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

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Abstract

We study the consequences of state-level price (rate) regulation for U.S. homeowners' insurance, a $15 trillion market that provides households protection against climate losses. Using two distinct identification strategies and novel data on regulatory filings and ZIP code level rates, we find that insurers in more regulated states adjust rates less frequently and by a lower magnitude after experiencing losses. Importantly, they overcome these rate-setting frictions by adjusting rates in less regulated states, consistent with insurers cross-subsidizing across states. In the long-run, these behaviors lead to a decoupling of rates from risks, implying distortions in risk sharing across states.

Keywords: Climate Risk; Homeowners' Insurance; Rate Regulation; Cross-subsidies; Insurance Availability.

JEL Codes: G22, G52, G28, G32, Q54

The unprecedented rise in natural disasters has led to catastrophic losses of more than $600 billion in the United States over the last two decades, roughly twice the losses of the previous 40 years combined.[1] The insurance sector acts as a front-line defense against climate risk by providing important risk sharing tools to households and firms. In exchange, consumers pay insurance premiums to protect against future climate losses. The level of premiums that consumers pay is a key determinant of how these losses are shared and therefore how risks are being redistributed across the economy.

We study the pricing of homeowners' (HO) insurance, which provides financial protection against property damages to households as well as to banks, who require insurance as a prerequisite to providing mortgage. A large and growing portion of these damages are a result of weather- and climate-related disasters (such as wildfires and hurricanes), and thus effectively much of the risk that HO insurance redistributes is climate risk (Jeziorski et al., 2021). Each year, insurers sell $15 trillion of HO insurance coverage catering to almost 85% of all U.S. homeowners who collectively pay $120 billion in premiums.[2] These premiums are subject to extensive regulations in the U.S. at the state level. Specifically, every time an insurer wants to change premiums (rates) they must submit rate proposals for regulatory review and approval. States, however, vary significantly in the inputs they allow insurers to use in rate-setting and in the degree to which insurers can charge a rate that is indicated by their loss models. As a result, regulators have the ability to influence rates and the manner in which risks are being shared in the economy.

In this paper, we provide evidence of decoupling of insurance rates from their underlying risks and identify regulation as a driving force behind this pattern. We identify two sources for this decoupling. First, rates have not adequately adjusted in response to the growth in losses in states we classify as "high friction", i.e. states where regulation is most restrictive. Second, in low friction states rates increase both in response to local losses as well as to losses from high friction states. Importantly, these spillovers are asymmetric: they occur only from high to low friction states, consistent with insurers cross-subsidizing in response to rate regulation. Our results point to distortions in risk sharing across states, i.e. households in low friction states are in-part bearing the risks of households in high friction states.

We start by developing a new state-level measure of rate-setting frictions, exploiting novel data on insurers' historical rate filings from 2009 to 2019, which are required and subject to regulatory approval every time insurers change rates. Our measure captures the extent to which the rate insurers receive after regulatory approval reflects the rate required to meet

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[1]Based on the Spatial Hazard Events and Losses Database for the United States.

[2]For comparison, the total coverage written under the federally run flood insurance program is about $1 trillion (Wagner, 2022).

their actuarial goals (target rate). Using this measure, we rank states into terciles: high, medium and low, where high (low) friction states appear farthest from (closest to) meeting actuarial goals and face the most (least) rate-setting frictions.

We validate our measure of rate-setting frictions by addressing two potential concerns. First, our measure could be driven by insurers' actions, e.g., their inclination to strategically inflate target rates, instead of capturing regulators' actions. However, several pieces of evidence show that the tendency to inflate target rates is both limited in the data and not heterogeneous across state types. Crucially, insurers in high friction states have systematically lower profits relative to insurers in low friction states. Moreover, higher levels of friction are associated with lower future profits. The second concern is that markups may still be rising in high friction states, implying that these states may not be truly strict. However, we show that in high friction states, rate changes have fallen behind changes in expected losses, indicating falling markups, while the opposite is true in low friction states.

We next present our main results, which we illustrate using two different data sources and two different empirical designs. First, using the state-level rate filings data, we track how rates respond to past losses. We exploit the institutional feature that rates are regulated in every state an insurer sells insurance in. As a result, we can compare the same insurer's rate responses across states that are differently regulated instead of comparing an insurer overseen by regulator A to another overseen by regulator B. We evaluate the responsiveness to two types of losses – losses occurring in the state in which the insurer is filing a rate change (same-state losses) as well as to losses occurring *outside* the filing state (out-of-state losses). First, we find that in response to same-state losses, an insurer is relatively less likely to file a rate change and receives a lower rate change in high friction states. Second, we find asymmetric spillovers. Rates respond to out-of-state losses in low friction states but not in high friction states. Crucially, rates respond to out-of-state losses only when the losses come from high and not when they come from low friction states.

Second, we implement a border discontinuity design using ZIP code-level rates data for a representative insurance contract and confirm the results on responses to same-state and out-of-state losses. We focus on ZIP codes along all the borders of high and low friction states in our data. We again compare the rate responses of a single insurer to local and distant losses but now across two sides of a state border, where the ZIP codes have different rate regulation but, due to their geographical proximity, near identical underlying risk exposures. Using a stacked differences-in-differences design, we show that in response to common local shocks around a state border, rates rise more in low friction ZIP codes than in bordering high friction ZIP codes. Similarly, using a stacked triple differences design we show that in response to out-of-state shocks, rates rise more in low friction ZIP codes than in bordering

high friction ZIP codes. However, crucially, this increase in rates is propagated by only those insurers that are significantly exposed to the out-of-state shock.

The two sets of analyses each provide distinct advantages. The border discontinuity design provides a micro-laboratory that helps alleviate identification concerns stemming from comparing geographically apart states that may have different risk exposures, which by itself could generate different pricing responses. In contrast, the more comprehensive analysis using rate filings data shows external validity and that the results generalize.

The following hypothetical example helps to summarize the main findings. Suppose an insurer operates in two high friction states (California and North Carolina) and two low friction states (Virginia and New Hampshire). Our results imply that if losses occurred in California, rates would not change significantly in California itself or in North Carolina, both of which are high friction, while they would rise meaningfully in Virginia and New Hampshire, both of which are low friction. Thus, the direction of the spillover is from *High to Low*, but not from *High to High* friction states. Suppose, instead that losses occurred in low friction Virginia. If so, rates would adjust meaningfully in Virginia itself, but not move in California and North Carolina (high friction) or in New Hampshire (low friction). Thus, there are no meaningful spillovers from *Low to High* or *Low to Low* friction states.

We interpret these findings as insurers cross-subsidizing their operations in high friction states in response to rate regulation. Several pieces of evidence strongly support this interpretation. First, we show no concurrent shifts in insurers' product offerings in low friction states, which otherwise would have suggested that the rate increases can be explained by improvements in product quality and should not be interpreted as cross-subsidies. In particular, we show the existence of rate increases even for a single contract type. Second, our findings are not due to insurers revising future expected loss estimates upon observing losses in other states, which would explain the rate increases but be inconsistent with cross-subsidization. In particular, the border discontinuity design and the asymmetric pattern of the spillovers allow us to rule out two potential learning channels: that the spillovers occur because both high and low friction states are exposed to common risks and that losses in high friction states provide a better signal about future expected losses than do losses in low friction states. Third, we show that cross-state differences in how large losses are, which could also cause asymmetric rate responses, do not explain our main findings. Fourth, using a battery of tests we show that cross-state differences in competition and insurers' market power cannot explain the asymmetric responses to losses across state types. Finally, because our setup compares the outcomes of the same insurer in differently regulated states, we can rule out differences in insurer characteristics driving our findings.

