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

Sangmin S. Oh† Ishita Sen‡ Ana-Maria Tenekedjieva§

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Abstract

Homeowners' insurance provides households financial protection from climate losses. To improve access and affordability, state regulators impose price controls on insurance companies. 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. In high friction states, insurers are more restricted in their ability to set rates and adjust rates less frequently and by a lower amount 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.

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†Oh: University of Chicago - Booth School of Business (oh@chicagobooth.edu).
‡Sen: Harvard Business School (isen@hbs.edu).
§Tenekedjieva: Federal Reserve Board of Governors (ana-maria.k.tenekedjieva@frb.gov).

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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., one of the salient ways 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 regulators subject insurance companies to heavy regulation, including price controls. However, such interventions could make it harder for insurers to set rates that reflect the growing losses from climate disasters, leading to distortions in market outcomes. Despite the increasing urgency of these issues, we have little systematic understanding of how 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 explore the consequences of rate setting frictions on the pricing and market structure of the U.S. homeowners' insurance market. Homeowners' insurance are retail contracts that provide households and lenders (who require insurance as a condition to a mortgage loan) protection against losses from climate events, e.g., wildfires, hurricanes, or windstorms. Homeowners is an important market both from the perspective of Property & Casualty (P&C) insurers, as it is the second largest market with over $100 billion of premiums written each year, and from the perspective of home owners, as it contributes to a large share of households' expenses towards owning a home.[3]

Using novel data, we construct a new measure of rate setting frictions for individual U.S. states and document that the frictions are large and binding in a subset of states, which also tend to be more exposed to climate losses. To overcome these frictions, insurers engage in large-scale cross-subsidization: in response to losses in high friction states, insurers respond instead by increasing rates in low friction states. As a result, rates have grown faster in low friction states despite lower climate risk exposure, suggesting a long-run decoupling of prices and risk. In high friction states, we also show that insurance availability has been negatively affected. We then conclude by providing a model of insurer rate-setting with regulatory frictions that parsimoniously captures these empirical patterns.

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, prices adjust

[1]The Intergovernmental Panel on Climate Change (IPCC) documents changes in extreme events' characteristics and forecasts that disasters in the years to come will increase in both severity and frequency (U.S. Global Change Research Program, 2017).

[2]Based on the 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]Homeowners costs as much as 60% of what households pay towards their mortgage interest expenses in the average state in the U.S. and there is also large cross-state variation in these costs (Figure 3).

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

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freely in response to shifts in marginal costs, demand elasticities, and financing frictions, all of which are potentially affected by losses from climate disasters. For example, after the massive losses from the California wildfires, insurers likely increased their expectations for future wildfires' frequency, thereby driving up the marginal cost of selling insurance. Furthermore, losses may also worsen insurers' financing conditions (Froot and O'Connell, 1999) and affect households' propensity to buy insurance as households adjust their priors (Dessaint and Matray, 2017), thereby contributing to higher equilibrium insurance prices. Thus, in theory, prices should respond to realized losses as homeowners contracts are short-dated (e.g., about 1 year) and can be repriced often. But under regulatory frictions, insurers may not actually be able to adjust prices to their desired extent or as frequently as they'd prefer.

To test the implications of rate setting frictions for pricing and supply of insurance, we start by constructing a new measure of rate setting frictions for individual states using a novel data on rate change filings. State regulators require that *all* rate change requests be filed with insurance departments in each state that an insurer sells homeowners insurance in, including detailed explanation of why a rate change is being requested. For each rate change filing, we observe the insurers' self-reported *target* (model implied) rate change for that state (RateΔTarget) and the rate change insurers finally *receive* (RateΔReceived) after state regulators have adjudicated the request.

Using these two features of the data, we compute the wedge between insurers' target rate change and what they receive from state regulators to quantify the extent of pricing frictions in each state. Specifically, we define Rate Wedge as the ratio of (RateΔReceived) to (RateΔTarget) for each insurer in each state and at a given point in time. Rate Wedge captures how far below the stated target insurers set rates. We document that insurer stated target rate change is significantly greater than the rate change received for a majority of the rate change filings and the median Rate Wedge is 0.5. However, crucially, there is significant variability in the average Rate Wedge across states. Exploiting this heterogeneity, we categorize U.S. states into three terciles by the prevalance of rate-setting frictions into High, Medium, and Low friction states. One advantage of our measure is that it accounts for regulators' actual actions rather than their stated objectives and policies, which may not fully capture state-specific heterogeneity and therefore suffer from potential implicit biases.[5]

We first demonstrate that our classification of states indeed captures the differential ability of insurers to easily update insurance prices across states. To do so, we estimate the

[5]For example, regulatory strictness can vary significantly 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.

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extent to which pricing behavior responds to realized losses differentially across states. We exploit the fact that many insurers operate in multiple states, which allows us to track the rate setting behavior of the same insurer across states. We document that insurers in high friction states are more restricted in their ability to adjust rates in response to losses than insurers in low friction states: (i) in high friction states, in response to losses, insurers are significantly less likely to file for a rate change; and (ii) future target rate changes increase more in response to losses than do future received rate changes, but only in high friction states. Instead, in low friction states, in response to losses, future received rate changes increase more than future received rate changes. Intuitively, and as we show theoretically, rate filings are costly and, in high friction states, the expected benefits of filing for a rate change are lower. As a result, insurers exert less effort in high friction states and their pricing behavior responds less to losses relative to low friction states, both in the propensity of filing and the magnitude of the received changes relative to target.

The preceding results on pricing frictions are consistent with multiple interpretations regarding the role of regulators and the behavior of insurers. For example, it could be the case that the regulator is fully informed of the underlying risks being insured and precisely knows the desired level of rate change to be passed through to consumers. On the other hand, the regulator could start uninformed and take time to learn the optimal Rate Wedge to be applied to insurers' requests. It may also be the case that the insurers are coordinating to report inflated target rate changes in the presence of an uninformed regulator. Distinguishing one interpretation from others is critical for interpreting the rate wedge as a *regulatory* friction and evaluating micro-foundations for the insurers' and regulators' behaviors.

To examine which interpretation is most consistent with data, we present three pieces of empirical evidence. First, we show that it takes longer to process rate changes that are greater in magnitude and get filed in high friction states. Second, the pricing frictions are larger for insurers that have greater market shares in a given state. Finally, we find that insurers reporting inflated targets is unlikely based on a predictive regression of future profitability on today's Rate Wedge. These findings imply that the pricing friction is driven mostly by regulators who seem not fully informed and actively spend time to decide on the approval. They also suggest that the degree of coordination among insurers is not strong enough to lead to inflated target rates across the board. Altogether, they support the interpretation of the friction as a regulatory one and the possibility of uncertainty associated with climate risk as the fundamental driver of the regulators' behaviors.

Given the important role of regulators in driving these pricing frictions, we next examine how the insurers' pricing behavior in *low* friction states responds to its losses in *high* friction states. To do so, we estimate the responsiveness of insurer's pricing behavior in a given state

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to losses in the other states it operates in (*out-of-state* losses) and proceed in two steps. First, we ask in which states insurers' pricing respond to out-of-state losses. We find the answer to be low friction states. In other words, when we track the same insurer's pricing behavior across sates, we find that the insurer responds to out-of-state losses by changing its pricing behavior – both propensity and the magnitude of the rate change – in low friction states but not in high friction states it operates in. The economic magnitude of the rate spillovers is large: after a large jump in out-of state losses (from 10^{th} to 90^{th} percentile), the average insurer is 13% more likely to apply for a rate change and receives a 24% larger rate change in low friction states relative to high friction states. Second, we ask if the response to out-of-state losses varies depending on whether the losses come from low, medium, or high friction states? We find that when an insurer responds to out-of-state losses, she responds *only* to losses occurring in other high (and medium) friction states it operates in but not to losses in low friction states. The intuition is that in low friction states, insurers are presumably already able to adjust rates in response to losses occurring within that state.

To examine the underlying mechanism further, we conduct several additional tests. First, we show that the pricing response to out-of-state losses is not driven simply by financial frictions as in Froot and O'Connell (1999) and Ge (2020). If prices shift simply because of financing constraints, then the cross-subsidization patterns are expected to be stronger in financially constrained insurers. Using definitions of financing constraints from Ge (2020), contrary to this hypothesis, we find similar rate spillover patterns for both constrained and unconstrained insurers. Second, the shift in prices could also occur because contract features change over time in a different manner across high and low friction states. While it is hard to rule this out completely due to data limitations, we provide three sets of evidence that contract features do not appear to have shifted in a different fashion across states in a meaningful way. Third, a necessary condition for cross-subsidization is relatively inelastic demand. One factor behind this is that homeowners insurance is mandatory to receive bank loans. Moreover, our findings on cross-subsidization are especially pronounced for large insurers who operate in a homogeneous set of states, thus making it more likely that competitive pressure does not counteract these spillovers. Nevertheless we do observe that the degree to which low friction states respond to out-of-state losses depends on the level of competition in these states and how exposed insurers operating in the states are to high friction states. Finally, we show that the responsiveness to out-of-state losses is not due to learning about climate risks from observing losses in states that share similar risk characteristics as the filing state.

Our findings on rate spillovers have implications for the evolution of long run insurance prices across states and the extent to which insurance rates get disjoint from historical loss

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estimates. To understand the extent of decoupling of insurance rates from the underlying climate exposures across states, we construct an index of aggregate prices by weighting the average rate changes received by each insurer operating in a state by market share. Prices in the average high friction state grew 10% slower than the prices in low and medium friction states between 2008 and 2018.

Crucially, an important feature of our measure of state-level rate setting friction is that it positively correlates with how exposed a state is to climate losses. High friction states, e.g. California, Texas, and North Carolina, have a higher exposure to climate events and yet are less likely to approve higher rate change requests. On the other hand, low friction states are less exposed to climate events and approve high price increases not only in response to own losses, but also in response to out-of-state losses. As a result, prices grow slower in high friction states, even though high friction states are more exposed to climate events. Indeed, when we compare how prices have increased relative to long-run growth in climate losses, we find that while price growth has roughly kept pace with losses in high friction states, price growth has outpaced growth in losses by several times in low friction states, suggesting a long-run decoupling of prices and risk.

To explore the implications of rate setting frictions on insurance availability, in addition to these price effects, we study the effect on quantities along two dimensions: (i) exits and (ii) residual insurance markets. We find that losses predict future exits in high friction states, but only among small insurers. We find that large insurers do not fully stop selling insurance in response to losses, even in the presence of high rate setting frictions, likely due to their adjustment to the friction on a different margin (e.g., cross-subsidization across states). We also find that residual insurance markets expand in high friction states over time. Residual markets are state-organized homeowners insurance "marketplaces of last resorts", which offer homeowners products with limited coverage of risks. We interpret that the relative expansion of residual market in high friction states to indicate worsening private insurance availability.

We conclude by presenting a simple model of insurance pricing under regulatory frictions. It extends a standard insurance supply framework by explicitly modeling the rate-filing behavior of insurers and generates the empirical patterns observed in the data. In period 1, the insurer chooses the target prices in two regions which differ in the degree of regulatory friction. Importantly, in a low-friction region, the insurer uses the average marginal cost across two regions in its pricing decision. In period 2, the insurer then seeks regulatory approval from each state and decides how much effort to allocate across the two regions. A key assumption in our model surrounds the role of uncertainty associated with the risks that is being insured. Specifically, we assume that the uncertainty is greater in a high-friction region and that the rate wedge depends on both the insurer's effort and the degree

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of uncertainty in each region. Given this setup, the model parsimoniously captures the documented patterns regarding cross-subsidization, rate filing efforts, and pricing behavior in response to losses.

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 papers 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 insurance availability and pricing. 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 the health insurance market (Finkelstein et al., 2009; Ericson and Starc, 2015; Simon, 2005). Liu and Liu (2020) examine regulatory frictions due to regulators' political motivations 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 high costs on insurers and lead to unintended pricing consequences for households present in less regulated states. This is the first paper to document the wedge between insurers' target rate changes and the rate changes received, and to formally study

[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. For example, (Autor et al., 2014) documents the negative externalities and distortions due to rent-control in Massachusetts. For early work on price controls resulting in cross-subsidization, see (Faulhaber, 1975) who focus on the utilities market, and (Curien, 1991) who focus on the telecommunications market.

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the effects of price setting frictions on how insurers set rates across different states.

Third, our findings are also related to several studies on climate change effects on financial institutions. Central bankers identify two main channels through which climate change can affect financial stability: physical risk, stemming from direct property damage, 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 poses significant risks that are already beginning to materialize, and Battiston et al. (2017) show that financial institutions are highly exposed to climate change risks. This paper contributes to the literature directly: insurers' ability to absorb losses is critical to preserving financial stability (Scott et al., 2017). Our results are the first to suggest that the current regulatory system is putting a strain on insurers' preparedness.

The rest of the paper is structured as follows. Section 1 provides an overview of the institutional details and data sources. Section 2 discusses how we construct a state-level measure of rate setting frictions. Section 3 describes our cross-subsidization empirical analysis and Section 4 its implication for insurance availability. Section 5 provides a simple illustrative model. Finally, Section 6 concludes with the implications of our findings on current policy debates.

1. Institutional Background and Data

1.1. *Institutional Background*

1.1.1. *Homeowners Insurance*

Homeowners' insurance are retail contracts that provide protection against losses from climate events, e.g., wildfires, hurricanes, or windstorms.[8] Homeowners contracts also provide protection against non-climate events (e.g., vandalism and theft), however climate losses constitute the majority of incurred losses in these contracts, in particular in the last two decades. Homeowners' is the second-largest and fastest-growing segment within the Property & Casualty (P&C) market with over $100 billion of premiums written in 2019. Figure 2 shows the evolution of aggregate premia from 1996 to 2019.

Homeowners insurance is mandatory if households have a mortgage on their property because lenders (banks) require insurance as a condition to a mortgage loan. Perhaps, as a result of this, the fraction of households that are insured is as high as 80%, according to

[8] Flood insurance is provided federally by the National Flood Insurance Program (NFIP).

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estimates from the National Association of Insurance Commissioners (NAIC). In most states, an overwhelming fraction of households purchase a type of contract known as HO3 (Figure B.1). HO3 contracts are the most standard contracts and provide the minimum features necessary in order to sustain a mortgage loan. As a majority of households purchase HO3 contracts, the extent of coverage received by households across states is largely comparable.

From the perspective of the households, homeowners insurance contributes to a large share of their expenses towards owning a home. Figure 3 shows the average homeowners insurance costs benchmarked against mortgage interest expenses for each state in the U.S.. In the average state, homeowners insurance costs as much as 60% of what households pay towards their mortgage interest expenses. Interestingly, there is also large cross-state variation in these costs: Oklahoma is the most costly, while California is the least costly state, conditional on comparing homeowners costs for a similarly valued property.

1.1.2. Rate Regulation

Since the early part of the 20th century, insurance prices across many P&C markets have been regulated in the U.S.. State regulators aim to curb monopolistic practices and prevent "excessive prices" in order to assure affordable insurance coverage for all consumers or for a sub-group of consumers (Tennyson, 2011).[9] Rate regulation is most commonly employed in automobile, homeowners', health, workers' compensation, and medical malpractice lines. Several pieces of anecdotal evidence point to instances of rate suppression by state regulators in the case of homeowners. 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 change is, and other useful information on insurers' pricing functions. The length of a typical rate filing is significantly upwards of 1000 pages. 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

[9] 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. In the past, insurers were allowed to pool information for pricing purposes, which led to fears about monopoly pricing. Over time, the focus of regulation has largely shifted to preventing high insurance prices. See Tennyson (2011).

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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.[10] 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 as described below.

1.2. Data

We obtain regulatory data on 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). These data encompass insurers' (i) statutory filings, which contain data on insurers' operations and financial statements and (ii) rate change filings. In addition, we also exploit data on climate losses from Spatial Hazard Events and Losses Database for the United States (SHELDUS) and data on homeowners insurance residual markets from Property Insurance Plan Service Office (PIPSO). We describe the last two data sources in the relevant sections.

1.2.1. Statutory Filings Data

To study the effects of past realized losses on pricing behavior, we collect data on losses experienced by insurers for the homeowners line of business. An insurer can and does operate (i.e. sell insurance) in several states in the U.S.. Insurers report the total premium underwritten and losses experienced for each line of business (e.g., homeowners) in each state they operate in at an annual frequency. We collect these data for the sample period starting in 2009 and ending in 2019. The start date is dictated by the availability of data on rate change filings (see below). We normalize past realized losses for each insurer by the premium they sell in each state, which we henceforth refer to as loss ratio.

To account for shifts in pricing behavior that might be unrelated to pricing frictions, we

[10] 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 and FICO scores in their pricing models (Issler et al., 2020).

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introduce a number of control variables. These variables include an insurer's total assets, Risk Based Capital (RBC) ratio, which is defined as the amount of available capital relative to required capital, percent of premiums re-insured, and premiums and losses in other P&C lines of businesses (e.g., auto insurance, workers compensation). These control variables are reported at an insurer-year level in the statutory filings.

The summary statistics are depicted in Table 1 for the year 2019. The average insurer sells $39 million of homeowners insurance in a given state and has close to $3 billion in total assets. The average insurer selling homeowners insurance operates in about 15 state. The loss ratio in the homeowners line is about 57% on average. In other words, 57% of premiums written by a given firm in a given state and year are spent covering homeowners' losses. The loss ratio in all other lines combined is slightly higher at 60% on average.

