Pricing of Climate Risk Insurance:
Regulatory Frictions and Cross-Subsidies[*]

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Abstract

Homeowners' insurance provides households financial protection from climate losses. State regulators impose price controls to improve access to insurance and affordability. Using novel data, we construct a new measure of rate setting frictions for individual states and show that different states exercise varying degrees of price control, which positively correlates with how exposed a state is to climate events. Insurers in high friction states are restricted in their ability to set rates and respond less after experiencing climate losses. In part, insurers overcome pricing frictions by cross-subsidizing insurance across states. We show that in response to losses in high friction states, insurers increase rates in low friction states. Over time, rates get disjoint from underlying risk, and grow faster in states with low pricing frictions. Our findings have consequences for how climate risk is shared in the economy and for long-term access to insurance.

Keywords: Climate Risk; Homeowners' Insurance; Price Controls; Financial Regulation; Cross-Subsidization; Financial Institutions.

1. Introduction

Due to climate change, natural disasters have been on an unprecedented rise across the world.[1] In the last two decades, the U.S. alone saw catastrophic losses of more than $600 billion, roughly twice the losses of the previous 40 years combined.[2] In the U.S., the main way through which households and businesses protect themselves against the growing challenges posed by climate risk is by purchasing private insurance. To improve affordability and access to insurance, state-level regulators subject insurance companies to heavy regulation, including price controls. However, such interventions make it harder for insurers to set rates that reflect the growing losses from climate disasters, which can lead to distortions in market outcomes. Despite the growing urgency of these issues, we have little systematic understanding of the ways in which these rate setting frictions impact the pricing and supply of climate risk insurance, households' finances, and the health of the insurance sector.

In this paper, we study the pricing and market structure of the U.S. homeowners' insurance market, the second largest and fastest growing segment within the Property & Casualty (P&C) market with over $100 billion dollars of premiums written in 2019.[3] Homeowners' insurance provides households and lenders (who require insurance as a condition to a mortgage loan) financial protection against various property damages, including damages due to climate events, e.g. wildfires, hurricanes, or windstorms. Using novel data, we construct a new measure of rate setting frictions for individual states and document mis-pricing, cross-subsidization, and distortions in market outcomes for homeowners insurance.

Standard insurance pricing models (e.g., Froot and O'Connell (1999) and Koijen and Yogo (2015)) do not incorporate regulatory frictions in price setting.[4] In these models, insurance prices adjust freely in response to shifts in marginal costs, demand elasticities, and financing frictions. Losses from climate disasters potentially affect insurance prices through all three channels. As losses are realized, insurers update their beliefs about the future loss distribution, which is unknown and constantly evolving. For example, after the massive losses from the California wildfires, beliefs about the frequency of future wildfires (and other climate disasters) have likely gone up. Thus, increase in losses from climate events increase the marginal cost of selling insurance and therefore prices in the future.

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[1] The Intergovernmental Panel on Climate Change (IPCC) document changes in the characteristics of extreme events and forecast escalation in both severity and frequency of disasters in the years to come (U.S. Global Change Research Program, 2017).

[2] Based on data from Spatial Hazard Events and Losses Database for the United States (SHELDUS), which includes losses from all known perils, including storms, wildfires, droughts, floods etc. See Figure 1.

[3] Figure 2 shows the evolution of aggregate premia for homeowners from 1996 to 2019.

[4] For example, Koijen and Yogo (2015)) model life insurers, where these frictions are not pervasive.

In addition, losses also worsen insurers' financing conditions (Ge, 2020; Ge and Weisbach, 2020) and potentially affect households' propensity to buy insurance as households adjust their priors, which implies further increases in equilibrium insurance prices.

If insurance contracts could be repriced freely, then insurers would not be exposed to shifts in the loss distributions as insurance prices would respond to changes in risk, demand, and financing constraints. On one hand, homeowners insurance contracts have relatively short maturities (e.g., about 1 year, compared to 10 or more years for life insurance contracts). Thus, in theory, insurance contracts can be repriced frequently. On the other hand, regulatory pricing frictions can impose significant repricing risk on insurance companies as insurers may not actually be able to increase prices to the extent they want to or as frequently as they want to. Therefore, in practice, regulatory frictions ultimately lead to insurers getting financially constrained in the long run.

We proceed by formulating testable predictions about how insurers respond to the regulatory pricing frictions. We hypothesize that the stricter the state, the more restricted insurers will be in rate setting: insurers will file fewer rate change requests and their filing behavior will be less responsive to losses. Thus, regulatory frictions would lead to lower expected profits in stricter states in the long run. This implies the following responses from insurers. They could choose to either exit and stop selling insurance in the high friction states or overcome regulatory pricing frictions by cross-subsidizing insurance in strict states by increasing rates in less strict states. In other words, in response to losses in states with high pricing frictions, insurers instead increase rates in states that have low pricing frictions.

To test these predictions, we exploit novel data and construct a new measure of rate setting frictions for individual states. State regulators require that all rate change requests be filed with insurance departments in each state that an insurer sells homeowners insurance, including detailed explanation of why a rate change is being requested. We use the rate change filings data, utilizing several of its unique features. First, we observe filings for 49 out of the 50 states. This allows us to study *across* state rate change behavior accurately. Second, the data are available over a long period of time, starting in 2009. Thus, we can study the evolution of rate setting behavior in the aftermath of several climate disasters of the last decade. Finally, and most importantly, for each filing we observe insurers' own target optimal rate change, in addition to the rate change insurers receive in each state at any point in time. Using these data, we calculate the wedge between insurers' optimal target rate change and what they receive from state regulators, which allows us to construct a novel measure to quantify the regulatory pricing frictions in each state. Our measure accounts for regulators' actual actions rather than their stated objectives and policies, which may not

fully capture state specific heterogeneity and suffer from potential implicit biases.[5]

Specifically, we define *Discount* as the ratio of rate change received to the insurer stated optimal target rate change for a given state at a given point in time. The *Discount* measure captures exactly how far below the stated optimal target insurers are able to set rates. We document that homeowners insurance is largely sold at a discount relative to the insurer stated optimal rate: *Discount* is below 1 for a significant proportion of filings in many states. However, we also find significant heterogeneity in the average *Discount* across states, which allows us to rank states according to how prevalent rate setting frictions are in a state.

Using our state level measure of rate setting friction, and consistent with the hypotheses outlined above, we document mis-pricing, cross-subsidization, and distortions in market outcomes for homeowners insurance.

First, we show that insurers are more restricted in their ability to set rates in high friction states in response to experiencing climate losses. Relative to low friction states, the same insurer in high friction states files 15% fewer rate change requests in response to a large jump in losses (from the median to 90th percentile). Moreover, rate changes received are less responsive to climate losses than are insurer stated target rate changes for an insurer in a high friction state relative to the same insurer in a low friction state. Intuitively, as rate filings are costly and expected benefits of filing for a rate change are lower in high friction states, insurers' rate filings - both the number of requests and the magnitude of the received changes - respond less to losses in high friction states than in low friction states. In addition, we find that insurers, especially the large ones, do not completely stop selling insurance in a state, even in the presence of high rate setting frictions.

Second, we examine how insurers' rate setting in a given state responds after these insurers experience out-of-state losses in the previous year. We document several facts that show insurers cross-subsidize insurance in high friction states by increasing rates in low friction states. (a) Both the number of filings and the amount of rate change received increase in a given state in response to out-of-state losses. However, crucially this behavior is prevalent only for rate filings in low friction states. Using insurer fixed effects to make within insurer comparisons, we track the same insurer's filing behavior across different states. We find that the insurer responds to out of state losses only in low friction states and not in high friction states. (b) Moreover, we find that when an insurance firm responds to out-of-state losses, it responds only to out-of-state losses occurring in high friction states. But it

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[5]For example, regulatory strictness can vary significantly e.g. due to state regulators' incentives (Liu and Liu, 2020; Leverty and Grace, 2018; Tenekedjieva, 2020), state insurance department budgets (Sen and Sharma, 2020), and other idiosyncratic rules.

does not respond to out-of-state losses in other low friction states. The intuition is that in low friction states, insurers are already able to adjust rates in response to losses occurring within that state. The economic magnitudes are large. For example, in response to a one standard deviation increase in losses in high friction states, the average insurer in low frictions states increases the magnitude of the received change by 18% and the number of filings by 12%.

Third, we document that our measure of state-level rate setting friction positively correlates with how exposed a state is to climate losses. High friction states, e.g. California, Texas, and North Carolina, also have higher climate losses per capita. This fact combined with our previous two findings have important consequences for the distribution of rate growth across states and its relation to climate risk. We show that insurance rates have increased more in low friction states than in high friction states in the past decade, even though high friction states are more exposed to climate events. Thus, insurance rates get disjoint from what historical loss estimates imply, and in particular, rates potentially fall below historical loss estimates in high friction states.

We present a number of additional analyses to rule out alternative explanations of these findings. First, a concern could be that we end up classifying states as high friction because insurers report inflated optimal rate targets. We show that a low *Discount* in one year predicts lower profits in the next year. Therefore, low *Discount* values are not solely driven by insurers inflating their optimal target prices. Moreover, we provide several additional facts consistent with regulatory price suppression. For example, we show that *Discount* is persistent, that regulators take longer to approve larger rate change requests, and that more than 70% of insurers request a rate increase each year. Second, to control for alternative factors for a rate change in any state, e.g., due to time varying unobserved state characteristics or local demand shocks, we add State × Year fixed effects. Third, to control for insurer specific characteristics that may drive rate change requests, e.g. due to financial constraints, we add size (total assets) and regulatory ratios as controls. Fourth, as rate change requests may be driven by shocks to reinsurance supply following climate losses (Froot and O'Connell (1999)), we control for the proportion of premia re-insured by each insurer. Finally, a necessary condition for cross-subsidization is inelastic demand. Indeed, we show that homeowners insurance market is highly concentrated and that our findings on cross-subsidization are especially pronounced for large firms, who have higher market power.

Related literature: Our paper contributes to three broad strands of the literature: the linkages between climate change and household finance, regulation of consumer finance products, and the impact of climate change on financial institutions.

First, this paper contributes to the upcoming literature on the linkages between climate risk and household finance. Several paper document the negative implications of climate risk: directly, through real estate prices (e.g., Bernstein et al. (2019); Baldauf et al. (2020); Murfin and Spiegel (2020); Issler et al. (2020)), or indirectly through discounts in municipal bond prices and issuance (e.g., Goldsmith-Pinkham et al. (2020)), and through the labor market (e.g., Kruttli et al. (2020) who show negative stock returns for firms with offices in exposed regions).[6] In fact, evidence suggests that real estate prices do not fully incorporate climate risk, and what we see is likely a lower bound (Baldauf et al., 2020; Murfin and Spiegel, 2020). Our work makes progress by documenting that climate risk has financial consequences for households through the availability and pricing of insurance. First, the current regulatory system may force firms to start exiting high-risk states in the long run. Second, cross-subsidization across states make it more difficult for households in low-risk areas to afford insurance.

Second, our work contributes to the literature on assessing the costs and benefits of regulating consumer financial products (e.g., Bar-Gill and Warren (2008); Campbell et al. (2011)). Several papers study the effects of regulatory interventions in rate setting for banking products, e.g., Agarwal et al. (2015) for credit cards.[7] Within insurance, several studies have examined the impact of specific types of price regulation on the coverage and equilibrium outcomes of health insurance market (Finkelstein et al., 2009; Ericson and Starc, 2015; Simon, 2005). Liu and Liu (2020) examine regulatory frictions due to political motivations of regulators in the context of long-term care insurance. Our paper examines the effects of rate regulation for contracts that protect against climate disasters, for which future loss distributions are uncertain and constantly evolving. As our findings show, these repricing frictions can impose significant costs on insurers and lead to unintended pricing consequences for households present in less regulated states. This is the first paper to document the existence of the wedge between insurers' target rate changes and the rate changes received, and to formally study the effects of price setting frictions on how insurers set rates across different states.

