The Effect of Political Frictions on Long Term Care Insurance

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Abstract

Despite sharply rising prices, the number of companies choosing to sell private long-term care insurance (LTCI) has dropped from over 100 to just over 30 today. This paper analyzes how product mispricing and regulators' political incentives jointly affected insurer participation in the LTCI market. Using detailed pricing data, we find that four attributes of the state regulator – time to re-election, political capital, political affiliation, and campaign funding – significantly affected price changes and insurer profits. To understand regulators' equilibrium effects on LTCI supply, we then develop and estimate a dynamic structural model. Our model captures the political incentives of the regulator and produces frictions in product pricing when cost shocks are large and unpredictable. Using the calibrated model, we find that removing regulators' election cycles would significantly increase social welfare – equivalent to removing 8% of total cost shocks.

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1 Introduction

Roughly 66% of Americans over age 65 are expected to need long term care (LTC) – a service that supports individuals who struggle with Activities of Daily Living (ADLs), such as eating, showering, and dressing. The cost of these services is both high and steadily rising. For example, nursing homes, which are a popular form of LTC in the United States, have increased their average annual (nominal) costs from $65,185 in 2004 to $97,452 in 2017 (Genworth 2017). Despite these high costs, public financing options are limited. Medicare does not cover LTC beyond a three month period, and Medicaid only covers individuals who have little or no financial assets. In the face of an aging population, private long term care insurance (LTCI) was introduced in the 1980's to provide a financial safety net for millions of Americans (Nordman 2016).

Today, the private LTCI market is unraveling, and our paper explores a novel driver behind this market failure: regulatory frictions in product pricing. While LTCI premiums are increasing for both new and existing policy holders, some of the largest providers, such as John Hancock, have chosen to withdraw from the market. In March 2017, a mid-sized American LTCI company named Penn Treaty was forced to declare bankruptcy and liquidate its assets. While over 100 companies were operating in the LTCI market at its peak, fewer than 30 insurers were still selling polices in 2016 (Nordman 2016).

Our paper sheds light on an important supply-side issue in the LTCI market, while the existing literature has primarily focused on demand-side issues such as adverse selection. In most studies, the effects of insurance regulators are entirely ignored. However, in practice, insurance prices are governed by state regulators, who face a trade-off between consumer protection and insurance company solvency. In this paper, we exploit novel data on insurance premiums to show that state regulators significantly limited insurers' ability to raise premiums. Overall, when a state experiences smaller premium increases, we find that its insurers reap lower profits and are more likely to drop out of the market.

We begin by providing evidence of mispricing in the LTCI market. For the largest 15 LTCI companies[1], we find that their *projected* annual costs are often lower than the *realized* annual costs of providing LTCI. This suggests that the product was underpriced. Furthermore, between years 2009 and 2015, we find that the majority of these companies continued to underprice LTCI over time. Since all price changes must be approved by the state regulator[2], we propose the hypothesis that long-run underpricing in the LTCI market is driven by regulatory frictions. To test this hypothesis, we identify and study four political incentives facing the state regulator: time to re-election, political capital, political affiliation, and campaign funding.

First, we find that premium changes are significantly smaller when the state regulator approaches re-election. Moving from the year before re-election to the year after re-

[1] We calculate size based on total annual LTCI premiums collected.

[2] The regulators must approve both prices on new policies as well as price changes on existing policies. In some rare cases, which depend on policy type and vary by state, LTCI prices may be changed without regulator approval.

election implies an aggregate premium change of 51 basis points, which is roughly one-fifth of the unconditional premium change. More specifically, we show that the observed change in average prices is driven by insurance regulators' response to premium change requests. When the state regulator approaches re-election, he (1) approves a smaller number of requests, (2) approves requests with a lower probability, and (3) grants a smaller magnitude of premium increases.[3]

Next, we look at the effect of the regulator's political capital, political party, and campaign financing on LTCI prices. We find that Democratic regulators allow smaller premium increases and are more likely to reject requests than Republican regulators. However, they are equally sensitive to the election cycle. On the other hand, regulators who were elected by a greater voting share or had a greater winning margin are significantly less sensitive to election cycles, and thus, feel less re-election pressure. Lastly, we find that regulators with more campaign funding approve smaller price increases. This suggests that either wealthier regulators feel less pressure to help insurers in exchange for campaign donations, or regulators re-elected most often are those that emphasize consumer welfare.[4] Campaign financing has no differential effect across election cycles, suggesting that both wealthy and poor commissioners feel election pressure.

Then, we conclude our empirical analysis by studying the link between regulator behavior and LTCI company dropout. Over time, profit shortfalls from political frictions can accumulate, driving insurers to exit the market. Consistent with this theory, we find that smaller premium increases are correlated with greater profit loss as well as a higher probability of company dropout. However, price-setting in the LTCI market depends upon consumer demand and vice versa, so reduced-form estimates cannot capture equilibrium outcomes. Thus, we complete our analysis with a structural model of the LTCI market.

Finally, in order to estimate equilibrium effects of political frictions and simulate counterfactual scenarios, we build a dynamic structural model of the LTCI market. For tractability, we choose to focus on the election cycle friction. In each period, the state regulator decides on a maximum allowable rate increase based upon expected company profits, expected consumer surplus, and his time until re-election. Companies, which face unpredictable future cost shocks, then decide whether to pay a fixed application cost to obtain the increase. When the companies' expected profits become negative, they drop out of the market. Using our calibrated model, we estimate that removing regulator election cycles would improve social welfare by \$115.2 million within an election cycle. This effect is equal to removing 8% of the cost uncertainty. Ultimately, our findings suggest that a rotating committee of regulators or regulators with longer term-lengths would improve novel, unpredictable markets such as LTCI.

The rest of our paper is organized as follows. Section 2 gives relevant background information on the LTCI market and provides evidence of persistent underpricing. We

[3]The number of rate change requests submitted to the regulator varies across states. As a result, while the number of approved requests is related to the probability of approving a request, they are not identical measures.

[4]Since revenues accumulate over time, incumbent regulators are often wealthier than newer candidates.

describe our data sources in Section 3. In Section 4, we show that regulators' election cycles, political capital, political affiliation and campaign financing significantly predict the size and timing of price changes. In Section 5, we show that company dropout by state is correlated with regulator strictness and sensitivity to election cycles. In Section 6, we discuss our structural model and show the calibration results. Finally, Section 7 concludes.

1.1 Related Literature

Our paper contributes to existing research on the private long term care insurance (LTCI) market, political economy of insurance markets, as well as applications of dynamic structural IO models.

First, we add to a rich literature exploring the causes of private LTCI market failure. One branch of this literature shows that the LTCI market is adversely selected. For example, Brown et al. (2012), Coe et al. (2015b), Ko (2016), Mommaerts (2015), and Oster et al. (2010) demonstrate that individuals who are more likely to use nursing homes are also more likely to purchase LTCI. More specifically, Hendren (2013) shows that the market has completely unraveled for the highest cost individuals. Another branch of this literature shows that demand for the product itself is low (Brown and Finkelstein 2007). This may be either due to Medicaid crowd-out of private LTCI (Braun et al. 2018, Brown and Finkelstein 2008), the fact that people do not value bequests and thus prefer to spend down their savings (Lockwood 2014), or the consumer's ability to fund LTC using home equity (Achou (2018), Boyer et al. (2017), Davidoff (2010)).

To our knowledge, our paper is one of only a few to focus on supply-driven causes of LTCI market failure. Comparing demand-driven to supply-driven causes of LTCI failure, Brown and Finkelstein 2007 find that there is significant evidence of supply-side inefficiencies such as imperfect competition, large transaction costs, and inability of insurers to diversify aggregate risk (see also Ameriks et al. (2016), Braun et al. (2018)). Pricing inefficiencies have largely been the focus of actuarial and regulatory reports, which find under-estimated morbidity rates and over-estimated lapse rates (Eaton 2016, Nordman 2016, Rubin et al. 2014). These studies imply that LTCI was underpriced, and if companies cannot obtain timely rate increases, growing profit shortfalls may lead to insurer dropout. To our knowledge, we are the first to test this claim systematically across the national LTCI market.

Next, this expands research on the political economy of regulators to the LTCI market, where product mispricing played a large role. Although a few studies have shown that regulators impact the insurance market (Berry-Stolzle and Born (2012), Grace and Phillips (2008)), this area remains relatively understudied. One branch of the broader political economy literature finds that public officials deliver positive news to increase popularity when they approach re-election (some examples include MacRae (1977), Nordhaus (1975), and Rogoff and Sibert (1988)). In the banking sector Brown and Dinc (2005) and Liu and Ngo (2014) show that regulators delay intervention for failing banks until after election, perhaps in order to avoid unfavorable news that may influence consumers' votes. Focusing on the life insurance market, Leverty and Grace (2018) find that regulators delay bail-outs in the year prior to re-election. To our knowledge, our paper is the first to demonstrate political and election cycle frictions in the context of LTCI.

Finally, on the theoretical side, our paper combines and extends the contributions of two related research topics: the effect of insurance regulation on equilibrium supply and the structural estimation of infinite horizon games. Our work broadly builds upon a rich literature that models the interaction between regulation and company behavior (Lim and Yurukoglu (2018), Wolak (1994), Abito (2014)). More specifically, in the health insurance industry, a few papers have looked at how one type of price regulation, community pricing, affects coverage rates (Simon (2005), Zuckerman and Rajan (1999)) and equilibrium outcomes (Ericson and Starc (2015), Finkelstein et al. (2009),Geruso (2017),Clemens (2015)). However, no papers have yet looked at the role of premium changes approvals on company dropouts, and no papers have studied these models in the context of the LTCI industry. To calibrate our model, our estimation procedure utilizes methods from the infinite horizon dynamic games literature, including Ericson and Pakes (1995), Bajari et al. (2007), Pakes et al. (2007), and Pesendorfer and Schmidt-Dengler (2008).

2 Background on Long Term Care Insurance

2.1 Overview

Long term care (LTC) is healthcare that assists with Activities of Daily Living, or ADLs. These include bathing, dressing, walking, eating, and using the toilet. The primary receivers of LTC are the elderly, although others suffering from disabling chronic conditions, injury, and mental illness may benefit as well. Although over half of Americans over age 65 are estimated to need LTC, empirically, about 32% (19%) of healthy 60-year-old men (women) will never need to use LTC until their death (Ko 2016). This suggests that there is substantial uncertainty over whether any given individual will need LTC in their lifetime. However, the risk of being financially unprepared for LTC is high, given the large and rising costs of nursing homes, assisted living facilities, and paid home care.

In the 1980's, private LTC insurance (LTCI) was created to provide financial support for LTC services, and its contracts are designed to be guaranteed renewable. This means that as long as the consumer continues to make annual premium payments, LTCI companies must honor the contract. This usually entails making daily payments to cover LTC once certain conditions are met, such as the inability to perform two or more ADLs. Premiums are set at the beginning of the contract, but they may change any time subject to demonstrated need and regulatory approval. Pricing can vary based on age, gender, very broad health conditions, as well as benefit size.

LTCI policies are difficult to price. To lock-in low premiums, the typical LTCI consumer buys into the policy around middle-age, but he may not start collecting claims unti 20 or 30 years later.[5] Unlike other insurance policies like life insurance, LTCI products are often uncapped, so that the final payout of the policy is uncertain at time of purchase. Finally, since the 1980's, a number of initial pricing assumptions have proven to be wrong. These include interest rate forecasts, assumed lapse rates (the rate at which customers stop paying premiums), and expected mortality rates that turned out to be too high. On the other hand, the estimated cost of healthcare was overall too low (Bodnar (2016)). These issues combined imply that LTCI premiums are underpriced.

As an insurance market, LTCI is fairly small. Less than 10% of Americans over the age of 60 have private LTCI. As of 2014, the number of private LTCI policies in force was estimated to be 7.2 million while the total number of premiums collected was an estimated $11.5 billion. However, according to the NAIC, the maximum potential value of all in-force policies is very large due to the uncapped nature of some policy payouts: $1.98 trillion (Cohen 2016).

Today, the LTCI market suffers from both rising premiums and declining supply. As Figure 1 shows, both the number of new policy holders as well as active companies in the LTCI market have steadily declined between 1995 and 2015. While roughly 100

[5] This substantial delay between premium collection and claims payout is illustrated for a typical policy in Figure A2.

companies were in the market in the early 2000's, only about 40 remain today. On the right-hand side, Figure 1 plots the average annual premiums, which have been steadily trending up over the same period. While the gross annual premium was about $1,020 in 1995, it is a little above $1,500 in 2015.[6]

2.2 Underpricing in the LTCI Market

Mispricing in the LTCI market has persisted over time. As Figure 2 shows, the largest 15 LTCI companies by premiums sold had difficulty matching expected to actual costs. If actual costs of LTCI were equal to projected costs, these companies would lie on the graph's 45-degree line. However, the majority of these companies lies to the right of the 45-degree line, suggesting that actual claims paid were higher than expected. In fact, between the years of 2009 and 2015, these companies seemed unable to correct their cost expectations over time and LTCI continued to be underpriced.

One significant pricing friction in LTCI is the regulation of new and existing premiums. All new premiums as well as premium changes must to be reviewed and approved by the state insurance commissioner (Brewster and Gutterman (2014)). In most states, the insurance commissioner is a political position, either directly elected or appointed by the state governor to serve terms of approximately four years. Since the state commissioner has an implicit obligation to protect his constituents, which include the consumers of LTCI, he may be very reluctant to allow large premium changes. His incentives may vary depending on the political climate and timing of his election cycles. Supporting this idea, Figure 3 shows that, even within one company (Genworth), approval rates can vary greatly across states.