1.2.2. Rate Changes Filings Data

The data on insurers' rate change filings come from Insurance Product filings, provided by S&P MI. Every time an insurer wants to change insurance prices in any state it operates in, it needs to file a rate change request at the Department of Insurance of that state. If the insurer wants to change prices in multiple states at once, it still needs to file in each of the states it wishes to change prices in. 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 data on the rate change filings for the period between 2009 and 2019 for the homeowners line of business. The starting point is 2009 because data before that year 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 throughout and the state is excluded from the analysis.[11]

For each rate change filing in a given state, there are two main ingredients. (i) We observe the insurer's *target* (model implied) rate change for that state (RateΔTarget), which is computed by the insurer in a manner consistent with the actuarial objectives prescribed by the state. (ii) We observe the rate change insurers finally *receive* after state regulators have adjudicated the request (RateΔReceived). In addition, we also observe the date of the filing, the amount of premium and the 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.

[11] 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, 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.

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Table 1 reports the summary statistics on the main variables, aggregated to the firm-year-state level.[12] Two key points stand out. First, the propensity to file for a rate change is very high at 70% for the average firm in a given state and year. This suggests that insurers are revising rates frequently - almost every year. Second, there is a large wedge between insurers' target rate change and what they receive. Conditional on filing for a rate change, the average (RateΔTarget) is 15.6% and the average (RateΔReceived) is 5.85%. To demonstrate that the difference between target and received rate change represents regulatory frictions, we provide a number of supporting facts in the next section.

2. Measuring and Dissecting the Pricing Frictions

2.1. *Measuring Pricing Frictions Across U.S. States*

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

$$\text{Rate Wedge}_{i,s,t} = \frac{\text{Rate}\Delta\text{Received}_{i,s,t}}{\text{Rate}\Delta\text{Target}_{i,s,t}} \tag{1}$$

where RateΔReceived is the rate change actually received and RateΔTarget is an insurer's target rate change for that filing. Rate Wedge$_{i,s,t} >= 1$ indicates that the insurer received a rate change greater than or equal to its target rate change for that state, i.e. there are no pricing frictions. Rate Wedge$_{i,s,t} < 1$ indicates that the insurer received a rate change less than its target rate change for that state. Thus, low values of Rate wedge$_{i,s,t}$ indicate high friction.

Figure 4 shows a histogram of Rate wedge$_{i,s,t}$ for the entire sample. A large fraction of filings have Rate wedge$_{i,s,t} < 1$, and the median Rate wedge$_{i,s,t}$ is 0.5.[13] In other words, the insurer stated target rate change is significantly greater than the rate change received for a bulk of the rate change filings. This shows that homeowners insurance is being sold at a large discount relative to insurers' stated target rate, potentially due to the existence of large scale regulatory frictions.

[12]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.

[13]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 Rate wedge$_{i,s,t}$ may be 0 or negative, but as we see from Figure 4 these cases are rare.

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2.1.1. *A State Level Measure of Pricing Frictions*

To rank states by the degree of pricing frictions, we construct a state-level measure of regulatory pricing frictions as described below:

$$\text{Friction}_s = 1 - \overline{\text{Rate wedge}_{i,s,t}} \tag{2}$$

where $\overline{\text{Rate wedge}_{i,s,t}}$ is the average rate wedge using only the top 20 largest insurers in each state, which account for more than 75% of the market share, to compute the average. We focus on the largest 20 insurers for the reason that these firms operate across most U.S. states. Thus, the average rate wedge is computed based on the same composition of firms in each state rather than a different set of firms.[14]

The measure $1 - \text{Rate wedge}_{i,s,t}$ represents the fraction of the target rate change that insurers do not receive. Thus, high (low) values of $Friction_s$ indicate states with potentially high (low) pricing frictions. We next split the 51 states into three terciles by $Friction_s$: high, medium, and low friction. States in the highest (lowest) tercile face the highest (lowest) pricing frictions.

2.2. *Severity of Pricing Frictions*

To evaluate whether insurers are restricted in their ability to adjust prices, we estimate the extent to which pricing behavior responds to realized losses differentially across states using the following regression:

$$\text{Y}_{i,s,t} = \alpha_{s,t} + \alpha_i + \gamma \text{Loss}_{i,s,t-1} + \gamma^M \text{Loss}_{i,s,t-1} \times I_s^{\text{Med Fric}} + \gamma^L \text{Loss}_{i,s,t-1} \times I_s^{\text{Low Fric}} + \theta X_{i,t} + \epsilon_{i,s,t}, \tag{3}$$

where the response variable $Y_{i,s,t}$ include (i) whether a rate change request is filed and (ii) the size of the rate change received relative to insurers' target rate change by insurer i in state s and year t. Thus, $Y_{i,s,t}$ measure both the extensive and the intensive margin of the pricing behavior. The main independent variable of interest are $\text{Loss}_{i,s,t-1}$, the loss ratio (losses divided by premia) of insurer i in state s and year $t-1$. We split states into high, medium, and low friction, as described above. $I_s^{\text{Med Fric}}$ ($I_s^{\text{Low Fric}}$) is an indicator that takes the value 1 if a state is a medium (low) friction state. We include state $\times$ year fixed effects ($\alpha_{s,t}$) to absorb time varying unobserved state characteristics and local demand shocks and insurer fixed effects (α_i) to ensure that the relevant coefficients are estimated off variation in loss

[14]Nevertheless, our state level rankings is robust to alternative definitions. Specifically we see similar ranking if we use top 50 firms, compute $Friction_s$ using different sub-samples 2009-2014 or 2015-2019, weigh each insurer's rate wedge by premium sold, and exclude insurers' fixed effect from the rate wedge before aggregating to the state level.

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ratio within an insurer and not off variation in the composition of insurers across all states. The control variables $X_{i,t}$ (log total assets, RBC ratio, non-state loss ratio, non-homeowners loss ratio, reinsurance) account for time-varying insurer-level characteristics that also affect insurers' pricing behavior. Finally, we cluster standard errors at the state level, to account for the common regulatory, climate, and demand conditions in a given state.

We expect that when losses increase, prices in future periods go up, e.g., because insurers update their beliefs about the frequency or severity of losses. Thus, $\gamma > 0$. However, to the extent pricing frictions are restrictive, the pricing response would be heterogeneous across states and, in particular, less pronounced in high friction states relative to low friction states.

Table 2 documents two main findings. First, column (1) shows that in response to losses, insurers are more likely to file for rate changes in low friction states relative to high friction states. γ is positive and $\gamma < \gamma^M < \gamma^L$. Moreover, only γ^L is statistically significant. As we include insurer fixed effects, we compare the same insurer's filing behavior across states. Thus, the estimates suggest that when we compare the same insurer's filing behavior across states, in response to losses, the insurer is more likely to file in low friction states than in high friction states. The magnitudes are large. In low friction states, insurers file 9% more rate change requests in response to a large jump in losses (from the 10th to 90th percentile).

Second, column (2) shows that γ is negative and statistically significant. γ^M is positive and insignificant, and γ^L is positive and statistically significant. Thus, for the same insurer in high friction states, future target rate changes respond *more* to losses than do future received rate changes. In contrast, for the same insurer in low friction states, future target rate changes respond *less* to losses than do future received rate changes (since $\gamma + \gamma^L > 0$). Thus, even when we compare the same insurer across states, it is harder to change rates in high friction states relative to low friction states, suggesting that at least in a subgroup of states the pricing frictions are more restrictive than in others.

Overall, the evidence shows that in response to losses, insurers are less likely to apply for rate changes and more likely to receive a lower rate change compared to their targets in high friction states than in low friction states. This suggests that the measure $Friction_s$ meaningfully captures the extent to which insurers are restricted in their ability to set rates in a relative sense.

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2.3. *Three Interpretations of the Rate Wedge and Empirical Tests*

2.3.1. *Interpreting the Rate Wedge*

The measured wedge between the target rate change and the received rate change is consistent with three potential interpretations, each with a different role for the regulators.

The first interpretation assumes the existence of a regulator who is well-informed of the risk that is being insured. Therefore, she already knows and applies the desired level of rate change to be applied to the target rates. We refer to this interpretation as one with *informed regulators*. If this were the case, then the time it takes to process each rate change should not differ too drastically across filings. Furthermore, it should also not depend on observable features of the filings such as their magnitudes and the characteristics of the applying insurers. We later present empirical evidence, however, suggesting that it does take longer to process larger requests which is potentially at odds with the existence of a fully informed regulator.

The second interpretation, which we refer to as the case of *uninformed regulators*, assumes that the regulator does not know the discount to be applied to the target rates. Instead, she takes time to learn about the underlying risk to ultimately decide on the final discount to be applied. While we do not take a stance on how she learns, one potential source is from a cross-section of rate filings from multiple insurers, which she can then use to form an estimate of the discount to be applied. One direct implication of this interpretation is that the more difficult it is to learn about the risk, the longer it will take for the rate to be approved. We later present evidence from across-state comparisons that is consistent with this interpretation.

The third interpretation similarly assumes the existence of an uninformed regulator. But importantly, it also assumes that the insurers can collude and coordinate to report inflated target rate changes. For this reason, we refer to this interpretation as that of *target inflation*. One prediction that follows is that if insurers are inflating the targets, the rate wedge today should not be correlated with future profitability. Furthermore, the rate wedge should be broadly similar across firms unless one expects the degree of inflation should be correlated with insurer characteristics like size. We show that both predictions do not hold much ground empirically, indicating that target inflation is unlikely.

Each interpretation takes a different stance on the regulator's understanding of the risks and the behavior of the firms. Distinguishing one from others is therefore critical for interpreting the wedge as a regulatory friction as well as contemplating potential micro-foundations for the the behaviors of insurers and regulators.

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2.3.2. Empirical Evidence: The Case for Uninformed Regulators

(i) Rate Processing Times. The average time it takes to process a rate change request is an important aspect of the rate change process that can shed light on which of the interpretations is empirically supported. We measure the gap between the insurers file for a rate change and the date regulators announce their decisions (execution time) and document two facts. First, there is significant variation in execution time across filings, and this heterogeneity is related to the size of requested rate change, which is at odds with the *informed regulator* prediction. We regress the execution time on the size of requested rate change and find that the larger the requested rate change, the longer the period from submission to final regulatory decision. The results in Table 4 show 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.

Second, we find that execution times are larger in high friction states. Figure 5 plots $Friction_s$ and the mean execution time for each state. We see that the higher the friction, the larger the average execution time in a given state. The average execution time in a low-friction state like New Hampshire is less than 50 days, while in a high-friction state like California it is over 150 days, more than three times the execution time of New Hampshire. We later document that $Friction_s$ positively correlates with the extent of climate risk in a state (measured using losses per capita). This suggests that the execution times are higher where climate risk is perceived to be higher, consistent with the *uninformed regulator* prediction.

(ii) Market Share and Rate Wedge. We document that the Rate wedge is smaller for insurers that have greater market share in a state, consistent with the idea that regulators suppress prices of insurers that matter more for consumers. Table B.1 shows a regression of Rate wedge$_{i,s,t}$ on various proxies of firm size (firm size rank within a state-year, market share and log premium). We include state $\times$ year fixed effects to ensure comparison within a state and time across insurers. Higher the size of a firm as measured by premiums or market share (lower the rank), lower is the rate wedge, implying a higher degree of pricing friction.

(iii) Possibility of Target Inflation. One explanation for why so many filings receive changes below the insurer stated target level could be 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 pricing discount (i.e. the rate wedge will be close to 1). To test whether this is the case, we examine whether the extent of pricing friction predicts future

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profitability. Specifically, we run the following regression:

$$\text{Underwriting Profit}_{i,s,t+1} = \beta \text{Friction}_{i,s,t} + \alpha_{s,t} + \alpha_i + \epsilon_{i,s,t+1}, \tag{4}$$

where Underwriting $\text{Profit}_{i,s,t+1} = 1 - \text{Loss Ratio}_{i,s,t+1}$ is the ratio of premium minus 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. The right-hand side variable is $\text{Friction}_{i,s,t} = 1 - \text{Rate wedge}_{i,s,t}$, which measures how far from the target is the received rate change for insurer i in state s in the prior year. $\alpha_{s,t}$ are state $\times$ year fixed effects and α_i are insurer fixed effects.

If $\text{Friction}_{i,s,t}$ is high because insurers report inflated price targets, then it should not be correlated with profitability in future periods. However, we find that β is negative and statistically significant (Table 3). Thus, when pricing frictions for a given firm are high, we observe lower underwriting profits in the following year. In other words, the measure $Friction_{i,s,t}$ predicts lower future profitability, contrary to the predictions of an inflated price target hypothesis.

Overall, the empirical tests suggest that regulators are unlikely to be fully informed in the sense that they have an immediate understanding of how much Rate Wedge to apply to the target rate filings by insurers. It seems also unlikely that the target rate changes are inflated as we find that a high friction today predicts low future profitability. Instead, the evidence lends more support to the scenario in which the regulator actively learns and subsequently decides on the Rate Wedge to be applied, the efforts of which are reflected in rate processing times that differ across states.

3. Cross-Subsidization and Long-run Pricing Effects

3.1. *Cross-Subsidization of Insurance Prices Across U.S. States*

We next explore to what extent insurers subsidize their operations in high friction states with their operations in low friction states by passing on the losses in high friction states to households in low friction states. We begin our analysis by showing that insurers' filing behavior responds to other state losses. To do so, we modify Equation 3 as follows:

$$Y_{i,s,t} = \gamma OtherStLoss_{i,\bar{s},t-1} + \underbrace{\theta_1 OwnStLoss_{i,s,t-1} + \theta_2 X_{i,t}}_{\text{Control Variables}} + \alpha_{s,t} + \alpha_{i,s} + \epsilon_{i,s,t}, \tag{5}$$

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where the main change is that now we focus on losses experienced out of the state, where rate change request is filed. Specifically, the variable of interest is $OtherStLoss_{i,\bar{s},t-1}$, is the lagged out-of state loss ratio (losses divided by premia) of insurer i in all states other than state s. We include state $\times$ year fixed effects ($\alpha_{s,t}$) to control for time varying unobserved state characteristics and local demand shocks. We also include insurer $\times$ state fixed effects ($\alpha_{i,s}$) to ensure that the estimation exploits variation in loss ratio within an insurer, and that we control for insurer's competitive position or market power in a given state, (and other firm-state specific characteristics). Like in Equation 3, we control for $OwnStLoss_{i,s,t-1}$, the lagged loss ratio of insurer i in the same state s. The control variables X_{it} (log total assets, RBC ratio, non-homeowners' insurance loss ratio, reinsurance), account for time-varying insurer-level characteristics that are known to affect insurance prices.

The response variables, whether a rate changes is filed and the size of the received changes, assess insurers' filing behavior on the extensive and intensive margins. If insurers are cross-subsidizing across states, we expect $\gamma > 0$ and significant. Columns (1) of Table 5 and column (1) of Table 6 show that indeed insurers cross-subsidize their operations across states, because $\gamma > 0$ and is statistically significant. Thus, both the the probability to file and the size of rate changes received increase not only in response to own state losses, but also in response to out-of-state losses.

To understand how price setting frictions impact behavior, we proceed in two steps. First, we split own state s by the intensity of price setting friction to understand which states respond to out-of-state losses. We then test whether insurers' response to out-of-state losses varies depending on whether the outside state is low, medium, or high friction.

3.1.1. Split own state losses

Columns (2)-(4) of Table 5 and Table 6 present the estimation of Equation 5, where we split state s into high, medium, and low friction. For likelihood of filing a rate change (Table 5) and for rate changes received (Table 6), we find that γ^H is statistically insignificant and small in magnitude. Thus, when the state is high friction, insurers do not respond to out-of-state losses. In contrast, γ^L is statistically significant. Thus, when the state is low friction, insurers respond to out-of-state losses. As we use insurer fixed effects, we make within insurer comparisons, i.e. we track the same insurer's filing behavior across different states. Thus, our findings imply that the same insurer responds to out-of-state losses in low friction states but not in high friction states. Moreover, we also find that $\gamma^H < \gamma^M < \gamma^L$, i.e. insurers' response to out-of-state losses is monotonic in price setting frictions.

We also formally test insurers' sensitivity to out-of-state losses by modifying Equation 5

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as follows:

$$Y_{i,s,t} = \gamma OtherStLoss_{i,\bar{s},t-1} + \gamma^M OtherStLoss_{i,\bar{s},t-1} \times I_s^{\text{Med Fric}} + \\ + \gamma^L OtherStLoss_{i,\bar{s},t-1} \times I_s^{\text{Low Fric}} + \theta_1 OwnStLoss_{i,s,t-1} + \theta_2 X_{i,t} + \alpha_{s,t} + \alpha_{i,s} + \epsilon_{i,s,t}, \tag{6}$$

where $I_s^{\text{Med Fric}}$ ($I_s^{\text{Low Fric}}$) is an indicator that equals 1 when state s is a medium (low) friction state. The coefficients γ^M/γ^L measure the difference in the same insurer's response to out of state losses if the filing state is medium/low friction compared to high friction state. The results of this regression are shown in Column (5) of Table 5 and Table 6 for, respectively, dependent variable being likelihood of filing or rate change size. We see that γ^L is positive and statistically significant, indicating that the same insurer's filing behavior is most sensitive in low friction states to out-of-state losses.

The estimated γ^L coefficients are also economically meaningful. For example, for low friction states, likelihood of filing and rate changes received respond similarly to own losses as it does for out-of-state losses. Specifically, suppose that the other states' loss ratio increases from the 10th percentile to the 90th percentile (i.e. loss ratio fraction increases by 0.56 from 0.30 to 0.86, see Table 1). This implies that for the average insurer in low friction state the likelihood of filing increase by 13% and the rate changes received increase by 24% in response to own state losses.