Finally, our findings are also related to several studies on the effects of climate change on financial institutions. Central bankers identify two main channels through which climate change can affect financial stability: physical risk, stemming from direct property damage,

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[6]See Giglio et al. (2020) for a comprehensive literature review on climate change and finance more broadly.

[7]A broader literature studies the effects of price control outside of financial services. See e.g., (Autor et al., 2014) who document negative externalities and distortions due to rent-control in Massachusetts. For early work on cross-subsidization resulting from price controls in utilities see (Faulhaber, 1975) and in telecommunications see (Curien, 1991).

and transition risks, which include a range of consequences resulting from a possible transition to a low-carbon economy (see reports from the U.S. Federal Reserve (Rudebusch, 2019), Bank of England (Scott et al., 2017), and Banque de France (Battiston, 2019). Indeed, Krueger et al. (2020) show that institutional investors believe climate change risks are significant, and beginning to materialize, and Battiston et al. (2017) estimate significant exposure of financial institutions to climate change risks. This paper contributes to the literature directly: insurers' ability to absorb losses is key in preserving financial stability (Scott et al., 2017), and our results are the first to suggest that the current regulatory system is putting a strain on insurance firms' preparedness.

The rest of the paper is structured as follows. Section 2 provides a brief overview of the institutional details on rate regulation and a discussion of standard insurance pricing models. Section 3 and 4 describe the data, how we construct a state-level measure of rate setting frictions, and other key variables. Section 5 describes our main analysis. Section 6 concludes.

2. Institutional Background and Testable Predictions

2.1. Institutional Background

Since the early part of the 20th century, insurance prices have been regulated in the U.S. at a state level.[8] State regulators aim to curb monopolistic practices and prevent "excessive prices" in order to assure affordable insurance coverage for all consumers or for a group of consumers (Tennyson, 2011).[9] Rate regulation is most commonly employed in automobile, homeowners', health, workers' compensation, and medical malpractice insurance. Several pieces of anecdotal evidence point to instances of rate suppression by state regulators for homeowners insurance. Appendix A provides a few examples, which show that regulators typically limit rate increases to a lower percentage than what is requested by the insurer.

State regulators require that all rate change requests be filed with insurance departments in each state that an insurer sells homeowners insurance in. These filings include a detailed explanation of why a rate change is being requested, what the insurers' target optimal rate

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[8]Historically, regulation of insurance prices arose for three main reasons: concerns about monopoly pricing, (ii) concerns about under-pricing to gain market share, and (iii) concerns about price discrimination across consumers. Over time, the focus of regulation has largely shifted to prevent high insurance prices. See Tennyson (2011).

[9]In the past, insurers were allowed to pool information for pricing purposes, which led to fears about monopoly pricing.

change is, and other useful information on insurers' pricing functions.[10] Regulators may approve or reject the requests after reviewing them.

Regulatory strictness varies considerably across states. One dimension of heterogeneity across states is in the filing and approval process. In some states, regulators require that insurers file their request, and wait for explicit approval from the state insurance department before implementing any changes. While in other states, insurers are required to file their rate change requests and at the same time they may start using the rates without approval. However, if subsequently found unacceptable, these rate changes have to be withdrawn. Finally, in some states insurers just need to file the rate change in order to keep state regulators informed. Regulators intervene in rare circumstances, e.g. if insurers are in direct violation of discrimination laws.

However, even when two states employ the same filing and approval system, regulatory strictness can vary significantly, e.g. due to state regulators' incentives (Liu and Liu, 2020; Leverty and Grace, 2018; Tenekedjieva, 2020), state insurance department budgets (Sen and Sharma, 2020), and other idiosyncratic rules.[11] To incorporate additional sources of state specific heterogeneity over and above the explicit filing and approval system, we construct a state level measure of regulatory pricing frictions from detailed data on the rate change filings. Section 4 documents our methodology and stylized facts.

2.2. Standard Insurance Pricing Model and Testable Predictions

In the standard insurance pricing model with market power and financing frictions (e.g., Froot and O'Connell (1999) and Koijen and Yogo (2015)), insurance prices are a function of three key inputs:

$$(1) \qquad\qquad P = \eta E[L]\Phi,$$

where $E[L]$ is the marginal cost of selling insurance and equal prices in a frictionless model. η is the markup over $E[L]$ and depends on demand elasticites.[12] Thus, $\eta E[L]$ is the price of insurance without financing constraints. Finally, Φ denotes financing frictions.

Equation (1) implies that, in response to losses, prices can increase for three reasons.

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[10] The median length of a rate filing is about 76 pages.

[11] For instance, some states limit risk based pricing for a subset of consumers or prevent the use of certain inputs into their pricing models. For example, California bans insurers from using reinsurance prices in their pricing models (Issler et al., 2020).

[12] Market power could arise because banks may prefer large and well rated insurers as the length of a typical mortgage loan contract is long.

First, as losses are realized, insurers update their beliefs about the future loss distribution, which is unknown and constantly evolving. For example, after the massive losses related to the California wildfires, beliefs about the frequency of future wildfires (and other related climate disasters) have likely gone up. To the extent that these losses are not simply idiosyncratic, such climate events shift priors about $E[L]$ and thus the marginal cost of selling an additional unit of insurance in the future.

Second, as losses are realized, insurers' financing conditions worsen as they pay increased amounts of households' climate related claims and their reserves and capital are depleted. If insurers can frictionlessly raise capital, then changes in climate losses have no impact on insurance prices. However, if raising capital is costly then following a period of losses insurance prices would tend to go up.[13] Thus, supply side shifts come from both shocks to insurers' marginal cost and financing constraints.

On the other hand, following a period of losses, demand for insurance may also increase, thus pushing up insurance prices. (Dessaint and Matray, 2017) document that following hurricanes, corporations tend to self-insure by holding more cash. These effects are likely to be particularly pronounced for climate risk insurance as loss distributions are unknown and households form expectations about future losses from past losses.

If insurers could frequently reprice contracts as they updated beliefs about the future loss distribution or when they faced financing constraints and demand shocks, then insurers would not be exposed to shifts in the loss distributions. Indeed, P&C insurance contracts (including homeowners insurance) typically have short maturities (e.g., about 1 year or less) unlike life insurance and annuities contracts which are much longer dated (e.g., about 10-20 years). Thus, in theory, insurance contracts can be repriced frequently. In practice, however, the presence of state level regulatory pricing frictions can impose significant repricing risk on insurance companies as insurers may not actually be able to increase prices to the extent they want to or as frequently as they want to. Thus, regulatory frictions ultimately lead to increases in financial constraints in the long run.

Optimal Pricing Responses under Regulatory Pricing Frictions: We derive testable predictions about how insurance prices respond to the regulatory pricing frictions.

Prediction 1a. *In response to a given level of loss, insurers are less likely to file for a rate change in a high friction state than in a low friction state.*

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[13]Raising equity could be expensive, e.g. due to informational asymmetry (Myers and Majluf, 1984) or agency costs (Diamond and Rajan, 2000)

Prediction 1b. *In response to a given level of loss, insurers are more likely to receive a lower rate change in a high friction state than in a low friction state.*

Prediction 2. *Exits: Insurers exit states that have high regulatory pricing frictions, all else equal.*

Intuitively, as rate filing is costly and expected benefits of filing for a rate change is lower in high friction states, insurers' rate filings are less responsive to losses in high friction states than in low friction states. Moreover, relative to low friction states, in high friction states, rate changes received are less responsive to losses than are insurer stated target rate changes. Thus, regulatory frictions translate into financial constraints in the long run, prompting insurers to exit high friction states.

Prediction 3a. *Cross-subsidization of insurance prices across U.S. states: insurers cross-subsidize insurance in high friction states by increasing prices in low friction states.*

Prediction 3b. *In the aggregate, insurance prices increase more in states with low regulatory pricing frictions relative to high regulatory pricing frictions.*

Intuitively, insurers overcome regulatory pricing frictions by cross-subsidizing insurance across states. In response to losses in states with high pricing frictions, insurers increase prices in states that have low pricing frictions. Thus, we expect insurance prices in low friction states to respond to losses in high friction states. Over time, insurance prices increase more in low friction states than in high friction states. Thus, prices get disjoint from what historical loss estimates would imply, i.e. insurance prices are below loss estimates in high friction states.

3. DATA

3.1. Statutory Filings Data

We obtain financial data on 1,405 Property and Casualty (P&C) insurers that sell homeowners insurance in the U.S. from the National Association of Insurance Commissioners and S&P Market Intelligence (S&P MI). To study the effect of past losses on pricing behavior, we collect data on losses and premiums for each insurer in each state.

An insurer can operate (i.e. sell insurance) in several states. Insurers report the total

premium underwritten and losses experienced by lines of business in each state they operate in at an annual frequency. We collect these data for our sample period that starts in 2009 and ends in 2019. The start date is dictated by the availability of data on rate change filings (see below). To estimate shifts in marginal cost, we compute loss ratios,

$$\text{(2)} \qquad \text{Loss ratio}_{i,s,t} = \frac{\text{Losses}_{i,s,t}}{\text{Premium}_{i,s,t}},$$

where i denotes an insurer, s denotes a state, and t denotes year.

To account for shifts in pricing behavior unrelated to pricing frictions, we introduce a number of control variables, which we collect from annual statutory filings. These variables include an insurer's total assets, Risk Based Capital ratio, which is defined as the amount of available capital relative to required capital, percent of premiums re-insured, and losses in other P&C lines of business. These control variables are reported at an insurer-year level.

The summary statistics of these variables are shown in Table 1. We see that the loss ratio (denoted as own state loss$_{i,s,t}$) is on average 57%. In other words, 57% of premiums written by a given firm in a given state and year are spent covering homeowners' losses. The average loss ratio of non-homeowners' insurance across all states (other lines loss$_{i,t}$) has similar mean, but smaller standard deviation, since it is aggregated across all states and all other lines of businesses.

3.2. Rate Changes Filings Data

The data on insurers' rate change filings come from Insurance Product filings, provided by S&P MI. An insurer can operate (i.e. sell insurance) in several states in the U.S.. Every time an insurer wants to change prices in the state it operates in, it needs to file a rate change request at the department of insurance of that state. For example, Illinois Union Insurance Company sold homeowners insurance in 5 states in 2019: Arizona, Massachusetts, Nevada, South Carolina and Vermont. The firm must file a rate change request in each of these states, if it wishes to change insurance prices in it. We collect the rate filings data for the period between 2009 and 2019 for the homeowners line of business as the data before 2009 are incomplete for many states. We observe a full panel of filings from 2009 to 2019 for 46 states. For Louisiana, Hawaii, and Texas filings are available only starting in later years. Filings in Ohio are incomplete and are excluded from the analysis.[14]

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[14]The US has 51 separate jurisdictions: the 50 states and DC. Of these, we observe all filings in the period except: the filings in Ohio, where the filings are only partially available so the state is excluded; Louisiana,

For each filing, we observe the insurance company making the request, the date of filing, the state in which the filing is requested, the rate change received from the state regulator ($\text{Rate}\Delta\text{Received}_{i,s,t}$), amount of premium and number of consumers affected by the rate change, and the decision date, i.e. the date on which regulators finally adjudicate the rate change request. Crucially, for each filing, we also observe what insurers' stated optimal target rate change is for a given state at a given point in time ($\text{Rate}\Delta\text{Target}_{i,s,t}$), which we use to compare the gap between insurer stated target rate change vis-a-vis the rate change received.[15]

We observe over 69,600 rate change filings across all states between 2009 and 2019. The states with the highest number of filings are Wisconsin and Florida, and the states with the lowest number of filings are Wyoming and Alaska. Table 1 reports the summary statistics on these data, aggregated to the firm-year-state level. The average insurer files 1.3 rate change requests in a given state in a given year.[16] Conditional on filing for a rate change, the average ($\text{Rate}\Delta\text{Received}$) is 5.1% and the average ($\text{Rate}\Delta\text{Target}$) is 5.3%.[17] To understand whether the difference between target rate change and received rate change represents regulatory frictions, we provide a number of facts in the next section.