Anecdotally, industry leaders have echoed the notion that regulators have been slow to allow price increases. Genworth, one of the largest LTCI providers, has stated that "[The] Massachusetts [regulator] lags behind virtually every other state in taking timely action in response to rate increase filings and in granting necessary rate increases" (Bartlett (2017)). In its annual 10Q statement, Genworth also makes it clear that regulatory frictions in price adjustment has led to its dropout from specific states: "We have suspended sales in Hawaii, Massachusetts, New Hampshire, and Vermont, and will consider similar actions [...] in other states where we are unable to make satisfactory rate increases..." (Genworth Financial (2018)). Supporting these claims, in a survey of 26 LTC insurance carriers, Gordon and Pahl (2016) find that 84% of rate increase rejections from 2013-2016 were due to political caps or non-actuarial reasons (e.g. requested increase is "unreasonable").

[6]In real terms, however, these values are roughly flat. In 2018 dollars, these values are $1,705 in 1995 and $1,613 in 2015 respectively. However, over this period, plans were also being offered with lower benefits, such as those including maximum benefit caps. Thus, the value of the plans was generally falling (Cohen (2016)).

3 Data

The data for this study is collected from a variety of sources. First, we collected average premiums and claims data from the National Association of Insurance Commissioner (NAIC) Long Term Care Experience Reports. This is a regulatory filing that all insurance companies which sold policies in the preceding year have to file. More specifically, we collected data for all life insurance companies which filed between 1997 and 2015. Each observation corresponds to a single company, year, and state. For each observation, we observe average premiums, average claims, expected claims, and total lives in force. Expected claims were only reported in the first version of the Long Term Care Experience Reports, published between 1997 and 2008.

Next, historical price change requests and approval decisions come from the California Long Term Care Rate and History Guide. For any company that ever sold LTCI in California over the past ten years, this dataset contains their detailed rate request and decision history across the United States. This means that in addition to its history in California, each company has to submit its rate increase history in *all other states* in which it sold LTCI. Based on our rough estimates, this sample covers 60% of nationwide company activity from 2007-2015. The data reports one observation for each policy, company, state, and year.

We hand-collected political data on election cycles and voting outcomes for each state and year from 1997 to 2015 through the states' Secretary of State election results websites. For the 12 states that elect the insurance commissioner directly, we collected the winning candidate's name, political party, winning percentage, as well as winning margin. For states that appoint their insurance commissioner through their elected governor, we collected the insurance commissioner's name and political party. Lastly, Alaska, Virginia, and New Mexico appoint commissioners using a committee, and their commissioners serve without term limits, so they are dropped from our election sample.

Finally, there are 11 states[7] that report campaign finance information on their Secretary of State websites. For each year and each state, we collected the total cash on hand at the beginning of the year. We also noted the total contributions received and total expenditures reported during each year.

[7] California, Florida, Georgia, Kansas, Louisiana, Mississippi, Montana, North Carolina, North Dakota, Oklahoma, and Washington report financing data. Delaware does not.

4 Reduced Form Rate Results

In this section, we demonstrate that regulators' political cycles, political capital, party affiliation, and campaign financing all significantly affect premiums in the LTCI market.

Examining political cycles, we find that when the regulator is closer to an election, he is significantly less likely to approve a premium change request, as well as more likely to approve a lower premium change amount. On the other hand, we find that companies submit premium change applications less often as well as apply for smaller rate increases when the regulator is just elected, although this is not statistically significant.

Political capital, as measured by either percentage of winning votes or margin of votes between winner and runner up, is positively correlated with regulator strictness. Interestingly, regulators with more political capital are also significantly less affected by election cycle pressures.

Compared to Republicans, Democratic regulators are tougher on premium changes. We find that they are significantly less likely to approve rate changes as well as significantly more likely to approve a smaller rate increase on average. Perhaps not surprisingly, we find that they are equally sensitive to election cycles as other regulators.

Examining campaign contributions, we find that regulators who have more cash-on-hand are more stringent on price increase requests. This could be because their strong financial position makes them less affected by the demands of insurance companies. Or, it may because cash-on-hand proxies for the length of a regulator's term, as regulators accumation cash over time. Regulators who serve longer terms may be more successful because they pay more attention to consumer demands.

Finally, as a robustness test, we utilize the granularity of our dataset to match premium change requests on a set of detailed criterion including company, policy number and policy characteristics, date of request, as well as size of the requested increase. Using these matched requests, we find some evidence that election cycles matter even for matched requests across different states. Within a matched group of near-identical price increase requests, if one state regulator is closer to re-election than another, then they are more likely to approve the price request.

4.1 General Research Design

To study the effect of insurance regulators on average prices and price increase requests in the LTCI market, we estimate the following baseline regression:

$$outcome_{ist} = \beta_1 X_{st} + \alpha_i + \alpha_s + \alpha_t + \epsilon_{ist},$$

for company i in state s and year t.

For the independent variable, X_t, we use variation in the timing of election cycles across states, regulators' political affiliations, regulators' political capital, or regulators' campaign contributions. Company-level outcomes include the percentage point change in average premium increases, the average size of allowed rate changes, and the approval probability of open filings.

4.2 Regulator Election Cycles

In the LTCI market, regulators are public officials who are either elected by his state or (generally) appointed by the governor of his state, who is elected. /footnoteWith a few exceptions, these election cycles are four years in length. In this subsection, we will examine the effect of the election process on prices in this market. In particular, we hypothesize that when the regulator is closer to election, he is more hesitant to approve rate increase requests, which bring a lot of negative press. Subsequently, average rate increases in his state are significantly lower. Because the timing of election cycles are exogenous to the factors that drive LTCI prices, our estimates of β_1 can be interpreted as estimates of the causal effect of cycles on company outcomes.

In Figure 4, for each state regulator, we show a binscatter with years left until re-election on the x-axis and average annual change in premiums in his state on the y-axis, residualized on state and year fixed effects. We see that as the regulator gets closer to election, average annual change in premiums becomes lower.

The relationship between election cycles and average annual premium change is statistically tested in Table 1, where we regress annual rate change on regulators' years-left-in-term, controlling for state and year fixed effects. We find that moving from the year before re-election to the year after re-election implies an average rate change of 0.51 percentage points. This is roughly a fifth of the baseline rate change, 2.7 %, in the LTCI market.

It is important to note that the previous results describe aggregate price movements in the market. Premiums, however, vary for many other reasons than regulator behavior. For example, aggregate premiums are an average of the prices of new and old policies sold, so they vary as the age and health distribution of new customers change. They could also vary depending on insurer application behavior or other market pressures. Thus, next, we will focus specifically on analyzing regulator behavior across the election cycle.

In Table 2, we examine various measures of regulator approval behavior. In the first column, we can see that as regulators are closer to re-election, they significantly approve lower premium increases. As the regulator moves from the year before re-election to just elected, he approves bigger premium increases by 1.5 % on average. This is a small but still significant portion of the average approved increase, which is 12 %. Going from column 2 to column 3, we find that as the regulator moves from the year before re-election to just elected: the regulator approves 0.21 more policies, which is a 12 % increase from the baseline approval of 1.7 policies; the regulator has a 5.1% higher chance of approving an open policy (a policy request which was submitted in the current year or remained outstanding from a previous year); and the regulator has 5.7% higher change of approving a new policy (a policy request which was submitted in the current year). Results in the first and fourth column are significant at the 95% confidence level, while results in the third column is significant at the 99% confidence level.

If it is well known that regulator actions are correlated with election cycles, it might seem natural for insurance companies to try and time premium change requests, either by requesting approvals more often after elections or asking for bigger premium increases right after elections. However, as we see in Table 3, insurance companies' decisions do not seem to be significantly affected by election cycles. As expected, when the state regulator goes from the year before election to the year just after election, companies on average ask for 0.09% bigger increases (column 1) as well as submit 0.12 more rate increase requests (column 2). Overall, both of these magnitudes are small and neither of these relationships are statistically significant.

There are two potential reasons behind the lack of company response to the election cycles. First, there is evidence that request applications are costly to put together, so companies usually submit multiple applications at once (Nordman 2016, Gordon and Pahl (2016)), even if the different states have different election cycles. Second, because premiums are designed to be constant over the life of the policy, the longer a company waits for a rate request, the larger the future rate change they must submit. This is because there is a tradeoff between the size of the rate request and probability of getting it approved, a finding which is reinforced in Gordon and Pahl (2016).[8]

4.2.1 Political Capital, Political Party, and Campaign Contributions

If it is true that changing re-election pressure drives differential behavior across the election cycle, other factors that affect political pressure should also have predictable effects on regulators and insurance prices. In this section, we examine three such factors - political capital, political party, and campaign funding.

We hypothesize that higher political capital alleviates re-election pressure and reduces the effect of election cycles on regulators' decisions on rate applications. In addition, due to their party's platform, Democratic regulators should be tougher on firms, leading to lower approval rates. However, both Democrats and Republicans alike face election cycle pressures. Finally, since corporations are often large financial contributors to political campaigns, candidates with more campaign contributions should have higher approval rates. Unfortunately, because our measure of campaign finances does not distinguish between industry and consumer contributions, this hypothesis cannot be empircally tested.

In Table 4, we regress two measures of regulator strictness, probability of approving a rate increase request and average size of approved increases, on election vote percentage. We use the election vote percentage from the latest election for each incumbent regulator. We further restrict the sample to only the states which directly elect, rather than indi-

[8]See Figure A1 for a demonstration of this using our rate request data.

rectly appoint, their regulator. Vote percentage serves as a proxy for political capital of the regulator; regulators which have more political capital should be elected with a higher share of votes. In columns 1 and 3, we regress only on election vote percentage, while in columns 2 and 4, we also interact vote percentage with the regulator's election cycle. We find that regulators with higher political capital are less sensitive to election cycles, as evinced by the negative and significant coefficient on the interaction term. They are also more likely to be lenient, but this result is only statistically significant in columns 3 and 4.

Next, in Table 5, we examine winning voting margins as an alternative measure of political capital, defined as the winner's vote percentage minus the runner up's vote percentage. Looking at columns 2 and 4, we find that higher political capital significantly predicts higher probability of approval as well as higher average size approved. In addition, similar to Table 4, we find that regulators with higher political cycle are significantly less sensitive to election cycles. On average, a one standard deviation increase in winning margin would increase approval probability by 4.5 percentage points and lower the cumulative effect of election cycles by 3.2 percentage points or 33%.

In Table 6, we examine the effect of the regulator's political party on rate request outcomes. We find that Democrats are more strict, and they are 8% less likely to grant a rate increase and they approve rate increases that are 4% lower on average. The economic magnitudes of these differences are large, and they are even larger than all of the observed variation over the election cycle. However, as hypothesized, they are no more sensitive to the election cycles than other parties.

Finally, we analyze the effect of campaign finances on regulator behavior. $CashonHand$ in Columns 1-3 in Table 7 is defined as the stock of money a candidate has already amassed at the beginning of each year. The results from these columns show that the wealthier a candidate's campaign is, the more strict they are with premium increase requests. This may be because they have more political capital and feel less pressure to raise donations from corporations in the industry. Conversely, columns 4-6 show that higher flows of campaign contributions in the same year are correlated with higher approval rates. This reinforces the hypothesis that same-year campaign contributions may come from corporations in exchange for a favor from the regulator. However, columns 3 and 6 show that campaign finances do not significantly affect re-election pressure; wealthy and non-wealthy candidates alike feel re-election pressure, and while this effect is always positive, it is only significant in columns 2 and 5.

4.2.2 Robustness using Matched Request Design

In the above regressions, we cannot be sure that the characteristics of policies applying for rate increases did not systematically change across the election cycle. If so, they would confound the estimated effects of election cycles on approval rates. In this section, we address this concern through a matched request design.

Often companies submit the same request to multiple states at the same time, and we can match these requests based on the following detailed criterion: company, policy number, policy type (e.g. Group or Individual), policy category (e.g. Home Care Only, Comprehensive, Nursing Facility Only, Tax Qualified), time of submission, and size of requested increase. Utilizing this granularity in the rate data, we ask: do these identical requests get treated differently in different states, depending that state's election cycle schedule?

Empirically, as shown in Figure A4, we find that many companies choose to submit the same request to multiple states at a time. This may help reduce the cost of preparing all of the necessary data to submit a request. In particular, about 3,800 requests were submitted to two states at the same time, 1,500 were submitted to three states at the same time, etc. For each of the applications within a matched set, we assigned them the same matched application ID (α_{ijt}).

To predict regulators' decisions on the same request based on how close they are to re-election, for each company i, matched application j, state s, and year t, we estimate:

$$outcome_{ijst} = \alpha_{ijt} + \alpha_s + \text{yrs left in term}_{st} + \epsilon_{ist}$$

The outcomes that we examine include the probability of approving a rate change request, the approved rate change, and the time until the application becomes approved. We show the effects of regulator election cycles on matched requests in Table 8. We find some evidence that the same request sent to multiple states are still affected by election cycles. More specifically, the request sent to a state where the regulator is further from re-election is significantly more likely to be approved. This effect is not driven by regulator timing of approvals; time between application and approval does not vary across election cycles. However, in this matched sample, election cycles do not seem to have any significant effect on the size of the increase granted, relative to the requested rate.

5 Reduced Form Dropout Results

The existence of pricing frictions over extended periods of time may create significant profit losses for insurers, and thus, increase the probability of insurer dropout. Widening profit shortfalls require higher premium increases, which are also harder to get approved by regulators. In this section, we examine the reduced form link between regulator stringency and insurance company dropouts, and we find some correlative evidence that higher election sensitivity leads to lower profits and more company dropouts. The election friction can also interact with and amplify other frictions, such as low demand and adverse selection, exacerbating the shrinkage of the market over time. Thus, in Section 6, we will also account for consumer demand using a structural model

Figures 5a and 5b show that lower state stringency, proxied by a higher probability of approval and a higher magnitude of approved rate change in respectively, is correlated with less insurer dropout. In order to proxy for insurer dropout at the state level, we count a firm as dropped in a state if they have not filed a LTCI experience form with the NAIC for that state in that year. This is a very conservative and potentially delayed measure, because companies are required to file as long as they have sold LTCI in the previous year.[9] We will refine this measure in future analyses as well as conduct a robustness test using data reported by the parent company in Section 5.1.