3.1.2. Split out-of-state losses

We next test whether insurers' response to out-of-state losses in low friction states varies depending on whether the <u>outside state</u> is low, medium, or high friction. To test this, we modify Equation 5 by splitting the variable $OtherStLoss$ based on the type of state they are coming from. Specifically, we estimate:

$$Y_{i,s,t} = \sum_{j \in \{H,M,L\}} \gamma_{\bar{s}}^j OtherStLoss_{i,\bar{s},t-1}^j + \theta_1 OwnStLoss_{i,s,t-1} + \theta_2 X_{i,t} + \alpha_{s,t} + \alpha_{i,s} + \epsilon_{i,s,t}, \tag{7}$$

where j takes three values high, medium or low friction, as defined in Section 2.1.1. For example, if j is high, for each insurer i that operates in state s we sum the losses experienced in year $t-1$ in all high friction states that are not s, and divide it by the premiums collected in these states. We restrict the sample to rate filings in low friction states, ($s = low$), because in these states insurers are most sensitive to out-of-state losses. We expect to see that sensitivity to out-of-state losses increases in the state's friction, i.e. $\gamma_{\bar{s}}^H > \gamma_{\bar{s}}^M > \gamma_{\bar{s}}^L$. In other words, we expect that insurers respond stronger to out-of-state losses coming from high friction states.

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Table 7 shows the main findings. We see that $\gamma^{L}_{\bar{s}}$ is insignificant for both the likelihood of filing and rate changes received. Thus, rate setting behavior in low friction states do not respond to out-of-state losses when these outside states are low friction themselves. In contrast, $\gamma^{H}_{\bar{s}}$ and $\gamma^{M}_{\bar{s}}$ are statistically significant for both the likelihood of filing and rate changes received. Thus, rate setting behavior in low friction states respond to out-of-state losses only when these outside states are either high or medium friction.

The intuition is as follows. In low friction states, insurers are already able to adjust rates in response to losses occurring within that state (as we show in Table 2). Thus, losses from low friction states do not get passed on to households in other states. However, insurers in high friction states are not fully able to adjust prices due to rate setting friction, leading them to pass on losses in high friction states to low friction states. The economic magnitudes of these rate spillovers are large. For example, in response to increase in losses in out-of-state high friction states, the average insurer in low frictions states experiences a rate increase of 26% and the likelihood of filing increases by 11%.

3.2. Long-run Pricing Effects and Decoupling from Risk

These findings bring up an important question: do insurance prices increase faster in low friction states as a result of cross-subsidization of losses in high friction states?

3.2.1. Aggregate price index

To examine this, we construct an index of aggregate prices in each state as follows. We first use the insurer level rate changes received to estimate the average price growth experienced in state s in year t. Specifically, we compute a weighted average of the rate changes received by insurer i in state s and year t, where the weights are the market share of each insurer in a state. Thus,

$$\Delta\text{Rate}_{s,t} = \sum_{i} \text{Market Share}_{i,s,t-1} \times \text{Rate}\Delta\text{Received}_{i,s,t}. \tag{8}$$

Next, we construct an aggregate price index, by growing prices in each state s between $t-1$ and t by $\Delta\text{Rate}_{s,t}$. Setting the price level of each state in year 2008 to be 1, we thus estimate the growth from 2008 to any year T in state s as $P_{s,T} = \Pi^{T}_{t=2009}(1 + \Delta\text{Rate}_{s,t})$. Figure 6 shows the evolution of average $P_{s,T}$ for states with high pricing frictions relative to all other states. For example, prices in the average high friction state grew 10% slower than the prices in low and medium friction states at the end of 2018.

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As a validation of our price index, we obtain the average premium for homeowners' insurance for each state and year for the period 2003-2017 from NAIC archives, which are updated annually.[15] For each state, we compute the price growth between 2003 and 2017 (the first and last available dates). We regress the price growth on whether a state is low friction or not: $P_s^{2017}/P_s^{2003} = \alpha + \beta I_s^{\text{low}} + \epsilon_s$. Consistent with the analysis above, Table B.2 shows that while the average state witnessed a price growth of 78% over a 14 year period, the growth was 12% larger for low friction states.

3.2.2. Regulatory pricing frictions and climate losses

We document that our measure of state-level rate setting friction positively correlates with how exposed a state is to climate losses. Thus, the slower growth in prices in high friction states does not fully reflect the extent of price suppression because high pricing friction states are also more exposed to climate losses.

Specifically, for each state s we compute the time-series average of property damage per capita between 2009 and 2019, where the data on climate losses for each state are from the Spatial Hazard Events and Losses Database for the United States.[16] Figure 7 shows the relationship between the realized climate losses and rate setting friction (computed from Equation 2). We observe a positive relationship between losses per capita and price setting friction. Thus, high friction states, e.g. California and North Carolina, also have have a higher exposure to climate events, and are less likely to approve higher rate change requests.[17]

3.2.3. Decoupling of insurance prices from risk

These findings imply that over time due to regulatory pricing frictions, insurance prices get disjoint from the underlying climate exposures across states. To explicitly illustrate this, for each state we compute how prices have changed relative to how losses have changed over a long time horizon. Specifically, we compute the growth of prices between 2008 and 2019, $\Pi = P_{s,2019}/P_{s,2008}$, for each state. We scale the price growth by growth in climate losses per capita, Γ, which we compute as the ratio of losses between 2008 to 2019 relative to losses between 1997 to 2007. Losses per capita are in log scale and are inflation adjusted.[18] Γ measures long-run growth in climate losses in real terms for each state. Thus, Π/Γ measures how prices have increased compared to long-run growth in climate losses.

Figure 8 shows the relationship between how prices have increased compared to long-run

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

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

[17] We assume that average realized losses are a measure of climate exposure.

[18] Property damages are inflation adjusted and are shown in 2018 dollars.

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growth in climate losses and rate setting friction (computed from Equation 2). We observe that states with high pricing frictions experience substantially lower price growth compared to the growth in losses. In contrast, states with low pricing frictions have experienced increase in prices that are several times the growth in losses in these states.

3.3. *Alternative Explanations and Robustness*

3.3.1. *Financial frictions*

One alternative explanation is that rather than regulatory frictions and climate-risk uncertainty, the cross-subsidization is driven only by insurers subject to financial frictions, as in Froot and O'Connell (1999) and Ge (2020). First, our findings are also unlikely to be driven by differences in financing frictions across insurers because estimations occur within an insurer. We compare rate setting behavior for the same insurer across states and find that the same insurer responds differently while filing in a low vs. high friction state and differently in response to when losses occur in a low vs. high friction state.

Second, we formally test if the results are driven only by insurers with more financial constraints. Specifically, we modify Equation 6 as follows:

$$\begin{aligned} Y_{i,s,t} = & \left(\gamma + \gamma^M \times I_s^{\text{Med Fric}} + \gamma^L \times I_s^{\text{Low Fric}}\right) \times OtherStLoss_{i,\bar{s},t-1} + \\ & + \left(\gamma_c + \gamma_c^M \times I_s^{\text{Med Fric}} + \gamma_c^L \times I_s^{\text{Low Fric}}\right) \times OtherStLoss_{i,\bar{s},t-1} \times I_{i,t-2}^{cons} + \\ & + \theta_1 OwnStLoss_{i,s,t-1} + \theta_2 X_{i,t} + \alpha_{s,t} + \alpha_{i,s} + \epsilon_{i,s,t}, \end{aligned} \tag{9}$$

where $I_{i,t-2}^{cons}$ is an indicator which equals 1 if insurer i is financially constrained in year t. If the results are driven only by financially constrained firms, we would expect to see that only financially constrained firms are sensitive based on filing states' strictness. In the specification here, this would manifest as either γ_c^L positive and significant, and γ^L not, or as γ_c^L being much larger than γ^L. To identify which insurers are financially constrained we follow the methodology of Ge (2020). Specifically, in year t, insurer i is financially constrained to peers if its double lagged net assets, RBC ratio, capital to assets are below median, or if its ultimate parent is privately held.[19]

Results are shown in Table 9 for the likelihood of filing and the size of the request. The only coefficient positive and consistent across specifications is γ^L, which is not consistent with the story that cross-subsidization is driven only (or mostly) by financially constrained

[19] Note that since public and private status doesn't vary too much across year and firm, instead of running the specification from Equation 9, we split the sample in two based on whether i is public/private, and on each sub-sample, we estimate the specification from Equation 6.

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insurers.

3.3.2. Different shift in product features across states

One alternative explanation is the price changes are due to insurance contracts changing over time in a different manner across high and low friction states. Specifically, prices may rise faster in the lower friction states, but the contract quality also increases. Addressing this concern completely would require data on precise product features, which are unavailable. To get around the data limitations, we provide three pieces of evidence that collectively show that contract features have likely not shifted differently across states in a meaningful way.

In the first, we focus on the fraction of HO3 insurance contracts. In Section 1.1.1 we discussed that HO3 is the standard contract, so we use changes in the fraction of homeowners who purchased an HO3 as a proxy for shift in the product distribution. However, we find that the product offering across states with varying level of friction is similar, and does not shift in a different manner over time across states. From Figure B.1 we see that fraction of HO3 is between 90-95% for high, medium and low friction states and stays around this level between 2008 and 2017.

Our second set of evidence looks at whether insurers in low friction states shift towards insuring different types of risk than in high friction states. In Figure B.4, we first plot the percentage growth in losses per insured property for the insurers in three groups of states sorted on friction. Given the similar growth in losses per property, we do not find evidence indicating that insurers in low friction states shift towards insuring riskier properties. In a similar vein, we plot in Figure B.5 the percentage growth in coverage for the policies in three groups of states. Similarly, we observe a similar growth in insurance coverage amount, which indicates that there is no salient shift towards more generous coverage amounts by insurers in low friction states. Moreover, in Figure B.6, we show that the percentage of insured properties has stayed relatively similar for the three states, indicating that the insurance penetration has not changed differentially across states.

Third, we ask whether insurers respond to out-of-state losses by changing the product features instead of shifting prices. Insurers have to file a rule change request with states regulators if they plan to change any feature of the insurance contract. In Table B.5, we test if the likelihood of a rule filing differs across states depending on their level of friction. Contrary to our previous finding on *rate* filings, here do not find differential response in low friction states compared to that in other states.

3.3.3. Market power and insurer size

A necessary condition for cross-subsidization is that demand is relatively inelastic, i.e. that insurers are able to increase prices in low friction states relatively easy without losing

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market share. This is likely true, since homeowners insurance is mandatory to receive mortgage loans. Note that in practice, homeowners insurance market is concentrated: the top 20 insurers control over 75% market share in the average state (Figure B.2).[20]

Second, our findings on cross-subsidization are especially pronounced for large insurers (most of whom tend to operate in all states). To illustrate this, we split insurers in a given state and year, to the largest 50, 30, and 20 insurers and re-run Equation 7 on the sample. The results are in Table 8. We find insurers' sensitivity to high friction out-of-state losses increases in an insurer's market share both for the likelihood of rate filings and for rate changes received. Specifically, the sensitivity to out-of-state losses of the top 20 firms is 1.65 times larger than the sensitivity of the top 50 firms for number of filings. Similarly, the sensitivity to out-of-state losses of the top 20 firms is 1.75 times larger than the sensitivity of the top 50 firms for rate changes received.

3.3.4. Heterogeneity in Cross-Subsidization - Role of Competition

We next ask if the degree of cross-subsidization differs among the low friction states depending on (i) the level of competition in these states and (ii) the exposure of insurers selling in these states to high friction states.

We first ask whether low friction states with high levels of concentration are more responsive to out-of-state losses, since firms in such states face less competitive pressure when raising prices. To answer this question, we first split low friction states into two groups using two measures of concentration: the market share of top 5 insurers and the Herfindahl–Hirschman Index (HHI). Table B.3 shows that the response to out-of-state losses – both the likelihood of filings and the average change received – is indeed generally higher in low-friction states with high degree of concentration than in those with low degree of concentration.

We next ask whether low friction states with greater exposure to high friction states are more responsive to out-of-state losses. The idea is that if most insurers are exposed to high friction states then their ability to raise prices may be higher because of greater coordination. To answer this question, we first compute for each insurer the fraction of its premium coming from high fraction states. We then split the low friction states into two groups based on how exposed the insurers in each state are to these high friction states. Table B.4 shows that the response to out-of-state losses is indeed greater in low-friction states with greater exposure to high-friction states.

[20]Note that Wagner (2020) finds demand for the federally-provided flood insurance to be relatively low and price-sensitive. However, demand for homeowner insurance is much higher: 85% of homeowners have an insurance, a fraction which is relatively constant over time and states of different friction level.

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3.3.5. Learning about similar risks

Another alternative explanation may be that insurers are learning about climate risk in one state, which leads them to respond in states that share similar characteristics. If this scenario were true, the responsiveness to out-of-state losses would be concentrated amongst states that share similar risk characteristics.

We test this hypothesis empirically and show that it is unlikely to be the case. Specifically, we modify Equation (6) by replacing the losses from other states ($OtherStLoss_{i,\bar{s},t-1}$) with the losses from other states that are outside of the geographical region of the filing state ($\text{Other Zone Loss}_{i,\bar{z},t-1}$). The geographical zones are taken from SNL and depicted in Table B.6. The assumption is that losses are correlated within a geographical region, but much less so across different regions. Specifically, we estimate:

(10)

$$\begin{aligned} Y_{i,s,t} = {} & \gamma \text{Other Zone Loss}_{i,\bar{z},t-1} + \gamma^M \text{Other Zone Loss}_{i,\bar{z},t-1} \times I_s^{\text{Med Fric}} + \\ & + \gamma^L \text{Other Zone Loss}_{i,\bar{z},t-1} \times I_s^{\text{Low Fric}} + \theta_1 \text{OwnStLoss}_{i,s,t-1} + \theta_2 X_{i,t} + \alpha_{s,t} + \alpha_{i,s} + \epsilon_{i,s,t} \end{aligned}$$

The results of estimating Equation (10) are in Table B.7. We find that γ^L is positive and statistically significant with a comparable magnitude to the estimates in Tables 5 and 6. In other words, both the likelihood of a rate filing as well as the average change received respond similarly, whether or not we exclude states that share similar risk characteristics (as the filing state) in computing the losses from other states.

4. Insurance Availability

In this section we test if states with higher frictions experience face a decrease in availability. We use two proxies for availability: insurers' exits (i.e. insurers choose to stop selling insurance in a given state) and the size of the residual markets. We find that while exiting is a rare strategy overall, it is concentrated in small insurers exiting high friction states. Also, residual markets shrank in low-friction states, but expanded in higher friction states. Both findings indicate gradual worsening of availability in higher friction states.

4.1. Exits

We first examine the extent to which insurers respond to the price setting frictions by exiting high friction states. Because we only want to capture exits from a particular state, we require that an insurer exits a particular state but continues to operate in at least one more state. Thus, we define $Exit_{i,s,t} = 1$ if an insurer i stops selling homeowners insurance in state s at

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time t but continues selling insurance elsewhere, and $Exit_{i,s,t} = 0$ if an insurer i continues to sell homeowners insurance in state s at time t. Table 10 documents the summary statistics. We split insurers by their market share in each state and group them into large and small, where large is defined as insurers with at least 1% market share in a state and small is defined as insurers with less than 1% market share in a state. We document that insurers rarely exit a state and most of the exits are concentrated among small insurers.

We next examine how exits respond to losses in a given state and whether these responses depend on the extent of price setting frictions. To formally examine this, we estimate the regression in Equation 3, where the response variable is $Exit_{i,s,t}$. The main variable of interest is the loss ratio of insurer by i in year $t-1$ and state s. Table 11 documents the main findings. Column (1) shows estimation on the full sample. We find that on average losses in a given state do not predict future exits. However, when these losses occur in high friction states, we find significantly more future exits, consistent with Prediction (2). Column (2) and (3) document findings on large and small insurers respectively.

Column (3) shows that the overall effects are concentrated only among small insurers. For large insurers, losses do not predict future exits even when these losses are in high friction states. Overall, these findings are consistent with Prediction (2) but only for a subset of insurers and imply that while price setting frictions are restrictive, insurers rarely choose to exit.

There could be several reasons why insurers choose not to exit high frictions states. First, it is plausible that insurers are uncertain about the long-term strictness of state regulators or whether high losses actually imply permanent shifts in marginal costs. Second, there could be high direct 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. Alternatively, the costs could be indirect, e.g., it is possible that insurers fear retaliation by regulators who could respond by being overtly strict in other lines of businesses. Third, operating across geographies provide diversification benefits.

4.2. Residual Markets

Another important proxy of insurance availability is the size of residual markets of homeowners' insurance. Residual markets are state-organized marketplaces, in which homeowners who are unable to obtain coverage from a private insurer can purchase a policy. In most cases, the resulting liabilities are distributed among insurers proportionally to market share.

A large residual market indicates that many homeowners are not able to receive proper coverage true the private marketplace, which indicates poor insurance availability for two

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reasons. First, residual market policies provide limited coverage. Second, to qualify for the residual market, homeowners need to be turned down by several insurers.

We find the residual market expanded more in higher-friction states between 2011 and 2019. At Figure 9 we plot the friction level of each state and the log change in total residual market premiums from 2011 to 2019.[21] We see that low friction states the residual market shrank, while in high friction states, the residual market expanded. This finding is consistent with the evidence that insurance availability worsened in states with higher friction.

5. A Model of Insurer Rate-Making with Regulatory Frictions

In this section we present a model of insurer rate-filing behavior under regulatory frictions. The goal is to show that a simple extension of a standard insurance supply framework can reasonably capture the provided empirical evidence on regulatory approval of rate filings as well as the cross-subsidization behavior of insurers.