4. Regulatory Pricing Frictions

To understand whether *Discount* represents regulatory frictions and to quantify the extent to which regulatory pricing frictions are prevalent across states, we compare insurers' optimal target rate change with the rate change they actually receive. Conditional on a firm requesting a rate change in a state, we define *Discount* for insurer i in state s at time t as

$$(3) \qquad Discount_{i,s,t} = \frac{\text{Rate}\Delta\text{Received}_{i,s,t}}{\text{Rate}\Delta\text{Target}_{i,s,t}}$$

where $\text{Rate}\Delta\text{Received}$ is the rate change actually received and $\text{Rate}\Delta\text{Target}$ is an insurer's optimal target rate change for that filing. $Discount_{i,s,t} >= 1$ indicates that the insurer

where data is fully available after 2015; Hawaii, where data is fully available since 2013; Texas, where data is fully available since 2016. In the last three states we include them after they are comprehensibly available.

[15]State regulators definition for optimal target rate change is "statewide premium change for the product determined by the company to achieve state stated actuarial objectives for the filing."

[16]Specifically, we extract the number of times a firm filed for rate change in a given state and submitted in a given year. If the firm did not request a change but sells insurance in a given state, the number of filings is 0.

[17]If the firm filed multiple rate change requests in a given state and year, we weigh each rate change received by the affected premium, and if there was no request, the variable is 0. All based on the year of submission.

received a rate change greater than or equal to its target rate change for that state, i.e. there is no friction. $Discount_{i,s,t} < 1$ indicates that the insurer received a rate change less than its target rate change for that state. Thus, low values of $Discount_{i,s,t}$ indicate high friction.

4.1. Regulatory Frictions

Figure 3 shows a histogram of $Discount_{i,s,t}$ for the entire sample. A large fraction of filings have $Discount_{i,s,t} < 1$, and the median $Discount_{i,s,t}$ is 0.5.[18] This implies that the insurer stated target rate change is greater than the rate change received for a bulk of the rate change filings. In other words, homeowners insurance is largely sold at a discount relative to the insurer stated target rate.

There are two potential explanations for why so many filings are receiving changes below the insurer stated target level. On one hand, regulators may be engaging in price suppression (see Section 2). On the other hand, it is also plausible that insurers report inflated price targets to achieve a higher price increase and that relative to the true price target, which we do not observe, there is no rate discount. To test whether this is the case, we examine whether $Discount$ predicts future profitability. We find evidence that the inflated price targets hypothesis is less likely. Specifically, we run the following regression:

$$(4) \qquad \text{Loss Ratio}_{i,s,t+1} = \beta \text{Discount}_{i,s,t} + \alpha_{s,t} + \alpha_i + \epsilon_{i,s,t+1},$$

where Loss Ratio$_{i,s,t+1}$ is the ratio of losses divided by premium for insurer i in state s at year $t+1$. The idea is that the fraction of premiums not spent on covering consumer losses is underwriting profit for the firm. $\alpha_{s,t}$ are state $\times$ year fixed effects and α_i are insurer fixed effects. Estimation is within the same state and year and is identified from variation in discount across insurers.

If $Discount$ is low because insurers report inflated price targets, then it is unlikely to be correlated with profitability in future periods. However, we find the opposite. We show that β is negative and statistically significant (see Table 2). Thus, when $Discount$ is low (and pricing frictions are high), we observe higher losses relative to premia in the following year. In other words, the $Discount$ predicts future profitability, contrary to the predictions of an inflated price target hypothesis.

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[18]Note that a firm may request increase in price for some customers and decrease for others, which can potentially average to RateΔReceived≤ 0. As a result the $Discount_{i,s,t}$ may be 0 or negative, but as we see from Figure 3 these cases are rare.

4.2. Other Aspects of Regulatory Frictions

We provide a number of additional facts that are consistent with the hypothesis that home-owners insurance is sold at a discount due to regulatory price suppression. First, we show that $Discount$ is persistent over time. Figure 4 plots the distribution of $Discount_{i,s,t}$ for each year. The distribution is stable and the median is about 0.5 across all years. The persistently low $Discount$ values imply that the state regulators predictably keep rate changes below a threshold over time.

Second, we establish that the time to process a filing varies significantly and is related to the size of request. This finding is consistent with regulatory suppression: If regulators were indifferent between small and large change in prices, they would spend comparable time processing each request. Specifically, the period between date of filing and the date regulators announce their decision (execution time) is on average 54 days, but Figure 6 shows that execution time varies significantly within filings submitted within a year. We test formally if larger requests take longer to process and we find that the larger the requested rate change, the longer the period from submission to final regulatory decision. Specifically, Table 3 shows that a one standard deviation increase in the size of the request (increase goes from 5.2% to 11.3%) increases execution days from 54 to 66 days, which is a 22% increase.

Third, we show that insurers ask for a rate change almost every year, which suggests that insurers receive rate increases slowly over a number of years. Figure 5 plots the fraction of top 20 insurers in a state that ask for a rate change. Close to 80% of the top 20 insurers ask for a rate change in the average state. Moreover, the distribution is tight and in most states more than 70% of the top 20 insurers ask for a rate change every year.

Finally, we find that the $Discount$ values are larger for insurers that have greater market share in a state, consistent with the idea that regulators suppress prices of insurers that really matter. Table 4 shows a regression of $Discount_{i,s,t}$ on various proxies of firm size (firm size rank within a state-year, market share and log premium). We include state × year fixed effects to ensure comparison within a state and time across insurers.

4.3. A State Level Measure of Regulatory Pricing Frictions

To rank states by the degree of pricing frictions, we construct a state-level measure of regulatory pricing frictions. Consistent with the finding that $Discount$ is large for insurers that have the highest market share, we focus on the largest 20 insurers in each state and compute

the average *Discount* of these insurers.

$$(5) \qquad Friction_s = -\frac{1}{I}\sum_{i=1}^{I} Discount_{i,s,t}$$

where $I = 20$.[19] As a high value of $Discount_{i,s,t}$ implies low friction, we multiply the averages by -1 for ease of interpretation. Thus, high values of $Friction_s$ imply high pricing frictions. We next split the states in three terciles by $Friction_s$: high, medium, and low friction. States in the highest (lowest) tercile face the highest (lowest) pricing frictions.

5. Main Empirical Results

In Section 4, we showed that insurers experience heterogeneous regulatory friction when it comes to price setting. In this section, we explore how insurers respond to the price frictions, using our predictions from Section 2.2 as a guidelines. We show that in high friction states insurers apply less frequently and receive smaller rate changes compared to target rates, consistent with Prediction (1a) and (1b). However, contrary to Prediction (2), we don't observe that insurers stop selling insurance following losses in a given state. This gives rise to cross-subsidization across states: when insurers experience losses in high friction states they apply for rate changes in less strict states, consistent with Prediction (3a). Finally, we show that the frictions and cross-subsidization lead to faster price growth in low friction states, consistent with Prediction (3b).

5.1. Pricing Responses to Losses

We begin our analysis by showing that in strict states insurers are restricted in their ability to adjust prices in response to losses. We compare freedom of price response in three groups of states, separated by how strict they are. To separate the strictness levels, we use $Discount_s$, estimated as shown in Equation 5. The states in the lowest tercile of the distribution of $Discount_s$ have the lowest average ratio of rate change received to rate change targeted, so we call them high regulatory friction states. Similarly, the middle/top tercile of states based on $Discount_s$, are states which experience medium/low regulatory friction.

To compare how restricted insurers are in their ability to change prices in response to

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[19]Limiting to top 30 or top 10 yield similar results.

losses, we run the following regression:

$$(6) \qquad Y_{i,s,t} = \alpha_{s,t} + \alpha_i + \beta Loss_{i,s,t-1} + \theta X_{i,s,t} + \epsilon_{i,s,t}$$

In Equation 6, the variable of interest is $Loss_{i,s,t-1}$, which is the loss ratio (losses divided by premia) of firm i in state s and year t. We estimate the shifts in marginal costs as deviation of from mean. Specifically, we expect that when the loss ratio increases, so does the marginal cost for providing insurance, and we expect prices in future periods to go up.

We use two different response variables $Y_{i,s,t}$ - number of rate filings and their average discount - to check if in strict states insurers are constrained on the extensive and the intensive margin. Consistent with Prediction (1a), we expect that in strict states, insurers will be less likely to apply for rate changes after losses. In other words, the correlation between loss ratio at $t-1$ and filings at t will be larger the less strict a state is: $\beta^{High} < \beta^{Med} < \beta^{Low}$. Similarly, consistent with Prediction (1b), we expect that among insurers who end up applying for changes, in low friction states loss ratios will be more correlated with $Discount_{i,s,t}$ (the ratio of rate change insurers receive compared to their target rate).

We include state $\times$ year fixed effects ($\alpha_{s,t}$) and firm fixed effects (α_i). The state-year firm effects absorb time varying unobserved state characteristics and local demand shocks. The firm fixed effects ensure that the relevant coefficients are estimated off variation in loss ratio within an insurer and not off variation in the composition of insurers across all states. Furthermore, we include controls $X_{i,s,t}$ to account for time-varying insurer-level characteristics. Consistent with the literature, we control for log total assets, RBC ratio, non-state s homeowners loss ratio, non-homeowners lines loss ratio, and percent of premiums which are re-insured. Finally, we cluster the estimates' standard errors at the state level, to account for the common regulatory, climate and demand conditions in a given state.

The results from Equation 6 are shown at Table 5. Consistent with Prediction (1a), when insurers suffer given level of loss, they file more rate change requests in a low friction state, and are no more likely to file in a high or medium friction state. From columns (1) through (3), we see a positive and significant correlation between losses at $t-1$ and number of filings at t only in low friction states. For a sense of magnitude, in states with low friction, if a firm experiences a large jump in its loss ratio (from its median to its 90th percentile), insurers will file 15% more requests in state s.

Consistent with Prediction (1b), when insurers suffer given level of loss, they are more likely to receive a lower rate change compared to target in a high friction state than in a

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low friction state. From the results in columns (4) to (6), we see that there is a positive relation between losses and $Discount_{i,s,t}$ only in low friction states (though not statistically significant). In fact, for high and medium friction states, we see that when losses increase in year $t-1$, the $Discount$ in year t is significantly smaller, so the rate change received is even smaller compared to the rate change targeted, i.e. insurers become more constrained. We observe that $\beta^{High} < \beta^{Med} < \beta^{Low}$, and that if a firm experiences a big jump in its loss ratio (from its median its 90th percentile) insurers will be 17% more/9% more/13% less constrained in low/medium/high friction states. In other words, consistent with Prediction (1b), in response to a given level of loss, insurers are less likely to file for a rate change in a high friction state than in a low friction state.

Taken together, the results imply that the regulatory frictions in strict states do limit insurers in their ability to set prices that fully reflect the level of risk in a given state. As a result, insurers have two choices: stop underwriting business in the state, or cross-subsidize across states. In the next two sections we address each of these strategies, and show that insurers rarely stop selling homeowners' insurance, and instead they choose to cross-subsidize their business in stricter states with their business in laxer states.