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We next provide evidence that the regulatory landscape has led to a growing disconnect between rates and risk. First, granular ZIP code-level rates data show that rates have become less reflective of risks in high friction states. In sharp contrast, there is a strong relationship between rates and risk in low friction states, as predicted by standard models (Koijen and Yogo, 2015). Second, over the long-run high friction states have experienced lower growth in rates compared to growth in expected losses, while the opposite is true in low friction states. We conduct two counterfactual experiments to quantify the impact of the regulatory frictions. First, we estimate counterfactual rate changes in the absence of spillovers in low and medium friction states and find that rates there would have grown 10 percentage points (pp) slower. Second, we estimate that if high friction states were similarly regulated to low and medium friction states, rates there would have grown 13 pp faster. Overall, in the absence of heterogeneous regulation, rates would have grown 20 pp faster in high friction states, whereas in reality rates grew 4 pp *slower*, relative to the other states.

Finally, we discuss the conditions necessary to rationalize our findings on insurers' rate responses. First, exits should be unattractive. Indeed, we show that exits, policy cancellations, and non-renewals have been relatively rare, especially for large insurers. We provide a range of reasons explaining why insurers have chosen to not exit high friction states despite regulatory costs. Second, the insurers' problem should depart from simple region-by-region profit maximization as otherwise losses from one region would not spill over to others. We provide evidence that financing frictions (Koijen and Yogo, 2015, Ge, 2022) and short-term capital market pressure could be two plausible candidates for such a departure. Third, states should not be sufficiently competitive to counteract the spillovers. Indeed, our results show that competition is limited, which is consistent with prior literature showing that insurers have market power (Koijen and Yogo, 2015). In the end, our empirical results are likely driven by a combination of several economic forces. Our central point is that heterogeneous rate regulation results in asymmetric rate responses across states, which leads to distortions in who bears climate risk, and it holds regardless of the precise forces that generate it.

The disconnect between rates and risk also has significance beyond risk sharing across states. First, insurance rates have a key role in climate adaptation as rates inform households of their local risks and have the potential to affect households' behavior. Rates that accurately reflect risks may prompt actions that help mitigate these risks by, for example, encouraging households to build more resiliently or by prompting migration to lower risk areas. Second, it portends future behavior of insurers in the face of rising climate risk, since they may further respond by exiting markets altogether or dropping important product features. These concerns further underscore the importance of studying the implications of rate regulation for homeowners' insurance pricing.

Related literature: Our paper contributes to several broad strands of the literature. First, this paper closely relates to the recent insurance literature that studies the supply-side implications of financial and regulatory frictions on product markets (Froot and O'Connell, 1999, Koijen and Yogo, 2015, Ellul et al., 2022, Ge, 2022, Sen and Humphry, 2018, Sen, 2021, Barbu, 2021).[3] We add to this literature in a number of ways. First, we expand to product market regulation, as opposed to studying the effects of financial regulation which has been the main focus so far. Second, we study homeowners' insurance, a large and relatively understudied market that is of growing importance given the rise in natural disasters and document pricing spillovers from one part of an insurer's business to other parts. Prior papers have also documented pricing spillovers, e.g., Ge (2022) in life and Froot and O'Connell (1999) in property and casualty insurance. Our novel contribution is to show that rate regulation leads to asymmetric pricing responses across states, which affects the degree to which underlying risks get incorporated in prices differentially across geographies.

Second, our work contributes to the broader literature on the effects of price regulation on financial products' pricing. For example, a growing body of work examines the consequences of price regulation in the market for banking products (Agarwal et al., 2015, Nelson, 2020, Hong et al., 2018, Pinheiro and Ronen, 2016, Henriquez Gallegos and Maimbo, 2014, Benmelech and Moskovitz, 2010).[4] In addition, Liu and Liu (2020) studies the effects of regulation in the context of long-term care insurance, focusing on the role of political incentives in regulators' approval decisions. We contribute to this literature by systematically examining the consequences of heterogeneity in rate regulation across different regulatory jurisdictions. To the best of our knowledge, we are the first to show that the heterogeneity in regulation leads to cross-jurisdiction subsidization, driven by the presence of a large number of multi-jurisdiction insurers that operate across the country.

Third, our findings are relevant to the burgeoning literature on the implications of climate risk for households' finances. This literature shows that households bear climate risk directly through mortgage markets (Issler et al., 2020), real estate prices (Baldauf et al., 2020, Murfin and Spiegel, 2020, Bernstein et al., 2019), and equity prices (Engle et al., 2020), and indirectly through labor markets (Kruttli et al., 2019) and discounts in municipal bond prices (Goldsmith-Pinkham et al., 2020). In a similar vein, our work addresses the question of "who bears climate risk" in the context of homeowners' insurance. We thus

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[3]A complementary line of work further emphasizes the role of the legal environment in amplifying the impact of regulation on insurance product market through judiciary rulings (Oh, 2020), the claims process (Gennaioli et al., 2021), and fiduciary regulation (Egan et al., 2021).

[4]A broader literature also studies the effects of price regulation outside of financial services, including rent control (Autor et al., 2014), utilities (Faulhaber, 1975), telecommunications (Curien, 1991), auto insurance (Boyer, 2000, Fields et al., 1990), workers' compensation (Danzon and Harrington, 2001), and health insurance (Ericson and Starc, 2015, Finkelstein et al., 2009, Simon, 2005).

also contribute to the body of work on regional redistribution in financial markets (Ouazad and Kahn, 2021, Lustig and Van Nieuwerburgh, 2010, Hurst et al., 2016) by showing that households in low friction states are essentially paying to insure households in high friction states against climate losses.

The rest of the paper is structured as follows. Section 1 discusses institutional details. Section 2 discusses data and the measurement of state-level rate-setting frictions. Section 3 and 4 present the main results using the rate filings data and the border discontinuity design. Section 5 contains alternative explanations and a discussion of key conditions necessary to rationalize our findings. Section 6 presents long-run implications. Section 7 concludes.

1. INSTITUTIONAL BACKGROUND

1.1. *Homeowners' insurance*

Homeowners' insurance (HO) are retail contracts that provide households financial protection against property damages. Losses sustained during natural disasters, e.g., wildfires, hurricanes, or windstorms, constitute a large portion of the total losses insured by these contracts. For example, estimates from SwissRE (2021) suggest that over 93% of the total losses are from natural disasters and that this share has risen sharply in the past two decades. While insurance payouts are triggered by specific weather events, growing evidence shows that evolving climate risk has made these events more frequent and severe (Seneviratne et al. (2021), Figure C.1), posing challenges for how insurers price these contracts. As a result, regulatory agencies have increasingly started focusing on the potential for disruptions in this market for communities exposed to climate risk (US Treasury, 2022).

The HO insurance market is large and economically important. Each year, insurers sell more than $15 trillion of coverage charging $100 billion in premiums, which makes HO one of the largest and fastest growing Property & Casualty (P&C) markets in the U.S. (Figure C.2). For households, HO insurance is an important financial product. First, it is a prerequisite to obtain a mortgage. As a result, HO contracts are widely used: 95% of homeowners with a mortgage and 85% of homeowners overall have insurance (Jeziorski et al., 2021). Thus, HO contracts offer a safety net to a large fraction of households as well as banks who lend to them. Second, HO insurance premiums are a large portion of homeownership expenses. Figure C.3 shows the average HO premiums benchmarked against mortgage interest expenses for each state in the U.S.. In the average state, HO premiums cost as much as 60% of what households pay towards their mortgage interest expenses.