5.1. Overview

An insurer sells policies in two regions – H with high regulatory friction and L with low regulatory friction – and chooses the target prices P^H and P^L separately in each region. We denote the underlying risk in each region as random variables $\tilde{V}^H$ and $\tilde{V}^L$, whose actuarial values are V^H and V^L. After choosing the target prices, the insurer files its rate with the regulator in each region and decides how much filing effort to allocate to each. A greater filing effort in a region reduces the discount that the regulator applies to the filed rate change.

Importantly, we assume that states with high regulatory friction are also those with greater uncertainty about the underlying risk that is being insured. In other words, the variance of $\tilde{V}^H$ and $\tilde{V}^L$ is greater in region H than in region L, i.e. $\sigma_H^2 > \sigma_L^2$.[22] In the model, high uncertainty also makes it more likely that the regulators will apply a higher discount to the target price, thereby micro-founding why regulators in some states might be "stricter" than those in others.

5.2. Period 1: Target Price Setting

In each region $R \in \{H, L\}$, the insurer would like to sell $Q^R\left(P^R\right)$ policies at price P^R while incurring a fixed marketing and administrative costs C. A_0 and L_0 are the insurer's assets

[21]The data is accessed through PIPSO. We observe the yearly dollar amount of premiums in each of the 32 states which provide residual market for homeowners.

[22]We discuss the empirical evidence supporting this assumption in Section 5.3

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and statutory reserves at the beginning of the period, and r the net return on its assets over the same period. In region H, the insurer prices its policy using V_H as the effective marginal cost, i.e.

$$\bar{V}_H = V_H$$

In region L, however, the insurer uses the average cost across the two regions as its marginal cost:

$$\bar{V}_L = 0.5V_H + 0.5V_L$$

This particular assumption of average cost sharing begs the following two questions: why would the insurer use a different marginal cost in the first place, and if so why would it only do so only in the low-friction region? One possible answer to these questions is to consider an insurer who not only cares about maximizing overall profits but also faces a target average profit margin per policy or an earnings target normalized by the size of firm operations. Then, in region L with non-stringent regulatory oversight, the insurer may be allowed to deviate from the true marginal cost in that region, while in region H it cannot.

Finally, we denote $\hat{V}^R$ as the amount of statutory reserves per policy set aside to pay for future policy claims in region R. For simplicity, we assume

$$\hat{V}^R = \phi\bar{V}^R$$

with $\phi \geq 1$.

5.2.1. Balance Sheet Dynamics

The insurance company's assets at the end of period 1, after the sale of new policies in each region, is:

$$A_1 = (1 + r)\, A_0 + P^H Q^H + P^L Q^L - C \tag{11}$$

The statutory reserves at the end of period 1 also satisfy:

$$L_1 = (1 + r)\, L_0 + \hat{V}_1^H Q^H + \hat{V}_1^L Q^L \tag{12}$$

We define the insurance company's statutory capital as the value of its assets relative to statutory reserves:

$$K_1 = A_1 - L_1 \tag{13}$$

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Together they imply the following law of motion for statutory capital:

$$K_1 = (1+r)\,K_0 + \left(P^H - \hat{V}^H\right) Q^H + \left(P^L - \hat{V}^L\right) Q^L - C \tag{14}$$

Note that this financial constraint applies for the entire insurer and is therefore not specific to a particular region.

5.2.2. Insurer's Problem

The insurer's profit in region R is defined as:

$$\Pi^R = \left(P^R - \bar{V}^R\right) Q^R - C \tag{15}$$

where C is some administrative costs. The total profits of the insurer is the sum of profits in each region:

$$\Pi = \sum_R \Pi^R = \Pi^H + \Pi^L \tag{16}$$

The insurer chooses the target prices P^H and P^L to maximize total profit subject to a risk-based capital constraint:

$$\begin{aligned} \max_{P^H, P^L} \quad & \Pi \\ \text{subject to} \quad & K_1 \geq 0 \end{aligned} \tag{17}$$

where $\Pi = \Pi^H + \Pi^L$.

5.2.3. Optimal Price

Let $\lambda_1 \geq 0$ be the Lagrange multiplier on the leverage constraint. The Lagrangian is then:

$$\mathcal{L} = \Pi + \lambda_1 K_1 \tag{18}$$

We first take the first-order condition with respect to P^H:

$$0 = \frac{\partial \Pi^H}{\partial P^A} + \lambda_1 \left[\left(P^H - \hat{V}^H\right) \frac{\partial Q^H}{\partial P^H} + Q^H\right] \tag{19}$$

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where Π^L does not appear because P^H does not appear in Π^L and also because we assume P^H does not affect Q^L. Rearranging (19) yields the optimal price in region A:

$$P^{H*} = V^H \eta^H \Phi \tag{20}$$

where

$$\eta^H \equiv \left(1 - \frac{1}{\epsilon_D^H}\right)^{-1}, \quad \Phi \equiv \frac{1 + \phi\lambda_1}{1 + \lambda_1}.$$

η^H is the markup applied in region H, which is a function of how inelastic the demand is $\left(\epsilon_D^H\right)$, and Φ is an insurer-specific term that captures how financially constrained the insurer is. If $\lambda_1 = 0$, then $\Phi = 1$ and the financial constraint is not binding, which does not affect product pricing. If $\lambda_1 > 0$, then Φ is increasing in ϕ, where $\phi \geq 1$ indicates how much reserves the insurer needs to set aside for each policy you sell. The expression for region L is analogous:

$$P^{L*} = \left(0.5V^H + 0.5V^L\right) \eta^L \Phi \qquad \text{where} \qquad \eta^L = \left(1 - \frac{1}{\epsilon_D^L}\right)^{-1} \tag{21}$$

Finally, we denote the hypothetical profits earned at target prices P^{H*} and P^{L*} as Π^{H*} and Π^{L*}, respectively.

5.3. *Period 2: Regulatory Approval*

In period 2, equipped with target prices P^{H*} and P^{L*} from the period 1 problem, the insurer seeks regulatory approval from each state's regulator. Specifically, it decides how much effort to allocate across the two regions.

5.3.1. *Regulatory Approval*

Each region R is associated with a regulatory approval function $g^R(\cdot)$ which lies in the interval $[0, 1]$. It represents the proportion of the target price actually received by the insurer in that region, which is equivalent to the Rate Wedge previously defined in Section 2.1. Therefore, $g^R \times P^{R*}$ is thus the final price that the insurer is able to charge post regulatory approval in region R.

We model g^R to depend on two quantities: the insurer's filing effort $\left(e^R\right)$ and the uncertainty associated with the risk (σ_R^2). We make the following assumptions regarding the shape of g^R. First, in each region, g^R is increasing in the insurer's effort but at a decreasing

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rate:

$$\frac{\partial g^R}{\partial e^R} > 0, \quad \frac{\partial^2 g^R}{\partial \left(e^R\right)^2} < 0 \tag{22}$$

In other words, to obtain a final price that is close to the target price, the insurer can exert more effort, albeit at a decreasing level of efficacy.

Second, g^R is greater if there is less uncertainty associated with the underlying risk:

$$\frac{\partial g^R}{\partial \sigma_R^2} < 0 \tag{23}$$

This condition captures the notion that regulators are more likely to be stringent in the approval when there is more uncertainty surrounding the underlying risk, resulting in a greater discount to the target price. We also provide empirical support for this assumption in Figure B.7, where we illustrate that states with higher regulatory frictions also seem to have higher average annual dispersion in target rates among the top 20 insurers. As shown in Equation (20), this price dispersion may be the result of dispersion in the perceived marginal costs, the markup, or the financial constraints. Given that we focus on the largest insurers who likely operate throughout the state, the dispersion likely comes from the disagreement in marginal costs, which naturally warrants the interpretation as uncertainty.

Finally, we assume that the effectiveness of the insurer's filing efforts ($\partial g / \partial e$) decreases as the uncertainty associated with the underlying risk (σ_R^2) increases:

$$\frac{\partial^2 g^R}{\partial e^R \partial \sigma_R^2} < 0 \tag{24}$$

5.3.2. The Insurer's Problem

The regulatory approval function is known to the insurer. Therefore, the insurer then solves how much effort e to allocate to region H, which then determines how much effort goes to region L:

$$\max_{e \in [0,1]} \quad g^H \left(e, \sigma_H^2\right) \Pi^{H*} + g^L \left(1 - e, \sigma_L^2\right) \Pi^{L*} \tag{25}$$

Note that the first term in the objective represents the profit to the insurer in region H post regulatory approval, as Π^{H*} is the profit to be earned when the final price equals the target price. Since the insurer operates in both regions, it maximizes the sum of profits and chooses e accordingly.

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5.3.3. *Optimal Filing Effort*

The optimal filing effort is characterized by the first-order condition:

$$\frac{\partial g^H\left(e, \sigma_H^2\right)}{\partial e} \Pi^{H*} = \frac{\partial g^L\left(1-e, \sigma_L^2\right)}{\partial\left(1-e\right)} \Pi^{L*} \tag{26}$$

Equation (26) says that the effort in a given region R is generally decreasing in the uncertainty associated with the underlying risk, σ_R^2. To see this, first note from (24) that an increase in σ_R^2, holding other parameters fixed, implies a decrease in $\partial g^R/\partial e$. Given (22), this implies that the insurer needs to exert less effort in region R to increase $\partial g^R/\partial e$ and make the first order condition bind again. Therefore, in response to a shock to σ_R^2 , the insurer ends up exerting more effort in other regions and less effort in region R. Now consider a slightly different scenario where an increase in σ_R^2 is accompanied by a simultaneous increase in V^R as well. In this case, $\partial g^R/\partial e$ decreases, same as before. But in addition, Π^{R*} may be affected by V^R. In fact, since $\Pi^{R*} = \left(P^R - V^R\right) Q^R - C$, it can be shown that for $\epsilon_D^R < 1$, Π^{R*} is increasing in V^A and for $\epsilon_D^R > 1$, Π^{R*} is decreasing in V^R.

5.4. *Empirical Predictions*

The model generates predictions that are consistent with the empirical patterns we have documented, which we summarize below.

1. *Insurers cross-subsidize insurance in high friction states by increasing prices in low friction states.* This prediction follows from the target pricing formula (20) and (21). It also shows that cross-subsidization does not happen in the other direction where insurers increase prices in high friction states instead.

2. *Insurer exerts more rate filing effort in low friction states than in high friction states, controlling for profits.* From the first-order condition (26), $\sigma_H^2 > \sigma_L^2$ implies that $e < 1 - e$ assuming $\Pi^{H*} = \Pi^{L*}$. Since high friction states are associated with high uncertainty, e is higher in low friction states.

3. *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.* A loss in a given region induces the insurer to reduce filing efforts in the region and increase filing efforts in the other region because the effectiveness of the insurer's filing efforts ($\partial g/\partial e$) decreases as the uncertainty associated with the underlying risk (σ_R^2) increases due to the loss. Assuming that the increase in uncertainty brought on by the loss is higher in a high friction

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state than in a low friction state, which is consistent with data, then the reduction in filing efforts is greater in a high friction state than in a low friction state.

4. *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.* Recall that a lower g^R is equivalent to a higher discount from the target price, and that g^R is increasing in e^R and decreasing in σ_R^2 . Since high friction states experience (1) a greater increase in uncertainty and (2) a greater decrease in filing efforts, g^R will decrease more than when a similar level of loss hits a low friction region.

6. Conclusion

In this paper, we study the pricing and market structure of the U.S. homeowners' insurance market. Using our new state-level measure of rate-setting frictions constructed from historical rate filings, we find that these frictions are severe and insurers are restricted in their ability to change rates. Importantly, there is significant heterogeneity in rate setting frictions across states which positively correlates with how exposed a state is to climate events. This pattern implies that insurers in high friction states, who are restricted in their ability to set rates, end up responding less after experiencing climate losses than in low friction states.

To overcome these frictions, insurers cross-subsidize their business in high friction states by increasing prices in low friction states. This behavior leads to prices increasing faster in low friction states which implies gradual decoupling of prices and risk. Moreover, we provide evidence that the supply of homeowner insurance is negatively affected over time in high friction states. Finally, we provide a model of insurer rate-setting with regulatory frictions which captures these empirical patterns.

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 climate risk) states are subsidizing insurance for households in more strict (and high climate risk) states. This cross-subsidization can potentially give rise to a moral hazard problem as rates get disjoint from underlying risk. Anecdotal evidence suggests that 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.

[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.

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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).

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Figures

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.

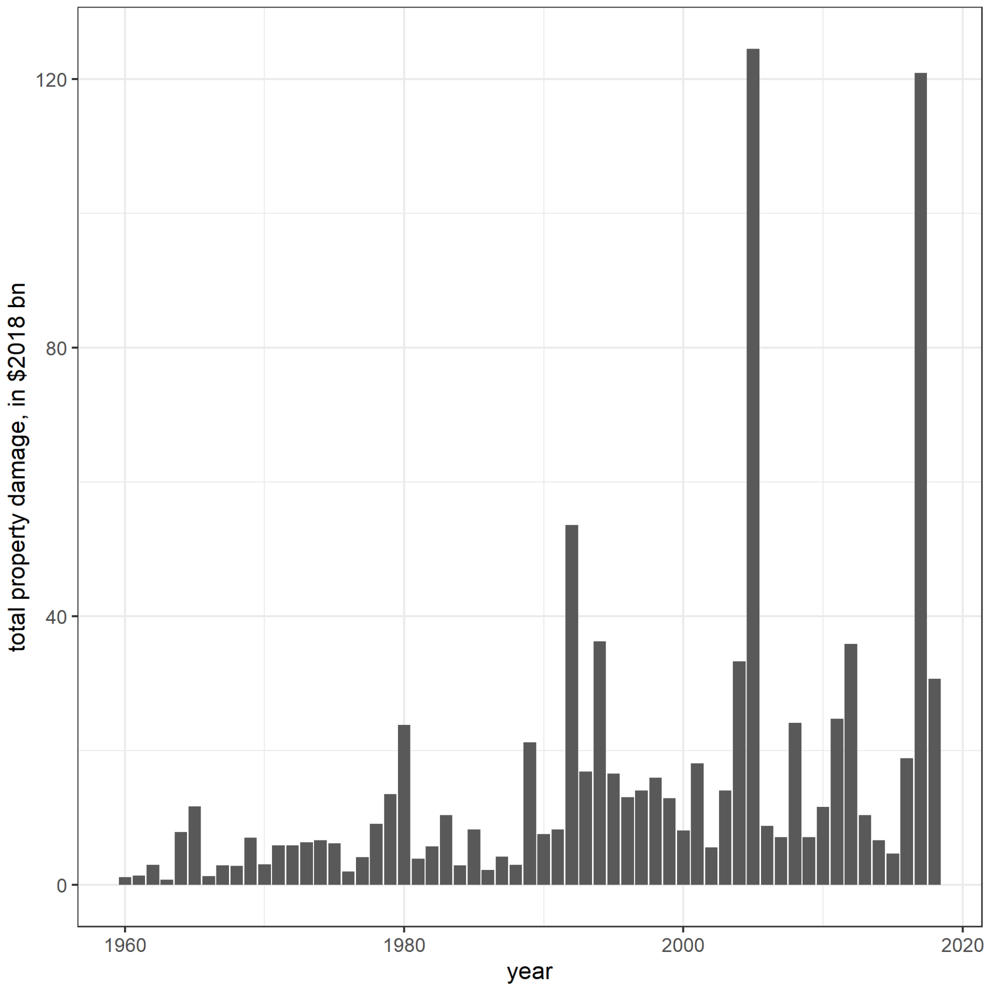

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Figure 2: Homeowners' insurance aggregate premia written

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.

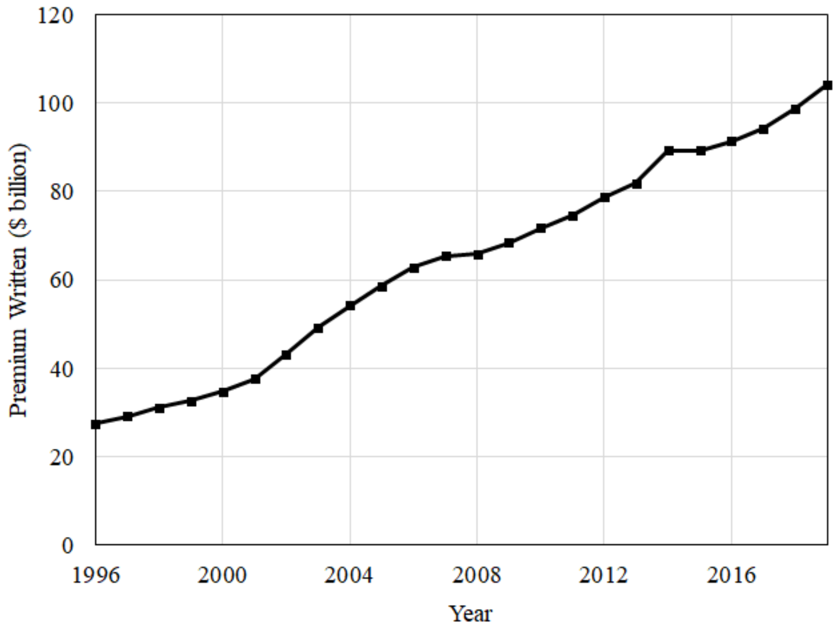

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Figure 3: Significance of homeowners' insurance for households

The figure plots average homeowners insurance (left scale), average mortgage interest expenses (left scale), and homeowners insurance as a fraction of mortgage interest expenses in each state in the U.S.. Insurance rates are based on a \$400k home with a \$300k insurance liability. Mortgage rates are based on a \$400k home and a \$300k mortgage loan for a 30 years term and for a consumer with an average FICO score (= 660-679).