5.2. Exits

In the previous section, we documented that insurers are less responsive to losses in high friction states than in low friction states. These results imply that regulatory frictions translate into financial constraints in the long run, which can potentially lead insurers to stop selling insurance in high friction states. For the rest of the section, when a firm stops selling homeowners' insurance in the state, we will call the event "exit".

However, insurers rarely exit a state, and most of the exits concern very small insurers - see Table 6. It shows that among the 51 jurisdictions between 2009 and 2018, one of the largest 50 insurers[20] in the state decided to exit on only 219 occasions. This means that on average, only 4 large insurers per state exited over 10 years and that the probability that an insurer exits in a given state and a given year is 0.2%. Note also that the larger the insurer, the less likely it is to exit a state.

Furthermore, we find that the decision to exit state s in year t is not predicted by increased losses in $t-1$. We test this idea formally using Equation 6. The response variable is an indicator which is 1 if a firm i exits state s in year t, and 0 otherwise, and the variable

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[20]Note that the top 50 insurers have market share of over 90% for homeowners' insurance - see Figure B.1

of interest is loss ratio experienced by i in year $t-1$ and state s. We include the same fixed effects and controls.

The results are shown at Table 7. We find that losses both in and out of a state do not predict a future exits from it. We also don't see significant difference in the predictive power of losses if we restrict our attention to high friction states. This finding is not consistent with Prediction (2), and implies that while frictions are restrictive for insurers, once in a state, insurers rarely choose to exit, and need to seek alternative exit strategies.

Why are insurers choosing not to exit despite experiencing pricing frictions? There are several potential reasons. First, insurers could be bundling various products: if it is easier for insurers to sell both homeowners' and say, auto insurance, an insurer may tolerate losses in homeowners' line if it is offset by profits in auto insurance. Alternatively, there are high costs associated with exiting and re-entering the market: rehiring brokers and state employees, re-establishing both brand recognition with clients, and relationships with regulators and lawyers. Third, it is possible that insurers are uncertain about the long-term strictness of state regulators, or whether higher losses actually imply permanent shifts in marginal costs. Finally, it is possible that insurers may fear retaliation by regulators, who could respond by being overly strict in other lines.

5.3. Cross-Subsidization of Insurance Prices Across U.S. States

In the previous sections we showed that insurers are constrained in their ability to set prices in high regulatory friction states (consistent with Predictions (1a) and (1b)). However, contrary to Prediction (2), they rarely stop selling insurance in a state, even in high friction states. In this section, we show that as a result, insurers cross-subsidize across states. More precisely, they subsidize their operations in high friction states with their operations in low friction states, consistent with Prediction (3a).

We begin our analysis by showing that insurers' filing behavior responds to other state losses. To do so, we modify Equation 6:

$$(7) \qquad Y_{i,s,t} = \alpha_{s,t} + \alpha_i + \beta OwnStLoss_{i,s,t-1} + \gamma OtherStLoss_{i,\bar{s},t-1} + \theta X_{i,t} + \epsilon_{i,s,t}$$

Again, we use two response variables - number of rate changes filed, and the size of received changes - to assess insurers filing behavior on the extensive and intensive margin. Specifically, for the extensive margin, we use the total number of rate filings made by insurer i in state s during year t, and if the firm doesn't file any change request, the variable is 0. For the

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intensive margin, we use the average change received by insurer i in state s during year t, conditional on the firm filing at least one rate change request.

The main change from Equation 6 is that now we focus on two variables of interest. The first one is $OwnStLoss_{i,s,t-1}$, which is the lagged loss ratio (loss divided by premia) of insurer i in the same state s. The second one is our measure of out-of state loss, $OtherStLoss_{i,\bar{s},t-1}$. It is the lagged loss ratio (loss divided by premia) of insurer i in all states other than state s. Finally, just as in Equation 6, we include state $\times$ year fixed effects ($\alpha_{s,t}$) and firm fixed effects (α_i), and control variables X_{it} to account for time-varying insurer-level characteristics. Specifically, we control for log total assets, RBC ratio, non-homeowners' insurance loss ratio, as well as reinsurance. All errors are clustered at the state level.

From the results shown earlier and Prediction (1a) and (1b), we expect that insurers will respond to their own losses, which would manifest in positive β coefficient. However, if insurers are cross-subsidizing across states, we also expect to see a positive γ coefficient.

From the results shown at columns (1) and (3) of Table 8 we see that insurers cross-subsidize their operations across states: both the number of filings and the size of changes increase in response to both own and other state losses. The coefficients are statistically and economically significant. Specifically, suppose that the loss ratio increases from its mean by one standard deviation. The increase will be followed in the next year by an increase in the number of rate filings by 3%, and in received changes by 22%. Similarly, suppose the same firm's other state ($\bar{s}$) loss ratio increases from its mean by one standard deviation. Then, in state s, the increase will be followed in the next year by an increase in the number of rate filings by 2%, and in received changes by 3%.

However, to show that price regulation leads to frictions, it is not sufficient to show that insurers request more and larger increases in their prices when losses in other state increase. To test if this is more than regular internal capital market redistribution, we check if the reaction of insurers to other state losses varies based on how strict a state is. We expect to see that insurers respond stronger to other-state losses coming from stricter states. The intuition is that if the losses come from less strict states, the firm will be able to adjust its prices within that state (as we showed in Table 5). To test this, we modify Equation 7 by splitting the other state losses based on the type of state they are coming from:

$$(8) \qquad Y_{i,s,t} = \alpha_{s,t} + \alpha_i + \beta OwnLoss_{i,s,t-1} + \sum_j \gamma^j OutsideLoss^j_{i,\bar{s},t-1} + \theta X_{i,t} + \epsilon_{i,s,t}$$

In Equation (8), j takes three values based on whether the state is high, medium or low

friction. For example, if j is high friction states, we sum the losses experienced in year $t - 1$ by firm i in all other states classified as high friction states based on Equation (5), and divide it by the premiums collected in these states. We expect to see that sensitivity to out-of-state losses increases in the group's friction: $\gamma_{HighF} > \gamma_{MedF} > \gamma_{LowF}$.

Results from this analysis are shown in columns (2) and (4) in Table 9: We see that insurers increase their number of filings and get larger rate changes in response to high friction out-of-state losses, and don't react to low friction out-of-state losses. It is interesting that in response to losses from medium friction states, insurers react only on the intensive margin. Specifically, if insurers are already filing a request, the rate change is larger, but they are not significantly more likely to apply for a filing change in the first place.

Theoretical frameworks on internal capital markets predict that insurers will shift costs between different states even without regulatory friction. However, it will be insufficient to explain the increase in prices in low friction states in response to shocks in high friction states. Specifically, in Table 9, under a simple internal capital markets hypothesis we would have expected that insurers respond equally to other state loss ratio$_{i,\bar{s},t}$ coming from strict and lax states. Yet, consistent with regulatory frictions, we see that insurers are sensitive only to losses from strict states.

Robustness checks

We conduct several robustness checks to our main analysis. First, we show that results are stronger for larger insurers, which are more likely to be subject to regulatory pressure as we showed in Table 4. This would imply that the cross-subsidization affect many consumers, since it is most pronounced in insurers with the highest market share. In Table 9, we limit the panel from the default 50 largest insurance sellers in a given state and year, to the largest 30, 20 and 10 insurers. First, insurers' sensitivity to own losses increases in size on the intensive and extensive margin. For number of filings, β increases from 0.12 for largest 50 insurers to 0.97 for the largest ten insurers; for rate change received, β increases from 3.3 to 4.9.

Furthermore, insurers' sensitivity to high friction out-of-state losses also increases in firm size on the intensive and extensive margin. To provide context for the increase in γ^{strict}, let's consider an increase from the mean in other state losses in strict states by standard deviation. The average top 20 firm will respond by increasing its number of filings by 12%, compared to 4% increase for a top 50 firm. Similarly, conditional on applying, the average top 20 firm will receive 18% larger rate change compared to 8% increase for a top 50 firm.

In the second robustness check we do, we look at how the insurers' response to other state losses changes as a function of whether the requests are filed in low, medium or high friction states. We re-estimate Equation 7 only for states s, which are of comparable level of friction (high, medium or low). Results for the number of filings are shown at Table B.2 and for received change - at Table B.3. Filing behavior in stricter states is less sensitive to losses coming from other states, which is a finding in the spirit of Prediction 3a. Specifically, given a level of other state loss, the received change increases in low friction states, but not in medium or high friction states. Similarly, Table B.2 shows that number of filings increases in response to other state losses only for states s being low or medium friction.

Furthermore, the results are unlikely to be driven by financial regulatory frictions. While price regulation varies greatly from state to state, states have a much more unified approach to solvency regulation (Born and Klein, 2015). The state-year and firm fixed effects should also absorb any remaining regulatory idiosyncrasies due to the individual regulator incentives.

5.4. Long Run Pricing Effects

In the previous three sections, we established that due to regulatory frictions, insurers raise prices in low friction states to cover with losses in high friction states. These findings bring up an important question: does the price of insurance increase faster in lower friction states as a result of the cross-subsidization? Consistent with Prediction 3b, we find that low friction states' prices indeed grew 12% faster in over the last 15 years.

To answer this question, we obtain the number of insured house-years and average premium for homeowners' insurance by state and year for the period 2003-2017 from archives of annually updated reports by NAIC.[21] For each state we compute the price growth in homeowners' insurance between 2003 and 2017 (the first and last available dates): P_s^{2017}/P_s^{2003}. Then, we classify each state as high(low) friction if the state's $Discount_s$, estimated from Equation 5 is below(above) the median of the distribution of $Discount$.

Using these data we regress the state homeowners' insurance price growth between 2003 and 2017 on whether the state is low friction or not: $P_s^{2017}/P_s^{2003} = \beta I_s^{\text{low fric}} + \epsilon_s$. The results are shown in Table 10. The average state witnessed price growth of 78%, however the growth was larger for less strict states. In the latter, the price increased by extra 12% over the last 15 years. Overall, these results are consistent with Prediction (3b).

We also find that our friction measure correlates with higher climate risk exposure. The

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[21] "Dwelling Fire, Homeowners' Owner-Occupied, and Homeowners' Tenant and Condominium/Cooperative Unit Owners' Insurance" (2005-2019).

relationship is shown in Figure 7. Specifically, for each state s we plot the estimated Friction$_s$ from Equation 5 versus the average property damage per person between 2009 and 2019.[22] We observe a linear relationship between log losses per person and friction in a given state. This implies that states which have a higher exposure to climate risk also have higher pricing friction and are less likely to approve higher rate change requests. From Figure 7 we know that low friction states experienced lower property damage per capita. They are also the states that experience the fastest 15 year growth. Our findings imply that over time due to regulatory pricing frictions, rates in stricter states reflect less the underlying climate risk than the rates in less strict states.

6. Conclusion

In this paper, we study the pricing and market structure of the U.S. homeowners' insurance market. State regulators impose price controls to improve access to insurance and affordability. We document significant heterogeneity in rate setting frictions across states. Different states exercise varying degrees of price control, which positively correlates with how exposed a state is to climate events. We find that insurers in high friction states are restricted in their ability to set rates and respond less after experiencing climate losses. We find that price controls makes it difficult for insurers in high friction states to adjust rates to fully reflect the true risks they are carrying. In part, insurers overcome pricing frictions by cross-subsidizing insurance across states. In response to losses in high friction states, insurers increase rates in low friction states. As a result, insurance prices grow faster in low friction states, even though they are less exposed to climate losses.

