix, we find that the initial rate responds substantially when we vary the initial rate regulatory cost, c^l_j. For

[47] 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 substantially increased c^1_{jk}. While the fixed cost component c^0 is also allowed to vary across markets, we consider adjusting c^1_{jk} as the RSR 2000 impacted c^1_{jk} more substantially than the fixed cost.

[48] The small response in initial rates is also affected by our estimates of relatively low demand elasticity with respect to price. In Online Appendix E.3, we show that a higher demand elasticity would generate larger responses in initial premiums. However, such a model generates substantially more modest responses from fringe firms.

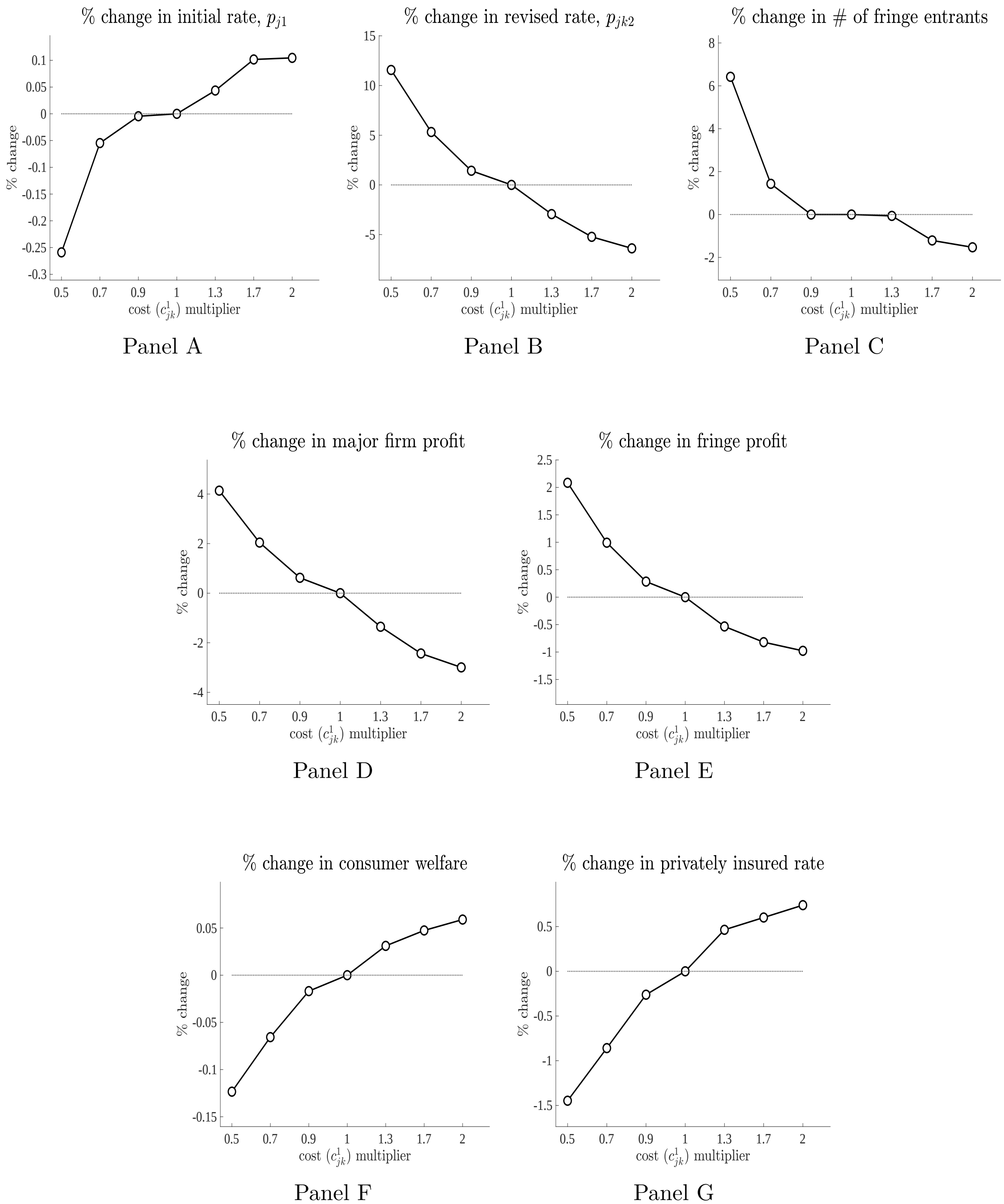


Figure 6: Counterfactual rate stability regulation
Notes: The figure presents the impact of alternative designs of rate stability regulation. Counterfactual simulations change the values of c^1_{jk} from 50% to 200% of its baseline estimate. All panels report the % change in the market outcome relative to the baseline estimate.

example, when c_j^l is halved, the initial rate increases by 6% relative to the baseline economy. Conversely, when the cost doubles, the initial rate decreases by 10%. As discussed in Section 6.4, the RSR 2000, which motivated our paper, increased rate adjustment costs while having little impact on initial rate regulatory costs. For this reason, we focus our counterfactual analysis on varying the rate adjustment cost.

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 12% 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 number of fringe entrants decreases in the regulatory cost. For example, when the regulatory cost is halved, the fringe variety measure increases by over 6%. 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 4%, and fringe firms' profits increase by about 2%. As discussed in Section 6.4, our estimates indicate that a significant source of the variations in rate adjustment costs stems from insurers' financial frictions. Consequently, stricter regulations could amplify the costs associated with these financial frictions.

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 0.05% 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. Finally, Panel G reports the impact on the LTCI coverage rate. As with consumer welfare, enrollment increases in the strictness of the regulation, but its impact is very modest.

In Online Appendix E.2, we report an additional counterfactual analysis where we simulate the impact of RSR 2000. Our model captures the impact of RSR 2000 by allowing rate adjustment cost parameters to differ across markets, as described earlier in Section 6.4. We find that the model-simulated impact of the regulation is consistent with the descriptive evidence presented in Section 4. For example, the model predicts that RSR 2000 will reduce the number of fringe entrants by 5.7%, which is close to the empirical magnitude of 6.6% reported in Section 4.