In order for prices to affect insurer dropout, insurance companies must *consistently* capture lower profits than expected over time. To test this, we construct a rough measure of cumulative actual and expected profits, which is calculated as total premiums collected minus total claims paid out, and expected total premiums collected minus expected total claims, respectively.[10] In Figure 6a, we compare the cumulative state-level profits of companies in high friction and low friction states. Election friction is calculated by regressing approval rate on election cycles for each state. High friction states are the half of states with the highest estimated election cycle effects. Over time, companies in high friction states experience lower cumulative profits, suggesting that they are not able to recuperate profit shortfalls experienced in election years.

Figure 6b shows that this gap also exists between actual and expected cumulative profits; not only are companies in high friction states experiencing lower profit growth, they are also experiencing lower profit growth than *they had expected.* This suggests that they are not able to adjust their expectations or behavior to accommodate these lower cumulative actual profits. Expected profits are calculated based on regulator-approved assumptions. Therefore, what we see here reflects that fact that the regulator-approved assumptions companies are using are not able to match what they actually experience. This could be due to the fact that companies are bad at predicting costs, or that regulators are being too strict.

[9]More specifically, even if a company has dropped out of a state, they may still file a form because they continue to service existing customers. In this way, this measure of dropout is correlated with actual dropout but is noisy.

[10]Note that for the expectations analysis, we use SERFF data from years 1995-2008. These are the only years for which we have state-level data on expected profits and expected claims.

Figure 7 also shows cumulative profits against regulator stringency, where regulator stringency is instead measured by average approval rates (on premium increase requests). Stringent regulators are defined as regulators in the half of states with the lowest average approval rates over our sample. Although actual cumulative profits are comparable between strict and lax regulators, as shown in Figure 7a; the gap between actual and expected profits is much larger for more stringent states, as shown in Figure 7b.

Actual cumulative profits may be inherently different between states, because they are strongly affected by parameters such as the age of the consumer and the duration of the policy. Since expected profits take these pricing parameters into account, they may paint a more holistic picture of profits over a policy's lifetime. The gap between actual and expected profits are a more complete comparison of the total potential profit on a policy over its lifetime, and based upon this, it appears that policies sold in more stringent states ultimately lost more profits.

Turning to cumulative dropout rates, Figure 8 shows that higher regulator stringency is correlated with faster dropout over time. Although our measure of dropout is crude, stricter states always have a higher number of dropouts than lax states. In fact, in Figure 8a the gap between strict and lax states appear to widen over time. Combined with Figures 6b and 7, this suggests that one mechanism through which election cycles affect insurer dropout is through lower cumulative profits.

5.1 Robustness Check on Dropout Data

Although we have to imperfectly infer company dropout at the state level for each company, NAIC data provides dropout data at the national level for each company. Thus, in this subsection, we conduct a robustness test of our dropout results using national data. Because it is not constructed or inferred, this dropout data is more reliable that those used in Figure 8.

In order to estimate the effect of regulator stringency on national-level dropout, we run a company-level analysis utilizing variation in companies' geographic concentrations. As shown in Figure A3, LTCI companies concentrate in very different geographies. For example, Bankers Fidelity is largely concentrated in the southeast and Texas, while Unum is more dispersed, with its highest concentration in the West Coast and the Midwest. This geographic variation allows us to run regressions at the company level, where each company is "treated" by their market concentration in each state multiplied by either the regulatory stringency (as measured by average approval rate) or the average sensitivity of that state's regulator to election cycles.

In Table 9, we find correlative evidence that company dropout is positively correlated with election cycle sensitivity, number of applications received, and cost of the insurance (claims paid). We find that company dropout is negatively correlated with number of applications approved and gross profit of the insurance (premiums collected).

6 Structural Model

In order to estimate the equilibrium effect of regulatory frictions on the LTCI market, we combine insurers' supply and consumers' demand using a structural model. More specifically, we build an infinite-horizon dynamic game between a regulator and LTC insurer j, in which they negotiate the future price of LTCI. To make estimation easier, we model one representative insurance policy. Each period is one year, and the players are forward-looking but discount future payoffs with factor β.

The state space consists of the insurer's annual premiums per person p, annual costs per person t, and the years left until the regulator faces re-election y. The cost of providing LTCI includes a base amount as well as a per-period random shock, θ. This is observed by both the regulator and insurer, but it is unknown in advance. θ is a crucial parameter in our model, because it captures uncertainty in healthcare costs as well as mispricing of key parameters, such as lapse rates. The interaction of large cost shocks with regulatory incentives create the key market friction in our model.

In each period, the regulator weighs expected future consumer surplus against insurer profits, and the weights depend upon his position in the election cycle. This is a reduced-form strategy to model the insurer's incentives, and it is equivalent to the regulator choosing between consumer votes and industry donations, which vary in importance across his political cycle. Based upon these considerations, the regulator chooses a maximum allowable per-person premium increase, $\hat{p}$. After observing $\hat{p}$ [11], the insurer chooses whether to spend a fixed application cost to obtain the rate increase. If the company expects to make zero or negative profits over all future periods, then it will drop out of the market.

Ultimately, we focus on pricing inefficiencies in this paper, modeling only one insurer and abstracting away from market structure considerations[12]. As we will demonstrate, the empirical and calibrated substitution elasticities in this market are small, so the behavior of a single firm in this market effectively has no effect upon its competitors. In addition, there are always over 100 firms in the LTCI market, each with small market shares. In essence, we assume that each insurer is perfectly competitive.

6.1 Model: Consumer Demand

There are a finite number of consumers, N, in the LTCI market. For tractability, we assume that each consumer has logit demand preferences over the J LTCI insurers in his state. That is, in each period, consumer i's utility from insurer j is

$$U_{ij} = \beta_j - \alpha p_j + \epsilon_{ij}$$

[11] This timing assumption is imposed to avoid the issue of multiple equilibria.

[12] However, we believe that the effect of regulatory frictions on market structure is a very important question, and we would like to extend our model to study this in the future.

where ϵ_{ij} is i.i.d and follows an extreme value distribution with mean 0, β_j is an unobserved company fixed effect, and p_j is the price of company j's LTCI policy.

In addition to choosing between the J insurers, onsumers can also choose the outside option, which is to buy no insurance (j=0) at price 0. In our model, the consumers do not have any expectations over future price changes, so the consumer's problem is not dynamic. In each period, the consumer either chooses to continue paying premiums and remain covered by the policy, or switch to another policy, including the outside option.[13] It follows that the market share s_j of company j is

$$\ln s_j = \beta_j - \alpha p_j + \ln s_0 - c \tag{1}$$

where s_0 is the percentage of participants in the market who choose to buy no insurance and c is the average utility of these participants. We estimate α_j, β_j using instrumental variables, because p_j could be endogeneously correlated with s_j.

Finally, following from consumer demand, expected consumer surplus is the discounted sum of average consumer surplus for company j from all future periods.

$E[CV(p_j, \omega; \nu)] = \sum_{m=0}^{\infty} \beta^m E[(\beta_j - \alpha p_{jm}) * N_{jm} | p_{j0} = p_j; \beta_j, \alpha]$.

For tractability, we only follow one representative cohort of consumers in our model. Thus, if the insurer chooses to drops out, consumer surplus will become 0. In this way, there are welfare consequences to insurer dropout, but they do not account for future customers who may lose the option value of purchasing from insurer j.[14]

6.2 Model: Insurer Problem

On the supply side of the model, the per-period insurer payoff, $u_j(apply_j, drop_j)$, is equal to per-period profits. As long as a company has not dropped out of the market, profits are a function of the total customers, $N = s_j * Q$, unit price p_j, unit cost t_j, regulator years-left-in-term y, application cost $AppCost$, maximum allowable rate increase $\hat{p_j}$, and current period cost shock θ_j:

$$\begin{aligned} u_j(apply_j, drop_j) = (p_j * (1 + \hat{p_j} * \mathbb{1}(apply_j = 1)) - t_j * (1 + \theta_j)) * N \\ - AppCost * \mathbb{1}(apply_j = 1) + ScrapValue \end{aligned} \tag{2}$$

$ScrapValue$ captures the inherent value of the insurance business line, including earned interest income and cost of equity capital Nissim (2010). It also includes the value of

[13]Theoretically, this specification suggests that consumers can costlessly switch between policies. This is not always true because switching policies forfeits past premium payments to the existing insurer and potentially creates higher premiums. We address this by estimating demand elasticities from the data, and incorporating the very small effect of changing prices upon consumer demand.

[14]Without considering future consumers, regulators underweight the effect of company dropout on consumer surplus in our model. We can address this in the future by introducing market structure dynamics that take into account decreasing competitiveness as a result of company dropout.

simply staying in business, since LTCI companies may not costlessly exit and re-enter the market. To sell LTCI, companies must have up-to-date licenses, actuarial models, sales staff, and most importantly, consumer trust (Eaton (2016), Cummins and Danzon (1997), Cohen et al. (2013)).

The insurer's dynamic problem is to choose application $apply_j$ and dropout $drop_j$ in each period to maximize:

$$V_j(p_j, t_j, y; \mu) = \max\{0, u_j + \beta E[V(p_j', t_j', y'; \mu)|p_j, t_j, y, \omega]\} \tag{3}$$

where p' is next period's premium level and t' is next period's claims. If the maximum is the first term on the right-hand side of Equation (3), then the insurer drops out of the market. Profits are subsequently zero in all future periods.

6.3 Model: Regulator Problem

As long as the insurer j chooses to stay in the market, in each period, the regulator chooses an allowed rate increase $\hat{p}$ to maximize:

$$V_r(p, t, y; \omega, \nu) = \underbrace{E[CV(p, \omega; \nu)]^{0.5} * E[V_j(p, t, y; \omega, \nu)]^{0.5}}_{\text{geometric mean of consumer surplus and profits}} + \underbrace{\gamma * CV(p, \omega; \nu)/y^{\kappa}}_{\text{re-election pressure}} \tag{4}$$

where γ and κ are parameters to be estimated.

When choosing $\hat{p}$, the regulator considers both future expected insurance profits V_j as well as consumer surplus CV_j. In the context of political incentives, these terms capture considerations for industry campaign donations and constituent votes respectively. The regulator may raise donations throughout his election cycle, but as re-election approaches, it is strategic for him to focus more on gathering constituent votes. This intuition is supported by our empirical findings as well as past literature on the incentives of regulators (for example, see Canes-Wrone et al. (2001) and Maskin and Tirole (2004)). We use a reduced-form approach to capture this election cycle trade-off by adding a term that puts more weight on CV_j as re-election approaches.

In the first term of Equation (4), the regulator places equal weight on consumer surplus and insurer profit. While the mission statement of most commissioner offices is to protect the consumer, many regulators maintain social and professional ties with industry leaders. In fact, after their tenure as regulator, commissioners may become industry consultants or take positions on insurance company boards. Thus, it is reasonable for insurance regulators to care about insurer profits. In this paper, we take a neutral stance and assume that outside of election considerations, consumer and insurer surplus are equally important to regulators. This is equivalent to assuming that regulators maximize total social surplus.[15]

In the second term of Equation (4), regulators place more weight on CV_j as years-left-in-term, y, decreases. This term captures the intuition that regulators become more sensitive to the wishes of their electorate as they approach re-election. γ can be interpreted as the overall level of importance regulators assign to re-election, and κ represents how much re-election pressure the regulator faces across the election cycle. We allow κ to potentially be non-linear, because Leverty and Grace (2018) find that regulatory behavior becomes significantly more sensitive to election pressure in the year before an election.

If the true consumer surplus weight is higher than 0.5, our estimate of γ, the overall level of importance regulators assign to re-election, and $AppCost$ from equation 3 will be overestimated. $ScrapValue$ will be underestimated. However, the optimal price and dropout policies, as well as the relative welfare effects of each counterfactual scenario should remain unbiased. This is because the positive price effect of a higher consumer weight on consumer welfare will be offset by the lower γ.

6.4 Equilibrium Definition

We define a strategy profile to be a markov perfect equilibrium (MPE) if:

- The insurer's policies are optimal given its value function and the regulator's policy functions.
- The regulator's policy functions are optimal given its value function and the insurer's policy functions.
- The insurer's value function and regulator's value function are equal to the expected discounted sums of per-period payoffs implied by the policy functions of the regulator and insurer.

6.5 Discussion of the Game

The players' incentives are as follows. Insurers always want to raise prices, since it strictly increases profits if consumers do not drop their policies. On the other hand, consumer welfare is strictly decreasing in prices as long as the insurer does not drop out. The regulator cares about both insurer profits and consumer welfare. Thus, if costs are higher than expected, then the regulator has an incentive to raise prices but also keep prices from being too high.

[15] Lim and Yurukoglu (2018), who also estimate the effect of regulation on industry prices, use a similar functional form.

Even if a rate increase is necessary to maintain non-negative profits in the current period, it may not be approved if the increase is large in magnitude. If an insurer does not obtain the requested rate increase in the current period, any revenue shortfalls will persist into subsequent years as well. Furthermore, if costs are rising every year, then companies will require even higher future premium increases to maintain non-zero profits. The accumulation of revenue shortfalls over extended periods of time lowers the present discounted value of insurer profits and increases the probability of insurer dropout.