Our findings show that the regulatory frictions have important consequences for how climate risk is shared across states. Our results imply that households in less strict (and low risk) states are subsidizing insurance for households in more strict (and high risk) states. This cross-subsidization can potentially give rise to a moral hazard problem as rates get disjoint from underlying risk. Anecdotal evidence suggest the availability of cheap insurance is one of the reason why high risk areas have experienced disproportionate increase in construction and real estate development.[23] Over time, this makes society less and not more prepared to tackle climate change related challenges. Instead of investing in better urban planning, such developments exacerbate climate losses and cause long-run damage to lives and livelihoods.

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[22]The property damage includes all perils except flooding, since this peril is covered by a federal program, and not by private P&C companies.

[23]A Wall Street Journal news article from October 2020 reports that high risk areas in California have been experiencing faster growth in real estate prices.

Our findings also have implications for the stability of insurers and the long-term access to insurance for households. Central bankers view a healthy insurance sector as a front-line defense against climate risk and a key for preserving financial stability. However, over the long run, price setting frictions make insurers less prepared to deal with large losses. A sudden wave of property losses can bring a strain on the economy directly, through loss of property and employment, and also indirectly, through lack of financial intermediation. All these problems call into question the sustainability of the current system, especially in the face of growing challenges posed by climate risk.[24]

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[24]According to a 2019 survey of insurance companies by the Deloitte Center for Financial Services, more than half of insurance regulators expressed concern for the effects of climate change on insurance availability (Deloitte, 2019). Moreover, a survey of insurance CFOs and CROs documents that large percent of industry leaders view natural catastrophes as a leading source of systemic risk (Pancaldi and Stegemann, 2016).

Figure 1: Losses from climate disasters in the U.S.

The figure plots the total property damages in the U.S. at an annual frequency from 1960 to 2018. The data are from Spatial Hazard Events and Losses Database for the United States (SHELDUS), which includes losses from all known perils, including storms, wildfires, droughts, floods etc. Property damages are inflation adjusted and are shown in 2018 dollars.
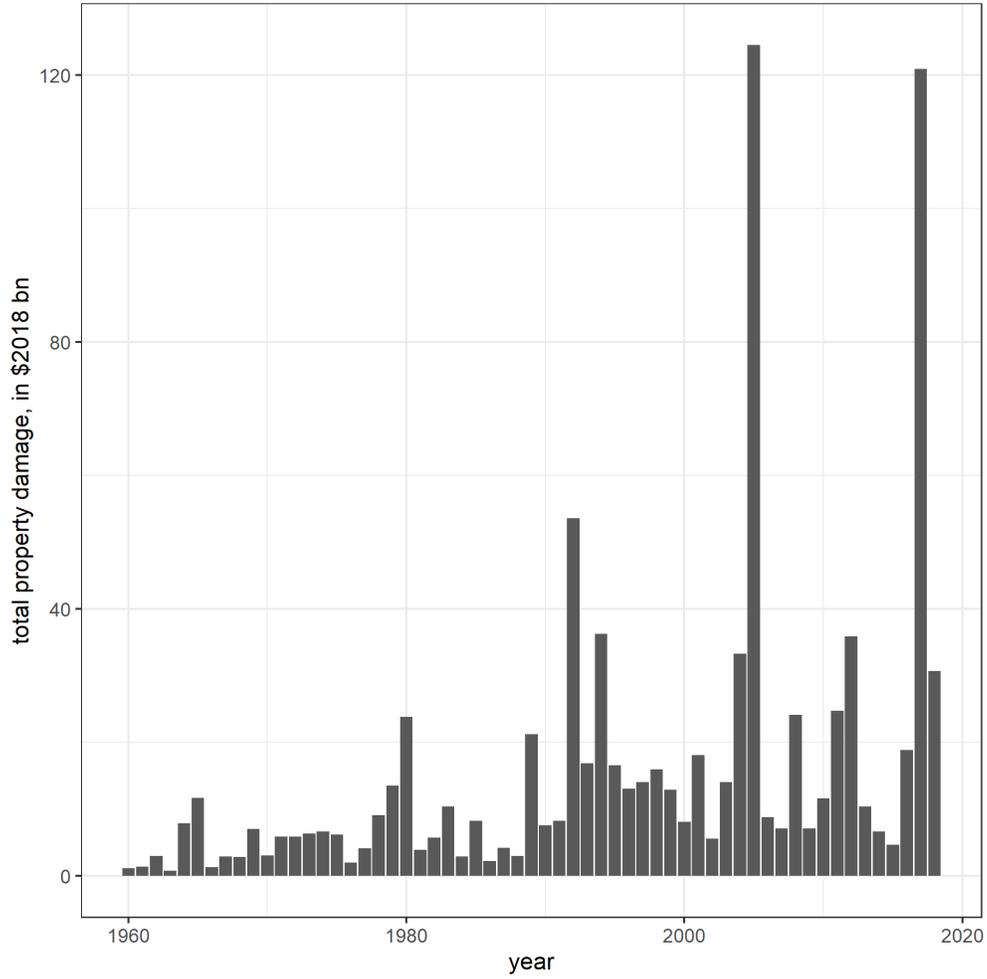
Figure 2: Homeowners' insurance aggregate premia written

The figure plots the aggregate amount of homeowners' insurance sold in the U.S. across all states between 1996 and 2019. The data are from S&P MI and the frequency is annual. Estimates are in billions of dollars.
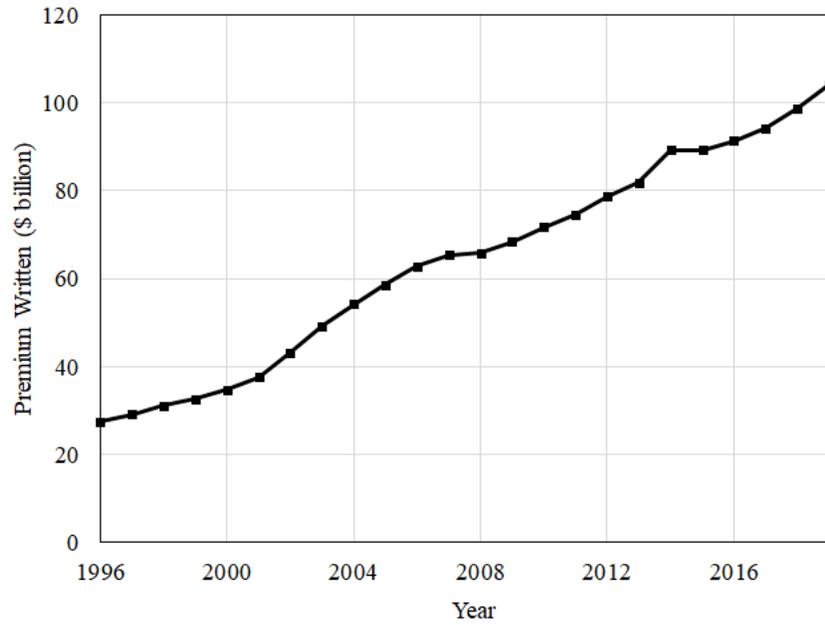
Figure 3: Distribution of rate discount

The figure shows the distribution of rate discount, which is defined as the ratio of rate change received to insurer stated optimal target rate change in state s in year t. The values are winzorsized to the 0.5% and 99.5% end of the distribution. The data are from insurance product filings accessed through S&P MI.
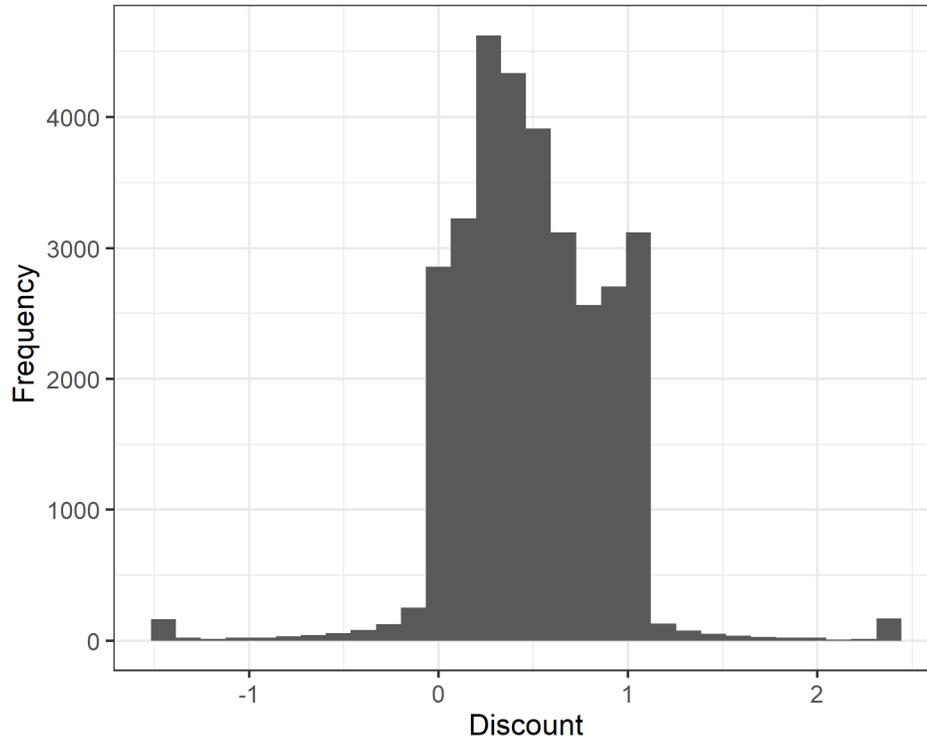
Figure 4: Rate discounts are persistent over time

The figure plots the distribution of rate discount, which is defined as the ratio of received rate change to insurer stated optimal target rate change in state s in year t. We show data from all filings in all states in a given year. The values are winzorsized at 0.5% and 99.5%. The data are from insurance product filings accessed through S&P MI.
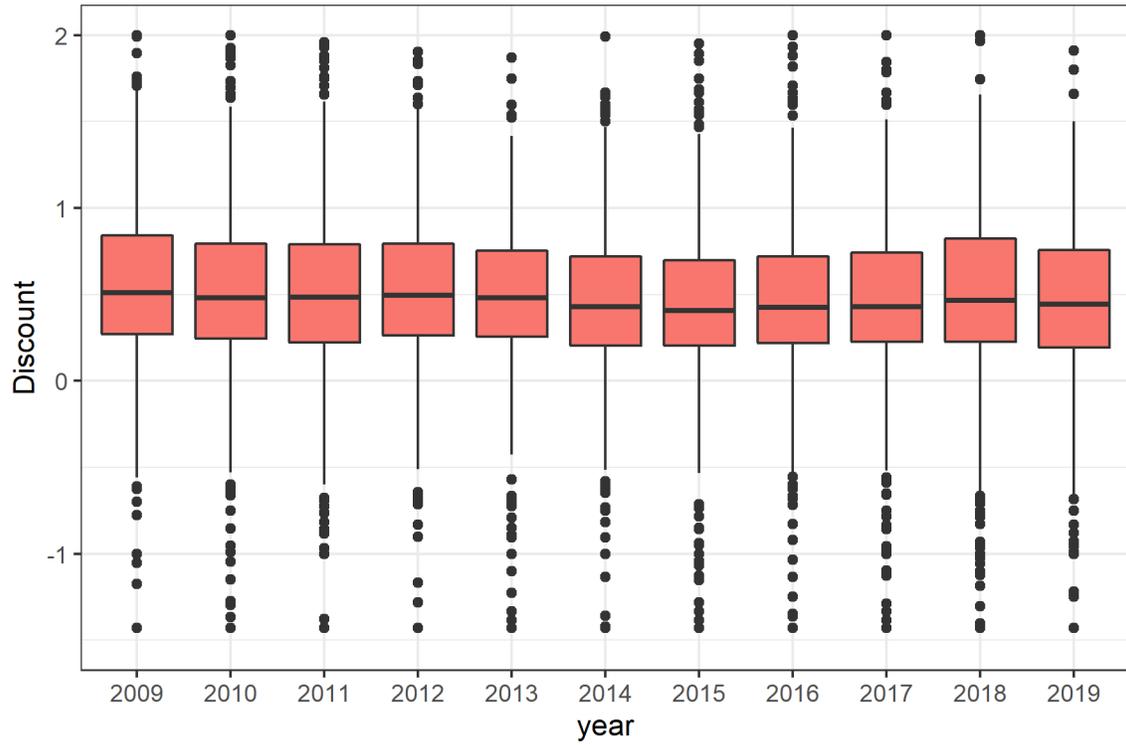
Figure 5: Insurers ask for rate increases often