HO insurance contracts have similar features across states. Contracts are short-dated,

with a typical duration of 1 year. The most popular contract type (known as HO3), which accounts for over 85% of all sold homeowners' contracts, covers the same 16 perils (fire, windstorms, hail, etc.).[5] The two main excluded perils are flood, which is federally provided, and earthquake, which is often provided by state-run programs. One of the reasons why this contract type is so ubiquitous is that it provides the minimum protections which banks require for mortgages. The homogeneity in the contract type and its wide use by households means that we compare products that have broadly similar features across states.

1.2. Rate Regulation

1.2.1. Background

Homeowners' insurance prices (henceforth rates) have been regulated in the U.S. since the early part of the 20th century.[6] Historically, regulation had three goals: to prevent (i) excessive; (ii) inadequate; and (iii) unfairly discriminatory rates (NAIC, 1945). Because HO insurance is a prerequisite to a mortgage, regulators seek to ensure that insurance is affordable and available to all consumers (Tennyson, 2011).

When an insurer wants to change rates in a given state, it must file a rate change request with that state's Department of Insurance (DOI). The regulatory approval process can be onerous and time consuming. A typical filing is more than 1,000 pages, requires insurers to provide detailed information on climate loss models and other rating variables, and involves significant back and forth between insurers and regulators. Regulators typically examine the filings over several months and may not approve the full extent of the requests.[7] Unlike other insurance products where risks have been relatively static over time, growing evidence suggests that climate losses have shifted in a large way. As a result, rate regulation can be particularly challenging for HO insurance because it affects the degree to which insurers can respond to shifts in the underlying loss distribution.

1.2.2. Key Features

Our analysis relies on several important features of the regulatory process. First, rates are regulated at a *state of operation* level. Specifically, if an insurer wants to change rates in a given state it operates (sells insurance) in, it needs to file a rate request with the state's DOI. If the insurer wants to change rates in multiple states at once, it still needs to file a request

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[5]There are several types of HO contracts for owner occupied houses by level of coverage: HO1, HO2, HO3, HO5 and HO8. A 2022 consumer report from *MyBankTracker* describes HO3 as the minimum required for a mortgage, making it the most popular contract type (see Figure D.1a).

[6]Rate regulation also occurs in automobile, health, workers' compensation, and medical malpractice lines.

[7]Figures C.4 and C.5 in Appendix C provide anecdotal evidence on the role regulators play in the rate-setting process.

in every single state.[8] For example, Illinois Union Insurance Company sold HO insurance in five states in 2019: Arizona, Massachusetts, Nevada, South Carolina and Vermont. If Illinois Union wishes to change rates in Arizona, it must make a rate filing at Arizona's DOI. Similarly, if it wants to change rates in Nevada, it must make a separate rate filing at Nevada's DOI. In other words, rates are regulated in every state the insurer sells insurance in. This feature is crucial from the standpoint of identification as a single insurer is exposed to multiple states and these states may differ with respect to how regulated they are.

Second, any change in an insurer's rate-setting model has to be filed. Insurers' pricing models contain many characteristics relevant to rate-setting. Any changes in the loadings have to be filed, which may result in either an increase or a decrease in rates at the state level. As a result, we can observe the full spectrum of the state-level rate changes.

Third, there are several sources of heterogeneity in regulation across states. States vary in the inputs they allow insurers to use in rate-setting. Prominent exclusions include the use of catastrophic models, passing reinsurance costs to consumers, extent to which territorial risk differences can reflect in rate-setting, and the use of credit scores.[9] Another dimension of cross-state heterogeneity is in the filing and approval process. Some states require active pre-approval of rate changes before consumers are affected, while others permit insurers to begin using a new rate while regulators are still reviewing the filing and if subsequently found unacceptable the rate changes have to be withdrawn.[10] Crucially, even when two states employ the same procedural rules and rate-setting inputs, regulatory strictness can vary significantly due to factors such as regulators' incentives or insurance department budgets.[11] Because we observe the outcomes of the regulatory approval process, we can incorporate the different sources of heterogeneity in measuring the extent of regulation across states, as discussed in the next section.

Fourth, the rate changes are binding, and quickly affect the entire customer base. Specifically, the filings point to a date when the rate changes take effect, and insurers have to apply the new rates after this date. The rate changes apply to all new customers and to any existing customer that comes up for renewals. As most policies are annually renewed,

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[8]It is important to distinguish rate regulation from financial regulation. Financial regulation is carried out by a single state - the state where the insurer is domiciled. In contrast, the same insurer is subject to rate regulation in *every* state it sells insurance in (i.e. there are multiple rate regulators).

[9]For example, California disallows the use of forward-looking projections and catastrophic models, the transfer of reinsurance costs to consumers, and FICO scores, while South Carolina allows the use of these factors (Issler et al., 2020, R-Street, 2018).

[10]In case regulators disapprove the rate changes, the new rates have to be rolled back. Conversations with practitioners revealed that the cost of rolling back and refunding consumers is prohibitively high. As a result, in practice, insurers typically seek pre-approval even in states which do not explicitly require one.

[11]See e.g., Liu and Liu (2020), Leverty and Grace (2018), Tenekedjieva (2021), Sen and Sharma (2020).

the entire customer base faces the new rates fairly quickly. Thus, the rate filings reflect the rates consumers actually pay in a given state.

Fifth, in addition to changes in rates, insurers are also required to file any material changes in contract features with regulators. This feature allows us to test whether products and rates change simultaneously. This helps to distinguish between two different interpretations of the rate spillovers: cross-subsidies or payment for improved product features.

2. Data and Measurement

2.1. Data

We combine data from two sources to construct the state-level measure of rate-setting frictions and for the empirical analyses in Section 3: (i) insurers' underwriting operations at the state-level and financial statements and (ii) their regulatory rate filings. We complement these data with granular (ZIP code level) data on insurance rates from Quadrant Information Services for the alternative identification strategy using a border discontinuity design, which we describe in Section 4.

2.1.1. Underwriting Operations and Financial Statements

Property and Casualty (P&C) insurers report underwriting data for each line of business and each state they operate in, which we collect from the Standard & Poor's Market Intelligence (S&P MI) database. Underwriting data contain information on total homeowners' premiums sold (which refers to the total sale of homeowners' policies) and total losses incurred (which refers to the claims insurers pay to consumers if an insured event takes place, e.g., a wildfire). The data are available at an annual frequency and for each state an insurer operates in. In addition, we also observe premiums and losses for other business lines (e.g., auto insurance, workers compensation, etc.). Insurers also report detailed financial statements as part of their regulatory filings, including balance sheets and regulatory capital positions, available at an insurer-year level. We obtain these data for the subset of P&C insurers that sell HO insurance in the U.S. for the period 2009 to 2019. The start date is dictated by the availability of rate filings data (see below).

2.1.2. Regulatory Rate Filings

Insurance companies are required to file rate change requests with the state's DOI every time they want to update rates in any state they operate in. We collect these novel data on rate filings from S&P's MI database on Insurance Product filings for the HO insurance line. Our rate filings sample includes 49 states and D.C. and, for the most part, spans the period

2009 to 2019. Appendix A provides additional details on these data.