	% change from baseline economy
Initial rate	1.81
Revised rate	-15.34
Fringe entrants	-4.96
Total enrollment	0.54
Consumer welfare	0.10
Major insurer profits	-7.68
Fringe insurer profits	-1.83

Table 3: Impact of insurer commitment
Notes: The table reports percent changes in outcomes as the economy moves from the baseline regime to a counterfactual regime where insurers commit to constant pricing, i.e., no rate increases in the second stage.

To sum, stricter rate stability regulation has a very limited impact on improving consumer welfare, while 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 participation. Overall, one can conclude that the current regulation is too strict, as it causes a significant loss in insurer profits and increases market concentration, while resulting in a negligible gain in consumer welfare.

7.2 Value of Commitment

We now consider the welfare impact of insurer commitment. Our model incorporates several mechanisms that contribute to insurers' lack of commitment, including consumer myopia and financial frictions. To evaluate the value of insurer commitment, we assume that insurers are required to commit to a constant price schedule. This would represent the equilibrium outcome when, for example, rate adjustment costs are prohibitively high. The welfare impact of this counterfactual scenario depends on several factors. Since insurers commit to a fixed pricing schedule, inefficiencies arising from consumer myopia would be eliminated. However, if financial frictions are significant, this regime could lead to reduced welfare, as insurers would be unable to raise premiums in response to substantial negative cost shocks.

Table 3 reports how the equilibrium outcomes change relative to the benchmark economy, where insurers are allowed to revise rates. The new equilibrium has higher initial rates on average, with substantially lower revised rates in the second period. Despite the improved price stability, the increase in consumer welfare is still modest due to a reduction in the

	% change from baseline economy
Initial rate	-2.10
Revised rate	-4.78
Fringe entrants	-67.53
Major insurer profits	-28.08
Fringe insurer profits	-27.96
Private LTCI coverage rate	-29.48

Table 4: Medicaid generosity and market outcomes
Notes: The table reports percent changes in outcomes as the economy moves from the baseline regime to a counterfactual regime with more generous Medicaid benefits.

number of active insurers. Insurers' profitability decreases significantly as they lose the ability to adjust rates depending on the realized aggregate states.

Overall, the results suggest that the impact of constant pricing, which would be the equilibrium outcome with prohibitively large regulatory costs, extends beyond merely preventing insurers from exploiting consumer myopia. It exacerbates insurers' difficulties in coping with financial frictions, leading to reduced market entry. The resulting gain in consumer welfare is limited, not only due to a reduced match value but also because of higher initial rates caused by increased market concentration.

7.3 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 consumption floor that is twice the baseline value. Table 4 reports the changes in equilibrium outcomes relative to the baseline economy. We find that increasing Medicaid benefits reduces the average initial rate by 2.1%. On the one hand, insurers might reduce the rate in response to a better outside option that consumers have. On the other hand, consumers who 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. We find that the former channel dominates, resulting in a modest price reduction. Rate increases are lower when Medicaid benefits are larger. This is because the marginal revenue from rate increases is proportional to the demand, which is smaller under generous Medicaid. Insurers

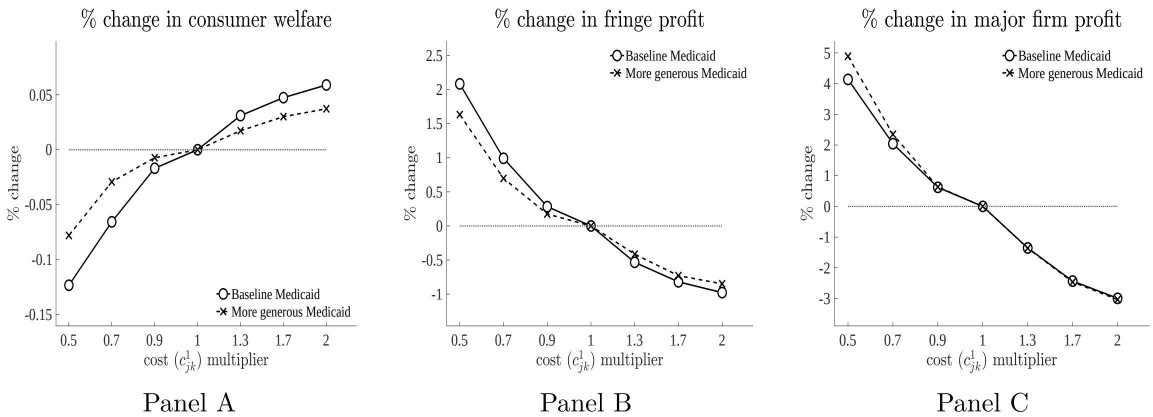


Figure 7: Counterfactual rate stability regulation under more generous Medicaid
Notes: Dashed lines with cross markers represent the change in the market outcome as we vary the regulatory cost under a more generous Medicaid program. Solid lines with circle markers are the same lines reported in Figure 6, which represent the change in market outcomes when we vary the regulatory cost, c^1_{jk}, from 50% to 200% of its baseline estimate under the baseline Medicaid program.

experience a substantial reduction in profits due to the lower demand. The loss of insurer profits leads to less entry, and the resulting number of fringes is lower by about two-thirds. As a result of a better outside option and reduced insurer participation, the equilibrium LTCI coverage rate decreases by about 30%.

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 baseline case where the regulatory cost is untouched and Medicaid provides more generous benefits (i.e., the equilibrium reported in Table 4). In Figure 7, dashed lines with cross markers represent the percent change in market outcomes when Medicaid is more generous. We find that the generosity of Medicaid acts to depress the effect of rate stability regulation on consumer welfare. Similarly, it also lowers insurers' profit losses from stricter rate stability regulations in almost all cases. 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. One policy implication is that the regulation could improve price stability at a smaller negative impact on insurers when Medicaid benefits are more generous.

8 Conclusion

Dynamic pricing regulation constitutes one of the most important market design policies in insurance markets. We have examined its equilibrium and welfare consequences in the LTCI industry. We find that the benefit of the regulation extends beyond merely improving premium stability. It also provides the additional advantage of mitigating consumer lock-in, which is critical in markets where firms do not commit and some consumers have misbeliefs about future rates. However, there are also unintended negative impacts of the regulation. The regulation aggravates insurers' cost from financial frictions. Consequently, the regulation reduces firm entry, resulting in increased market concentration and reduced varieties. We present a unified framework to quantitatively assess these various margins surrounding the regulation. We find that stricter regulation has a negligible impact on improving consumer welfare, while reducing insurer profits and participation.