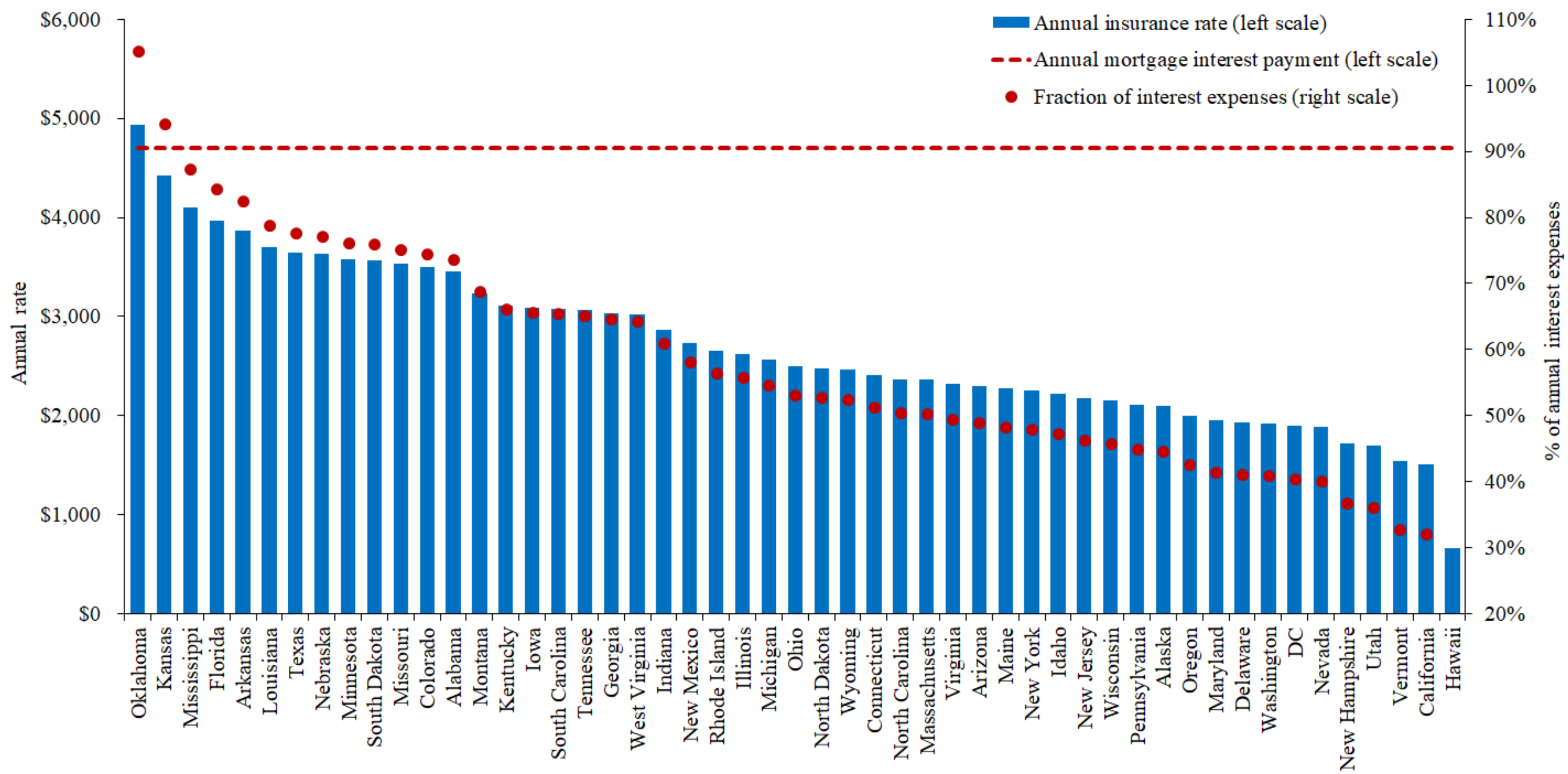

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Figure 4: Distribution of rate wedge

The figure shows the distribution of rate wedge, 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 -0.5 and 1.5, and each of the ends carries approximately 1% of the values. The data are from insurance product filings accessed through S&P MI.

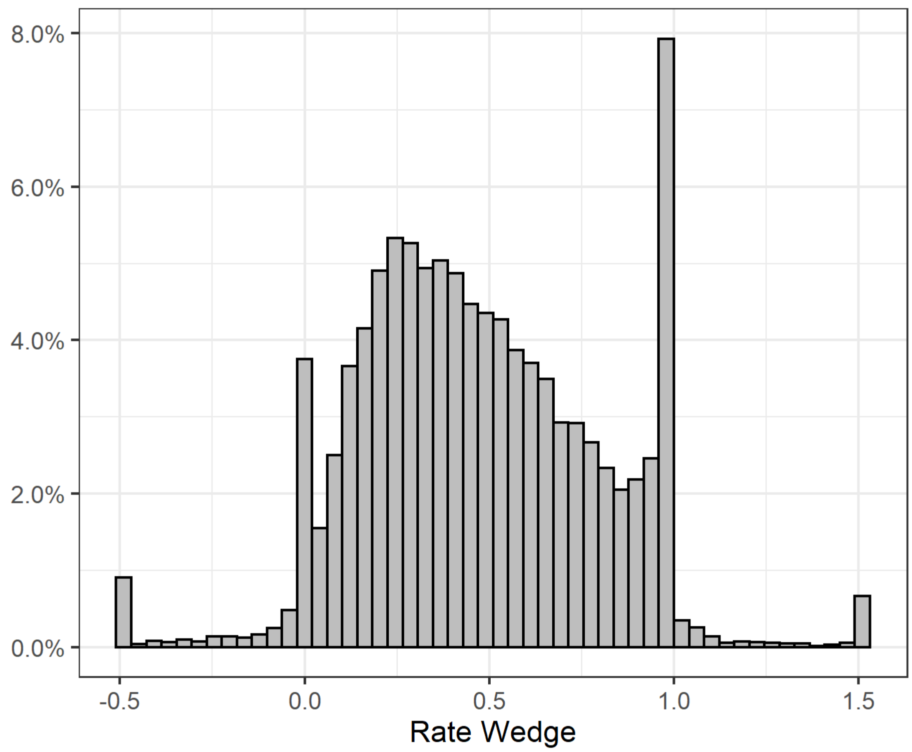

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Figure 5: Mean execution time is longer in stricter states

The figure plots the The graph plots Friction_s, estimated as in Equation 2 and the time it takes each state to approve filings (mean execution time) in days in each state. The blue line is a fitted line from the following linear regression: $\text{Mean execution time}_s = \alpha + \beta \text{Friction}_s + \epsilon_s$, where each state is weighted by the total premium. The data are from insurance product filings accessed through S&P MI.

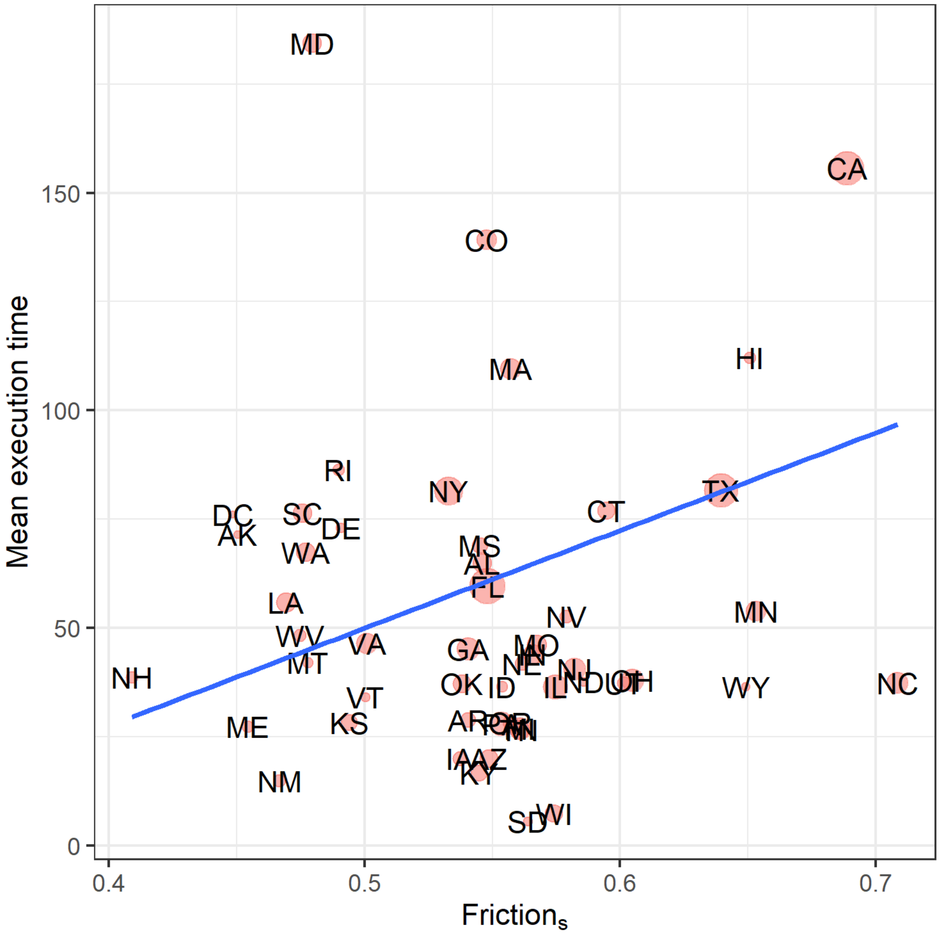

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Figure 6: Long-run growth in insurance prices

We estimate the average growth of prices between 2008 and 2019 for high frictions states vs non-high friction states. we construct an aggregate price index, by growing prices in each state s between $t-1$ and t by $\Delta\text{Rate}_{s,t}$ as described in Section 3.2.1. Setting the price level of each state in year 2008 (base year) to be 1, we estimate the growth from 2008 to any year T in state s as $P_{s,T} = \Pi_{t=2009}^{T}(1 + \Delta\text{Rate}_{s,t})$. The data are from insurance product filings accessed through S&P MI.

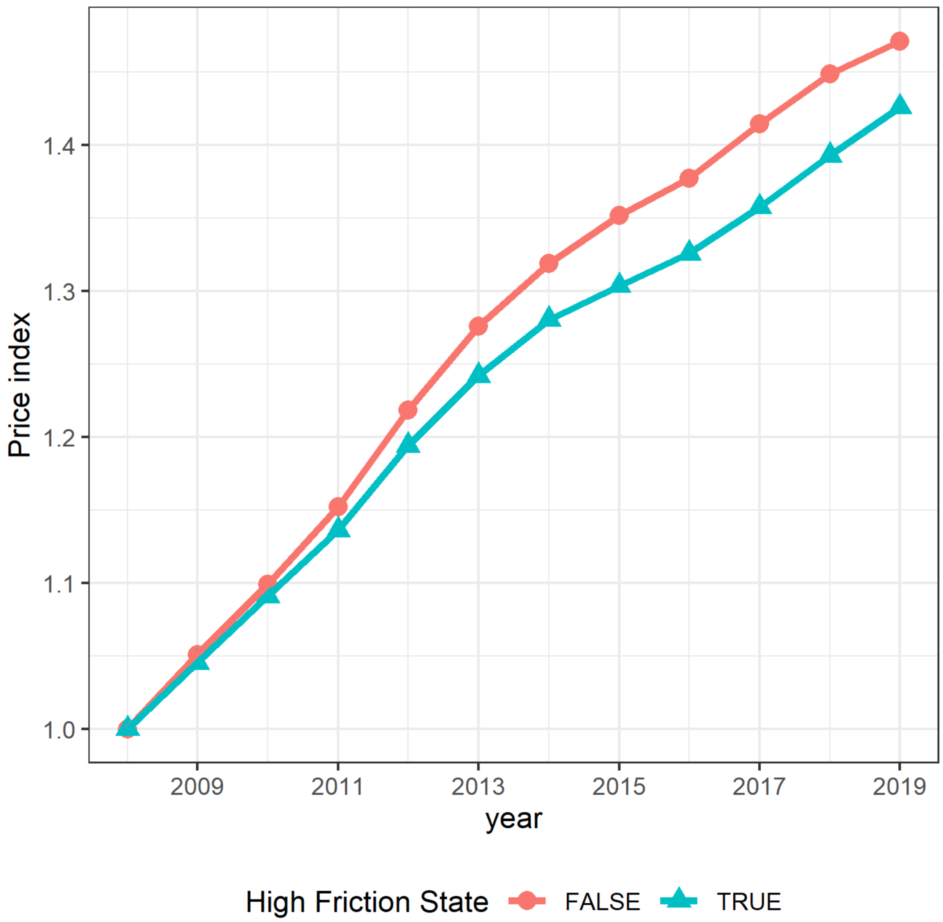

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Figure 7: Regulatory pricing frictions and climate losses

The graph plots $Friction_s$, estimated as in Equation 2 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.

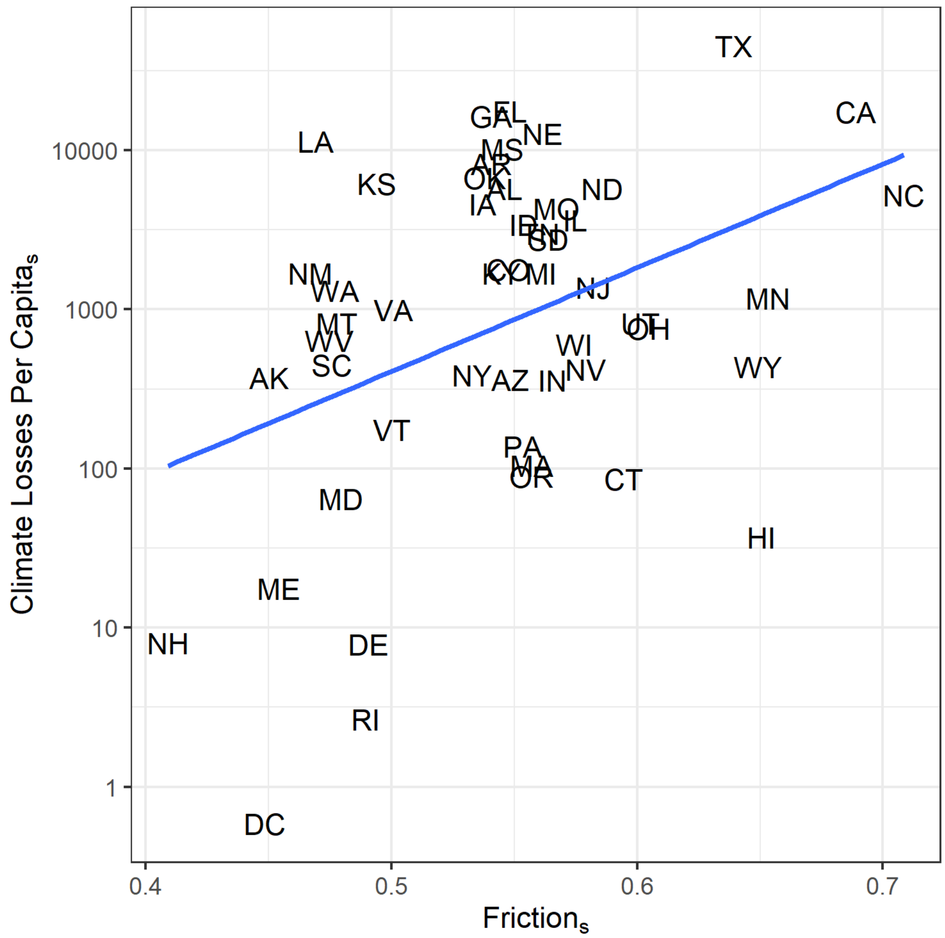

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Figure 8: Decoupling of insurance prices from risk

The graph plots $Friction_s$, estimated as in Equation 2 and the ratio of how prices have increased compared to long-run growth in climate losses in each state. We compute the growth of prices between 2008 and 2019, $P_{s,2019}/P_{s,2008}$. We scale the price growth by growth in climate losses per capita, which we compute as the ratio of losses between 2008 to 2019 relative to losses between 1997 to 2007. Losses per capita are in log scale and are inflation adjusted. The blue line is a fitted line through the scatter plot using a linear regression. The data on climate losses are from SHELDUS. The data on insurance product filings are from S&P MI.