There are two main features of each rate filing. First, we observe the insurer's *target* rate change (RateΔTarget). Target rate change is the rate change necessary for an insurer to meet its actuarial goals (e.g., to cover expected losses) (Ben-Shahar and Logue, 2016). Thus, a critical input in estimating the future target rate is a forecast of future losses, which insurers form either by using historical losses or by making forward projections using catastrophe models. Second, we observe the rate change an insurer *receives* after state regulators have reviewed the request (RateΔReceived).[12] The gap between the target and the received rate captures the degree to which received rates reflect insurers' actuarial goals in a state.

We merge the rate filings data with the underwriting and financial statements data to obtain a firm-state-year level panel.[13] Table 1 reports the summary statistics on the final sample. The average insurer in our sample operates in about 15 states, collects $39 million in HO insurance premiums, and has close to $3 billion in total assets. Two key points stand out on insurers' rate filings. First, the propensity to file for a rate change is very high at 70% for the average insurer in a given state and year. This suggests that insurers are trying to revise rates frequently - almost every year. Second, there is a large gap between insurers' target rate change and what they receive, suggesting the existence of regulatory rate-setting frictions in HO insurance.

2.2. Measuring Rate-setting Frictions across U.S. States

To measure the extent of rate-setting frictions for individual states, we exploit the outcomes of the regulatory review process, specifically the wedge between the target and the received rates. We define Rate Wedge for insurer i in state s at time t as

$$(1) \qquad \text{Rate Wedge}_{ist} = \frac{\text{Rate}\Delta\text{Received}_{ist}}{\text{Rate}\Delta\text{Target}_{ist}}.$$

Rate Wedge ≥ 1 indicates that the insurer is close to meeting or exceeding its actuarial goals for a given state. In contrast, Rate Wedge < 1 indicates that the insurer fell short of meeting its actuarial goals for that state. Figure 1 shows a histogram of Rate Wedge. A large fraction of the filings have Rate Wedge < 1 with the median Rate Wedge at 0.5.

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[12]In reality, insurers are updating their pricing models and the loadings on the characteristics relevant to rate-setting. This may result in a change in rates for all or a subset of consumers in a state. RateΔTarget and RateΔReceived refer to the *average* rate change in a state at a given point in time for an insurer.

[13]The details of the data construction are described in Appendix A.1 and A.2.

We next define Friction$_s$ to quantify the extent of rate-setting friction in each state:

$$\text{(2)} \qquad\qquad\qquad \text{Friction}_s = 1 - \text{Rate Wedge}_s$$

where Rate Wedge$_s$ is the average Rate Wedge in state s aggregated across insurers operating in the state and across years and minus sign is for ease of interpretation. In constructing the Rate Wedge$_s$, we exclude filings from small insurers and use the full sample from 2009 to 2019 (see Appendix B.1 for details and robustness of the baseline measure). Friction$_s$ can be interpreted as the average gap between the prevailing rate in a state and the rate necessary to meet insurers' actuarial goals in the state. Finally, we group states into terciles by $Friction_s$: High, Medium, and Low ("state types" henceforth). States in the high (low) group are states farthest from (closest to) the insurers' actuarial goals and impose the highest (lowest) rate-setting frictions.

2.3. Addressing Measurement Concerns

In this section we address two potential measurement concerns about our metric of regulatory rate-setting frictions. First, it is plausible that the underlying heterogeneity in Rate Wedge is driven by insurers' and not regulators' actions. For example, insurers could be strategically inflating their rate change targets to gain larger rate increases. Thus, states may be classified high friction not because regulators are not granting sufficient rate increases, but because insurers are inflating their targets. Second, even if Rate Wedge reflects regulatory behavior only, it may still not be a good proxy for strictness. For example, a regulator in a state with a large Rate Wedge may still be allowing markups to rise. Note that the underlying driver for both concerns is the same - actual shifts in marginal costs (expected losses) are not directly observed, which is the case in most settings in economics and finance. We mitigate these concerns with a battery of tests, as described below.

2.3.1. Is Rate Wedge insurer driven?

To illustrate the first concern, suppose state A has RateΔTarget $= 10\%$ and RateΔReceived $= 5\%$, state B has RateΔTarget $= 5\%$ and RateΔReceived $= 5\%$, and both states experienced a change in expected losses $\Delta\mathbb{E}[L] = 5\%$. In reality, both states have similar rate-setting friction as rates increased in line with changes in expected losses, but we may classify state A as high friction (as RateΔTarget is inflated) and state B as low friction (as RateΔTarget is not inflated). If the tendency to inflate targets is pervasive among insurers,

then our metric would mostly reflect insurers' strategic behavior.[14] Several tests, however, show that target inflation is both limited and not heterogeneous across state types.

First, we compare insurers' underwriting profitability across state types. If insurers inflate RateΔTarget in high friction states, then their profitability in these states should not be smaller on average. Figure 2, however, shows that insurers in high friction states have systematically lower underwriting profits relative to insurers in low friction states. Second, using a predictive regression analysis, we find that when an insurer faces high friction (distance from actuarial goal rises), it has lower *future* profitability (see Appendix B.2). Indeed, if Rate Wedge were smaller simply due to insurers inflating their target rates, then we would see either no or even a positive relationship with future profits.

Third, we show that the tendency to inflate does not differ across state types.[15] To illustrate, we examine whether RateΔTarget responds to realized losses differentially across state types. If the degree of target inflation is heterogeneous, we should observe differential sensitivity to losses across states. However, Table B.2.2 shows that RateΔTarget responds to losses similarly across states, indicating that the degree of target inflation (to the extent it exists) is similar and therefore unlikely to be driving our classification of states.

Finally, we construct the friction measure in three alternative ways to absorb time varying and state specific insurer driven variation in Rate Wedge (e.g., by including insurer-year fixed effects). Crucially, we instrument RateΔTarget using past losses and use the predicted rate targets to construct an alternative measure of friction. Appendix B.2.3 details the construction of these alternative measures. Table B.2.3 shows that the correlation between $Friction_s$ (computed as per Equations (1) and (2)) and the alternative measures is very high at 0.84 on average across the three approaches, suggesting that any insurer driven bias inherent in RateΔTarget is limited.

2.3.2. Rate Wedge and markups

To illustrate the second concern, suppose states A and B both have RateΔTarget = 10% and RateΔReceived = 5%, but in state A, $\Delta\mathbb{E}[L] = 6\%$, and in state B, $\Delta\mathbb{E}[L] = 4\%$. In both cases, Rate Wedge is 0.5, and thus both states will share the same classification. However,

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[14]Having said that, target inflation is not necessarily the optimal response of insurers, as we show theoretically in Appendix F. If regulators penalize high markups and insurers internalize the regulators' response in their rate-setting decision, then target inflation will be limited in equilibrium.

[15]To illustrate why the heterogeneous tendency to inflate targets may be a potential threat to measurement, we can decompose Rate Wedge into two components: Rate Wedge = RateΔReceived/RateΔTarget $= \frac{\text{Rate}\Delta\text{Received}/\Delta E[L]}{\text{Rate}\Delta\text{Target}/E[L]}$, where we can think of the numerator as a true proxy of rate-setting frictions and the denominator reflects the extent of target inflation. The concern is that our classification is driven by the inflation component (denominator). However, if the tendency to inflate is similar across state types, the classification will reflect the true extent of rate-setting frictions.

in state A, the regulator allowed markups to rise, whereas in state B she forced markups to fall. In other words, high friction states may conflate two types of regulators: those that are truly high friction (falling markups) and those that are not truly high friction (rising markups, e.g., cases like state A).[16] However, our earlier result showing that profitability is lower in high friction states implies that on average high friction states are not dominated by cases where regulators are allowing markups to rise significantly.