The figure plots the distribution across states' of the proportion of the largest 20 insurers that applied for a rate increase in a given year. The data are from insurance product filings accessed through S&P MI.
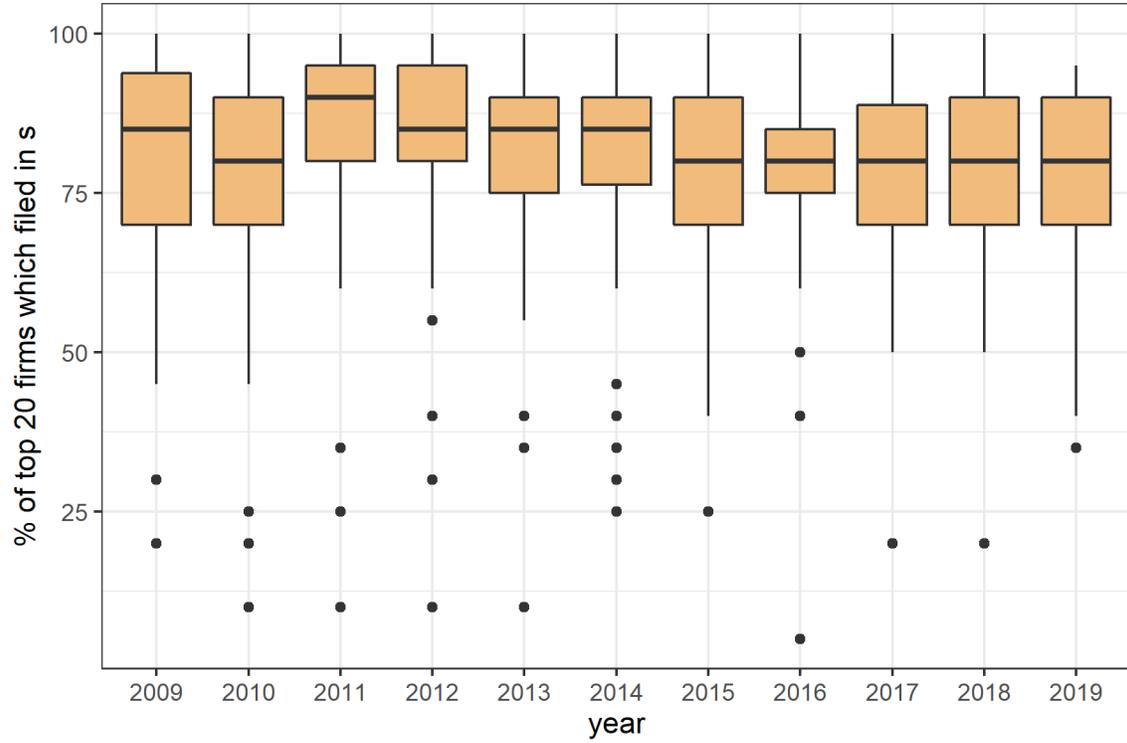
Figure 6: Distribution of the filings' execution time

The figure plots the distribution of the (log) days between a filing's submission date and the regulators' decision date for that filing for each year in our sample. The data are from insurance product filings accessed through S&P MI.
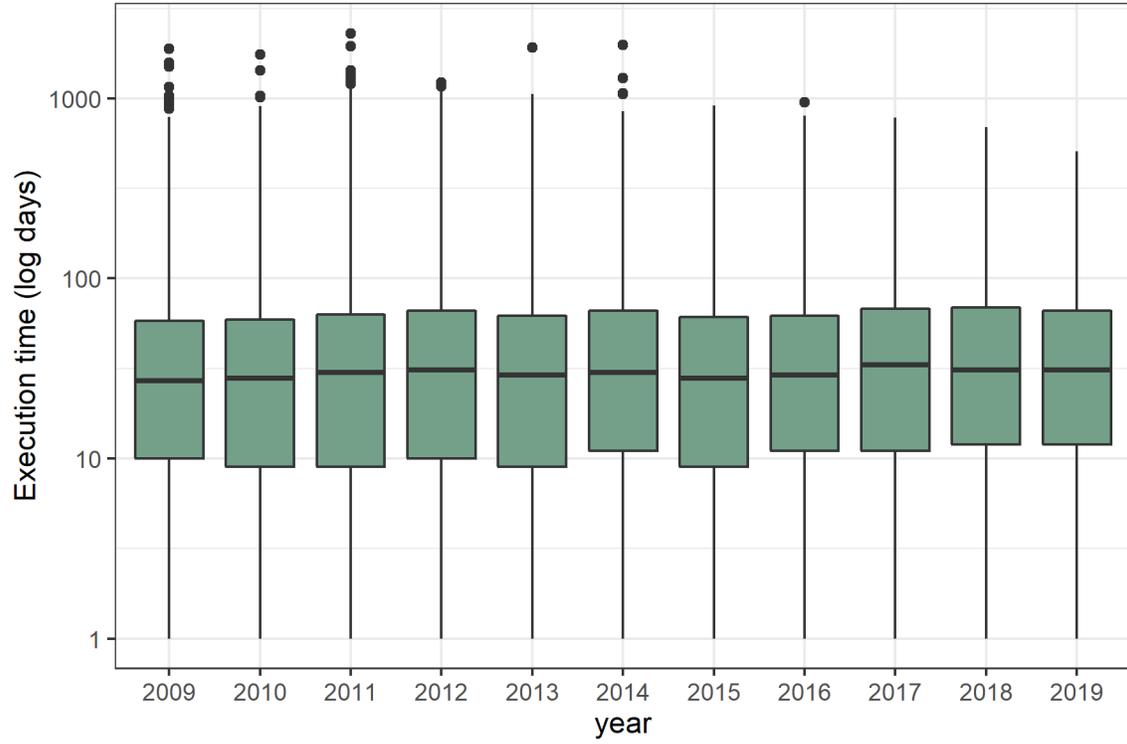
Figure 7: Regulatory pricing frictions and losses from climate disaster

The graph plots $Friction_s$, estimated as in Equation 5 and the average property damage per capita over 2009-2019. We see that states with higher regulatory frictions have higher realized damage per capita. The blue line is a fitted line from the following linear regression: log Property per cap$_s = \alpha + \beta$Friction$_s + \epsilon_s$. The data on climate losses are from SHELDUS. Property damages are inflation adjusted and are shown in 2018 dollars. The data on insurance product filings are from S&P MI.
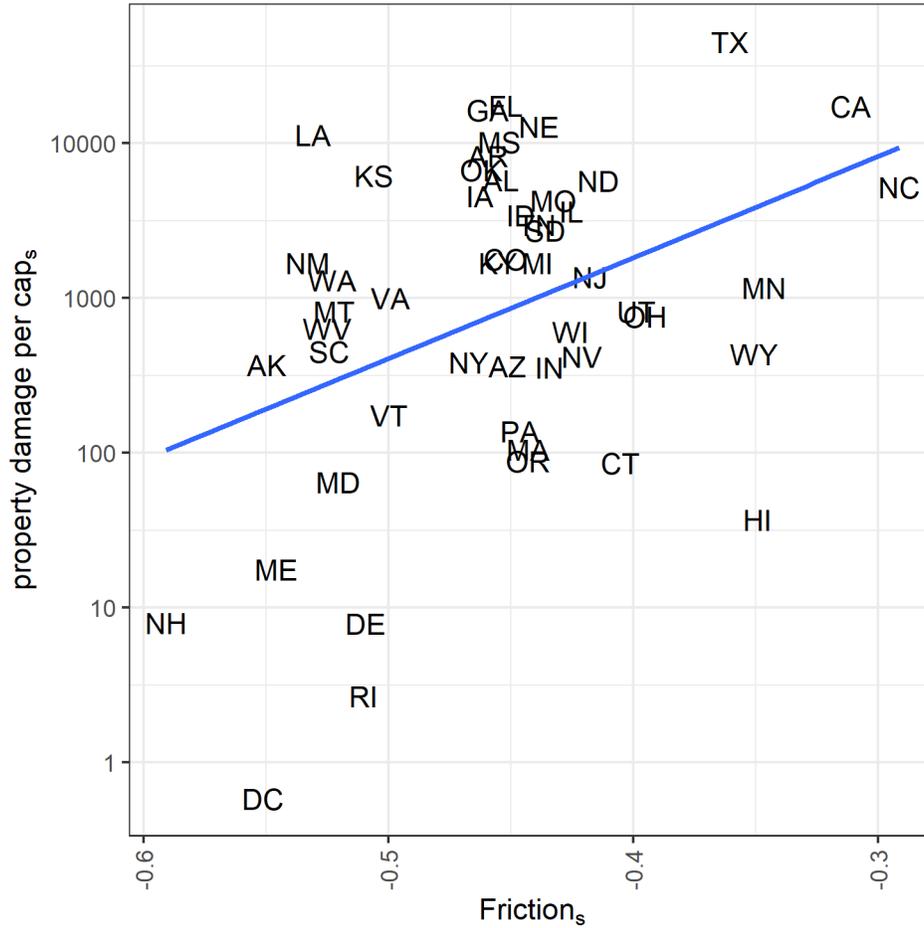
8. TABLES

Table 1: Summary statistics

Below are summary statistics of rate filings and insurer annual filings aggregated at the firm-state-year level for the period between 2009 and 2019. The variables are estimated over a full firm-year-state panel. If a dependent variable is missing, because the firm didn't file for a rate change in a given state and year, the estimates assumes that the number of filings is 0 and the request size is 0. Own st $loss_{i,s,t}$ is the loss ratio (loss/premium) of firm i in year t and state s; other st $loss_{i,\bar{s},t}$ is the loss ratio of f firm i in year t and all states $\bar{s}$ that are not state s; other lines loss estimate the aggregate loss ratio over all lines of business that are not homeowner's insurance. The statistics shown, from left to right, are number of observations, mean, standard deviation, and 1st percentile, 10th percentile, median, 90th percentile, and 99th percentile.

	n	mean	sd	p1%	p10	median	p90	p99
Dependent variables								
n filings$_{i,s,t}$	27942	1.33	1.59	0.00	0.00	1.00	3.00	7.00
request size$_{i,s,t}$	27942	3.54	5.16	-3.48	0.00	1.50	10.00	20.19
Variables of interest								
own st loss$_{i,s,t}$	27932	0.57	0.36	0.00	0.25	0.50	0.93	1.85
other st loss$_{i,\bar{s},t}$	27940	0.55	0.91	0.00	0.24	0.54	0.83	1.47
Control variables								
log net assets$_{i,t}$	27869	13.53	2.06	9.04	10.99	13.29	16.39	17.59
log RBC ratio$_{i,t}$	27793	7.41	1.37	5.74	6.13	6.98	9.99	10.86
other lines loss$_{i,t}$	21623	0.59	0.13	0.29	0.45	0.59	0.74	0.88
reinsurance ratio$_{i,t}$	27869	0.10	0.20	0.00	0.00	0.03	0.27	0.91

Table 2: Discounts predict future losses

The table presents estimates from Equation 4. Loss Ratio$_{i,s,t+1}$ is the ratio of losses divided by premium for insurer i in state s at year $t+1$. Discount$_{i,s,t}$ measures the average discount from filings of insurer i in state s at year t. The panel is conditional on insurer i applying for rate change and being among the largest j insurers by premium sold in state s and year t, where j is 50, 30, 20 or 10 in columns (1), (2) (3) or (4).