The results in this paper raise the question of what the optimal policy design would be to address aggregate risks in these markets. One possibility is to explore multiple policy instruments, including reinsurance subsidies. While reinsurance subsidies are not currently available in the LTCI market, they could theoretically help insurers manage aggregate risks. However, a potential concern is whether introducing such subsidies might create moral hazard, encouraging insurers to take on excessive risks and potentially increasing government expenditures. Additionally, it would be interesting to extend the model to explore the long-run implications of policy interventions where consumers' beliefs about rate increases are updated. With sufficient data, examining how insurers risk screen consumers and the role of brokers in steering consumer decisions would also be interesting.

Finally, applying our framework and its insights to other settings where aggregate risks are relevant would provide further valuable analysis. For example, insurers managing climate risks face significant aggregate uncertainty and are subject to dynamic pricing regulations. It would be interesting to examine the welfare and equilibrium impacts of the regulations in these markets.

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Online Appendix (Not For Publication)

A Further Discussion on the Simple Framework

This section provides details on the interpretation of the rate adjustment cost function, C_k^{rs}, introduced in Section 2 of the main text. We build on Koijen and Yogo (2015, 2016) to motivate our cost function which captures not only financial frictions but also regulatory environments. Suppose that an insurer chooses the second-stage premium to maximize

$$(p_{k2} - \mu_{k2})s_{k2} \tag{A1}$$

subject to

$$(p_{k2} - \mu_{k2})s_{k2} \geq \Delta_k \quad \text{and} \tag{A2}$$

$$p_{k2} \leq \Phi(p_1, \mu_{k2}). \tag{A3}$$

The first constraint (A2) captures the financial friction, requiring firms to maintain a certain amount of capital reserves, Δ_k, when the realized state is k. This constraint can be interpreted as capital requirements, where maintaining adequate reserves is necessary to avoid regulatory intervention, such as a downgrade in the insurer's credit rating. It can also be understood as a bankruptcy constraint, as in severe cases, failing to meet capital requirements can lead to insolvency. The second constraint (A3) captures other costs of rate adjustments, including reputation and regulatory costs. By how much the insurer can increase the price depends on the insurer's initially committed price, p_1, and the realized claims cost, μ_{k2}. We can form a Lagrangian problem as

$$(p_{k2} - \mu_{k2})s_{k2} + \lambda_1 \left((p_{k2} - \mu_{k2})s_{k2} - \Delta_k\right) + \lambda_2 \left(\Phi(p_1, \mu_{k2}) - p_{k2}\right). \tag{A4}$$

This problem looks similar to our second-period optimization problem (3) in Section 2, which can be considered as turning the "hard" constraints into "soft" constraints.[1]

The same argument is made in Koijen and Yogo (2015), who model financial frictions as both hard constraint and soft constraint and show the equivalence of the optimality conditions of insurer pricing. It also follows their subsequent paper, Koijen and Yogo (2016),

[1] While our rate adjustment cost function in equation (3) of Section 2 does not explicitly have claims μ_{k2} as an argument, it still indirectly depends on claims as the cost function is allowed to vary across different states of world, k.

where the financial friction is modeled as a soft constraint based on their previous finding. Throughout the paper, we take the soft constraint approach as the hard constraint approach requires the perfect measurement of when the constraint actually binds. We infer the influence of financial frictions on rate adjustments by analyzing variations in aggregate shocks. See Section 5.2.3 for additional discussions about the interpretation of the cost function and the mapping with the empirical model.

B 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.7 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.

C Additional Descriptive Evidence

C.1 Additional Event Study Analysis

In Figure A.1, we perform additional regressions using the event study specification described in equation (4) in Section 4.3. In Panels A and B of Figure A.1, we examine the impact of RSR 2000 on the number of insurers conditional on their type, major or fringe. 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. Table A.2 of Online Appendix provides summary statistics of firms by type. We find that the regulation had no significant impact on major firms' participation decisions (Panel A of Figure A.1), while it reduced the number of fringe firms by 1.72 in two years since the adoption (Panel B of Figure A.1). As the mean number of fringes in a given market is about 26, it translates into a reduction of 6.6%. In Panel C of Figure A.1, we examine the impact of the regulation on the initial rate for a restricted subset of observations. First, we only use plans that first appear on the market in a given year. This restriction ensures that we only consider the impact of the regulation on brand new plans and removes any potentially different treatments of new vs. existing plans in premium setting. Second, in computing market-level average premiums, we exclude over 10% of observations that are in the left and right tails of the distribution. Panel C shows that in two years since the adoption of RSR 2000, the initial rate for this subset of plans increased by $330, which translates into an increase of 17%.

The main specification of our event study framework assumes homogeneous treatment effects with respect to the timing of policy implementation. To examine the robustness with respect to this assumption, we follow Borusyak et al. (2024) to allow for heterogeneous treatment effects and use the entire sample, including states that did not adopt RSR 2000 during the sample period. Figure A.2 shows the estimated average effects, which are both qualitatively and quantitatively similar to those under the main specification. The adoption of RSR 2000 reduces the number of products and the number of insurers, while its effect on the average initial premium is statistically insignificant.

C.2 Regulation Effect vs Composition Effect

We examine whether the descriptive finding in Section 4.3.2 is due to a composition effect, i.e., plans which survived after the regulation adoption were those that relied less on rate increases. To explore this possibility, we look at potential effects of the regulation on claims. If the composition effect is important, we expect the claims distribution to be affected by the regulation adoption in a meaningful manner. Specifically, we expect plans sold after the regulation adoption to have lower claims costs which could result in lower rate increases.

From our NAIC data, we use claims that were submitted about 10 years since the sales of the contract. We do this because plans sold after the regulation are younger by definition and are likely to cover younger policyholders who have smaller claims to submit in any given calendar year. Our sample selection is intended to mitigate this issue. We find that plans sold after the regulation adoption had realized claims that were higher by about 9.3%. This suggests that the composition effect is unlikely to generate the changes in premium increases documented in Section 4.3.2.