Even so, an alternative measure of rate-setting frictions that fully dispels this concern would compare RateΔReceived and $\Delta\mathbb{E}[L]$. RateΔReceived $> \Delta\mathbb{E}[L]$ would imply that regulators allowed markups to increase (low friction), while RateΔReceived $< \Delta\mathbb{E}[L]$ would imply falling markups (high friction).

A key issue, however, is that estimating $\Delta\mathbb{E}[L]$ is quite challenging in many aspects. First, it is difficult to get a long enough history of climate losses from regulatory filings. Second, the high skewness in the time-series of climate losses makes it challenging to estimate expected losses using a realized sample with limited history. Most importantly, as the dynamics of climate risk changes, past loss experience may not necessarily be an indicative and reliable predictor of future losses. These factors imply that the estimates of $\Delta\mathbb{E}[L]$ will be noisy and potentially subject to many assumptions.

Recognizing this operational difficulty, we do not attempt a full reclassification of states by comparing RateΔReceived and $\Delta\mathbb{E}[L]$. Rather, we employ a number of different measures of expected losses to compute the gap between RateΔReceived and $\Delta\mathbb{E}[L]$ and examine how it differs between high and low friction states (see Appendix B.3 for details). Figure B.3.1 shows the main findings. For high friction states, we find that RateΔReceived has trailed $\Delta\mathbb{E}[L]$ on average, indicating that the regulator is likely forcing markups to fall instead of allowing it to rise. For low friction states, we find the opposite pattern: RateΔReceived has exceeded $\Delta\mathbb{E}[L]$ on average, indicating that the regulator is likely allowing markups to rise. These results dispel the concern about potential misclassification of states stemming from

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[16]The following decomposition of Rate Wedge helps further clarify how a given level of Rate Wedge may conflate two types of regulators.

$$\text{Rate Wedge}_t = \frac{\text{Rate}\Delta\text{Received}_t}{\text{Rate}\Delta\text{Target}_t} = \frac{\text{Rate}_t - \text{Rate}_{t-1}}{\text{Target Rate}_t - \text{Rate}_{t-1}} = \frac{(\text{Markup}_t - \text{Markup}_{t-1}) + \Delta\mathbb{E}_t[L]}{(\text{Target Markup}_t - \text{Markup}_{t-1}) + \Delta\mathbb{E}_t[L]}$$

where $\Delta\mathbb{E}_t[L]$ denotes the change in expected losses from $t-1$ to t. We have omitted insurer and state subscripts for brevity. On one extreme end, suppose expected losses stay constant ($\Delta\mathbb{E}_t[L] \approx 0$). Then any positive Rate Wedge, even a low one, would mean that the regulator allowed markups to rise since $(\text{Markup}_t - \text{Markup}_{t-1}) > 0$ for Rate Wedge to be positive. Note that we are assuming $(\text{Target Markup}_t - \text{Markup}_{t-1}) > 0$. In such a scenario, high friction states may include states that are not truly high friction. Now, suppose that $\Delta\mathbb{E}_t[L] > 0$, but approved markup decreases $(\text{Markup}_t - \text{Markup}_{t-1} < 0)$ such that Rate Wedge is still positive and low. However, now the regulator is forcing markups to fall and the state is truly high friction.

the inability to directly observe shifts in expected losses.

3. Rate Responses to Regulation: Evidence from Rate Filings

In this section, we present our main results using the rate filings data: (i) that insurers are restricted in their ability to change rates in high friction states; and (ii) that insurers cross-subsidize high friction states by raising rates in low friction states.

Our empirical strategy examines how rate-setting behavior responds to past realized losses. We evaluate the responsiveness to two types of losses – losses occurring in the state in which the insurer is filing a rate change (same-state losses) as well as to losses occurring outside the filing state (out-of-state losses). This is motivated by standard insurance pricing models (e.g., Koijen and Yogo (2015)), which suggest that rates respond to shifts in marginal costs (expected losses), demand elasticities, and financing frictions. Realized losses, both same-state and out-of-state losses, potentially affect all of these elements, ultimately affecting rates. For example, losses could lead insurers to update their estimates of future expected losses, worsen insurers' financing conditions, or increase households' propensity to buy insurance. In the absence of heterogeneous rate-setting frictions, we expect that rates would respond to realized losses similarly across states, especially since HO contracts are short-dated and therefore can be repriced often. However, rate-setting frictions may restrict insurers' ability to adjust rates in response to losses, and the degree to which they are restricted would depend on the level of friction prevailing in a state.

Our identification strategy exploits the institutional feature that rates are regulated in every state an insurer sells insurance in. As insurers typically operate in multiple states, the same insurer may be exposed to multiple state regulators who vary in the degree of rate-setting frictions. Thus, we can compare the same insurer's rate responses across states that are differently regulated instead of comparing an insurer overseen by regulator A to another insurer overseen by regulator B.

3.1. Responses to Same State Losses

We first test how rate-setting behavior responds to losses in the filing state. This allows us to examine if insurers have differential ability to update rates across state types that differ in the degree of rate-setting frictions. Specifically, we estimate the following regression:

$$(3) \quad Y_{ist} = \gamma SSL_{ist-1} + \gamma^M SSL_{ist-1} \times Med_s + \gamma^L SSL_{ist-1} \times Low_s + \alpha_{is} + \alpha_{st} + \theta X_{it} + \epsilon_{ist},$$

where the response variables Y_{ist} include (i) whether a rate change is filed (extensive margin) and (ii) the rate change received (intensive margin) by insurer i in state s and year t.[17] The main variable of interest is Same-State Losses (SSL), i.e. losses experienced by an insurer in the state in which the rate filing is made. Note that losses are lagged one year and scaled by the lagged total premium sold (loss ratio). To evaluate the differential response to losses, we interact SSL with dummy variables for whether the filing state is medium (Med_s) and low (Low_s) friction. Under the standard model with no regulatory frictions, we do not expect differential effects, i.e. we only expect $\gamma > 0$ (if losses increase today, rates go up in the future similarly for all state types). However, if rate regulation is binding and our classification captures the differential ability of insurers to update rates, we expect $\gamma^L > \gamma^M > 0$, i.e., it would be easier to update rates in low friction than in high friction states.

We include insurer $\times$ state fixed effects (α_{is}) to ensure that the relevant coefficients are estimated using variation in SSL within the same insurer in the same state and not using variation in the composition of insurers across all states. We include state $\times$ year fixed effects (α_{st}) to absorb time varying unobserved state characteristics and local demand shocks. The control variables X_{it} (log total assets, RBC ratio, non-homeowners loss ratio, reinsurance) account for time-varying insurer-level characteristics that may also affect insurers' rate responses. Finally, we cluster standard errors at the state level to account for the common regulatory, climate, and demand conditions in a given state.

Table 2 documents two main findings. First, column (1) shows that the correlation between losses and whether an insurer chooses to make a rate filing is strongest in low friction states since $\gamma^L > \gamma^M > 0$, with only γ^L statistically significant. In other words, the same insurer is more likely to file a rate change in a low friction than in a high friction state. Moreover, the magnitudes are large: there is a 10% greater likelihood to file in low friction states in response to a large jump in losses (from the 10th to 90th percentile).