Note: *p<0.1; **p<0.05; ***p<0.01

	loss ratio$_{i,s,t+1}$			
	(1)	(2)	(3)	(4)
Discount$_{i,s,t}$	−1.486**	−1.659*	−0.895*	−1.984***
	(0.695)	(0.850)	(0.523)	(0.632)
rank	≤50	≤30	≤20	≤10
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	11,309	7,599	5,365	2,953
R^2	0.619	0.708	0.771	0.834
Adjusted R^2	0.582	0.668	0.733	0.785

Table 3: Larger requests take longer time

The table shows results regression results of log execution days$_{f,s,t}$ = size of change$_{f,s,t}$ + α_x + $_{f,s,t}$. The dependent variable log execution days is log of the days between the date that insurer i's submitted filing f (in state s in year t), and the final regulatory decision. The variable of interest is the rate change received in f. Column (1) includes no fixed effects ($\alpha_x = \alpha$). Column(2) includes filing state-year submission fixed effects ($\alpha_x = \alpha_{s,t}$). Column (3) includes insurer-year-state fixed effect ($\alpha_x = \alpha_{i,s,t}$). The standard errors in column (2) are clustered at the state level. The standard errors in column (3) are clustered at the insurer and state level.

Note: *p<0.1; **p<0.05; ***p<0.01

| | log execution time (days) | | |
	(1)	(2)	(3)
requested change	0.019***	0.026***	0.034***
	(0.001)	(0.005)	(0.008)
E[LHS]	3.17	3.17	3.17
FE		$s \times t$	$i \times s \times t$
Observations	49,521	49,521	49,521
Adjusted R^2	0.008	0.375	0.391

Table 4: Discount and company size

We regress the average insurer's Discount on proxies for size: $\text{Discount}_{i,s,t} = \beta \text{Firm Size}_{i,s,t} + \alpha_x +_{i,s,t}$. In columns (1) and (2) we proxy for insurer's size by the rank of the insurer within a given state and year, e.g. if a insurer's $\text{rank}_{i,s,t}$ is 7, this means that insurer i is the 7th largest insurer by premium sold in year t in state s. In columns (3) and (4) we proxy for insurer's size using log of the homeowners' insurance premium sold by insurer i in year t and in state s. In columns (5) and (6) we proxy for insurer's size by the insurer's market share, e.g. the homeowners' insurance premium sold by insurer i as a fraction of all insurance sold in state s and in year t. Estimates in columns (1), (3), and (5) include no standard error clustering or fixed effects ($\alpha_x = \alpha$). Estimates in columns (2), (4), and (6) have standard errors clustered at the state level and state-times-year fixed effects ($\alpha_x = \alpha_{s,t}$).

Note: *p<0.1; **p<0.05; ***p<0.01

	Discount$_{i,s,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
rank$_{i,s,t}$	0.0004***	0.001***				
	(0.0001)	(0.0001)				
log premium$_{i,s,t}$			−0.011***	−0.009***		
			(0.001)	(0.003)		
market share					−0.625***	−0.669***
					(0.078)	(0.107)
Constant	0.470***		0.581***		0.501***	
	(0.004)		(0.012)		(0.003)	
E[LHS]	0.49	0.49	0.49	0.49	0.49	0.49
Fixed Effects		$s \times t$		$s \times t$		$s \times t$
Observations	24,465	24,465	24,430	24,430	24,465	24,465
Adjusted R^2	0.002	0.026	0.003	0.025	0.003	0.027

Table 5: Price setting response to own losses

The table present regression results from Equation 6. The dependent variable in columns (1) to (3) is the number of rating change requests filed by insurer i in state s and year t; if the insurer submitted no rate filings, the variable is 0. The dependent variable in columns (4) to (6) is the average discount (rate change received/ rate change target) of the filings filed by insurer i in state s and year t. This variable is conditional on a insurer filing at least one rate change request in state s and year t. Own st $loss_{i,s,t}$, is the losses to premiums of insurer i in state s in year t. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and percent of premiums covered by reinsurance of insurer i in year t. The panel in columns (1) and (4)/(2) and (5)/(3) and (6) is restricted to the largest 50 insurers by premium sold in states s which have high/medium/low level of friction, as estimated by average discount (see Equation 5). All regressions include insurer and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

Note: *p<0.1; **p<0.05; ***p<0.01

	n rate filings$_{i,s,t+1}$			Discount$_{i,s,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
own st loss$_{i,s,t}$	0.198	0.011	0.143**	−0.059*	−0.040*	0.060
	(0.141)	(0.052)	(0.055)	(0.031)	(0.023)	(0.043)
State friction	High	Medium	Low	High	Medium	Low
E[LHS]	1.2	1.5	1.1	0.4	0.5	0.5
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	5,984	6,508	6,538	2,928	3,822	3,136
Adjusted R^2	0.358	0.394	0.321	0.178	0.173	0.092

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Table 6: Number of firms which exited a state between 2009 and 2018

We count the times a given firm stopped selling homeowner insurance (exits) in a given state, by the rank of the firm in the year before exit. We show the percentage of exits of state-years in each category. For example, we observe 7 exits by firms that were formerly in the ten largest in the state. Given that there are 10 years, 51 state jurisdictions, the number of exits is 0.14% from the state-year-top 10 observations.

firm size	n exits	pct exited
top 10	7	0.14
top 11-20	22	0.43
top 21-30	42	0.82
top 31-50	148	1.47
rest	2425	5.62

Table 7: Effect of in and out-of-state loss ratios on decision to exit

The table present regression results from Equation 6. The dependent variable is an indicator, which equals 1 if insurer i stopped selling insurance in state s in year $t+1$ and 0 otherwise. Own st $\text{loss}_{i,s,t}$, is the losses to premiums of insurer i in state s in year t. Other st $\text{loss}_{i,s,t}$, is the losses to premiums of insurer i in all states *except* s in year t. The period is 2009 to 2018, since our data ends in 2019, so it is unknown if a insurer will exit in $t+1 = 2020$. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and percent of premiums covered by reinsurance of insurer i in year t. The panel in column $(1)/(2)/(3)/(4)$ is restricted to any/high/medium/low friction states and the largest 50 insurers in a given state and year by premium sold. All regressions include insurer and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

Note: *p<0.1; **p<0.05; ***p<0.01

	is exit $\text{year}_{i,s,t+1}$			
	(1)	(2)	(3)	(4)
own st $\text{loss}_{i,s,t}$	0.002	0.005	0.006	−0.003
	(0.002)	(0.003)	(0.004)	(0.004)
other st $\text{loss}_{i,\bar{s},t}$	0.007	0.020	−0.005	0.012
	(0.008)	(0.014)	(0.004)	(0.009)
E[LHS]	0.008	0.008	0.006	0.009
State friction	Any	High	Medium	Low
Controls	Yes	Yes	Yes	Yes
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	17,413	5,459	5,971	5,983
Adjusted R^2	0.299	0.291	0.302	0.386

Table 8: Cross-Subsidization of insurance rates across states

The table shows results from the regression shown in Equation 7 in columns (1) and (3), and from Equation 8 in columns (2) and (4), where other state loss are split in three groups based on the regulatory frictions in the other states $\bar{s}$. Columns (1) and (2) use as a dependent variable number of rate filings which insurer i filed at state s in year t, and if the insurer did not apply for a rate change, the variable is 0. Columns (3) and (4) use as a dependent variable the average change received, weighted by affected premium, among the filings of insurer i at state s in year t, conditional on applying. In row $(1)/(2)$, the independent variable is the loss ratio from only stats s/all states except s. In row $(3)/(4)/(5)$, the independent variable is the loss ratio from other states, which are high/medium/low friction. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and percent of premiums covered by reinsurance of insurer i in year t. The panel is restricted to the largest 50 insurers in a given state and year. All regressions include insurer and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

Note: *p<0.1; **p<0.05; ***p<0.01

	n rate filings$_{i,s,t+1}$		rate Δ Received$_{i,s,t+1}$	
	(1)	(2)	(3)	(4)
own st loss$_{i,s,t}$	0.121***	0.117***	3.372***	3.341***
	(0.043)	(0.041)	(0.316)	(0.316)
other st loss$_{i,\bar{s},t}$	0.083***		0.576***	
	(0.029)		(0.180)	
other st loss$_{i,\bar{s},t}^{hFrct}$		0.113**		0.919***
		(0.045)		(0.205)
other st loss$_{i,\bar{s},t}^{mFrct}$		0.068		0.961***
		(0.058)		(0.308)
other st loss$_{i,\bar{s},t}^{lFrct}$		0.093		0.393
		(0.055)		(0.299)
E[LHS]	1.3	1.3	5.4	5.4
Controls	Yes	Yes	Yes	Yes
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	19,030	19,064	12,422	12,448
Adjusted R^2	0.360	0.362	0.280	0.280

Table 9: Cross-Subsidization of insurance rates across states: by insurer rank

The table shows results from the regression shown in Equation 8, where other state loss are split in three groups based on the regulatory frictions in the other states $\bar{s}$. In row (2)/(3)/(4), the variable is the loss ratio from other states, which are high/medium/low friction. Columns (1) to (4) use as a dependent variable number of rate filings which insurer i filed at state s in year t, and if the insurer did not apply for a rate change, the variable is 0. Columns (5) to (8) use as a dependent variable the average change received, weighted by affected premium, among the filings of insurer i at state s in year t, conditional on applying. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and percent of premiums covered by reinsurance of insurer i in year t. The panel in columns (1) and (5) is restricted to the largest 50 insurers in a given state and year. Similarly, columns (2) and (6) restrict the panel to the largest 30 insurers, columns (3) and (7) restrict the panel to the largest 20 insurers, and columns (4) and (8) restrict the panel to the largest 10 insurers. All regressions include insurer and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

Note: *p<0.1; **p<0.05; ***p<0.01

| | n rate filings$_{i,s,t+1}$ | | | | rate Δ received$_{i,s,t+1}$ | | | |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
own st loss ratio$_{i,s,t}$	0.117***	0.223***	0.352***	0.864***	3.341***	3.395***	4.204***	4.849***
	(0.041)	(0.083)	(0.119)	(0.221)	(0.316)	(0.395)	(0.518)	(0.844)
other st loss ratio$_{i,\bar{s},t}^{strict}$	0.113**	0.233***	0.374***	0.266	0.919***	1.119***	1.769***	1.553**
	(0.045)	(0.082)	(0.122)	(0.195)	(0.205)	(0.299)	(0.371)	(0.666)
other st loss ratio$_{i,\bar{s},t}^{med}$	0.068	0.187*	0.213	0.021	0.961***	0.582	0.743	1.424*
	(0.058)	(0.106)	(0.170)	(0.262)	(0.308)	(0.364)	(0.486)	(0.734)
other st loss ratio$_{i,\bar{s},t}^{lax}$	0.093	0.077	0.103	0.209	0.393	0.515	0.011	-0.235
	(0.055)	(0.095)	(0.116)	(0.178)	(0.299)	(0.341)	(0.396)	(0.496)
E[LHS]	1.29	1.46	1.58	1.75	5.43	5.2	4.96	4.6
rank	$\leq$50	$\leq$30	$\leq$20	$\leq$10	$\leq$50	$\leq$30	$\leq$20	$\leq$10
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	19,064	11,504	7,643	3,739	12,448	8,135	5,652	2,927
Adjusted R^2	0.362	0.363	0.372	0.408	0.280	0.289	0.311	0.307

Table 10: Price setting frictions and long-term growth in insurance rates

We regress the price growth between 2003 and 2017 in each of the 51 jurisdictions on a proxy for state-level pricing frictions. We estimate each state's average Discount_s, as in Equation 5. The proxy for pricing frictions is an indicator variable which is 1 if state s is in the top half of Discount_s, i.e. is less strict.