D Estimation Details

D.1 Estimation of Aggregate Risks and State-contingent Rate Increases

This section describes how we estimate the distribution of premium increases. The realization of premium increases may depend on the aggregate state vector $k = (l, m, n)$ where l is the interest rate, m is the nursing home price, and n represents other claims-relevant aggregate shocks. We first explain how we identify the distribution of n and predict n-contingent rate increases. Then, we discuss how we identify the distribution of interest rate (l) and nursing home price shocks (m) and adjust the predicted rate increases to account for their dependence on l and m.

Identifying the Distribution of n. We utilize rate increase data, where we observe plans' cumulative premium increases over time. We have variations in plans across geography, as well as variations in plans sold by insurers over time. Fix a geographical state s. Let r_j denote the cumulative rate increase for plan j in state s observed in the rate increase data covering the period from 2007 to 2017. Define $y_j = \ln(r_j + 1)$. We represent the density of y_j by the following finite mixture model:

$$f(y_j) = \sum_{g=1}^{G} \pi_{g|s} f_g(y_j | x_j' \beta_g). \tag{A5}$$

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 y_j follows a normal distribution. We estimate $\{\pi_{g|s}, \beta_g\}$ by a maximum likelihood estimator.

For geographical state s, define the probability of being in aggregate state $n \in \{1, ..., N\}$ as the following:

$$\pi_{n|s} = \begin{cases} \pi_{g=1|s} \text{ if } n = 1 \\ \pi_{g=2|s} Pr(q_{n-1} < y_{j|s} \leq q_n) \text{ if } n = 2, ..., N, \end{cases} \tag{A6}$$

where q_n represents the n^{th} quantile value of the second class distribution which is normal.

We predict n-contingent rate increase as

$$\ln(r_{jn}+1)=\begin{cases}0 \text{ if } n=1\\ E[y_j|q_{n-1}<y_{j|s}\leq q_n] \text{ if } n=2,...,N.\end{cases} \tag{A7}$$

We set $N = 5$ and choose $\{q_n\}_n$ such that we have quartile values of the second class distribution. Combined with the NAIC data on initial rates, we recover how premiums vary by n.

Identifying the Distribution of (l, m). We recover the distribution of (l, m) consisting of interest rate l and nursing home price m. Consider a market defined by geographical state s and sales year t_0. As the first stage lasts n_1 years and the second stage lasts n_2 years in our model, the calendar years that correspond to the second stage of the model is from $t_0 + n_1$ to $t_0 + n_1 + n_2 - 1$. We classify the n_2 years of the second stage into four groups, depending on whether the annual interest rate was "high" or "low" and whether the nursing home price was "high" or "low". For interest rates, we use the 5-year treasury bond rate and use the threshold of 2%.[2] For nursing home prices, we use the mean nationwide costs obtained from Genworth's Annual Cost of Care Survey. We classify nursing home prices as low if the growth rate is less than 3% and high otherwise.[3] Then, we use the bin estimator to compute the distribution of interest rate and nursing home shocks. For example, the probability that contracts sold in year t_0 are faced with a high interest rate (l =high) and a low nursing home price (m =low) in the second stage is computed as

$$\pi_{l=\text{high},m=\text{low}|t_0}=\frac{\sum_{\tau=t_0+n_1}^{t_0+n_1+n_2-1}1[\tau\in\mathcal{T}_{l=\text{high}}\cap\mathcal{T}_{m=\text{low}}]}{n_2}, \tag{A8}$$

where $\mathcal{T}_{l=\text{high}}$ is the set of calendar years when the interest rate was "high", and $\mathcal{T}_{m=\text{low}}$ is the set of calendar years when the nursing home price was "low".

To get the joint distribution of $k = (l, m, n)$, we assume (l, m) and n are independent. Then, for a given geographical state s and sales year t_0, we recover the distribution of aggregate states as

$$\pi_{k=(l,m,n)}=\pi_{lm|t_0}\cdot\pi_{n|s}. \tag{A9}$$

[2] Between 2007-2017, the 5-year treasury bond rate ranged from 0.7% to 4.4%, and the mean was around 2%.

[3] Between 2007-2017, the growth rate of nursing home costs ranged from -1% to 10%, and the mean was around 3%.

We adjust $n-$contingent rate increases in (A7) to account for the impact of interest rate risk (l) and nursing home price shock (m). Rate increases contingent on all aggregate state variables $k = (l, m, n)$ are predicted as

$$r_{jk} = \begin{cases} r_{jn} \text{ if } l = \text{high}, m = \text{low} \\ \eta_1 r_{jn} \text{ if } l = \text{high}, m = \text{high} \\ \eta_2 r_{jn} \text{ if } l = \text{low}, m = \text{low} \\ \eta_3 r_{jn} \text{ if } l = \text{low}, m = \text{high}. \end{cases} \tag{A10}$$

We compute η's directly from the rate increase data as the ratio of mean price increases relative to the baseline years. As evident in equation (A10), we consider years with high interest rates and low nursing home costs ($l = \text{high}, m = \text{low}$) as the baseline years, representing the most favorable conditions for insurers. For example, η_1 is calculated as a fraction where the numerator is the mean rate increase in years when both the interest rate and nursing home cost were high, and the denominator is the mean increase in baseline years.

From the rate increase data, we obtain $\eta_1 = 1.23$, $\eta_2 = 1.40$, and $\eta_3 = 1.37$. These estimates imply that when nursing home cost growth is low, moving from a high to a low interest rate is associated with a 40% larger rate increase. When nursing home cost growth is high, moving from a high to a low interest rate is associated with a $\frac{1.37}{1.23} = 11\%$ higher rate increase. Therefore, the realization of low interest rates drives rate increases higher. Regarding nursing home costs, we find that a large nursing home cost growth relative to a small one is associated with a 23% higher rate increase when the interest rate is high. However, when the interest rate is low, the realization of a large nursing home cost growth is in fact associated with a 2% decrease in rate increases. This suggests that the impact of nursing home cost shocks on rate increases is limited when insurers already face adverse financial conditions stemming from low interest rates.