The regulator values consumer welfare more and is tougher on premium increases as he approaches re-election. When rate increases are needed, companies have to decide whether they will accept a lower rate increase immediately or to delay. As profit shortfalls accumulate over time, the required premium increase is greater in subsequent years when the insurer chooses to delay. If the required increase is too high, the regulator may not grant it even in the year after election. Therefore, frictions caused by election cycles overall lower insurer profits and exacerbate cumulative losses over time.

6.6 Model Estimation

6.6.1 Model Inputs

Data for insurer profits (eg annual premiums, annual claims, and number of lives covered), election cycles, and company dropouts are discussed in detail in Section 3.

The total size of the LTCI market, N, is taken from the US census. It is calculated as the number of individuals aged 50 and over who do not have Medicaid in each year and state, and it is estimated to be about 1.18 million customers based upon our data. Company market shares are calculated by dividing lives covered by each company by the total market size in each state and year.

We drop all observations that have any negative or missing values for the variables listed above. Our final estimation sample has 2,803 company-state-year observations for model estimation, spanning the years 2009-2015. Table 10 provides descriptive statistics of all variables.

6.6.2 Calibration of Demand Elasticity

From Equation 1, estimates of α and β_j will be used to calculate consumer surplus. We estimate these parameters using the following equation:

$$log(s_{sjm}) - log(s_{s0m}) = c + \alpha p_{sjm} + \beta_j + \delta_s + \rho_m + \phi_{sjm} \tag{5}$$

for state s, company j, and year m. The estimating equation includes state, year, and company fixed effects.

Ideally, we would examine the decisions of old and new customers separately, because the demand functions of old and new customers are different. Older customers tend to be more liquidity constrained and price sensitive, but they are also locked into a revolving contract so their costs of switching policies are higher. Since we only observe aggregate prices and aggregate demand for each company, we instead estimate the demand for an average representative consumer.

In our model, the LTCI company cannot discriminate between old and new policies. If price discrimination actually plays a significant role in the market, then our company profits may be underestimated and our model fit may be worse than the case with price discrimination. However, in order to maintain fairness between old and new consumers, regulatory pressures may keep the presence of price discrimination quite low in practice.[16]

Since market prices and market share jointly influence each other, we use state insurance commissioner election cycles as an instrumental variable for company premiums. As demonstrated in earlier sections, election cycles significantly affect insurance prices. However, the prices of LTCI policies do not affect state election cycles, making this a good candidate for a price instrument. Using the instrumental variable model, we estimate a value of 0.00046 for α.

In addition to estimating consumer surplus in each period, our estimate of α is used to understand how market share s_j for company j changes as p_j changes. Because empirical α is small, it suggests that the effect of competitor companies' prices has a small effect on own company demand. To calculate these demand elasticities, we use the established relationship between market share and price in logit demand models:

$$\frac{\partial s_j}{\partial p_j} = -\alpha * s_j * (1 - s_j)$$

$$\frac{\partial s_j}{\partial p_k} = \alpha * s_j * s_k$$

6.6.3 Calibration of Other Parameters

Estimation parameters β_j and s_j are set to represent a typical company across all states and years. For our baseline calibration, we use the average of all company fixed effects from the estimation of equation 5 as an estimate for β_j. We use the average 0.275% (representing roughly 3,245 customers) as the starting market share of company j. We use a vector of length 29, with elements ranging from 0.00264% to 3.1308% for the market shares of company j's competitors in the market. The market size N is the average number of individuals aged 50 and over who do not have Medicaid across each year and state.

[16] It is reassuring to note that when we spoke to state regulators, they stated that they do not believe in price discrimination between old and new policyholders. According to regulators, they evaluate prices based upon projected costs. For example, they would not allow higher prices on new policyholders in order to offset losses on existing policyholders.

Each period, the annual per-person cost shock a company faces is drawn from a normal distribution with mean \$352 and standard deviation \$1,354, the average and spread of the difference in expected and actual claims per person found in our sample. We fix the yearly discount factor of the players, β, at 0.86 (Lim and Yurukoglu (2018)).

6.7 Estimation Steps

6.7.1 Overview

We estimate four parameters: the cost of applying for a price increase $AppCost$, the inherent value of the LTCI business line $ScrapValue$, and parameters γ and κ that govern regulator stringency.

To solve for $\mu = (AppCost, \gamma, \kappa, ScrapValue)$, we use a two-step procedure for dynamic games following Lim and Yurukoglu (2018). This method was first developed by Hotz and Miller (1993a) and Hotz et al. (1994), and then further refined by Bajari et al. (2007), Pakes et al. (2007), and Pesendorfer and Schmidt-Dengler (2008). This procedure avoids a computationally costly re-solving of the full dynamic model to obtain optimal value and policy functions. Instead, in the first stage, empirical policy functions are estimated non-parametrically, and these estimates are used to forward-simulate value functions. At each point in the state space, these value functions are used as continuation value function estimates to calculate optimal policy choices. Finally, we estimate the structural parameters by choosing the parameters that generate policy choices most closely matching key data moments.

6.7.2 Detailed Description

More specifically, the estimation procedure is as follows. We discretize the state space into a three-dimensional matrix of 20 points for the price level, 20 points for the cost level, and 4 points representing each year of a regulator's term. Given a set of candidate parameters and a position in the state space, we obtain empirical estimates of regulator and insurer decision rules (also known as empirical policy functions). To do this, we run a linear regression of each decision on our three state variables: premiums, costs, and years-left-in-term. The decision rules we estimate include company rate increase application, size of requested price increase, as well as insurer dropout.

Starting from each point in the state space, we forward-simulate insurer and regulator actions for 100 periods including random normal cost shocks, and we average the discounted sum of flow payoffs over all simulated paths to derive the continuation value. The optimal policies chosen are the actions that maximize player utility, given the estimated continuation values.

To calculate how company j market share changes if company j applies for a rate increase, we use successive competitor best-replies that maximize their profit functions. In particular, we set optimal competitor h prices at $\frac{1}{1-s_h} + cost_h$. This equation comes from maximizing truncated regulator utility $= (price_h - cost_h)^{0.5} * N_h$, where $N_h = Q * \frac{ds_h}{dp_h}$. Here, we conservatively assume that regulators do not care about consumer surplus and estimate an upper bound on the effect of competition in the market. In general, prices approach convergence after one or two iterations of competitor best replies, suggesting that there are only small effects on competitors when an insurer updates pricing.

To evaluate model fit, our criterion function compares the estimated optimal policies to the true observed policies in the data. Following Lim and Yurukoglu (2018), we minimize the squared difference between observed policies and predicted policies averaged over different points in the state space. In other words, we match the following moments:

$$M(\mu) = \begin{bmatrix} \frac{1}{N_{p,t,y}} \sum_{p,t,y} \left(\hat{p}(p,t,y) - \hat{\hat{p}}(p,t,y;\mu)\right) \\ \frac{1}{N_{p,t,y}} \sum_{p,t,y} \left(apply(p,t,y) - \widehat{apply}(p,t,y;\mu)\right) \\ \frac{1}{N_{p,t,y}} \sum_{p,t,y} \left(drop(p,t,y) - \widehat{drop}(p,t,y;\mu)\right) \\ \frac{1}{N} \sum_{i=1}^{N} \hat{p}_i - \bar{\hat{p}}_i(\mu) \\ \frac{1}{N} \sum_{i=1}^{N} apply_i - \overline{apply_i}(\mu) \\ \frac{1}{N} \sum_{i=1}^{N} drop_i - \overline{drop_i}(\mu) \end{bmatrix} \tag{6}$$

where $\hat{x}$ for policy x denotes the optimal choice at point (p,t,y) in the state space implied by μ. N denotes the number of observations in our data sample, and $N_{p,t,y}$ denotes the number of observations at point (p,t,y) in the state space. We minimize the weighted sum of squares $\hat{\mu} = \underset{\mu}{\operatorname{argmin}}(M(\mu)'WM(\mu))$, where W is the identity matrix. We compute confidence intervals using a bootstrap procedure.

6.8 Estimation Results

We present some heuristic arguments for the identification of our structural parameters. The cost for an insurer to apply for a rate increase is identified by variation in application rates across the state space. As application rates rise, the estimated cost of application falls. Insurer scrap value is identified using empirical dropout rates. As observed dropout rates rise, the estimated scrap value falls. Finally, the variation in average rate increases help identify the re-election pressure parameters. As average price increases rise, estimated γ rises. As price increases in states with regulators that are just elected become higher relative to price increases in other states, κ rises. In other words, differential price increases throughout the election cycle help identify κ separately from γ.

Table 11 shows the parameter estimates from our model. On average, the cost of applying for a rate increase is around \$100 per application. This estimate is small but nonzero, which is reasonable because insurers have to calculate actuarial costs and fill out the appropriate forms. The value of the LTC business ($ScrapValue$) is around \$4.7 million, roughly 67.5% of average annual premiums and 182% of average annual profits, per company, state, and year. The positive estimates of κ and γ. are consistent with the perception that insurance commissioners face significant re-election pressure, and that this pressure increases as election year approaches.

6.8.1 Model Predictions

In Figure 9, we plot the optimal policy functions from our calibrated model as a function of the regulator's years-left-in-term. Overall, we see that approved premium increases and application rates decrease across the election cycle. As re-election considerations become more salient, regulators increase their weight on consumer surplus and decrease approved price increases. This lowers the likelihood that insurers will apply for rate increases as an election draws near and increases the likelihood they will need higher rate increases in the future. The net present value of future profits also decreases.

In Figure 10, we plot the optimal policy surfaces at the estimated parameters as functions of profit-per-capita and regulator's years-left-in-term. As illustrated, application rates and approved rate increases decrease as an election year approaches. Both policies also increase as profits decrease. When profits are positive and large, regulators do not approve any rate increases, and companies cannot apply for one. Conversely, when profits are very negative, companies will apply for rate increases even if they are very small. Finally, optimal dropout policy behaves in the opposite way. When profits are very negative, companies drop out of the market because they cannot obtain the high rate increases they need for non-zero profits.

6.8.2 Model Fit

The model fit based on these moments are represented in Table 12 and Figure 11. In general, the targeted and simulated moments in Table 12 match well.

In Figure 11, we show the conditional moments across the election cycle, which are untargeted by the model but arises from the re-election term in Equation (4). We see that our model produces downward sloping patterns in price increases and application rates as re-election nears, which fits with our empirical findings. Also, our model is able to capture the relatively high rates of price increases and application rates seen in the data.

One notable deviation is that premium increases are higher in the model than empirically observed. For simplicity, our model assumes that insurers apply for a price increase already knowing what they receive. Thus, insurers would never apply to receive a price increase of 0%, and regulators never reject a request. In contrast, in the data, we find that many rate increase applications are rejected, and rate increases of 0% are often observed. As a result, the prices and application rates in our model appear more sensitive to elections than the empirical data.

Finally, the empirical dropout data is quite volatile, so while there appears to be a pattern in the dropout rates across the election cycle, it is statistically insignificant. Our model also does not find a monotonic pattern of insurer drop out over the election cycle, in contrast with the dropout and price graphs.

6.9 Counterfactual Experiment

Our empirical findings suggest that the LTCI market suffers from election cycle frictions as well as high cost uncertainty. In this section, we consider what happens if these factors were removed. Starting from our estimated parameter values, we analyze how equilibrium supply and welfare would change if (1) election cycle pressures were removed, (2) cost shocks were decreased, and (3) if elections cycles were removed *and* cost shocks decreased. Case (1) could arise from electing a rotating committee of regulators, or abolishing regulator term limits. Case (2) could arise if adverse selection in the market was mitigated or if actuarial technology improved in the future. We compare the outcomes in each counterfactual scenario to the outcomes from the baseline model solution.

In the first experiment, we set the election cycle pressure parameter κ in equation 4 to 0. In order to preserve the same utility values from consumer surplus on average, we set γ to 48. The dotted red line in Figure 12a shows the price effect of removing elections but keeping average regulator stringency (γ) constant. We see that premium increases across the election cycle are flat, and average premiums are lower. Since the removal of election cycles also removes delays in price adjustments, profit shortfalls are smaller and regulators are more likely to approve lower price increases. However, average dropout rates increase slightly in Figure 12b as price increases fall more than profits rise. In this calibration, much of the welfare gain from removing the regulatory friction is returned to consumers in the form of lower prices rather than to insurers.

In the second experiment, we change the mean of θ to 150, an approximately 50% reduction in average cost shocks. We also explore the effect of setting θ to 150 in conjunction with setting κ to 0 and γ to 48. The effect of this on prices is shown using the black dashed line in Figure 12a. With a lower price shock, required rate increases and approved rate increases are both lower. In addition, we consider experiment (3) when both election cycles are removed and cost shocks are reduced in the black dashed and dotted line. We find that average price increase trends are again flat. However, average premiums do not fall as much as in the case with higher cost shocks. The removal of election cycles has a larger effect on profits and equilibrium prices when cost shocks are higher, because price increase delays are more costly when costs are rising quickly.

Figure 12b illustrates the change in dropout rate trends across these experiments. Overall, lower cost shocks decrease dropout rates. Due to lower prices and decreased company profits, average dropout rates rise slightly when election cycles are eliminated.

One potential reason dropout rates rise more than in experiment (1) is because baseline price increases are low in the low cost case, so a reduction in premium increases accounts for a larger proportion of total price variation. Thus, it has a larger effect on expected profits. Finally, Figure 12c shows application rates across the three experiments. We find that application rates are lower in experiment (2) because approved rates are lower. However, within the low cost scenario, application rates are higher when election cycles are removed because profits are relatively lower.

The short-term welfare effects of the price inefficiencies caused by election cycles are shown in Figure 13. Ultimately, we find that the removal of election cycles increases total social surplus (insurer plus consumer surplus) by \$51,000 annually relative to the baseline scenario for each state and company. Thus, across all states and companies, this amounts to roughly \$28.8 million annually, or \$115.2 million across a four-year election cycle.[17],[18] This is a very rough estimate because our model has abstracted away from market structure considerations such as dynamic price setting among companies. However, it demonstrates that political frictions have a significant economic impact on this market.