Note: *p<0.1; **p<0.05; ***p<0.01

	Avg $\text{Price}^{HO}_{s,2017}$/Avg $\text{Price}^{HO}_{s,2003}$
Least strict half s	0.120*
	(0.070)
Constant	1.775***
	(0.049)
E[LHS]	1.83
Observations	51
Adjusted R^2	0.037

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A. Rate Filings and Anecdotal Evidence

Figure A.1: Anecdotal Evidence: Rate Regulation

Allstate Wins 30% Rate Hike: **Homeowners with Allstate Insurance policies will face a 30 percent increase in 2002** after approval of a base rate increase at Thursday's meeting of the State Board for Property and Casualty Rates.

Although it will be little consolation, the increase could have been worse. **Allstate had asked for a 48.6 percent increase** yielding more than $22 million. However, from the time Allstate filed its request in August, **approval of such a large rate hike appeared unlikely** -- the board has a long-standing policy of not granting rate increases of more than 25 percent.

Allstate officials said a changing marketplace has left the company with no other option than to ask for a huge increase. **Although the company has a goal of making a 5 percent underwriting profit each year, Allstate has failed to do so "for years" in Oklahoma,** officials said. **For five of the last six years, Allstate has lost money on homeowners underwriting in Oklahoma**, officials said, with losses of more than $70 million.

Source: The Journal Record, November 2001

Figure A.2: Anecdotal Evidence: Cross-Subsidization

Allstate spikes Illinois homeowners insurance rates for almost 200K policyholders:

The second largest home insurer in the state is raising rates by 8 percent in early 2020. Allstate will be increasing its Illinois homeowners insurance rates **by the largest amount the state has seen in several years.** By early next year, policyholders will be paying an average of 8 percent more for their coverage than they are this year.

As of yet, Allstate has not officially announced specifically why the premiums for home coverage were increased to that extent in the state. That said, Illinois is a state in which homeowners insurance rates are unregulated. This gives insurers complete control over when and why their rates change.

The Illinois homeowners insurance rates are far from the only ones in the country to rise. **Many states are watching their home insurers increase their premiums** as a result of many factors, **particularly weather events linked with climate change. California's wildfires provides a clear example of this trend.**

Source: The Journal Record, November 2019

Figure B.1: Market Concentration of Homeowners' Insurance Market

The figure plots the market share of homeowners' insurance sold by the largest insurers in a given state. Market share is computed as premium sold by the largest insurers divided by total premium sold in the states in a given year and state - and averaged over the 11 years between 2009 and 2019. States are ordered from low to high market share of the top 5 insurers.
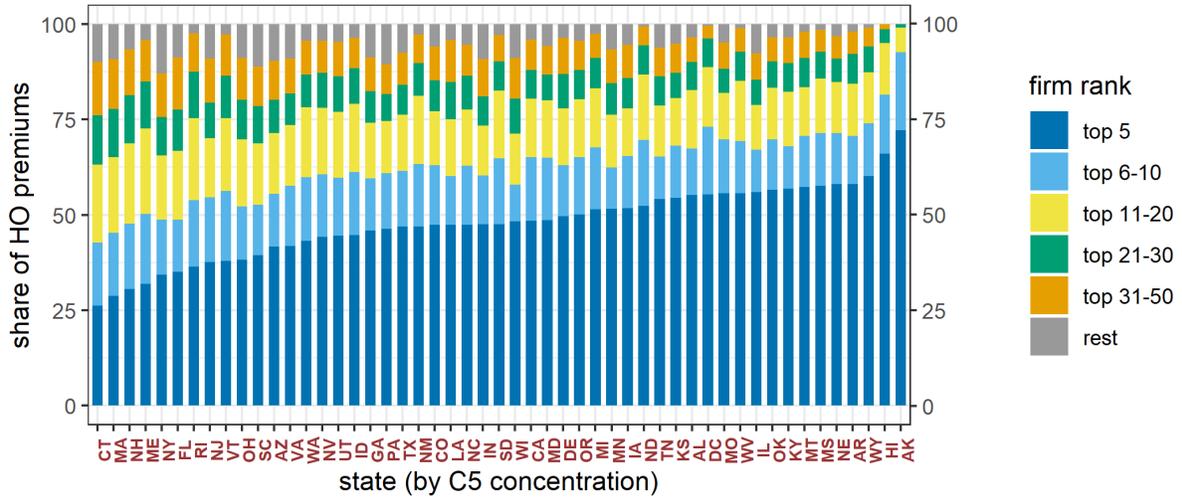
Table B.1: Firms' response to losses in other states: robustness to firm size

The table shows results from the regression shown in Equation 7. Columns 1 to 4 use as a dependent variable number of rate filings which firm i filed at state s in year t, and if the firm did not apply for a rate change, the variable is 0. Columns 5 to 8 use as a dependent variable the average change received, weighted by affected premium, among the filings of firm i at state s in year t, and the panel is conditional on firms applying for a rate change. If the firm did not apply for a rate change, the variable is 0. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and percent of premiums covered by reinsurance of firm i in year t. The panel in columns (1) and (5) is restricted to the largest 50 firms in a given state and year. Similarly, columns (2) and (6) restrict the panel to the largest 30 firms, columns (3) and (7) restrict the panel to the largest 20 firms, and columns (4) and (8) restrict the panel to the largest 10 firms. All regressions include firm and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

Note: *p<0.1; **p<0.05; ***p<0.01

	n rate filings$_{i,s,t+1}$				rate Δ received$_{i,s,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
own st loss$_{i,s,t}$	0.121***	0.233***	0.377***	0.861***	2.134***	2.532***	3.669***	4.925***
	(0.043)	(0.085)	(0.120)	(0.216)	(0.278)	(0.382)	(0.476)	(0.842)
other st loss$_{i,\bar{s},t}$	0.083***	0.162**	0.196	0.522***	0.581***	0.717***	0.660**	1.077**
	(0.029)	(0.080)	(0.122)	(0.195)	(0.170)	(0.263)	(0.276)	(0.529)
E[LHS]	1.3	1.5	1.6	1.7	3.6	3.7	3.7	3.6
Rank	≤50	≤30	≤20	≤10	≤50	≤30	≤20	≤10
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	19,030	11,485	7,630	3,733	19,030	11,485	7,630	3,733
Adjusted R^2	0.360	0.362	0.371	0.393	0.244	0.262	0.273	0.285

Table B.2: Firms' response to losses (number of filings) - split s by high, medium, and low friction states

The table shows results from the regression shown in Equation 7, estimated for various types of filing states, split by regulatory frictions. The dependent variable number of rate filings which firm i filed at state s in year t, and if the firm did not apply for a rate change, the variable is 0. If the firm did not apply for a rate change, the variable is 0. State s in columns (1-4)/(5-8)/(9-12) is restricted to high/medium/low regulatory friction states. The data in columns (1), (5), and (9) is restricted to the largest 50 firms in a given state and year. Similarly, columns (2), (6), and (10) restrict the data to the largest 30 firms, columns (3), (7), and (11) restrict the data to the largest 20 firms, and columns (4), (8) and (12) restrict the data to the largest 10 firms. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and percent of premiums covered by reinsurance of firm i in year t. All regressions include firm and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

Note: *p<0.1; **p<0.05; ***p<0.01

	n rate filings$_{i,s,t+1}$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
own st loss$_{i,s,t}$	0.198	0.359	0.421	0.818**	0.011	0.075	0.246	0.727**	0.143**	0.225**	0.434**	0.933*
	(0.141)	(0.246)	(0.242)	(0.333)	(0.052)	(0.132)	(0.152)	(0.285)	(0.055)	(0.099)	(0.157)	(0.494)
other st loss$_{i,\bar{s},t}$	0.083	0.256	0.292	0.498	0.068*	0.075	0.104	0.401	0.235***	0.488***	0.612***	0.686
	(0.056)	(0.177)	(0.202)	(0.292)	(0.035)	(0.060)	(0.102)	(0.448)	(0.072)	(0.123)	(0.196)	(0.396)
E[LHS]	1.2	1.4	1.5	1.7	1.5	1.7	1.8	2	1.1	1.3	1.4	1.6
State friction	High	High	High	High	Med	Med	Med	Med	Low	Low	Low	Low
Rank	≤50	≤30	≤20	≤10	≤50	≤30	≤20	≤10	≤50	≤30	≤20	≤10
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	5,984	3,577	2,404	1,166	6,508	3,921	2,591	1,230	6,538	3,987	2,635	1,337
Adjusted R^2	0.358	0.363	0.392	0.541	0.394	0.379	0.379	0.383	0.321	0.332	0.335	0.323

Table B.3: Firms' response to losses (rate Δ received) - split s by high, medium, and low friction states

The table shows results from the regression shown in Equation 7, estimated for various types of filing states, split by regulatory frictions. The dependent variable is the average change received, weighted by affected premium, among the filings of firm i at state s in year t. If the firm did not apply for a rate change, the variable is 0. State s in columns (1-4)/(5-8)/(9-12) is restricted to high/medium/low regulatory friction states. The data in columns (1), (5), and (9) is restricted to the largest 50 firms in a given state and year. Similarly, columns (2), (6), and (10) restrict the data to the largest 30 firms, columns (3), (7), and (11) restrict the data to the largest 20 firms, and columns (4), (8) and (12) restrict the data to the largest 10 firms. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and percent of premiums covered by reinsurance of firm i in year t. All regressions include firm and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

Note: *p<0.1; **p<0.05; ***p<0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						rate Δ received$_{i,s,t+1}$						
own st loss$_{i,s,t}$	1.642***	1.960**	3.148***	4.782***	2.247***	2.528***	3.323***	4.626***	2.196***	2.837***	4.310***	5.569***
	(0.515)	(0.671)	(0.850)	(1.384)	(0.367)	(0.337)	(0.566)	(1.451)	(0.470)	(0.871)	(0.957)	(1.385)
other st loss$_{i,\bar{s},t}$	0.179	0.651	0.563	0.247	0.663**	0.578**	0.479**	1.336	1.501***	1.741**	2.745***	2.684*
	(0.188)	(0.478)	(0.516)	(0.691)	(0.274)	(0.268)	(0.216)	(1.045)	(0.413)	(0.608)	(0.769)	(1.436)
E[LHS]	3.3	3.4	3.3	3.3	4.4	4.5	4.5	4.1	3.1	3.3	3.3	3.4
State friction	High	High	High	High	Medium	Medium	Medium	Medium	Low	Low	Low	Low
Rank	≤50	≤30	≤20	≤10	≤50	≤30	≤20	≤10	≤50	≤30	≤20	≤10
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$	$s \times t + i$
Observations	5,984	3,577	2,404	1,166	6,508	3,921	2,591	1,230	6,538	3,987	2,635	1,337
Adjusted R^2	0.262	0.265	0.285	0.317	0.295	0.302	0.308	0.316	0.174	0.206	0.218	0.244