D.2 Estimation of Claims

We predict state-contingent claims μ_{jk} outside the model based on a procedure similar to the one used in the estimation of state-contingent rate increases. From the NAIC data, we construct claims variable at the insurer-state-year level and utilize both time and geographical variations to identify its distribution. First, for a given geographic state s, we incorporate cross-sectional variations by defining quantiles of the claims distribution using $\{\pi_{n|s}\}_{n=1}^{N}$ estimated in equation (A6). We then compute the mean for each quantile of the claims distribution conditional on insurer characteristics, which results in μ_{jn}.[4] Next, we adjust for the impact of the nursing home price shocks (m) on claims and predict k-contingent claims as the following[5]:

$$\mu_{jk} = \begin{cases} \mu_{jn} \text{ if } m = \text{low} \\ \gamma\mu_{jn} \text{ if } m = \text{high.} \end{cases} \tag{A11}$$

We compute γ as a fraction where the numerator is the mean annual nursing home cost when the growth rate was high (above 3%), and the denominator is the mean cost when the growth rate was low. The ratio is computed as $\gamma = \frac{\$96{,}167}{\$89{,}131} = 1.08$. As $\gamma > 1$, insurers face a claims distribution that is shifted to the right when the realized nursing home price is high.

As our model allows for selection, insurers' final claims are impacted by the composition of their enrollees. We assign each consumer type z with a relative weight ω_z, which we use to scale insurers' claims μ_{jk}. For the construction of ω_z, we turn to the HRS which provides information about formal LTC risk conditional on consumer type. Let ω_z^u be the normalized LTC risk of consumer type z. We set $\omega_z = \frac{\omega_z^u}{\sum_{z'} \omega_{z'}^u \times s_{z'}}$ where s_z is the empirical share of the privately insured that are of type z.

D.3 Estimation of Rate Adjustment Cost

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

$$c_{jk}^1(p_{jk2} - p_{j1}) = s_{jk2}. \tag{A12}$$

The individual likelihood contribution is

$$\begin{aligned} Pr(p_{jk2}) &= Pr\left(c^0 < (p_{jk2} - p_{j1})s_{jk2} - \frac{c_{jk}^1}{2}(p_{j1} - p_{jk2})^2\right) \times \ln N\left(c_{jk}^1 = \frac{s_{jk2}}{p_{jk2} - p_{j1}}\right) && \text{(A13)} \\ &= F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right) \times f\left(\frac{s_{jk2}}{p_{jk2} - p_{j1}}; \mu_c, \sigma_c\right). && \text{(A14)} \end{aligned}$$

[4] This is based on the empirical observation that, in the data, realized rate increases and claims are positively correlated: a 1% increase in claims is associated with a 0.1% increase in rate increases.

[5] For notational simplicity, we index the predicted claims by $k = (l, m, n)$ although the interest rate l does not affect the claims.

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

$$c^1_{jk}(p^*_{jk2} - p_{j1}) = s_{jk2}. \tag{A15}$$

Then, the likelihood contribution is

$$\begin{aligned} Pr(p_{jk2} = p_{j1}) &= Pr\left(c^0 > (p^*_{jk2} - p_{j1})s_{jk2} - \frac{c^1_{jk}}{2}(p_{j1} - p^*_{jk2})^2\right) && \text{(A16)} \\ &= 1 - F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right). && \text{(A17)} \end{aligned}$$

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

$$\begin{aligned} \max_{c^0,\mu_c,\sigma_c} \quad & \sum_{j,k} 1(p_{jk2} = p_{j1}) \log\left(1 - F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right)\right) \\ & + 1(p_{jk2} > p_{j1}) \log\left(F\left(\frac{(s_{jk2})^2}{2c^0}; \mu_c, \sigma_c\right) f\left(\frac{s_{jk2}}{p_{jk2} - p_{j1}}; \mu_c, \sigma_c\right)\right). && \text{(A18)} \end{aligned}$$

E Counterfactual Appendix

E.1 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 consumers' expected utility. It is given by

$$\begin{aligned} EV_{z_i} &= \log(\sum_{j=0}^{J} \exp(v_{z_i j})) \\ &= \log(\sum_{j=0}^{J} \exp(\alpha \sum_t B_t u(c_{z_i jt}) + \overline{v}_{z_i j})), && \text{(A19)} \end{aligned}$$

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

$$EV^{new}_{z_i} = \log(\sum_{j=0}^{J} \exp(\alpha \sum_t B_t u((1+\Delta)c_{z_i jt}) + \overline{v}_{z_i j})). \tag{A20}$$

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

$$\begin{aligned}
\exp(EV_{z_i}^{new}) &= \sum_{j=0}^{J} \exp(\alpha \sum_t B_t u((1+\Delta)c_{z_i jt}) + \overline{v}_{z_i j}) \\
&= \sum_{j=0}^{J} \exp(\alpha \sum_t B_t u(c_{z_i jt}) + \overline{v}_{z_i j}) \exp \alpha \sum_t B_t \log((1+\Delta))) \\
&= \exp(EV_{z_i}) \exp(\alpha \sum_t B_t \log((1+\Delta))). \qquad \text{(A21)}
\end{aligned}$$

Then, after some algebra, we have

$$\log\left(\frac{\exp(EV_{z_i}^{new})}{\exp(EV_{z_i})}\right) = \alpha \sum_t B_t \log((1+\Delta))), \qquad \text{(A22)}$$

and we can therefore characterize Δ as

$$1 + \Delta = \exp\left(\frac{EV_{z_i}^{new} - EV_{z_i}}{\alpha \sum_t B_t}\right). \qquad \text{(A23)}$$

E.2 Additional Counterfactual Analysis: No RSR 2000 vs. All RSR 2000

We use the estimated model to simulate the impact of adopting RSR 2000 and compare the results with descriptive evidence presented in Section 4. We first simulate an economy where no states have RSR 2000 in place. Then, we simulate another counterfactual economy where all states have RSR 2000 in place. As described in Section 6.4, we find that RSR 2000 increases the fixed cost of rate adjustment by 24% and the variable coefficient by 194%. To simulate the No RSR 2000 regime, we identify the markets that had RSR 2000 in place during the sample period and scale down the estimated parameters of the rate adjustment cost function using the multipliers mentioned above (24% for fixed cost and 194% for variable coefficient). To simulate the All RSR 2000 regime, we identify the markets without RSR 2000 and scale up their rate adjustment cost parameters.

Table A.8 reports percent changes in outcomes as the economy moves from the No RSR 2000 regime to the All RSR 2000 regime. Consistent with descriptive evidence in Section 4, the model predicts that RSR 2000 has a very limited impact on the initial rate, while substantially reducing premium volatility. The model predicts that the regulation will reduce the number of fringe entrants by 5.7%. This is consistent with the empirical magnitude reported in Figure A.1 in Online Appendix: in two years since the regulation, the number of fringe firms was reduced by 1.72, and as there were on average 26 fringe firms in a market, the impact translates into a reduction of $\frac{1.72}{26} = 6.6\%$.