One of the largest challenges facing the LTCI market is the size of its cost shocks due to the product's novelty as well as long life span. Supporting this, we find that reducing the magnitude of cost shocks by 50% itself increases insurer surplus by \$49,000 and consumer surplus by \$130,000 per state and company annually. In addition, removing election cycles in conjunction with a reduction in cost shocks increases total surplus by \$15,000 per state and company annually. Thus, election cycles have a larger welfare effect when cost shocks are higher.

Overall, our estimates suggest that election cycle frictions have small but nontrivial effects on insurer profits and dropout. They have roughly the same effect on profits as changing average cost shocks by 8%. Even though the model does not predict strong dropout effects, election frictions and company dropout may still be correlated in the cross section if any of the model assumptions are too restrictive or if we are missing important state-space variables. For example, if more stringent regulators also face high election frictions or if states with high election frictions are also more mispriced, our welfare effects may be underestimated. Ultimately, to resolve frictions arising from election cycles, there are a number of actionable policy options. For example, consumers could elect a rotating committee of regulators or the abolish regulator term limits.

[17] After the data cleaning process outlined in Section 6.6.1 there were on average 12 companies operating in each state per year.

[18] Annual revenue estimates come from NAIC data and are derived from the 2014 estimates given in Nordman (2016).

7 Conclusion

Novel financial products are difficult to price, and they present significant regulatory challenges. The long term care insurance (LTCI) market is relatively new, and it contains high cost uncertainty due to the long-run nature of the product. Its pricing difficulties have led to repeated negotiations between insurance companies and regulators, which in turn have impacted the ability of insurers to make profits. Examining these interactions over the last two decades, we present new evidence that political frictions may have lead to persistent underpricing in the private LTCI market.

Our findings are important, because if LTCI is underpriced over an extended period, profit shortfalls will widen and companies may choose to drop out of the market. First, we show that regulators' political incentives can significantly predict their probability of approving a premium changes as well as the size of the premium change approved. For example, we show that regulators are tougher on premium increases when they have lower political capital or when they are closer to re-election. Next, we find that tougher state regulators are correlated with lower insurer profits as well as higher rates of insurer dropout. Finally, a dynamic structural model allows us to calibrate equilibrium outcomes, and we estimate that removing regulators' elections could improve social welfare by \$115.2 million per election cycle.

Not only do these findings have social implications for the millions of Americans entering old age who have to find funding for LTC, but there are valuable lessons from the LTCI market which could be extended to other settings. For instance, our model suggests that a nationaly organized, rotating committee of regulators or regulators can attenuate election cycle frictions and improve novel, unpredictable financial markets. Some examples of new insurance markets that exist today and could play an even bigger role in the future include subsidized plans under the Affordable Care Act (ACA) and hybrid annuity products seeking to replace LTCI.

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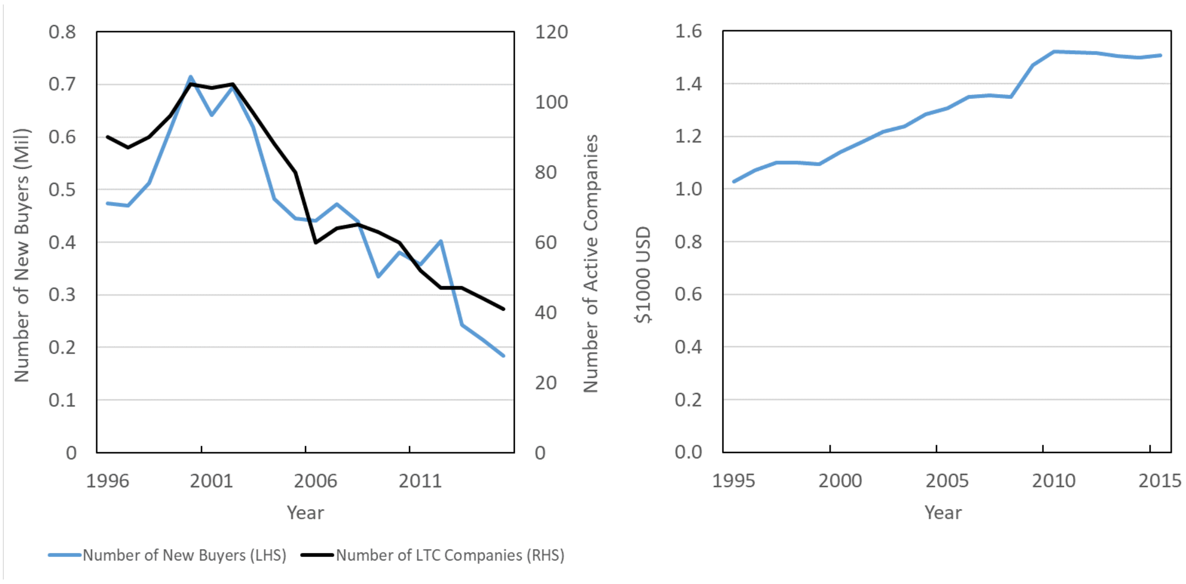
Figures

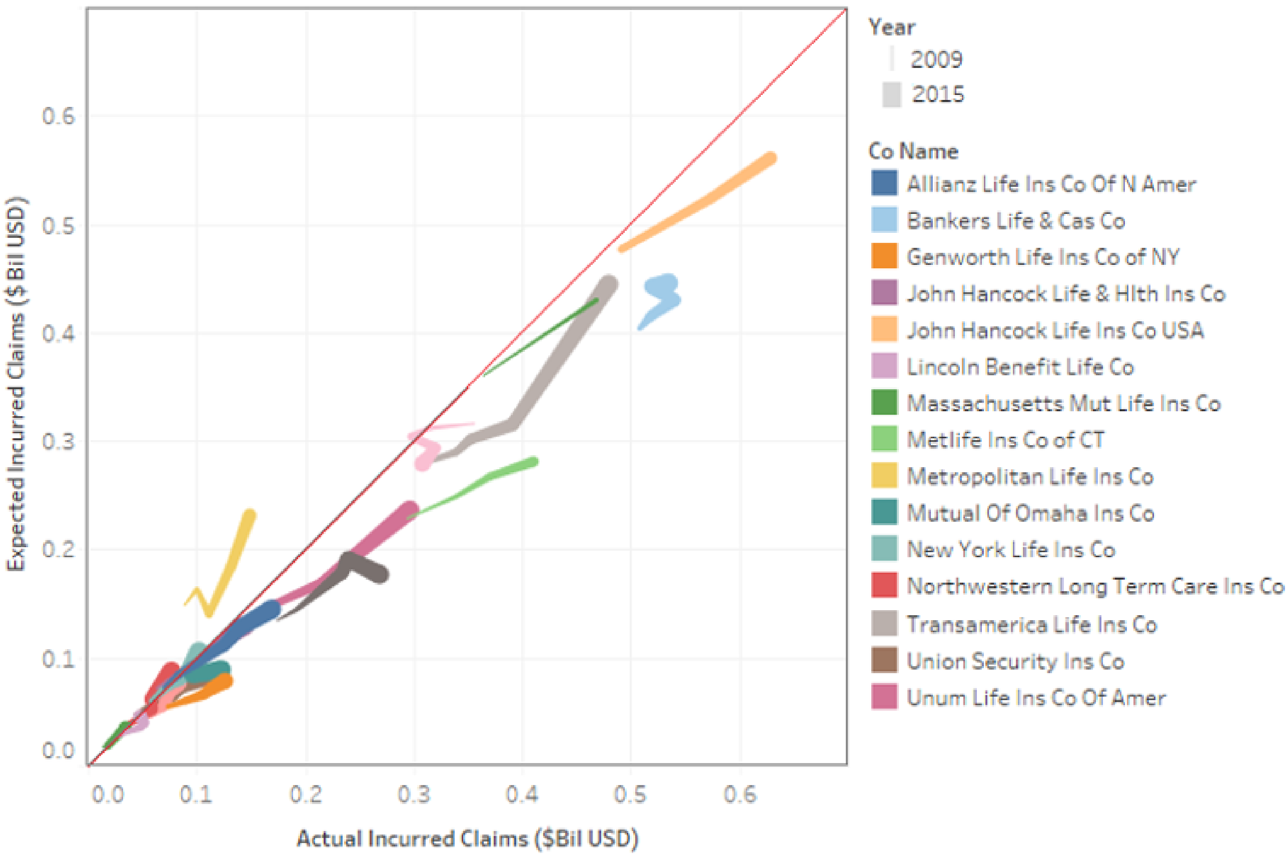
Figure 1: Summary of LTCI Market Trends

(a) New Buyers and Active LTCI Companies (b) Average Annual LTC Premiums



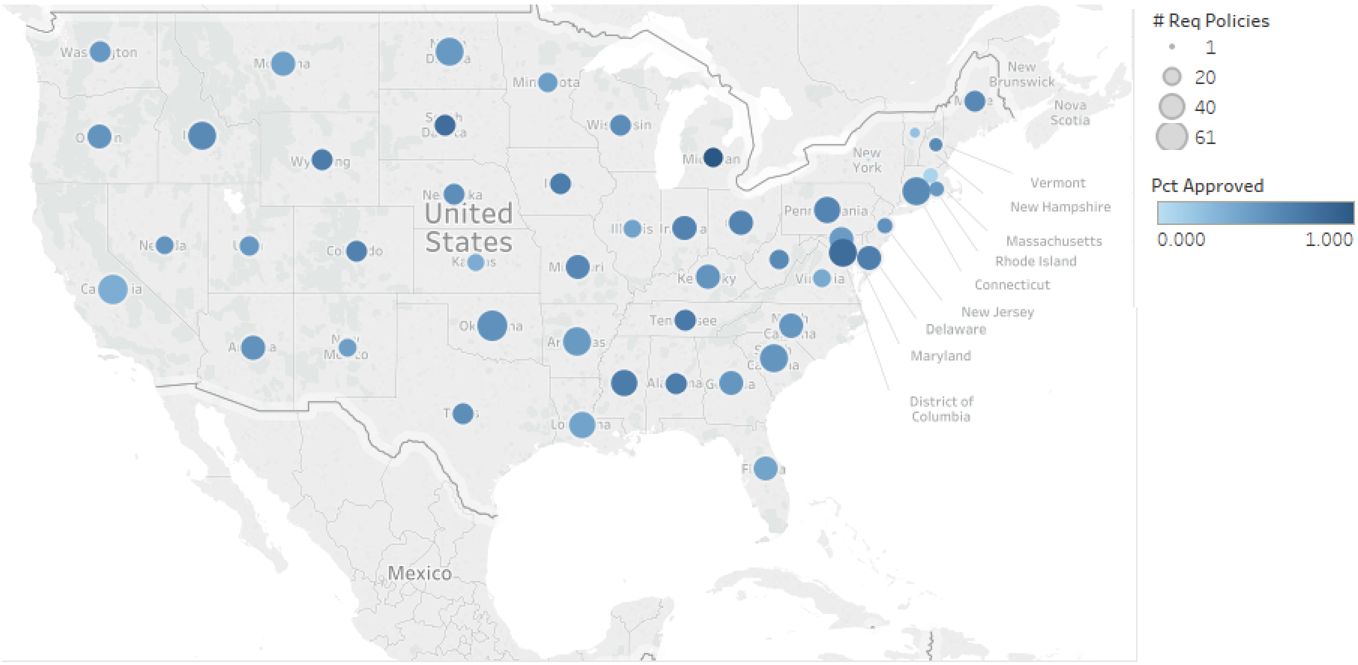
Source: Author's calculations using NAIC LTC Experience Forms.