Second, column (2) compares the responsiveness of received rates to losses across state types, i.e., the γ coefficients measure the degree to which losses pass through to received rates differentially across states. We find that only γ^L is positive and statistically significant, while both γ and γ^M are insignificant and small in magnitude. Thus, the degree to which losses pass through to received rate varies significantly across states. Rates respond to past losses for an insurer in a low friction state relative to the *same* insurer in a high friction state.

Overall, the evidence shows that in response to losses, insurers are less likely to make a rate filing and more likely to receive a smaller rate change in high friction states than in low friction states. These results also demonstrate that our measure $Friction_s$ accurately

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[17]By "year" we refer to year of filing throughout the paper.

captures the extent to which insurers are restricted in their ability to set rates across states.

3.2. Asymmetric Rate Spillovers Across U.S. States

Next, we test how rate-setting behavior responds to losses occurring outside the filing state (out-of-state losses). We find that in response to rate-setting frictions there are asymmetric rate spillovers: rates in low friction states respond to losses in high friction states, while the opposite is not true. Exploiting the fact that the *same* insurer is exposed to multiple regulators, we proceed in two steps. First, we ask in which state types an insurer's rates respond to out-of-state losses. We show that rates respond to these losses in low friction states but not in high friction states. Second, we ask whether the response to out-of-state losses varies depending on where the losses come from, i.e. low, medium, or high friction states. Here we find that only out-of-state losses coming from high and medium friction states affect rates in low friction states.

3.2.1. Step 1: Which filing states respond to out-of-state losses?

To implement the first step, we estimate the following regression:

$$(4) \quad Y_{ist} = \beta OSL_{ist-1} + \beta^M OSL_{ist-1} \times Med_s + \beta^L OSL_{ist-1} \times Low_s + \theta X_{ist} + \alpha_{is} + \alpha_{st} + \epsilon_{ist}.$$

The dependent variables Y_{ist} are as described in Equation (3). The main variable of interest is an insurer's "out-of-state" losses (OSL) in the prior year. To compute OSL, we sum an insurer's lagged losses in all the states it operates in other than the filing state s, which we scale by lagged total premiums in states not s. Suppose an insurer operates in four states: California (CA), North Carolina (NC), Virginia (VA), and New Hampshire (NH). When we examine its rate-setting behavior in CA, OSL refers to losses in NC, VA, and NH only.

To examine the differential response to OSL across states, we interact OSL with dummy variables for whether the filing state is medium (Med_s) and low (Low_s) friction. Splitting the responsiveness to OSL by filing state helps understand which states respond to OSL and whether rate-setting frictions matter. We include insurer $\times$ state fixed effects (α_{is}) to ensure that the estimation exploits variation in losses within the same insurer in the same state. In addition, it allows us to control for an insurer's market power in a given state and other firm-state specific characteristics such as an insurer's bargaining power with regulators. We include state $\times$ year fixed effects (α_{st}) to control for time varying unobserved state characteristics and local demand shocks. We control for insurers' same-state losses (SSL), which affect rate responses, as discussed earlier. In addition, we also control for other time-varying insurer characteristics that are known to affect insurance rates, as before.

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If rates respond to OSL, we expect $\beta > 0$ and statistically significant. Moreover, if the responsiveness varies meaningfully across states, we expect β^L or β^M, which measure the $\underline{\text{same}}$ insurer's additional responsiveness to OSL in low and medium friction states, to be statistically significant and economically meaningful.

Tables 3 and 4 document the main results, separately for the two dependent variables. Column (1) of each table shows the estimation of Equation (4) without the interaction terms. Both the likelihood of filing and the size of the rate change received increase in response to out-of-state losses ($\beta > 0$ and statistically significant). Columns (2) to (4) show the results by splitting the filing state into high, medium, and low friction. Insurers do not respond to OSL in high friction states: column (2) shows that both the likelihood of filing and the size of the rate change received are statistically insignificant and economically small in magnitude. In contrast, both outcome variables strongly respond to OSL in low friction states, as shown in column (4). Importantly, $\beta(Med) < \beta(Low)$, which suggests that the insurers' response to OSL is decreasing in rate-setting frictions.

Column (5) shows the estimation of Equation (4), which allows us to track the $\underline{\text{same}}$ insurer's filing behavior across different states. We find β^L is positive and statistically significant, while β is insignificant. Thus, the rate-setting behavior of the same insurer positively responds to OSL in low friction (since $\beta + \beta^L > 0$) but not in high friction states. Importantly, the magnitude of this spillover in low friction states is economically meaningful. For example, in response to large out-of-state losses, the average insurer increases rates by 0.94% per year in low states, which is 28.5% of the increase low states experience annually.[18]

3.2.2. Step 2: Which out-of-state losses matter?

In the second step, we ask whether the response to out-of-state losses varies depending on where the losses come from. To this end, we estimate the following regression:

$$(5) \qquad Y_{ist} = \sum_{j \in \{H,M,L\}} \tilde{\beta}^j OSL_{ist-1}^j + \theta X_{ist} + \alpha_{is} + \alpha_{st} + \epsilon_{ist}.$$

In Equation (5), we split the main variable of interest OSL by the type of states the losses come from. Specifically, j takes three values: high, medium or low friction. For example, OSL^H refers to the sum of lagged losses occurring in all the high friction states an insurer operates in (scaled by total lagged out-of-state premiums, as before). We restrict the sample to rate filings in low friction states because rates are most responsive to OSL in these

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[18]We multiply $\beta + \beta^L = 1.679$ by 0.56 (the difference between the 10th (0.30) and the 90th percentile losses (0.86), see Table 1) to get 0.94. We divide by 3.3, which is the unconditional average of rate change received in low states, to get 28.5%.

states, as discussed above. In other words, the regression asks when the rate filings in low friction states respond to OSL, does it matter where the losses come from? If insurers are cross-subsidizing because of regulatory rate-setting frictions then we expect to see that the responsiveness to OSL would be higher for losses coming from high friction states than from low friction states, i.e. $\tilde{\beta}^H > \tilde{\beta}^L$.

Table 5 shows the main findings. $\tilde{\beta}^L$ is statistically insignificant for both the likelihood of filing and the rate change received. This implies that rates in low friction states do not respond to OSL when these losses come from other low friction states. Presumably, this is because in low friction states, insurers are able to adjust rates in response to losses occurring within the state to a greater extent (as shown in Table 2). Thus, losses arising in low friction states tend to not get passed on to households in other states. In contrast, $\tilde{\beta}^H$ and $\tilde{\beta}^M$ are statistically significant for both the likelihood of filing and the rate change received. Thus, rates in low friction states respond to OSL only when these losses come from high or medium friction states, where rates do not adjust in response to same-state losses to a similar degree as in low friction states.

Taken together, our main finding is that rate regulation results in asymmetric rate spillovers. The following example helps to summarize it. Consider again the insurer that operates in 4 states: CA, NC, VA, NH. Our results imply that if losses occurred in CA (high friction), the insurer's rates would increase in VA and NH (both low friction). In contrast, rates would not move in NC (high friction). Suppose instead that losses occurred in VA (low friction). If so, rates would not move in CA or any other state the insurer operates in. Thus, the spillovers are asymmetric and only present from high to low friction states, but not vice versa. In the next section, we show that there are no accompanying changes to product features, allowing us to interpret these spillovers as cross-subsidies.