E.3 Implications of Higher Demand Elasticity

We evaluate the implications of alternative demand elasticities on the market equilibrium. We calibrate the parameter α, as first introduced in equation (6) of the main text, to generate a demand elasticity consistent with Goda (2011). The demand elasticity reported in Goda (2011) is about -3.3. We find that $\hat{\alpha} = 2.475$ generates an elasticity of -3.3 in our model. Subsequently, we re-estimate the supply-side parameters and conduct a counterfactual experiment by varying the strictness of rate stability regulation.

Figure A.4 presents our main findings, where we vary c^1_{jk} of the rate adjustment cost function. Qualitatively, we observe a similar pattern to that reported in our main analysis with the estimated demand model (Figure 6). Stricter rate stability regulation results in a small welfare gain for consumers but leads to a significantly larger profit loss for firms. Unlike the results shown in Figure 6, we observe a much larger response in the initial premium p_{j1}, reflecting the higher demand elasticity with respect to price. However, the entry response of fringe firms is considerably smaller. The limited response of the entry margin makes it difficult for this alternative model to rationalize the observed entry response to the adoption of RSR 2000.[6] Therefore, it appears important to have a small demand elasticity with respect to price to account for the observed market structure.

F Model Extension: Endogenous Lapses

We extend our model to allow for endogenous lapses. Consumers in the second stage now optimally decide whether to terminate their contract by solving

$$\max\{u^{stay}_{z_i jk} + \varepsilon^{stay}_{2ij}, u^{lapse}_{z_i k} + \varepsilon^{lapse}_{2ij}\}. \tag{A24}$$

ε^{stay}_{2ij} and $\varepsilon^{lapse}_{2ij}$ are *i.i.d.* Type I Extreme Value shocks associated with keeping and terminating the contract, respectively. The term $u^{stay}_{z_i jk}$ is the same as in equation (10) of the main text, which depends on the revised rate p_{jk2}. Note that even misinformed consumers who did not expect any rate increases ex ante and used $p_{jk2} = p_{j1}$ in calculating $v_{z_i j}$ will observe

[6] We examined many different values of σ_F which is the scale parameter of the entry cost distribution but were not able to generate a reasonable entry response.

the actual revised rate in the second stage and decide whether to keep or terminate their contract based on it. The term $u^{lapse}_{z_i k}$ is modified to include (dis)utility from terminating the contract, γ^{lapse}:

$$u^{lapse}_{z_i k} = \int_\lambda \alpha u(y_{z_i} - oop(\lambda, y_{z_i})) f_{z_i k}(\lambda) d\lambda + \gamma^{lapse}. \tag{A25}$$

The probability of terminating the contract is given as

$$\frac{\exp(u^{lapse}_{z_i k})}{\exp(u^{stay}_{z_i jk}) + \exp(u^{lapse}_{z_i k})}. \tag{A26}$$

Using the estimates from the baseline model, we calibrate γ^{lapse} by targeting the empirical lapse rate as explained in Section 6.2. We obtain an estimate of $\hat{\gamma}^{lapse} = -3.2$.

To examine whether endogenizing lapses alters our main results, we repeat the counterfactual analysis of varying the rate adjustment cost presented in Section 7.1. The main challenge that arises with endogenous lapses is that the solution for the optimal second-period price no longer has a closed-form formula. We need to numerically solve for the second-period price for each insurer and for each possible aggregate state, resulting in substantially longer computation time. This is one of the reasons why we do not incorporate endogenous lapses in our baseline specification.

Figure A.3 reports the results with endogenous lapses. We find that, compared to the predictions under our benchmark specification, changes in second-period premiums become slightly smaller when the strictness of rate stability regulations is adjusted. However, the overall predictions remain largely consistent with the baseline model. The primary reason why endogenizing lapses has little impact is the large utility cost associated with terminating the contract in the second stage. Consequently, consumers' responses to rate increases remain largely unresponsive, exerting a small influence on insurers' incentives to raise rates.

References

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G 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 A.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) 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 A.2: 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.

	Initial price
Own mean initial price in neighboring states	0.573***
	(0.069)
Observations	7,555
F statistic	69.48

Table A.3: First-stage regression of initial price

Notes: The table reports the estimates from regressing the insurer's initial price on its mean initial price in neighboring states. Insurer and year fixed effects included. Standard errors are in parentheses and are clustered at insurer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

		(1)	(2)
Consumer income	Availability of family care	Formal LTC risk	Share
Low	Not available	0.53	0.18
Middle	Not available	0.48	0.18
High	Not available	0.41	0.20
Low	Available	0.36	0.11
Middle	Available	0.31	0.15
High	Available	0.27	0.17

Table A.4: Formal LTC risk by consumer type

Notes: Column (1) reports the probability of using formal LTC services in the second stage conditional on income group and the availability of family care. Column (2) reports the share of each consumer type.

	(1)	(2)
Composition among LTCI holders	Model	Data (HRS)
By income:		
Low income	0.17	0.13
Middle income	0.33	0.27
High income	0.50	0.60
By family care availability:		
Family care not available	0.59	0.62
Family care available	0.41	0.38

Table A.5: Demand fit

Notes: Column (1) reports model-predicted composition among private LTCI holders by income (first three rows) and by availability of family care (last two rows). Column (2) reports the corresponding statistics from the data (HRS).