Figure 2: Actual To Expected LTCI Claims for Top 15 Companies



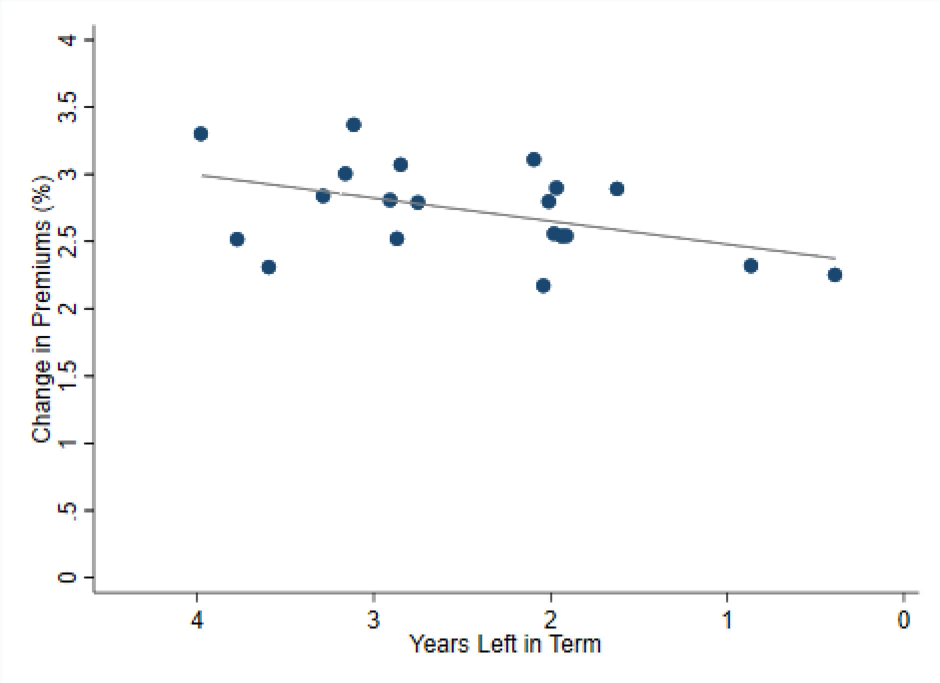
Source: Authors' calculations using NAIC Long-Term Care Experience Forms, 2009-2015

Figure 3: Results of Genworth's Price Increase Requests Across States



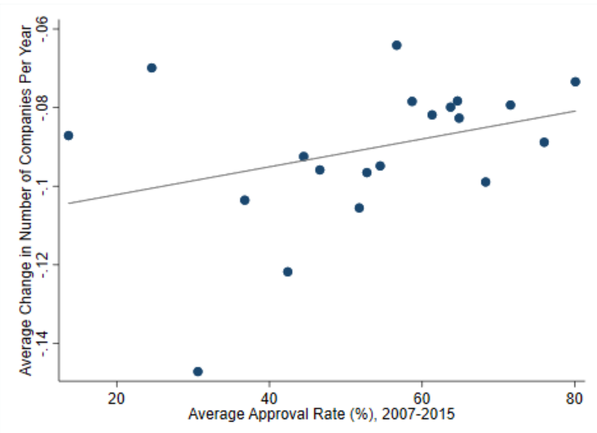
Source: Authors' calculations using California's Rate History Data, 2007-2017

Figure 4: Annual Average Premium Increase Across the Election Cycle

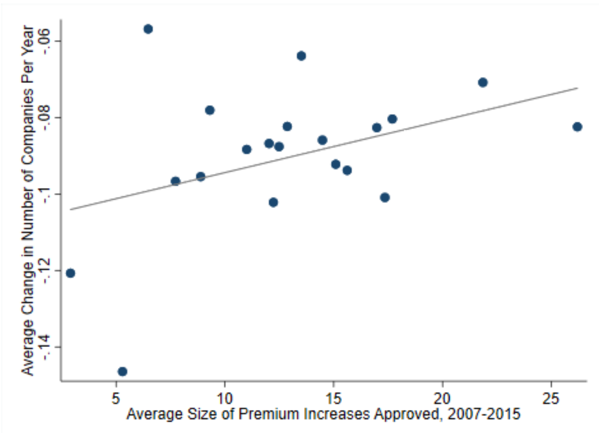


Note: The scatterplot graphs average premium changes by regulator term length, controlling for state and year fixed effects. The data sample is drawn from the NAIC Long-Term Care Experience Forms, 2009-2015.

Figure 5: Effect of Regulator Stringency on Company Exit Per Year in State Market



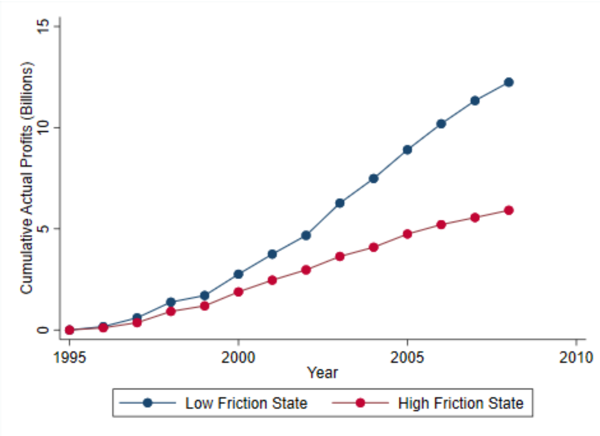
(a) Number of Company Exits versus Probability of Approval



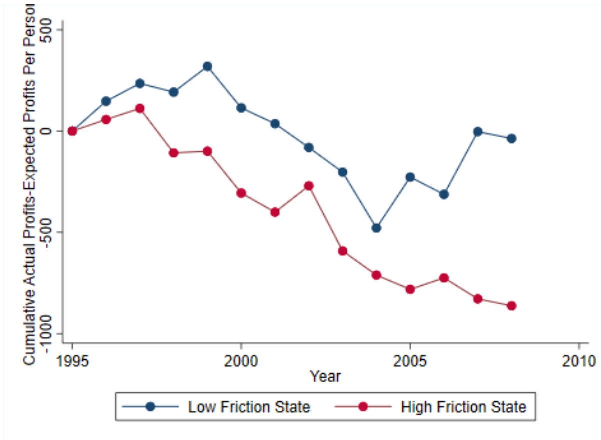
(b) Number of Company Exits versus Size of Approved Increase

Source: Author's calculations using the California Long Term Care Rate and History Guide and NAIC LTC Experience Reports.

Figure 6: State Frictions and Cumulative Profits, 1995-2008



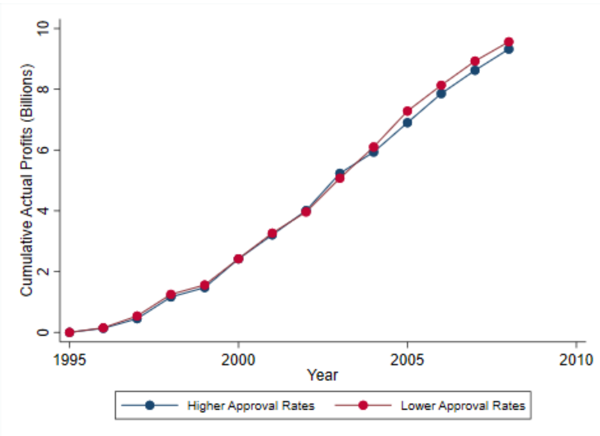
(a) Actual Profits



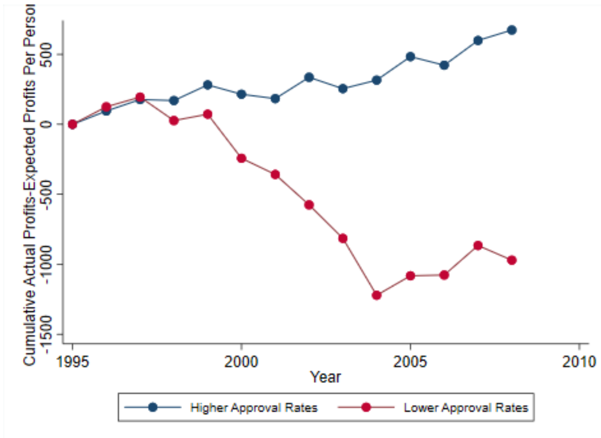
(b) Actual Minus Expected Profits

Source: Author's calculations using the California Long Term Care Rate and History Guide and NAIC LTC Experience Reports. Note that high friction states are state where election cycles are estimated to have a larger effect on regulator behavior. See text for details.

Figure 7: Regulator Stringency and Cumulative Profits, 1995-2008



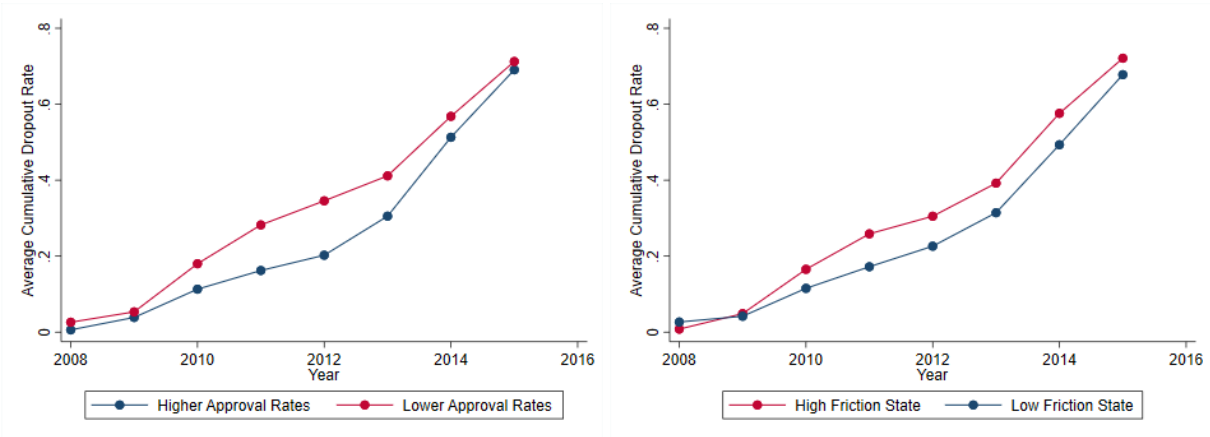
(a) Actual Profits



(b) Actual Minus Expected Profits

Source: Author's calculations using the California Long Term Care Rate and History Guide and NAIC LTC Experience Reports.

Figure 8: Regulator Stringency and Dropout Rate, 2009-2015

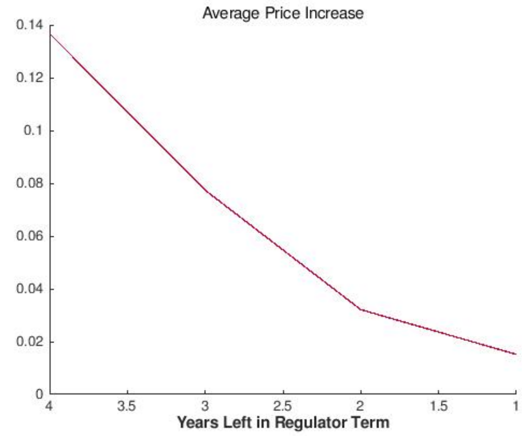


(a) Company Dropout Rate by Regulator Stringency

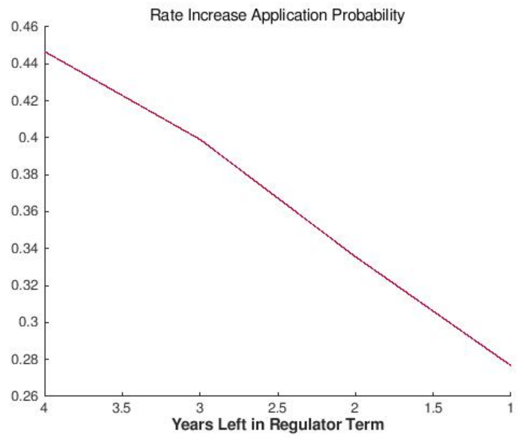
(b) Company Dropout Rate by Election Cycle Frictions

Source: Author's calculations using the California Long Term Care Rate and History Guide and NAIC LTC Experience Reports. Note that high friction states are state where election cycles are estimated to have a larger effect on regulator behavior. See text for details.

Figure 9: Optimal Policy Functions at the Estimated Parameters



(a) Average Predicted Price Increases Across the State Space



(b) Average Predicted Application Rates Across the State Space

Figure 10: Optimal Policies of Insurer and Regulator

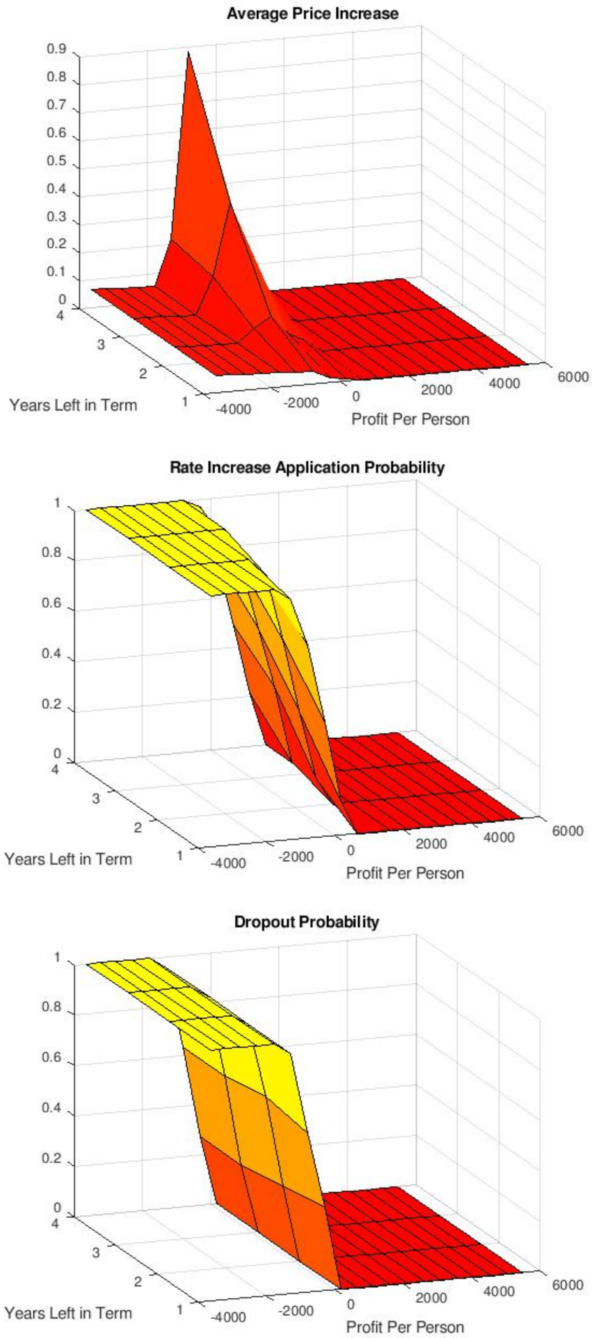
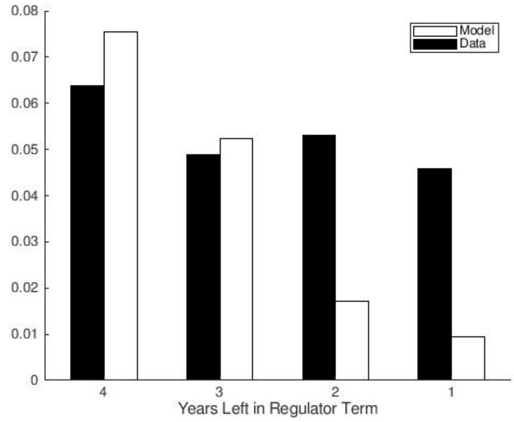
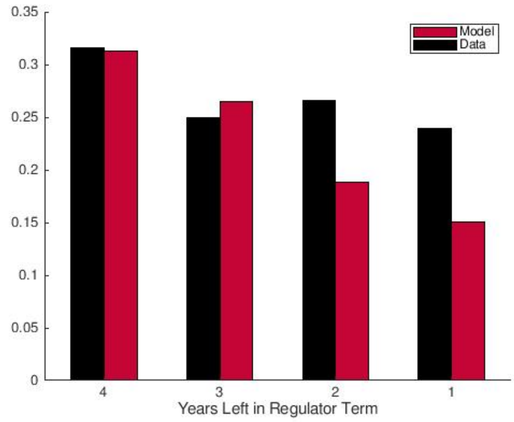