Persistence and economic magnitude. The spillovers are likely to have long-lasting effects as rate reversals are quite limited. Overall, only about 6.7% of the rate filings request rate decreases. Moreover, the average negative rate change is only about -2% as opposed to a 6% average positive rate change. These observations suggest that the spillovers likely persist over time and lead to a substantial transfer of risks from high to low states. Assuming that rates grow according to historical growth rates, consumers in low friction states will pay an additional $8 billion in HO premiums over the next 10 years. Our estimates in Tables 4 and 5 then imply that of the $8 billion, $2.4 billion or about 30% would be due to rate spillovers from high friction states.[19]

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[19]These estimates assume (i) that rates grow at the historical average level in low states and (ii) that losses and rates in high states grow in a way that the loss ratio (i.e. losses per dollar of premium) remains constant. In an alternative scenario where losses grow twice as quickly but rates grow at historical levels

4. Rate Responses to Regulation: Evidence from Border Discontinuities

In this section, we validate the findings in Section 3 using granular rates data and an alternative empirical design exploiting state-border discontinuities. Specifically, the previous section examined how insurers' rate responses vary across states that differ in the degree of rate regulation. One concern with this empirical strategy is that we may be comparing geographically distant states and these states may therefore have different underlying risk exposures. This difference in risk exposures can by itself generate different pricing responses, either due to differential learning about expected losses or because losses may not be large enough in low friction states and can adjust locally without spilling over to the other states. We address this concern by exploiting state-border discontinuities. We compare rate responses across two bordering ZIP codes that have near identical underlying risk exposures but different regulatory friction. These results corroborate our main findings on the role of rate regulation in driving distortions in insurance rates.

4.1. Data and Empirical Strategy

We obtain granular ZIP code-level data on insurance rates from Quadrant Information Services (QIS) for the period 2011 to 2020. The data cover over 34,000 ZIP codes across all 51 states in the US. As a representative product, we focus on a contract providing insurance coverage of $350,000 with a deductible of $1,000 on a 30-year old single-family home for an average credit profile household.[20] The QIS database tracks pricing data for the largest insurers selling HO insurance in a state. On average, we observe insurance rates for about 16 insurers per state, who collectively hold about 62% of the market share by total premiums in a state. For these insurers, we observe insurance rates for all ZIP codes within the state. The rates reported in the QIS database represent quotes rather than actual transaction prices, which is useful because quotes are closer to depicting insurers' supply schedule rather than equilibrium prices.

For our empirical analysis, we zoom in on the ZIP codes on either side of a state border, where the two bordering states are of opposite regulatory classification (high and low friction). For example, the state pair of North Carolina and South Carolina shares a border and are classified high and low friction respectively according to our state-level measure of regulatory friction. In total, there are 11 such state pairs that border each other and have

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(this amounts to loss ratio increasing by one standard deviation after 10 years), consumers would pay an additional $1.2 billion due to rate spillovers from high states.

[20]These product features come close to a representative HO insurance contract in the U.S.: the median age of a home is 37 years and the average home costs $348,000.

the opposite classification. These 11 state pairs contain 514 ZIP codes, which serve as the laboratory of our analysis. The main idea behind the empirical tests is that ZIP codes that are geographically close share similar underlying risk exposures and therefore should have similar pricing patterns in the absence of regulation. However, if the regulatory frictions are meaningful then an insurer's rate response across bordering ZIP codes would vary despite similarities in risk exposures.

Panel (a) of Table 6 presents key summary statistics and the first evidence that regulation distorts pricing patterns. The average insurance rate in high friction ZIP codes is 14% lower than the rate in low friction ZIP codes. Similarly, the growth in insurance rates over our sample period (from 2011 to 2020) is 7 percentage points lower in high friction relative to low friction ZIP codes.

4.2. Responses to Local Shocks

We next present evidence on how insurance rates respond across high and low friction bordering ZIP codes to common local shocks using a difference-in-differences design. Consistent with Section 3.1, we find that rates in high friction ZIP codes respond less to losses than rates in bordering low friction ZIP codes. To identify common local shocks that affected bordering ZIP codes, we identify years when loss ratios are one standard deviation above their respective means in *both* states.[21]

To examine how insurance rates have shifted in response to common local shocks on either side of a border, we do a stacked difference-in-differences (DiD) event study (Cengiz et al., 2019), which allows us to circumvent the common issues associated with staggered DiD estimators (Baker et al., 2022). Specifically, we stack the panel in event time rather than in calendar time (i.e., t=0 for each state pair is the date of the common shock), and for each event include 4 years of data (2 years before and 2 years after the event). We run the following regression:

$$(6) \qquad Y_{iz(\in b)t} = \gamma Low_z \times Post_{bt} + \alpha_{ib} + \alpha_z + \alpha_{bt} + \xi X_{it} + \epsilon_{izt},$$

where the dependent variable is insurance rates (in logs) charged by insurer i in year t in ZIP code z, where the ZIP code belongs to a given state border pair b. Low_z is an indicator variable that takes the value of 1 for ZIP codes that are in a low friction state and 0 if in a

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[21]If we found no such common shocks for a state pair during the sample period, we dropped those state pairs. Note that there is a look-ahead bias in the definition of the shocks since we need the whole sample to compute when loss ratios are high in both states. However, this does not matter for our results because we are trying to identify the differential rate responses across states.

high friction state. $Post_{bt}$ is an indicator variable that takes the value of 1 after the shock in a given border pair b and 0 before. We include insurer $\times$ border fixed effects (α_{ib}) to compare the rates for the same insurer across high and low friction ZIP codes belonging to the same border pair. We add ZIP code fixed effects (α_z) to control for unobserved variation at the ZIP code level (e.g., differences in competitive structure) and border $\times$ year fixed effects (α_{bt}) to control for common trends. X_{it} are insurer specific controls, as discussed in the previous section, and standard errors are clustered at the ZIP code level to account for common regulatory, climate, and demand conditions.[22]

Panel (b) of Table 6 reports various specifications of Equation (6) and column (3) presents results for the fully saturated regression. Column (1) shows that Low_z is positive and statistically significant, implying that on average rates are higher in low friction ZIP codes than in bordering high friction ZIP codes. Also, $Post_{bt}$ is positive and statistically significant, implying that on average rates increase after the shock across all ZIP codes. Crucially, the coefficient on the interaction term γ is positive and statistically significant across all specifications. This implies that in response to local shocks, rates increase more in low friction ZIP codes than in bordering high friction ZIP codes after the shock. Importantly, the economic magnitude of this shift in rates is large. Rates increase by 4-6% more in low friction ZIP codes across the various specifications, which is comparable to the average unconditional annual rate increase in low friction states. Collectively, the evidence from common local shocks show that insurers in high friction states are restricted in their ability to set rates across states.

4.3. Responses to Out-of-state Shocks

We next show how insurance rates across high and low friction bordering ZIP codes respond to out-of-state shocks. Given the asymmetry in spillovers from high to low friction states (Section 3.2), we focus on out-of-state shocks originating from high friction states and identify the year in which the loss ratios in a state had a large increase (defined as loss ratios in the highest decile). For example, California (CA) experienced a very large increase in losses following the wildfires in 2017. We can then use this event in CA (along with events in other states) to trace the effect on insurance rates across our laboratory of bordering ZIP codes. We use a stacked triple differences event study design. As before, we stack the panel in event time rather than in calendar time (i.e., t=0 is the date of the event). To ensure we are only

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[22]Note that there may be substantial within-state heterogeneity in regulation because of restrictions in the use of territorial risk differences (Section 1) and the tendency of regulators to focus more on certain jurisdictions within a state (Adriano, 2017), which our state-level regulatory friction measure does not fully capture due to data limitations. Moreover, an alternative clustering at a state level is likely to misstate estimator precision (Cameron and Miller, 2015) due to the relatively small number of states in the sample.

capturing responses to out-of-state shocks, we exclude a border pair for any given shock if the shock occurred inside the border pair, but otherwise include all remaining border pairs.[23] As before, we include 4 years of data (2 years before and 2 years after the event).