	(1) Less stringent	(2) More stringent
Initial rate	5.84	-9.57
Revised rate	4.11	-7.13

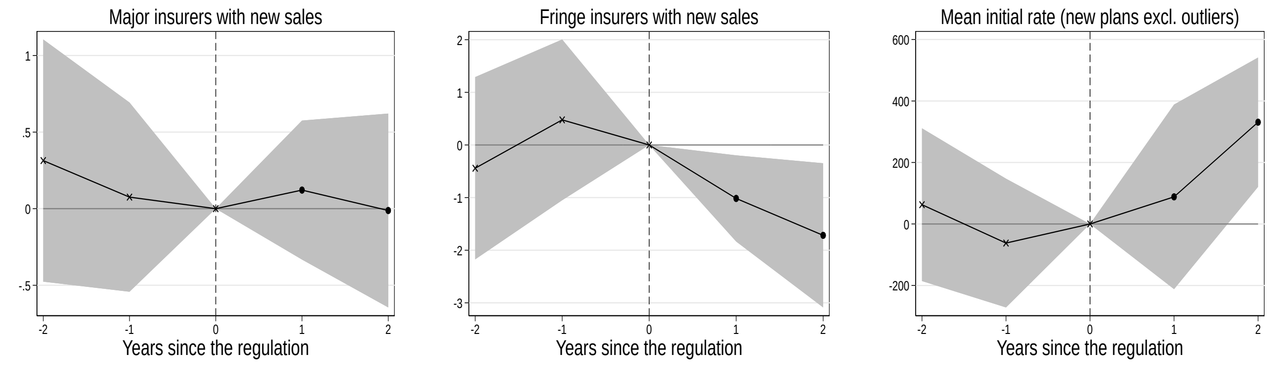
Table A.6: Price dynamics under counterfactual initial rate regulation
Notes: The table reports percent changes in outcomes relative to the baseline economy as we vary the initial rate regulatory cost. In column (1), we decrease the initial rate regulatory cost to a half of the baseline estimate. In column (2), we double the cost.

# 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.7: 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.

	% change from No RSR 2000
Initial rate	1.28
Revised rate	-11.17
Fringe entrants	-5.71
Total enrollment	0.26
Consumer welfare	0.08
Major insurer profits	-5.84
Fringe insurer profits	-2.25

Table A.8: Moving from No RSR 2000 to All RSR 2000
Notes: The table reports percent changes in outcomes as the economy moves from a counterfactual world where no market has RSR 2000 in place to another counterfactual regime where every market adopts RSR 2000.



Panel A Panel B Panel C

Figure A.1: Additional analysis of the RSR 2000

Notes: Data = Form C NAIC reports 2000-2007. The shaded area indicates 90% confidence intervals. Standard errors are clustered by state. The first two graphs report the impact of RSR 2000 on firms conditional on their type (major vs. fringe). The last graph reports the impact of RSR 2000 on intial premiums for a subset of brand new plans in the market.

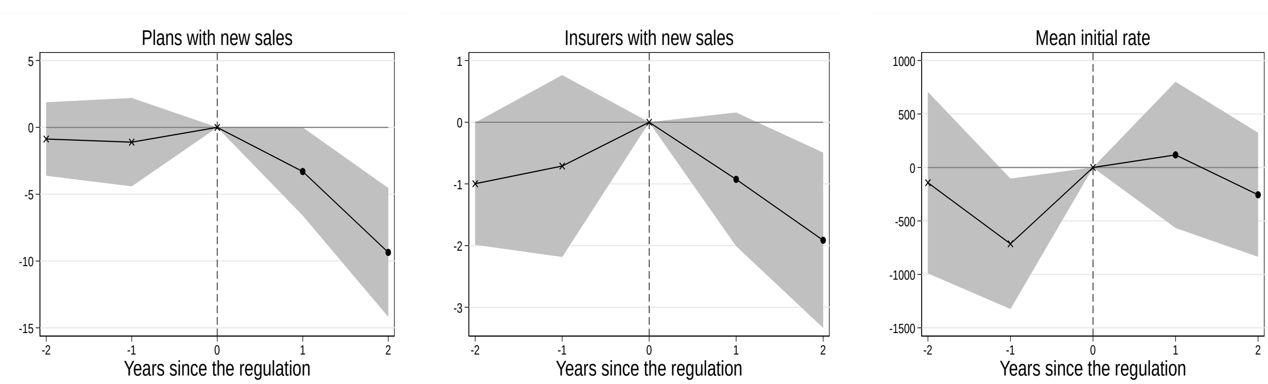


Figure A.2: Robustness analysis of the RSR 2000

Notes: Data = Form C NAIC reports 2000-2007. The shaded area indicates 90% confidence intervals. Standard errors are clustered by state. Compared to Figure 3 of the main text, this figure is generated allowing for heterogeneous treatment effects (Borusyak et al., 2024).