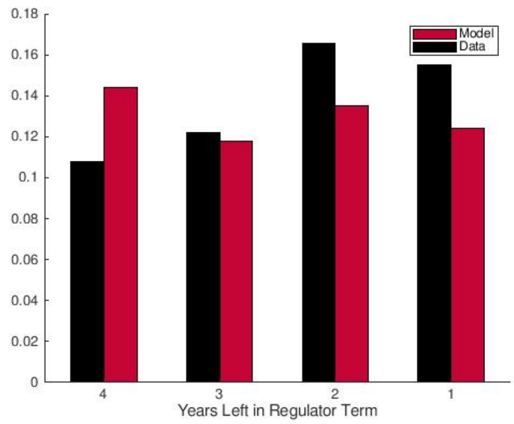
Figure 11: Model Fit for Conditional Moments



(a) Average Predicted And Actual Price Increases

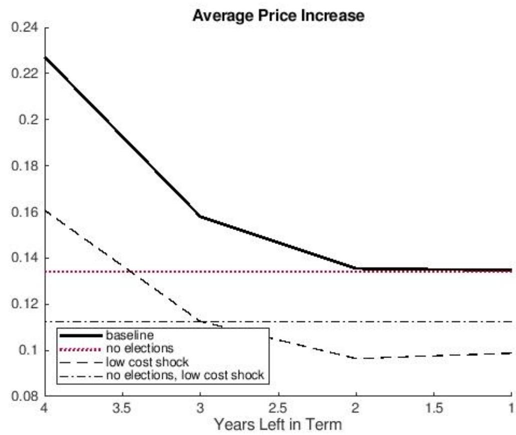


(b) Average Predicted And Actual Application Rates

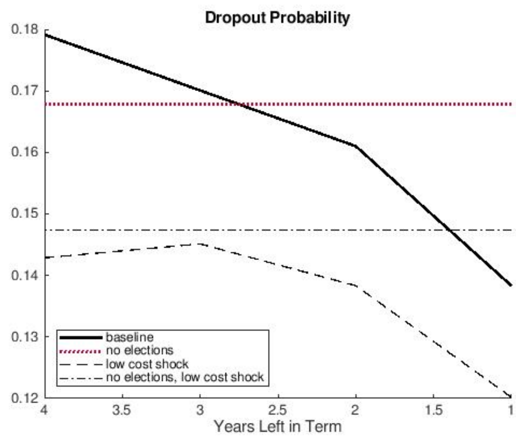


(c) Average Predicted And Actual Dropout Rates

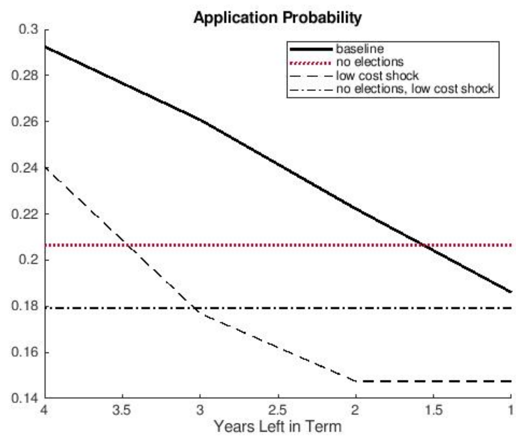
Figure 12: Counterfactual Policies



(a) Optimal Price Increases



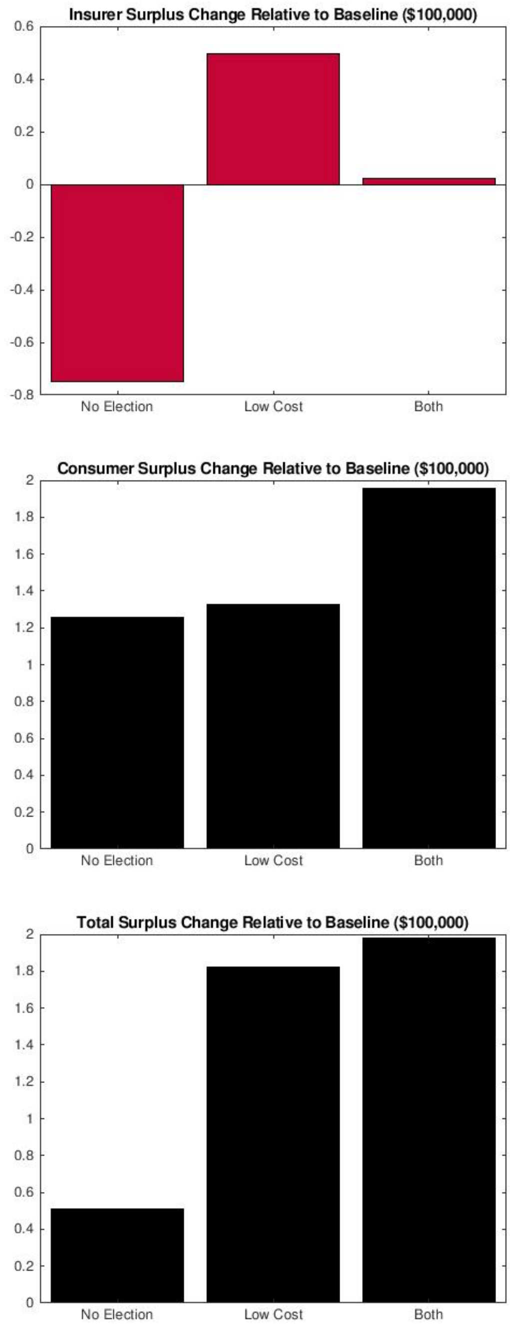
(b) Optimal Dropout Rates



(c) Optimal Application Rates

Note: The figure graphs optimal policies averaged across the state space for each scenario listed in the legend. All scenarios use baseline parameters unless otherwise stated. The no elections scenario solves for optimal policies setting κ to 0 and γ to 48 in equation 4. The low cost shock scenario sets the average cost shock θ to be 150. The no elections, low cost shock scenario sets θ to 150, κ to 0, and γ to 48.

Figure 13: Counterfactual Welfare Gains in the Short Term



Note: The figure graphs the relative welfare change averaged across all observations for the counterfactual scenarios depicted Figure 12. Flow utilities are dollarized using average marginal utility of income α. The no elections scenario solves for optimal policies setting κ to 0 and γ to 48 in equation 4. The low cost shock scenario sets the average cost shock θ to be 150. The no elections, low cost shock scenario sets θ to 150, κ to 0, and γ to 48.

Tables

Table 1: Effect of Election Year on Average Premium Increase (%)

	Premium Increase (1)	(2)
Years Left in Term	0.17**	0.17**
	(0.07)	(0.07)
Constant	2.06***	-1.67***
	(0.52)	(0.54)
Mean Dependent Variable	2.70	2.70
State FE and Year FE	Yes	Yes
Company FE	No	Yes
Number of Observations	51,437	51,437
R-squared	0.01	0.03

Note: The table displays the effects of regulator election cycle on average LTCI premium increases (measured in percentage points). Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 2: Regulator Behavior Across the Election Cycle

	(1) Size of Increase	(2) Number Approved	(3) Approval Rate, All	(4) Approval Rate, New
Years Left in Term	0.57***	0.06*	1.84***	2.09**
	(0.19)	(0.03)	(0.62)	(0.90)
Constant	12.98***	-1.37***	85.77***	85.74***
	(2.99)	(0.29)	(13.73)	(16.68)
Mean Dependent Variable	13.02	1.56	54.64	53.52
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	9,043	21,956	9,043	6,108
R-squared	0.17	0.19	0.21	0.20

Note: The table displays the effects of regulator election cycle on the magnitude and number of approved rate increases, the percentage of all open applications approved, and percentage of new applications approved, respectively. All observations at the company, state, year level and measured in percentage points. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 3: Company Behavior Across the Election Cycle

	(1) Size of Requested Increase	(2) Number of Requests
Years Left in Term	0.03	0.04
	(0.11)	(0.03)
Constant	-6.01***	-0.93***
	(0.88)	(0.19)
Mean Dependent Variable	10.03	1.70
State FE and Year FE	Yes	Yes
Company FE	Yes	Yes
Number of Observations	21,956	21,956
R-squared	0.11	0.20

Note: The table displays the effects of regulator election cycle on the magnitude and number of rate requests, respectively. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 4: Effect of Winning Percentage on Rate Request Decisions

	Approval Probability		Size of Approved Increase	
	(1)	(2)	(3)	(4)
Years Left in Term	2.40***	5.77	0.85***	6.11**
	(0.57)	(3.45)	(0.19)	(1.99)
Election Vote Percentage	0.01	0.17	-0.09***	0.16*
	(0.15)	(0.17)	(0.02)	(0.08)
Years Left in Term × Election Vote Percentage		-0.06		-0.09**
		(0.05)		(0.03)
Constant	48.07***	41.48**	1.57	-8.74
	(14.43)	(16.13)	(2.39)	(5.53)
Mean Dependent Variable	58.33	58.33	12.12	12.12
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	2,291	2,291	2,291	2,291
R-squared	0.24	0.24	0.16	0.17

Note: The table displays the effects of political capital on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Election Vote Percentage is a continuous variable representing the share of votes the current regulator received in the last election. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 5: Effect of Winning Margin on Rate Request Decisions

	Approval Probability		Size of Approved Increase	
	(1)	(2)	(3)	(4)
Years Left in Term	2.39***	3.11**	0.84***	1.89***
	(0.57)	(1.00)	(0.19)	(0.57)
Winning Vote Margin	0.04	0.13	-0.04**	0.09**
	(0.07)	(0.09)	(0.01)	(0.04)
Years Left in Term × Winning Vote Margin		-0.03		-0.05**
		(0.03)		(0.02)
Constant	46.95***	47.88***	-2.64	-1.30
	(10.52)	(10.50)	(2.16)	(2.68)
Mean Dependent Variable	58.33	58.33	12.12	12.12
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	2,291	2,291	2,291	2,291
R-squared	0.24	0.24	0.16	0.17

Note: The table displays the effects of political capital on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Winning Vote Margin is a continuous variable representing the difference in share of votes the current regulator received over the closest runner-up in the last election. The higher the margin, the more votes the current regulator received. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 6: Effect of Political Party on Rate Request Decisions

	Approval Probability		Size of Approved Increase	
	(1)	(2)	(3)	(4)
Years Left in Term	1.77***	1.40*	0.54***	0.50*
	(0.61)	(0.83)	(0.18)	(0.26)
Democrat	-8.30***	-10.27***	-3.91***	-4.14***
	(2.32)	(3.49)	(0.85)	(1.27)
Years Left in Term x Democrat		0.79		0.09
		(1.31)		(0.43)
Constant	87.35***	88.11***	13.72***	13.81***
	(14.03)	(13.99)	(3.15)	(3.21)
Mean Dependent Variable	51.78	51.78	12.54	12.54
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	9,043	9,043	9,043	9,043
R-squared	0.21	0.21	0.17	0.17

Note: The table displays the effects of political party on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Democrat is a dummy variable equalling 1 if the current insurance commissioner (or governor) identifies with the Democratic Party, and is 0 otherwise. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 7: Effect of Campaign Contributions on Rate Request Decisions

	Approval Probability	Size of Approved Increase		Approval Probability	Size of Approved Increase	
	(1)	(2)	(3)	(4)	(5)	(6)
Years Left in Term	1.97*	0.77**	0.66*	1.86*	0.75**	0.65
	(0.92)	(0.24)	(0.34)	(0.84)	(0.24)	(0.39)
Cash on Hand	-0.32*	-0.17**	-0.25*			
	(0.15)	(0.06)	(0.13)			
Years Left in Term x Cash on Hand			0.03			
			(0.04)			
Campaign Contributions				0.20***	0.03***	-0.08
				(0.04)	(0.01)	(0.21)
Years Left in Term x Campaign Contributions						0.03
						(0.05)
Constant	55.63***	-1.50	-1.13	40.41***	-4.99**	-4.25
	(13.44)	(2.20)	(2.54)	(10.85)	(2.02)	(2.69)
Mean Dependent Variable	57.54	11.88	11.88	57.43	11.85	11.85
State FE and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,167	2,167	2,167	2,148	2,148	2,148
R-squared	0.25	0.17	0.17	0.26	0.17	0.17

Note: The table displays the effects of campaign financing on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Cash on Hand is a continuous variable representing the net balance of current regulator's campaign at the beginning of the year. Campaign Contributions indicates how much money the regulator received during the year. Outcome variables are measured in hundreds of thousands. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 8: Differential Regulator Behavior Regarding the Same Application

	(1) Size of Increase	(2) Approval Probability	(3) Days Until Approval
Years Left in Term	0.076	1.28**	-1.84
	(0.23)	(0.47)	(1.97)
Constant	24.6***	94.4***	83.3***
	(1.44)	(1.96)	(11.6)
Mean Dependent Variable	21.44	88.22	155.91
Request FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Number of Observations	8,022	8,022	7,210
R-squared	0.67	0.64	0.62