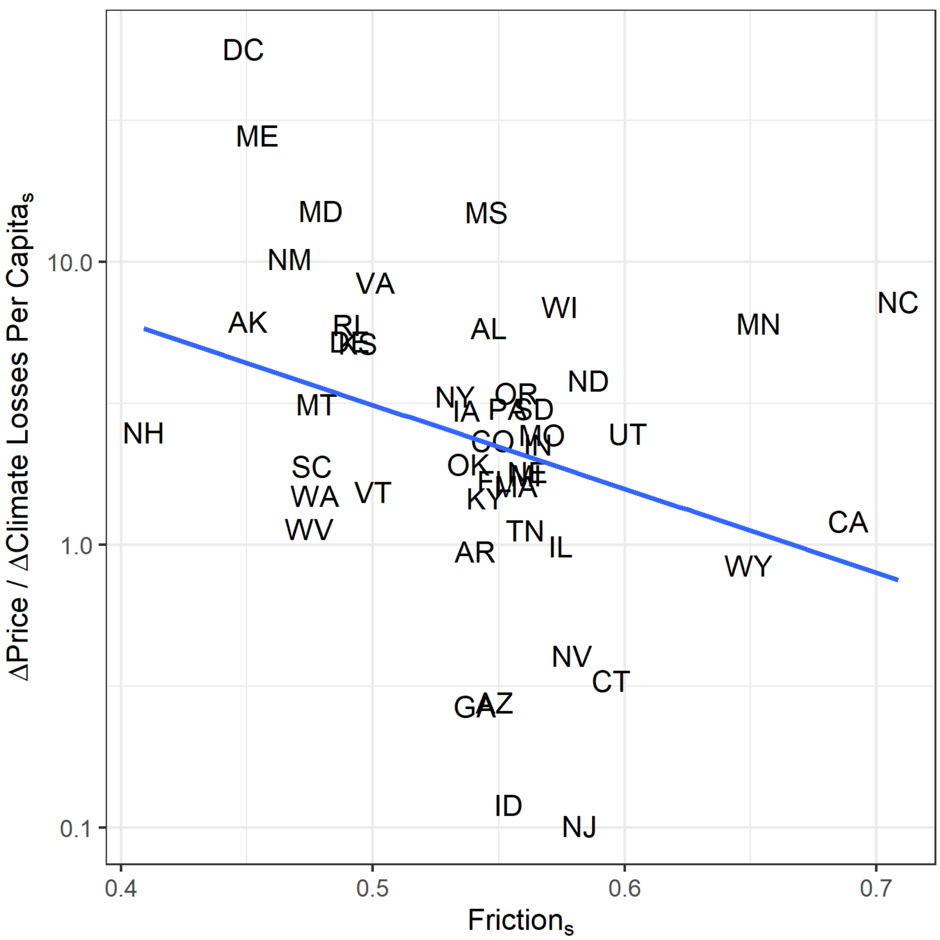

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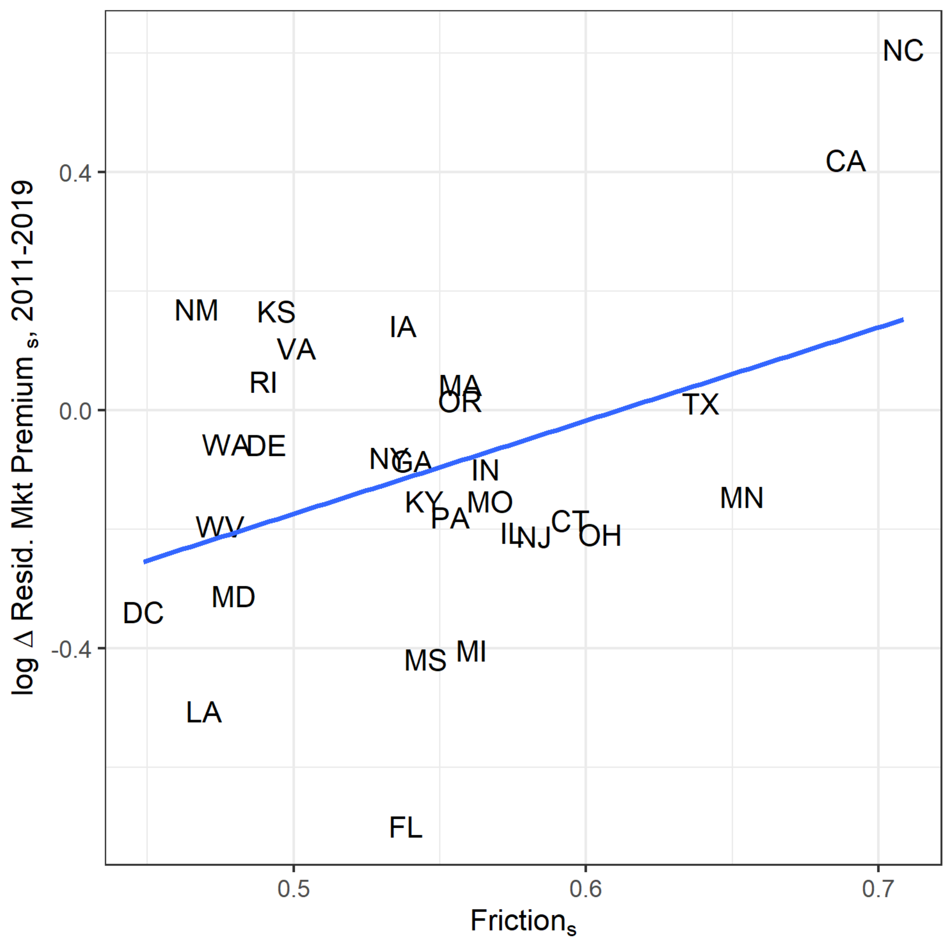
Figure 9: Change in homeowners' residual market (2011-2019) and regulatory friction

The graph plots $Friction_s$, estimated as in Equation 2 and the log difference in residual market premiums between 2011 and 2019, for the 32 states which provide residual market for homeowners' insurance. The data on residual market is from PIPSO.



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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 insurers are limited to the 50 largest insurers in a give year, who sell homeowners' insurance in at least 2 states, and who have sold at least $100,000 in premiums in each of the previous three years. From the rate change filings: the indicator any filings equals 1 when insurer i requested rate change in state s in year t. The variable is computed over all complete insurer-state-year panel. Rate Δ received/rate Δ target are the percentage change which insurer i received from regulators/stated as a target in their filings to state s in year t. These two variables are estimated based on actual rate filings in this table. In the main analysis, if an insurer doesn't file for rate change in a given state and year, rate Δ received is set to 0. From the variables from financial statements: own st loss is the loss ratio (loss/premium) of insurer i in year t and state s; other lines loss estimate the aggregate loss ratio over all lines of business that are not homeowner's insurance; reinsurance ratio shows the fraction of insurer i total homeowners' premiums are re-insured in year t. The statistics shown, from left to right, are number of observations, mean, standard deviation, and 1$^{\text{st}}$ percentile, 10$^{\text{th}}$ percentile, median, 90$^{\text{th}}$ percentile, and 99$^{\text{th}}$ percentile.

	n	mean	sd	p10	p25	median	p75	p90
Rate change filings:								
Any filings	17980	0.70	0.46	0.00	0.00	1.00	1.00	1.00
Rate Δ target	12563	15.60	15.97	0.00	5.20	11.70	21.44	35.59
Rate Δ received	12563	5.85	5.55	0.00	2.03	5.00	8.70	12.86
Financial statements (2019):								
Premium (homeowners, \$M)	1530	39.03	95.72	1.90	4.95	13.01	33.53	79.77
Loss (homeowners, \$M)	1530	22.39	62.11	0.80	2.54	6.55	17.62	46.87
Loss ratio (homeowners)	1530	0.57	0.31	0.30	0.40	0.52	0.66	0.86
Loss ratio (non-homeowners)	253	0.60	0.15	0.49	0.54	0.58	0.64	0.71
Net assets (\$B)	253	2.86	7.33	0.07	0.13	0.33	1.75	6.79
RBC ratio (logged)	253	6.58	0.55	5.92	6.18	6.57	6.91	7.24
Reinsurance ratio	253	0.18	0.25	0.00	0.01	0.08	0.22	0.51
N states a firm sells homeowners	253	14.62	16.04	2.00	3.00	7.00	21.00	45.80

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Table 2: Price setting response to own losses

The table present regression results from Equation 3. The dependent variable in column (1) is the likelihood of a rating change filed by insurer i in state s and year t. The dependent variable in column (2) is the average rate wedge (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 is restricted to the largest 50 insurers by premium sold in states s which sold at least \$100,000 in premium. 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

	Any filings$_{i,s,t+1}$	Rate Wedge$_{i,s,t+1}$
	(1)	(2)
own st loss$_{i,s,t}$	0.007	-0.061^{**}
	(0.030)	(0.024)
own st loss$_{i,s,t}$ $\times$ $\mathrm{I}_s^{\text{Med Fric}}$	0.035	0.034
	(0.035)	(0.030)
own st loss$_{i,s,t}$ $\times$ $\mathrm{I}_s^{\text{Low Fric}}$	0.109^{***}	0.120^{**}
	(0.037)	(0.049)
E[LHS]	0.71	0.48
Controls	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes
Insurer Fixed effects	Yes	Yes
Observations	19,312	9,975
Adjusted R^2	0.332	0.154

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Table 3: Rate wedge predict future losses

The table presents estimates from Equation 4. Underwiting profit$_{i,s,t+1}$ is ratio of premium minus losses divided by premium for insurer i in state s at year $t+1$. Friction$_{i,s,t}$ measures the one minus the average rate wedge 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

	Underwriting profit$_{i,s,t+1}$			
	(1)	(2)	(3)	(4)
Friction$_{i,s,t}$	-0.014^{**}	-0.016^{*}	-0.009^{*}	-0.020^{***}
	(0.007)	(0.008)	(0.005)	(0.006)
rank	≤50	≤30	≤20	≤10
Controls	Yes	Yes	Yes	Yes
State × Year Fixed effects	Yes	Yes	Yes	Yes
Insurer Fixed effects	Yes	Yes	Yes	Yes
Observations	11,284	7,585	5,358	2,951
R^2	0.619	0.708	0.771	0.834
Adjusted R^2	0.581	0.668	0.732	0.785

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Table 4: Larger requests take longer time

The table shows results regression results of log execution days$_{f,s,t}$ = size of change$_{f,s,t}$ $+ \alpha_x + \epsilon_{f,s,t}$. 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

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Table 5: Cross-subsidization across states: number of rate filings

The table shows results from the regression shown in Equation 5 at columns (1-4) and in Equation 6 at column (5). The dependent variable is the likelihood for a rate filings for insurer i at state s in year t. The independent variable of interest is other st $\text{loss}_{i,s,t}$, which is the loss ratio experienced by insurer i in year t in all states except s (sum of all losses in states which are not s divided by all premiums collected in states which are not s). The indicator variables $\text{I}_s^{\text{Med Fric}}$ and $\text{I}_s^{\text{Low Fric}}$ equal 1 if the state s is, correspondingly, medium or low friction states. The panel is restricted to the largest 50 insurers in a given state and year, and insurers i which sell homeowners' insurance in more than 2 states in a given year which sell more than $100,000 in premium a year. Furthermore, in column (1) and (5) we include all states in the panel, while in columns (2)/(3)/(4) is restricted to state s being a high/medium/low friction state. All regressions control for loss ratio in the (same) state s, 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. All regressions include insurer-filing state 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

	any $\text{filings}_{i,s,t+1}$				
	(1)	(2)	(3)	(4)	(5)
other st $\text{loss}_{i,\bar{s},t}$	0.027*	−0.004	0.013	0.151***	−0.006
	(0.015)	(0.022)	(0.012)	(0.033)	(0.021)
other st $\text{loss}_{i,\bar{s},t} \times \text{I}_s^{\text{Med Fric}}$					0.019
					(0.025)
other st $\text{loss}_{i,\bar{s},t} \times \text{I}_s^{\text{Low Fric}}$					0.162***
					(0.041)
E[LHS]	0.7	0.7	0.8	0.7	0.7
State friction	All	High	Medium	Low	All
Controls	Yes	Yes	Yes	Yes	Yes
State × Year Fixed effects	Yes	Yes	Yes	Yes	Yes
Insurer × State Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,980	5,656	6,231	6,093	17,980
Adjusted R^2	0.365	0.471	0.310	0.288	0.366

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Table 6: Cross-subsidization across states: rate change requested

The table shows results from the regression shown in Equation 5 at columns (1-4) and in Equation 6 at column (5). The dependent variable is the average change received, weighted by affected premium, among the filings of insurer i at state s in year t; if the insurer did not apply for a rate change, the variable is 0. The independent variables of interest are other st $\text{loss}_{i,s,t}$, which is the loss ratio experienced by insurer i in year t in all states except s (sum of all losses in states which are not s divided by all premiums collected in states which are not s). The indicator variables $\text{I}_s^{\text{Med Fric}}$ and $\text{I}_s^{\text{Low Fric}}$ equal 1 if the state s is, correspondingly, medium or low friction states. The panel is restricted to the largest 50 insurers in a given state and year, and insurers i which sell homeowners' insurance in more than 2 states in a given year and sell more than $100,000 in premiums a year. Furthermore, in column (1) and (5) we include all states in the panel, while in columns (2)/(3)/(4) is restricted to state s being a high/medium/low friction state. All regressions control for loss ratio in the (same) state s, 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. All regressions include insurer-filing state 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

	rate Δ $\text{received}_{i,s,t+1}$				
	(1)	(2)	(3)	(4)	(5)
other st $\text{loss}_{i,\bar{s},t}$	0.632***	0.085	0.758**	1.709***	0.075
	(0.212)	(0.196)	(0.350)	(0.487)	(0.193)
other st $\text{loss}_{i,\bar{s},t} \times \text{I}_s^{\text{Med Fric}}$					0.693*
					(0.401)
other st $\text{loss}_{i,\bar{s},t} \times \text{I}_s^{\text{Low Fric}}$					1.604***
					(0.528)
E[LHS]	3.7	3.4	4.5	3.3	3.7
State friction	All	High	Medium	Low	All
Controls	Yes	Yes	Yes	Yes	Yes
State × Year Fixed effects	Yes	Yes	Yes	Yes	Yes
Insurer × State Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,980	5,656	6,231	6,093	17,980
Adjusted R^2	0.280	0.296	0.309	0.207	0.281

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Table 7: Cross-subsidization across states: split $\bar{s}$ by rate setting friction

The table shows results from the regression shown from Equation 7 where other state loss are split in three groups based on the regulatory frictions in the other states $\bar{s}$. Column (1) uses as a dependent variable the likelihood of a rate filings for insurer i filed at state s in year t. Column (2) uses as a dependent variable the average change received, weighted by affected premium, among the filings of insurer i at state s in year t; if the insurer did not apply for a rate change, the variable is 0. In the first/second/third row, the independent variable is the loss ratio from other states, which are high/medium/low friction. The panel is restricted to states s which are low regulatory friction, the largest 50 insurers in a given state and year, and insurers i which sell homeowners' insurance in more than 2 states in a given year. All regressions control for loss ratio in the (same) state s, 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-filing state 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

	any filings$_{i,s,t+1}$	rate Δ received$_{i,s,t+1}$
	(1)	(2)
other st loss$^{\text{High Fric}}_{i,\bar{s},t}$	0.136***	1.560***
	(0.025)	(0.311)
other st loss$^{\text{Med Fric}}_{i,\bar{s},t}$	0.127***	1.418***
	(0.031)	(0.406)
other st loss$^{\text{Low Fric}}_{i,\bar{s},t}$	0.022	0.360
	(0.042)	(0.779)
E[LHS]	0.7	3.3
State friction	Low	Low
Controls	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes
Observations	6,093	6,093
Adjusted R^2	0.288	0.207

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Table 8: Cross-Subsidization of insurance rates across states: by insurer rank

The table shows results from the regression shown from Equation 7 where other state loss are split in three groups based on the regulatory frictions in the other states $\bar{s}$. Columns (1) to (3) use as a dependent variable the likelihood for a rate filings for insurer i filed at state s in year t, and if the insurer did not apply for a rate change, the variable is 0. Column (4) to (6) 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; if the insurer did not apply for a rate change, the variable is 0. In the first/second/third row, the independent variable is the loss ratio from other states, which are high/medium/low friction. The panel is restricted to states s which are low regulatory friction and insurers i which sell homeowners' insurance in more than 2 states in a given year and the premium exceeds $100,000. Furthermore, the panel in columns (1) and (4)/(2) and (5)/(3) and (6) is also restricted to the largest 50/30/20 insurers in a given state and year. All regressions control for loss ratio in the (same) state s, 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-filing state 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

	any filings$_{i,s,t+1}$			rate Δ received$_{i,s,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
other st loss$^{hFrct}_{i,\bar{s},t}$	0.136***	0.202***	0.225***	1.560***	2.044***	2.742***
	(0.025)	(0.036)	(0.044)	(0.311)	(0.562)	(0.621)
other st loss$^{mFrct}_{i,\bar{s},t}$	0.127***	0.182***	0.199***	1.418***	1.706**	2.240***
	(0.031)	(0.036)	(0.049)	(0.406)	(0.599)	(0.679)
other st loss$^{lFrct}_{i,\bar{s},t}$	0.022	−0.021	−0.012	0.360	0.419	0.635
	(0.042)	(0.047)	(0.063)	(0.779)	(0.729)	(0.668)
E[LHS]	0.67	0.72	0.74	3.26	3.33	3.32
State friction	Low	Low	Low	Low	Low	Low
Rank	≤50	≤30	≤20	≤50	≤30	≤20
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Insurer × State Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,093	3,830	2,584	6,093	3,830	2,584
Adjusted R^2	0.288	0.294	0.329	0.207	0.259	0.246

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Table 9: Sensitivity to out-of-state losses by financial friction