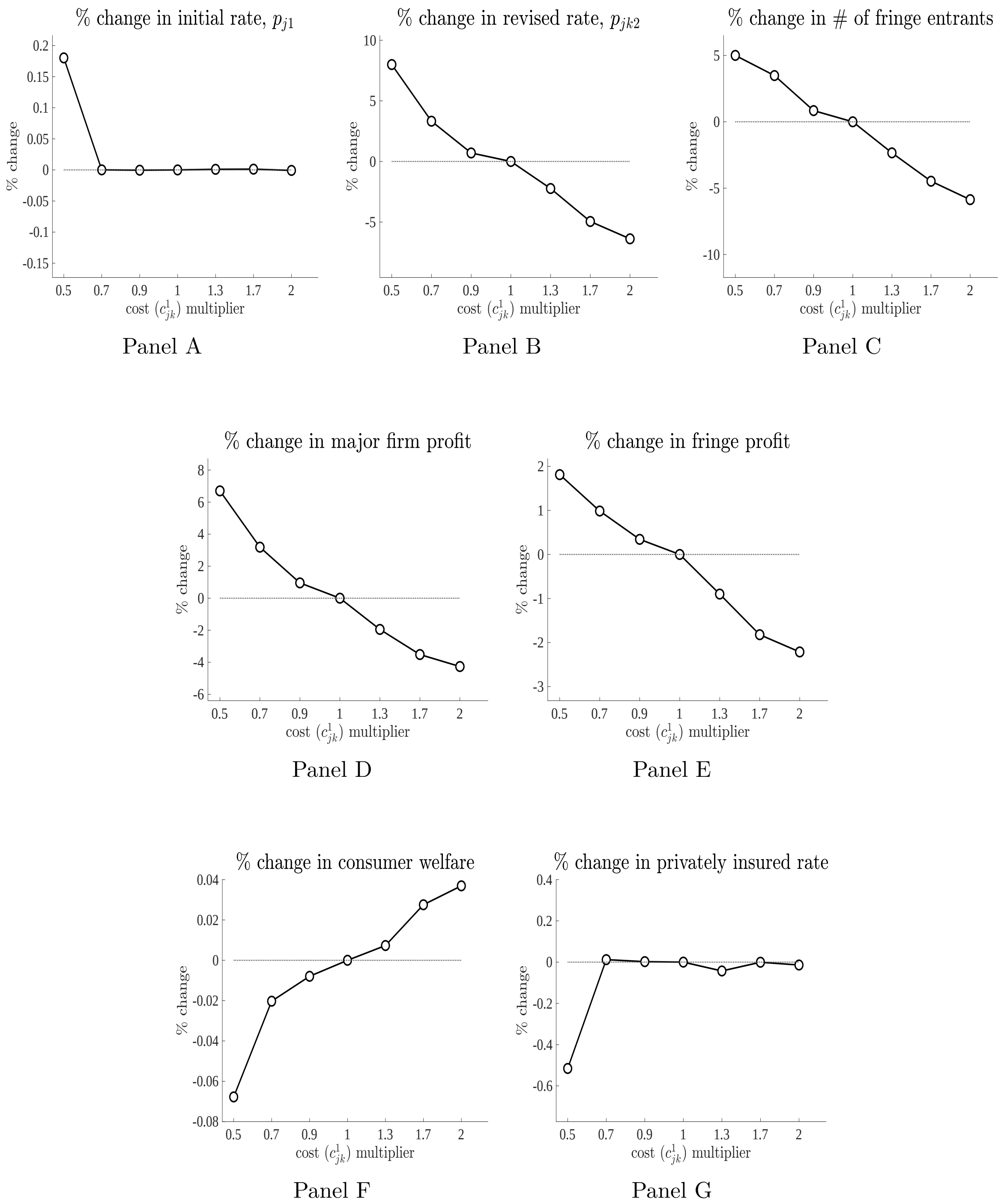


Figure A.3: Counterfactual rate stability regulation with endogenous lapses
Notes: The figure presents the impact of alternative designs of rate stability regulations when consumers' lapses are fully endogenously determined. Counterfactual simulations change the values of c^1_{jk} from 50% to 200% of its baseline estimate. All panels report the % change in the market outcome relative to the baseline estimate.

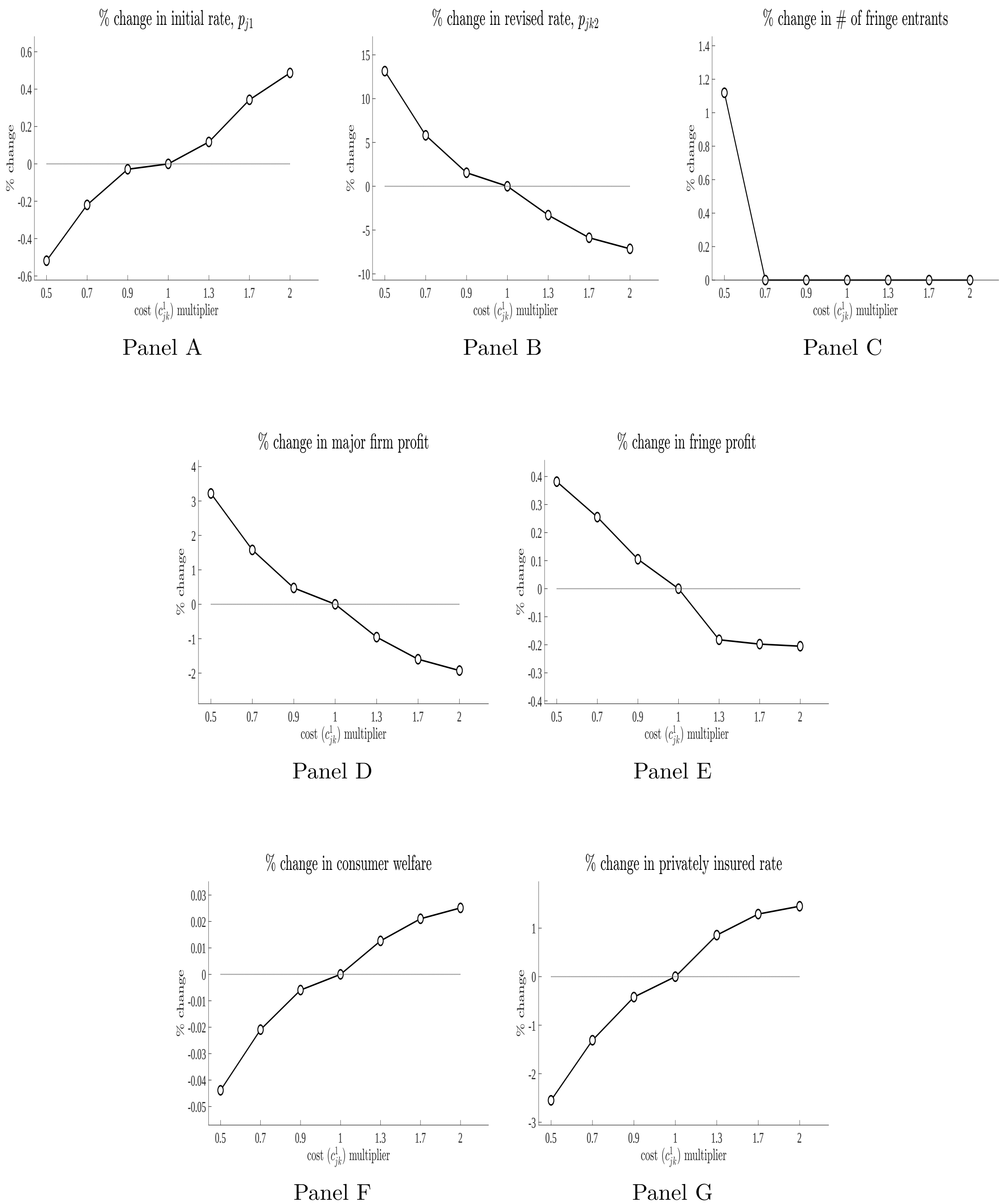


Figure A.4: Counterfactual rate stability regulation under higher demand elasticity
Notes: The figure presents the impact of alternative designs of rate stability regulations under the higher value of demand elasticity. The demand elasticity is calibrated to fit with the one reported by Goda (2011). Counterfactual simulations change the values of c^1_{jk} from 50% to 200% of its baseline estimate. All panels report the % change in the market outcome relative to the baseline estimate.