Note: The table displays the effects of regulator election cycle on regulator behavior, controlling for application fixed effects. Standard errors, in parentheses, are clustered by application. Units of columns (1) and (2) in percentage points. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 9: Regression of Dropout on State Characteristics

	Nationwide Dropout Probability			
	(1)	(2)	(3)	(4)
Election Pressure (state-weighted)	0.57**			0.30
	(0.17)			(0.20)
Applications Received (state-weighted)		0.002**		0.002*
		(0.001)		(0.001)
Rate Applications Approved (state-weighted)		-0.002		-0.002
		(0.001)		(0.001)
Annual Earned Premiums (Mil)			-0.09*	-0.07*
			(0.04)	(0.03)
Annual Claims Paid (Mil)			0.12	0.10
			(0.08)	(0.08)
Constant	0.28+	-0.63*	0.97**	-0.26
	(0.17)	(0.32)	(0.11)	(0.35)
Number of Observations	218	218	218	218
Pseudo R-squared	0.06	0.11	0.11	0.18

Note: The table displays the effects of various company-level characteristics on company dropout. Observations are at the company level. The outcome variable is a dummy variable indicating 1 if the company is not currently selling LTCI. Election pressure is the magnitude of the election cycle effect in each state. The first three LHS variables are state-weighted, meaning that election pressure, number of applications received by each state, and the number of applications approved in each states, are averaged across all the states each company operates in, weighted by the percentage of its premiums earned in that state. Outcome variables are measured in percentage points. Standard errors are in parentheses. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 10: Estimation Sample Summary Statistics

Variable	Mean	Standard Deviation
Annual Total Claims (Mil)	4.44	9.79
Annual Total Premiums (Mil)	7.06	14.50
Lives in Force	4163.98	8491.40
Company Dropout	0.14	0.35
Election Year	0.26	0.44
Annual Approved Increase (%)	5.30	10.68
Annual Requested Increase (%)	7.93	16.33
Number of Policies Approved	2.55	7.96
Number of Increases Requested	3.38	9.00
Applied for Any Rate Increase	0.27	0.44
Market Share	0.0040	0.0081
Total Observations		2,803
Unique Companies		59

Note: All observations at the state, company, and year. Election Year, Company Dropout, Applied for Rate Increase are binary variables indicating that the current observation is in an election year, that the current observation is the last for the company in that state, and that an application for a rate increase was submitted, respectively. Market share is defined as the number of covered lives for a particular company, state, and year divided by the total number of 50+ year olds without Medicaid coverage in that state and year.

Table 11: Insurer and Regulator Preference Parameter Estimates

Parameter	Notation	Estimate	S.E.
Rate Increase Application Cost	AppCost	105.35	15.45
LTC Business Scrap Value (millions)	ScrapValue	4.73	0.81
Overall Political Pressure	γ	106.20	18.74
Political Pressure Changes Over Election Cycle	κ	1.28	0.19

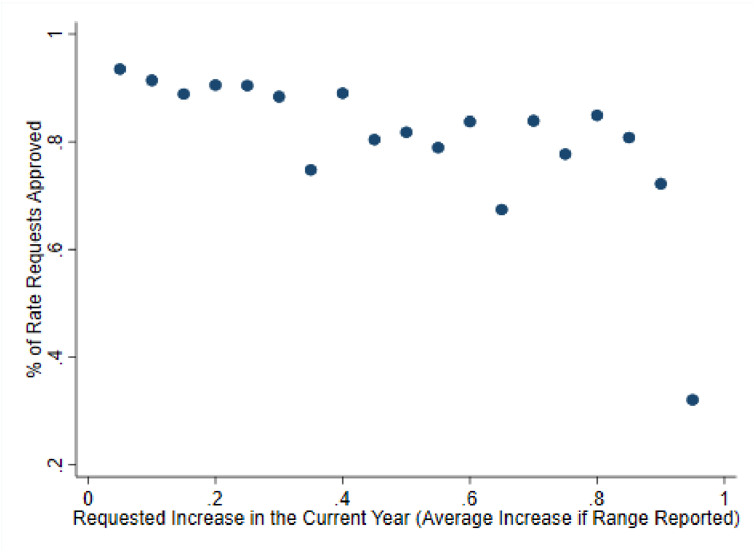
Notes: The table reports estimates for the preference parameters listed in the insurer and regulator utility functions from equations 3 and 4. Standard errors are computed using 25 bootstrap samples.

Table 12: Model Fit

	Model Moments	Data Moments
Targeted Moments		
Mean Predicted Premium Increase	0.04	0.05
Mean Dropout Probability	0.13	0.14
Mean Application Probability	0.22	0.27
Un-Targeted Moments		
Std. Dev. Premium Increase	0.14	0.11
Std. Dev. Dropout Probability	0.34	0.35
Std. Dev. Application Probability	0.42	0.44

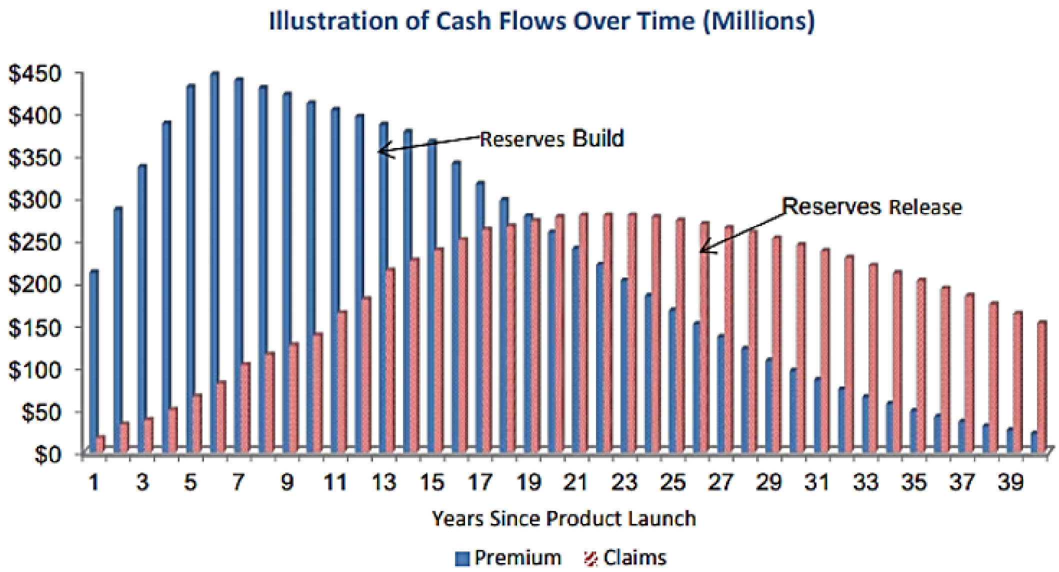
Appendices

Figure A1: Tradeoff Between Rate Increase Requested and Probability of Approval



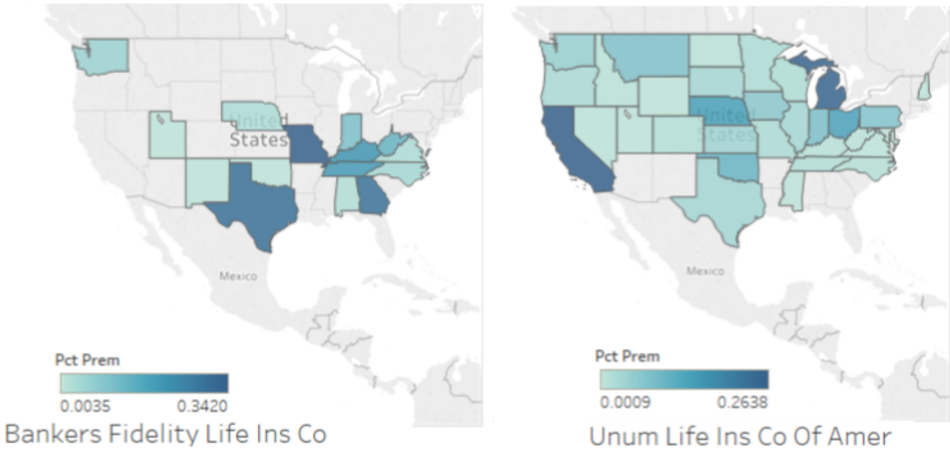
Source: Authors' calculations using the California Long Term Care Rate and History Guide.

Figure A2: Example of Cash Flow for Typical LTCI Policy



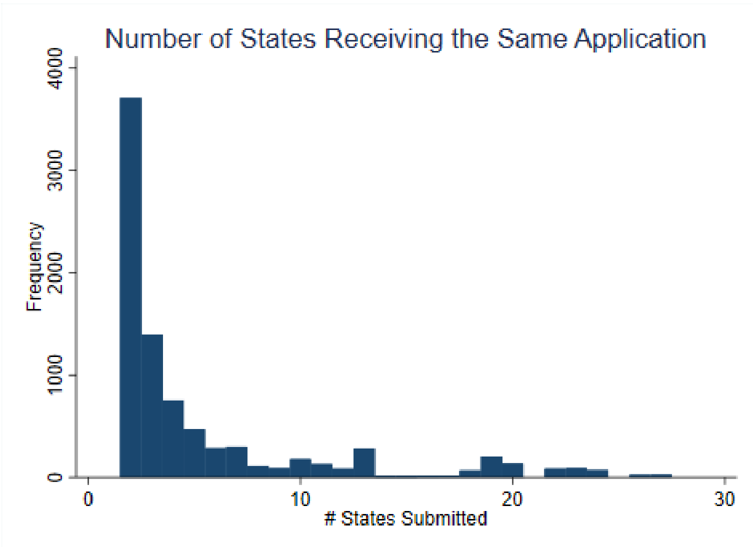
Source: Bodnar (2016)

Figure A3: Geographic Concentrations of Bankers Fidelity and Unum



Source: Author's calculations using the NAIC LTC Experience Reports.

Figure A4: Distribution of Multi-State Requests



Source: Authors' calculations using the California Long Term Care Rate and History Guide. Requests submitted to multiple states were determined to be the same request if the two (or more) submissions fulfilled the criteria listed in the text.

Table A1: Rate Request Decisions, Elected Regulators Only

	Commissioner Directly Elected		Appointed Commissioner	
	(1)	(2)	(3)	(4)
	Approval Probability	Size of Approved Increase	Approval Probability	Size of Approved Increase
Years Left in Term	1.86**	0.68**	1.51	0.38
	(0.74)	(0.24)	(0.99)	(0.26)
Constant	51.27***	-3.70	84.59***	13.71***
	(10.78)	(2.21)	(16.21)	(3.54)
Mean Dependent Variable	58.03	11.95	52.52	13.15
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	2,369	2,369	6,674	6,674
R-squared	0.23	0.16	0.21	0.17

Note: The table displays the effects of appointment type on regulator behavior. The analysis in Columns (1) and (2) uses only directly elected commissioners. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table A1 shows that both directly elected officials and appointed commissioners are both affected by re-election pressure. Appointed commissioners also respond to the election cycle to help their governor with re-election. Similar to directly elected officials, winning re-election would also help them keep their position. The coefficients on years-left-in-term are not statistically different across columns in Table A1.

Table A2: Elected and Appointed Commissioners

State	Elected	Governor-Appointed	Neither
Alabama		X	
Alaska			X
Arizona		X	
Arkansas		X	
California	X		
Colorado		X	
Connecticut		X	
Delaware	X		
Florida	X*		
Georgia	X		
Hawaii		X	
Idaho		X	
Illinois		X	
Indiana		X	
Iowa		X	
Kansas	X		
Kentucky		X	
Louisiana	X		
Maine		X	
Maryland		X	
Massachusetts		X	
Michigan		X	
Minnesota		X	
Mississippi	X		
Missouri		X	
Montana	X		
Nebraska		X	
Nevada		X	
New Hampshire		X	
New Jersey		X	
New Mexico			X
New York		X	
North Carolina	X		
North Dakota	X		
Ohio		X	
Oklahoma	X		
Oregon			X
Pennsylvania		X	
Rhode Island			X
South Carolina		X	
South Dakota		X	
Tennessee		X	
Texas		X	
Utah		X	
Vermont		X	
Virginia			X
Washington	X		
West Virginia		X	
Wisconsin		X	
Wyoming		X	

Note: Florida's insurance commissioner became an appointed position in 2003.

Table A3: Summary Statistics

Variable	Obs	Mean	Standard Deviation
Annual Premium Change (%)	55,661	2.70	21.13
Annual Total Claims (Mil)	59,072	3.35	18.41
Annual Total Premiums (Mil)	59,072	7.55	36.72
Lives in Force	38,769	1278	5434
Cumulative Company Dropout (state-level)	13,120	0.30	0.46
Commissioner Directly Elected	59,072	0.23	0.42
Election Vote Percentage (%)	16,145	57.55	9.39
Election Year	50,972	0.24	0.42
Average Size of Approved Increases (%)	10,233	12.35	16.35
Average Size of Requested Increases (%)	23,419	10.20	22.38
Number of Policies Approved	23,419	1.66	5.14
Number of Increases Requested	23,419	1.92	5.50
Probability of Approval, All Open Filings (%)	10,228	50.09	47.60
Probability of Approval, New Filings (%)	6,563	50.91	48.68
Applied for Rate Increase	23,419	0.24	0.43
Campaign Contributions (Mil)	4,292	0.52	2.75
Unique Companies			235

Note: All observations at the state, company, and year level. Election Year, Company Dropout, Commissioner Directly Elected are binary variables indicating that the current observation is in an election year, that the current observation is the year time the company submitted advertising material for approval, and that the insurance commissioner is directly elected rather than appointed by the governor. Election Vote Percentage is the share of votes the commissioner received in the latest election.