The table shows results from Equation 9. The dependent variable in columns (1-5)/(6-10) is any filings/rate change received for the filings requests submitted by insurer i in state s in year $t+1$. $\mathrm{I}^{cons}_{i,t-1}$ is 1 if insurer i is financially constrained according to the following definitions: below the median net assets in columns (1) and (6); RBC ratio in columns (2) and (7); capital to assets ratio in columns (3) and (8). In columns (4) and (9)/(5) and (10) we ran Equation 6 over the subset of publicly traded/privately held insurers, with the implication that private firms are more financially constrained than private ones. All regressions control for loss ratio in the (same) state s, 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, which sell more than \$100,000 in premiums in a given state-year. All regressions include insurer-filing state 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)

	any rate filings$_{i,s,t+1}$					rate Δ received$_{i,s,t+1}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
other st loss$_{i,\bar{s},t}$	-0.003	0.014	0.026	-0.040^{*}	0.056^{**}	0.194	0.499	0.342	-0.104	0.393
	(0.020)	(0.029)	(0.032)	(0.021)	(0.022)	(0.188)	(0.411)	(0.301)	(0.225)	(0.352)
other st loss$_{i,\bar{s},t}\times$ $\mathrm{I}_s^{\text{Med Fric}}$	0.010	-0.020	-0.006	-0.027	-0.045	0.579	0.125	-0.049	3.086^{***}	0.217
	(0.026)	(0.037)	(0.036)	(0.078)	(0.027)	(0.479)	(0.530)	(0.425)	(0.799)	(0.474)
other st loss$_{i,\bar{s},t}\times$ $\mathrm{I}_s^{\text{Low Fric}}$	0.175^{***}	0.133^{***}	0.152^{***}	0.145^{**}	0.070^{*}	1.795^{***}	1.394^{**}	1.235^{**}	1.842^{**}	1.326^{**}
	(0.038)	(0.043)	(0.044)	(0.068)	(0.037)	(0.520)	(0.669)	(0.542)	(0.700)	(0.574)
other st loss$_{i,\bar{s},t}\times$ $\mathrm{I}^{cons}_{i,t-1}$	-0.026	-0.023	-0.038			-0.990^{*}	-0.482	-0.309		
	(0.043)	(0.025)	(0.026)			(0.520)	(0.398)	(0.290)		
other st loss$_{i,\bar{s},t}\times$ $\mathrm{I}_s^{\text{Med Fric}}\times$ $\mathrm{I}^{cons}_{i,t-1}$	0.036	0.044	0.025			0.830	0.610	0.890^{**}		
	(0.050)	(0.027)	(0.027)			(0.656)	(0.445)	(0.363)		
other st loss$_{i,\bar{s},t}\times$ $\mathrm{I}_s^{\text{Low Fric}}\times$ $\mathrm{I}^{cons}{}_{i,t-1}$	-0.031	0.028	0.00002			0.284	0.234	0.495		
	(0.054)	(0.037)	(0.032)			(0.603)	(0.498)	(0.355)		
E[LHS]	0.7	0.7	0.7	0.8	0.7	3.7	3.7	3.7	4.5	3.4
Firm Constraint	net A	RBC	K/A	public	private	net A	RBC	K/A	public	private
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,980	17,980	17,980	4,801	13,179	17,980	17,980	17,980	4,801	13,179
Adjusted R^2	0.366	0.366	0.366	0.312	0.471	0.281	0.281	0.281	0.283	0.311

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Table 10: Number of insurer exits from a state between 2009 and 2018

We count the times a given firm stopped selling homeowner insurance (exits) in a given state, by the market share of the firm in the year before exit. We show the percentage of exits of state-years in each category. Large insurers have more than 1% market share in a state and small insurers have less than 1% market share in a state. To avoid spurious results, we exclude insurers that have less than 0.5% market share in any given state.

	All States		High Friction		Medium Friction		Low Friction	
Market share	n exits	% exited	n exits	% exited	n exits	% exited	n exits	% exited
Large	17	0.15	5	0.14	4	0.11	8	0.21
Small	27	0.41	13	0.56	8	0.36	6	0.28

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Table 11: How exits respond to losses

The table present regression results from Equation 3. The dependent variable is an indicator, which equals 1 if insurer i stopped selling homeowners insurance in state s in year $t+1$, but continued doing so in other states, and 0 otherwise. Own st $\text{loss}_{i,s,t}$, is the losses to premiums of insurer i in state s in year t. $I_s^{HighFric}$ is an indicator, which equals 1 if the state has a high friction regulatory environment. 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 the losses to premiums of insurer i in all states except s in year t, 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. Column (1) shows all insurers, column (2) shows insurers that more than 1% market share in a state, and column (3) shows insurers that are below 1% market share in a state. To avoid spurious results, we exclude insurers that have less than 0.5% market share in any given state. 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)	(2)	(3)
own st $\text{loss}_{i,s,t-1}$	-0.014	0.0001	-0.022^{*}
	(0.010)	(0.003)	(0.013)
$I_s^{\text{High Fric}} \times$ own st $\text{loss}_{i,s,t-1}$	0.036^{**}	0.001	0.060^{**}
	(0.016)	(0.003)	(0.025)
E[LHS]	0.0027	0.0014	0.0048
Firms	all	large	small
Controls	Yes	Yes	Yes
State × Year Fixed effects	Yes	Yes	Yes
Insurer Fixed effects	Yes	Yes	Yes
Observations	11,667	7,369	4,298
Adjusted R^2	0.164	0.170	0.176

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A. Rate Filings and Anecdotal Evidence

Figure 10: 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 11: 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

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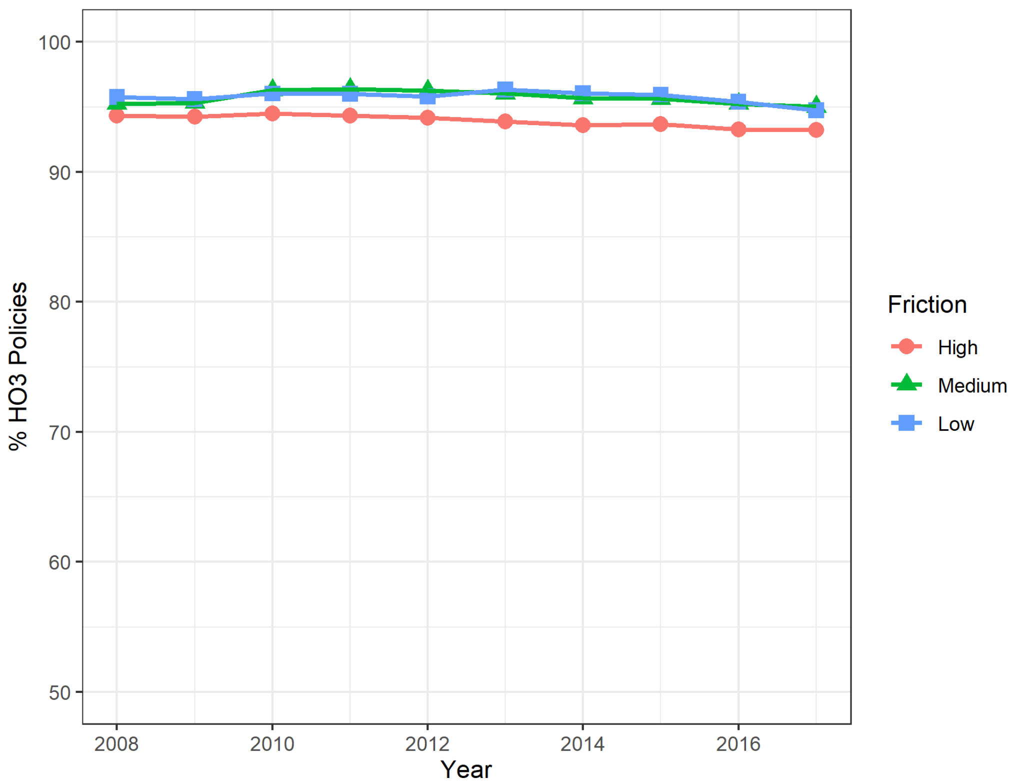
B. Additional Figures and Tables

Figure B.1: Homeowner contracts through time

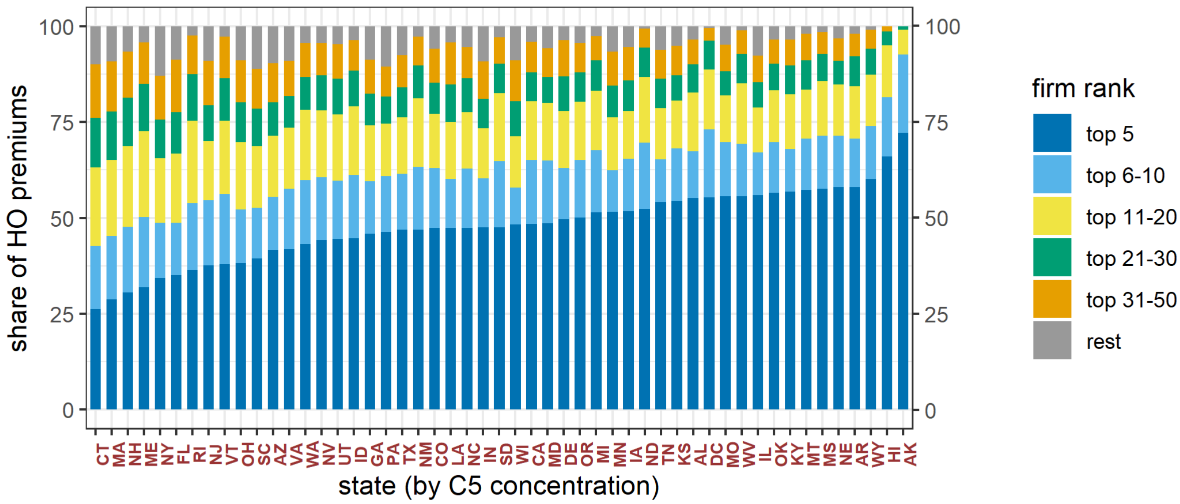
The figure shows the proportion of insurerd households that purchase HO3 policies through time and for each subgroup of states: High, Medium, and Low friction. The data are from NAIC Homeowners Compendiums and span the period 2008 to 2017.



Electronic copy available at: https://ssrn.com/abstract=3762235

Figure B.2: Market concentration of homeowners' insurance market

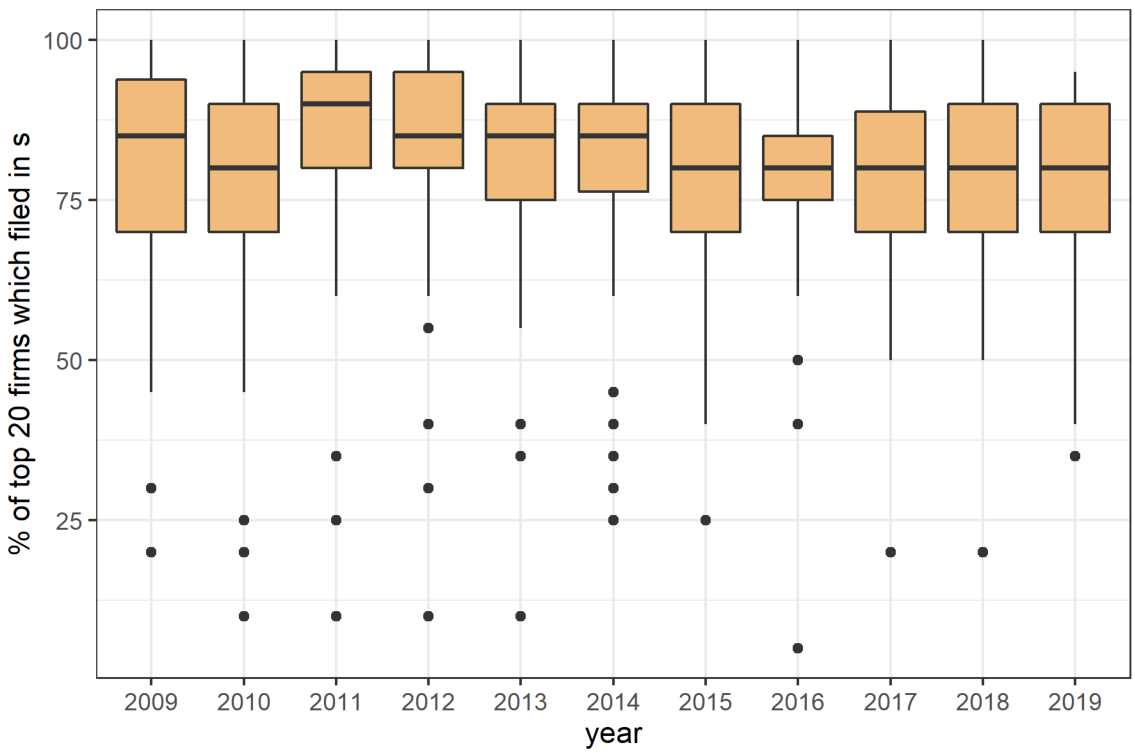
The figure plots the market share of homeowners' insurance sold by the largest insurers in a given state. Market share is computed as premium sold by the largest insurers divided by total premium sold in the states in a given year and state - and averaged over the 11 years between 2009 and 2019. States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



Electronic copy available at: https://ssrn.com/abstract=3762235

Figure B.3: Insurers ask for rate increases often

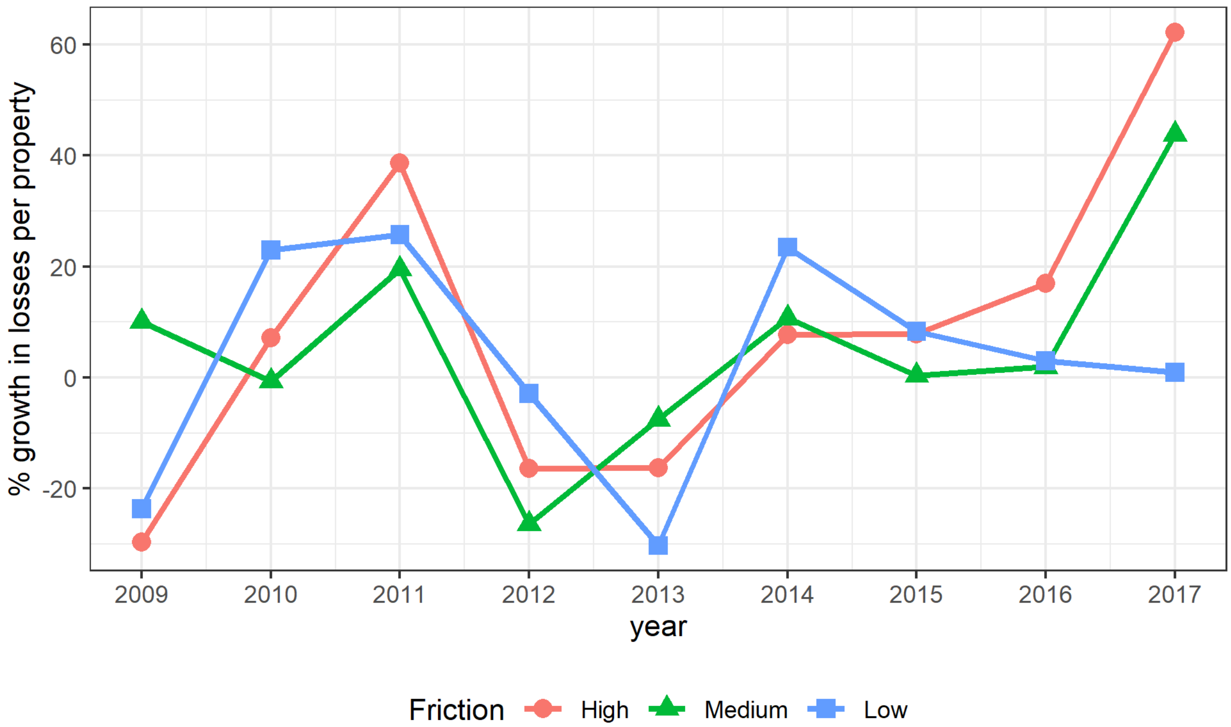
The figure plots the distribution across states' of the proportion of the largest 20 insurers that applied for a rate increase in a given year. The data are from insurance product filings accessed through S&P MI.



Electronic copy available at: https://ssrn.com/abstract=3762235

Figure B.4: Insured risk through time

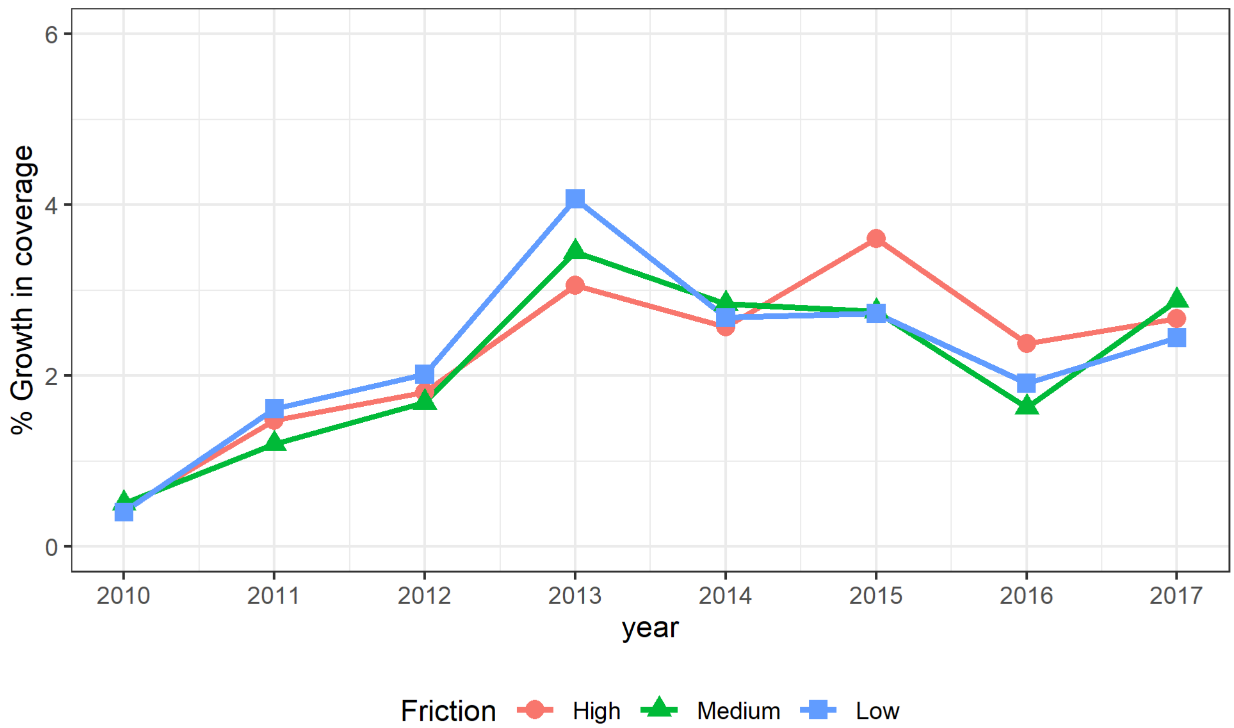
This figure shows the percentage growth in losses per insured homes through time and for each subgroup of states: High, Medium, and Low friction. The data span the period 2008 to 2017. The number of insured homes in a given state comes from NAIC's *Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance.* Losses are aggregated from insurer-state-year level losses in the Homeowner lines and come from S%P Market Intelligence.



Electronic copy available at: https://ssrn.com/abstract=3762235

Figure B.5: Average coverage through time

This figure shows the percentage growth in purchased coverage through time and for each subgroup of states: High, Medium, and Low friction. The data span the period 2008 to 2017. The average coverage of insured properties in a given state comes from NAIC's *Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance.*



Electronic copy available at: https://ssrn.com/abstract=3762235

Figure B.6: Homeowners' insurance market penetration through time

This figure shows the percentage growth in insured properties through time and for each subgroup of states: High, Medium, and Low friction. The data span the period 2010 to 2017. The numerator is estimated from the number of insured properties in a given state-year and it comes from NAIC's *Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance.* The denominator is estimated from the number of owner-occupied properties in a given state-year and it comes from American Community Survey (2010-2017).

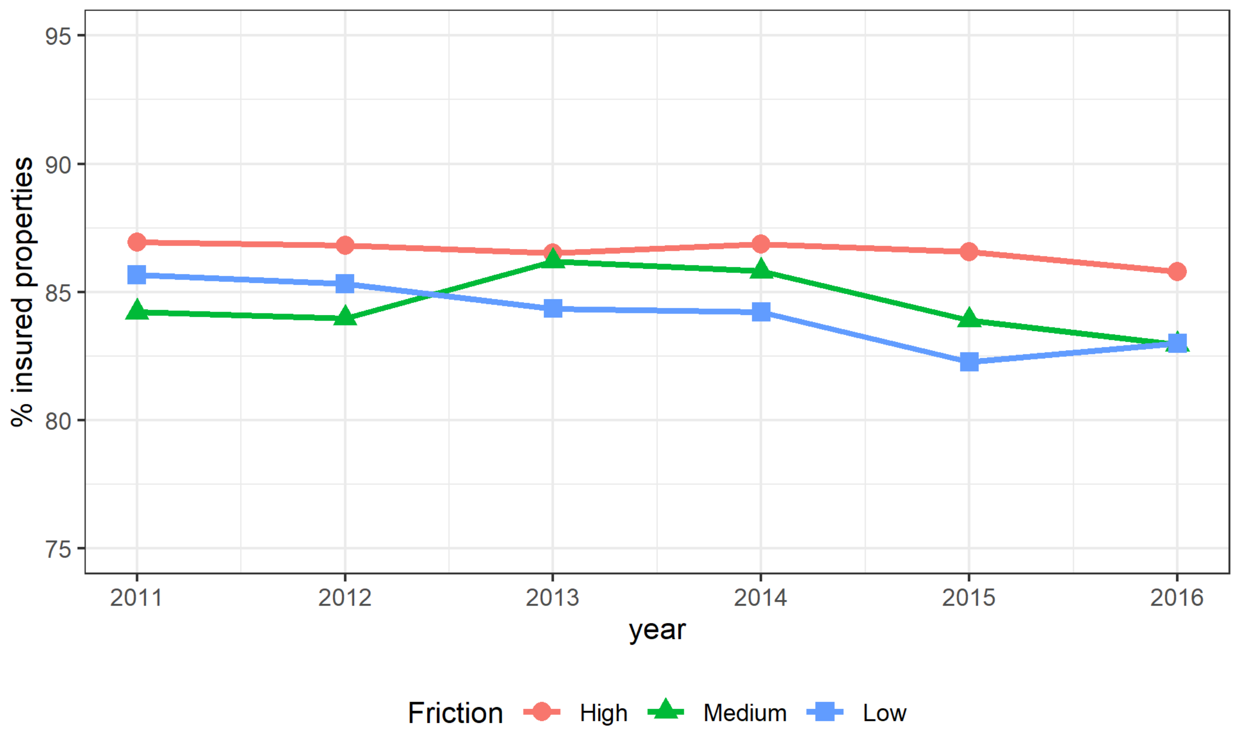


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Figure B.7: Friction and average annual dispersion in target rates

The graph plots $Friction_s$, estimated as in Equation 2 and the average annual standard deviation of the target rates of the top 20 insurers' filings over 2009-2019 in each state. We see that states with higher regulatory frictions have higher dispersion of target rate. The blue line is a fitted line from the following linear regression: SD(rate Δ target)$_s = \alpha + \beta$Friction$_s$ + ϵ_s. The data on insurance product filings are from S&P MI.

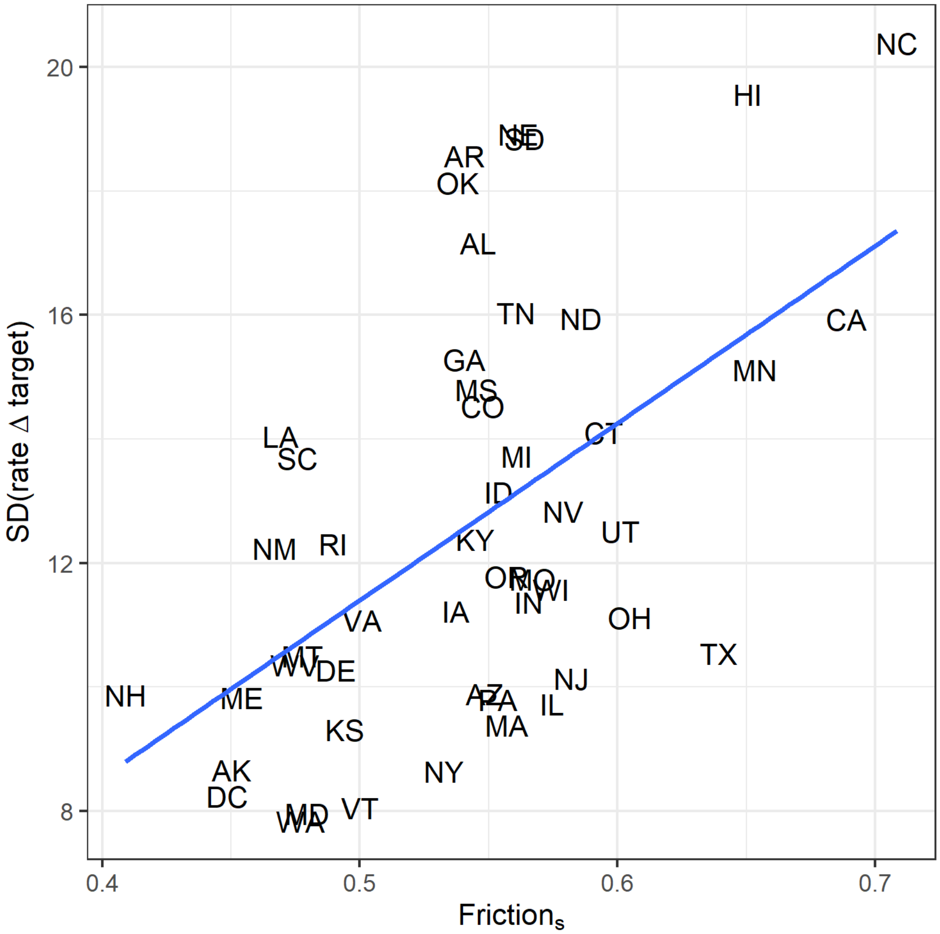

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Table B.1: Rate wedge and company size

We regress the average insurer's Rate Wedge on proxies for size: Rate $\text{Wedge}_{i,s,t} = \beta \text{Firm Size}_{i,s,t} + \alpha_x +_{i,s,t}$. 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 7^{th} 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

	Rate $\text{Wedge}_{i,s,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{rank}_{i,s,t}$	0.0004^{***}	0.001^{***}				
	(0.0001)	(0.0001)				
log $\text{premium}_{i,s,t}$			-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

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Table B.2: 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 Rate Wedge$_s$, as in Equation 2. The proxy for pricing frictions is an indicator variable which is 1 if state s is in the top half of Rate Wedge$_s$, i.e. is less strict. The average price of homeowners' insurance in a state-year comes from NAIC's *Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance.*

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

	Avg Price$^{HO}_{s,2017}$/Avg 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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Table B.3: Heterogeneity in cross-subsidization: By concentration

This table shows results from the regression shown in Equation 6. Columns (1) through (4) use as as a dependent variable the likelihood of a rate filings for insurer i filed at state s in year t, and columns (5) through (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; if the insurer did not apply for a rate change, the variable is 0. The indicator variables $\mathrm{I}_s^{\text{Med Fric}}$ and $\mathrm{I}_s^{\text{Low Fric}}$ equal 1 if the state s is, correspondingly, medium or low friction states. The panel is restricted to states s which are high, medium or a subsample of low friction states. The subsample is based on the low friction's state concentration, where the concentration is measured either as the market share of top 5 insurers (C5) or the HHI. All regressions control for loss ratio in the (same) state s, 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. All regressions include insurer-filing state and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

	any filings$_{i,s,t+1}$				rate Δ received$_{i,s,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
other st loss$_{i,\bar{s},t}$	−0.006	−0.006	−0.006	−0.006	0.080	0.070	0.077	0.074
	(0.021)	(0.021)	(0.021)	(0.021)	(0.193)	(0.193)	(0.193)	(0.193)
other st loss$_{i,\bar{s},t}\times$ $\mathrm{I}_s^{\text{Med Fric}}$	0.019	0.019	0.019	0.019	0.691*	0.694*	0.694*	0.692*
	(0.025)	(0.025)	(0.025)	(0.025)	(0.403)	(0.400)	(0.403)	(0.400)
other st loss$_{i,\bar{s},t}\times$ $\mathrm{I}_s^{\text{Low Fric}}$	0.228***	0.116***	0.175**	0.152***	2.278***	1.090	1.723**	1.489**
	(0.058)	(0.043)	(0.070)	(0.038)	(0.712)	(0.671)	(0.800)	(0.666)
Low Fric$_s$ with	Hi C	Lo C	Hi C	Lo C	Hi C	Lo C	Hi C	Lo C
Concentration	C5	C5	HHI	HHI	C5	C5	HHI	HHI
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer × State Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,693	15,174	14,511	15,356	14,693	15,174	14,511	15,356
Adjusted R^2	0.394	0.371	0.392	0.372	0.295	0.291	0.297	0.290

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Table B.4: Heterogeneity in cross-subsidization: By exposure to high-friction states

This table shows results from the regression shown in Equation 6. Columns (1) and (2) use as as a dependent variable the likelihood of a rate filings for insurer i filed at state s in year t, and 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; if the insurer did not apply for a rate change, the variable is 0. The indicator variables $\mathrm{I}_s^{\text{Med Fric}}$ and $\mathrm{I}_s^{\text{Low Fric}}$ equal 1 if the state s is, correspondingly, medium or low friction states. The panel is restricted to states s which are high, medium or a subsample of low friction states, where the subsample based on the degree of exposure to high friction states (below/above median in columns (1) and (3)/(2) and (4)). Each low friction state's exposure to high friction state is computed as the average annual percent of out of state losses coming from high friction states. All regressions control for loss ratio in the (same) state s, 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. All regressions include insurer-filing state and filing state-year of submission fixed effects. The standard errors of all variables are clustered at the state level.

	any filings$_{i,s,t+1}$		rate Δ received$_{i,s,t+1}$	
	(1)	(2)	(3)	(4)
other st loss$_{i,\bar{s},t}$	-0.005	-0.006	0.078	0.073
	(0.021)	(0.021)	(0.193)	(0.193)
other st loss$_{i,\bar{s},t} \times \mathrm{I}_s^{\text{Med Fric}}$	0.019	0.019	0.692^{*}	0.693^{*}
	(0.025)	(0.025)	(0.403)	(0.400)
other st loss$_{i,\bar{s},t} \times \mathrm{I}_s^{\text{Low Fric}}$	0.140^{***}	0.188^{***}	1.359^{*}	1.857^{**}
	(0.047)	(0.060)	(0.719)	(0.727)
Exposure to H states in L friction states:	low	high	low	high
Controls	Yes	Yes	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes	Yes	Yes
Observations	14,285	15,582	14,285	15,582
Adjusted R^2	0.387	0.377	0.295	0.291

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Table B.5: Product changes in response to out-of-state losses

The table shows results from the regression shown in Equation 5 at columns (1-4) and in Equation 6 at column (5). The dependent variable is the likelihood of a rule filing for insurer i filed at state s in year t, and the independent variables of interest are other st $\text{loss}_{i,s,t}$, which is the loss ratio experienced by insurer i in year t in all states except s (sum of all losses in states which are not s divided by all premiums collected in states which are not s). The indicator variables $I_s^{\text{Med Fric}}$ and $I_s^{\text{Low Fric}}$ equal 1 if the state s is, correspondingly, medium or low friction states. The panel is restricted to the largest 50 insurers in a given state and year, and insurers i which sell homeowners' insurance in more than 2 states in a given year and sell more than $100,000 in premiums a year. Furthermore, in column (1) and (5) we include all states in the panel, while in columns (2)/(3)/(4) is restricted to state s being a high/medium/low friction state. All regressions control for loss ratio in the (same) state s, 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. All regressions include insurer-filing state 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

	any rule $\text{filings}_{i,s,t+1}$				
	(1)	(2)	(3)	(4)	(5)
other st $\text{loss}_{i,\bar{s},t}$	0.006	−0.007	0.001	0.051	−0.007
	(0.009)	(0.012)	(0.008)	(0.048)	(0.012)
other st $\text{loss}_{i,\bar{s},t} \times I_s^{\text{Med Fric}}$					0.009
					(0.014)
other st $\text{loss}_{i,\bar{s},t} \times I_s^{\text{Low Fric}}$					0.058
					(0.049)
E[LHS]	0.7	0.6	0.7	0.7	0.7
State friction	All	High	Medium	Low	All
Controls	Yes	Yes	Yes	Yes	Yes
State × Year Fixed effects	Yes	Yes	Yes	Yes	Yes
Insurer × State Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,980	5,656	6,231	6,093	17,980
Adjusted R^2	0.347	0.448	0.312	0.267	0.347

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Table B.6: Classification of geographical regions

The table lists the geographical classification of U.S. states into geographical regions. The classification is provided by S&P Market Intelligence.

Region	**States**
Mid-Atlantic	DC, DE, MD, NJ, NY, PA
Midwest	IA, IL, IN, KS, KY, MI, MN, MO, ND, NE, OH, SD, WI
Northeast	CT, MA, ME, NH, RI, VT
Southeast	AL, AR, FL, GA, MS, NC, SC, TN, VA, WV
Southwest	CO, LA, NM, OK, TX, UT
West	AK, AZ, CA, HI, ID, MT, NV, OR, WA, WY

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Table B.7: Cross-subsidization across states: robustness to correlation of losses across states

The table shows results from the regression shown in Equation 10. Column (1) uses as a dependent variable the likelihood of a rate filings for insurer i filed at state s in year t. Column (2) uses as a dependent variable the average change received, weighted by affected premium, among the filings of insurer i at state s in year t; if the insurer did not apply for a rate change, the variable is 0. The independent variables of interest are other zone $\text{loss}_{i,\bar{z},t}$, which is the loss ratio experienced by insurer i in year t in all states outside of z, the zone of the filing state s (sum of all losses in states which are not in z divided by all premiums collected in states which are not z). The indicator variables $\text{I}_s^{\text{Med Fric}}$ and $\text{I}_s^{\text{Low Fric}}$ equal 1 if the state s is, correspondingly, medium or low friction states. The panel is restricted to the largest 50 insurers in a given state and year, and insurers i which sell homeowners' insurance in more than 2 states in a given year and sell more than $100,000 in premiums a year. Furthermore, each insurer needs to sell in at least 1 non-neighboring state and the total premium sold outside of zone z is over $100,000. All regressions control for loss ratio in the (same) state s, 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. All regressions include insurer-filing state 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

	any $\text{filings}_{i,s,t+1}$	rate Δ $\text{received}_{i,s,t+1}$
	(1)	(2)
other zone $\text{loss}_{i,\bar{z},t}$	0.027	0.238
	(0.034)	(0.256)
other zone $\text{loss}_{i,\bar{z},t}\times$ $\text{I}_s^{\text{Med Fric}}$	−0.002	0.746*
	(0.042)	(0.400)
other zone $\text{loss}_{i,\bar{z},t}\times$ $\text{I}_s^{\text{Low Fric}}$	0.122**	1.189**
	(0.054)	(0.588)
E[LHS]	0.7	3.8
Controls	Yes	Yes
State × Year Fixed effects	Yes	Yes
Insurer × State Fixed effects	Yes	Yes
Observations	15,796	15,796
Adjusted R^2	0.374	0.281

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