The question of interest is if rates increase more in low friction ZIP codes relative to bordering high friction ZIP codes following an out-of-state shock, and if so, whether the shock is propagated by insurers that are affected by the out-of-state shock. To examine this question, we run the following regression:

$$(7) \qquad Y_{iz(\in b)te} = \beta Low_z \times Post_{te} \times Affected_{ie} + \alpha_{zie} + \alpha_{zte} + \alpha_{ite} + \epsilon_{zite},$$

where all the subscripts, variables, and the analysis window are as defined in Equation (6), except for the following two changes. First, the additional subscript e now denotes a particular non-bordering out-of-state event. Second, $Affected_{ie}$ ($= 1$) identifies insurers affected by the event e, where an insurer is deemed to be affected if at the time of the event it had underwritten a substantial share (more than 2%, which is the median share in the data) of its total premiums in the state experiencing the event. For example, insurers selling a substantial portion of their total premiums in CA in the year 2017 would be classified as affected for this particular event.

The first difference Low_z identifies whether rates respond differently in low friction ZIP codes relative to bordering high friction ZIP codes. The second difference $Post_{te}$ identifies whether there is a response to the out-of-state shock. Finally, the third difference $Affected_{ie}$ identifies if the spillover is propagated by insurers affected by the out-of-state shock. An advantage of adding this third difference is that it helps to rule out the possibility that there may have been a simultaneous local shock in the bordering ZIP codes and therefore the rate shifts may be in response to a local, and not to the out-of-state shock. The third difference also allows us to test whether *all* insures respond in a similar way to the shock or whether only a subset who are exposed to the out-of state shock do.

Table 7 shows that the coefficient on the triple interaction term, β, is positive and statistically significant across a range of specifications. These results indicate that rates have indeed increased in low friction ZIP codes relative to similarly exposed high friction ZIP codes following an out-of-state shock. Moreover, this differential increase is driven by insurers affected by the shock. The economic magnitude of these spillovers is large: following out-of-state shocks rates increase by 3-6% more for affected insurers in low friction ZIP codes, which is close to the average unconditional annual rate increase in the data.

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[23]For example, in studying the response to a shock in high friction North Carolina, we would exclude the NC-SC border pair but include all other remaining 10 state border pairs.

Compared to our main analysis in Section 3, the identification strategy here relies on a smaller sample since it requires focusing on areas where high and low friction states border each other and uses rates for only a subset of the insurers due to data availability. Nonetheless, the results lend further support to our core findings that rates do not adequately adjust to losses in high friction states when compared to low friction states, and that rates in low friction states also respond to losses in high friction states.

5. Alternative Explanations and Discussion

In this section, we evaluate a number of alternative explanations and show that rate regulation likely is the first-order driver of insurers' rate responses. We also discuss the conditions necessary to rationalize our findings on insurers' rate responses.

5.1. Alternative Explanations

(i) Shifts in product features. A key question is whether in response to OSL insurers offer better product features or increase their risk exposures (e.g., by insuring riskier homes) in low friction states. Under this scenario, we could interpret the rate spillovers as consumers in low friction states paying higher rates for greater risk protection. However, if the rate spillovers occur despite no change in product features, then the interpretation is that insurers cross-subsidize across states. Several pieces of evidence show that the rate responses are unrelated to shifts in product features.

First, the ZIP code analysis in Section 4 tracks the rates of the same contract over time offered to the same demographic group. We find strong evidence of spillovers from high to low friction states for a single contract type, thereby alleviating this concern.

Second, we exploit the fact that insurers are also required to file any material changes in contract features with state regulators. We re-estimate Equation (4) by changing the dependent variable to whether such contract changes were filed. Table 8, however, shows no evidence of contract changes in response to out-of-state losses in low friction states. This finding is also supported by several pieces of aggregate evidence at the state level. (i) The fraction of HO3 contracts remains stable across state types and over time (Figure D.1a). (ii) The growth in insurance coverage purchased is also similar across state types (Figure D.1b). (iii) Ultimately, any change in contract features (e.g., changes in deductibles, inclusion of a new risk) or expansion to riskier areas would show up in insurers' realized losses. We therefore track the evolution of losses per property over time and across states. Figure D.1c shows no evidence that losses have shifted differentially in low friction states.

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Third, even if ex-ante product features are the same, ex-post product quality (e.g., the likelihood of a claim to be paid out) may be different (Gennaioli et al., 2021, Barbu, 2021). Rates in low friction states may be rising because the ex-post product quality is improving (a claim now has a higher likelihood to result in a payout). However, Figure D.1d shows that the percentage of claims unpaid has remained stable over time across state types. These results indicate that the spillovers are unlikely due to concurrent changes in the product.

(ii) Learning about risks. An alternative explanation for the rate spillovers is learning about risks, i.e. insurers update their expectations of future expected losses upon observing losses in other states. In particular, there are two potential concerns.

First, if high and low friction states are both exposed to common risks (e.g., wildfire), we would naturally expect spillovers between the two state types since losses in one type are informative about the future expected losses in the other.[24] However, the evidence is inconsistent with this concern. (i) The ZIP code analysis shows that the low friction side of the border responds more strongly to the out-of-state shock. However, given the proximity of the ZIP codes along the border, we expect both sides of the border to be equally correlated to the out-of-state shock, which is not consistent with learning. (ii) If high and low friction states are both exposed to common risks, then we would expect to see *both* high-to-low and low-to-high spillovers, a pattern that we do not observe (see Section 3.2).[25]

Second, losses in high friction states may in general provide a better signal about future expected losses than do losses in low friction states. As a result, we may see a high to low spillover, but not the opposite. However, the evidence is inconsistent with this explanation. (i) The ZIP code analysis shows that the spillovers are primarily driven by *affected* insurers, i.e. insurers who have a substantial presence in the state where the out-of-state shock occurred. In contrast, a learning based explanation would imply that *all* insurers should respond to out-of-state shocks similarly as all of them should update future estimates of expected losses to a similar degree. (ii) If losses in high friction states are more informative then we would expect to see that insurers respond strongly to their own losses in high friction states, which is not what we see (Section 3.1). (iii) The ZIP code analysis shows that there is limited high to high spillovers, even controlling for risk.

So far we have focused on whether the spillovers are driven by insurers' learning about

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[24]For example, after experiencing wildfire losses in California, insurers may plausibly update their risk models and raise rates in neighbouring Oregon, which may also experience more wildfire losses in the future.

[25]We further re-estimate Equation (4) by excluding from out-of-state losses the losses that occur in the same geographical region of the filing state. For example, when we examine rate responses in CA, we exclude losses occurring in all states in the western region of the U.S. to further alleviate the concern that losses are correlated within a geographical region, but less so across different regions. Table D.1 shows that the new spillover estimates are both qualitatively and quantitatively similar to the baseline estimates.

risks. For the same reasons described above, we can also rule out spillovers driven by households learning about risks (i.e. that demand is correlated across states).

(iii) Financing frictions. Differences in firm characteristics, e.g., financing frictions due to costly external finance, could be an alternative explanation in settings where one compares an insurer overseen by regulator A to another overseen by regulator B. However, we can rule out financing frictions as a driver of the asymmetric rate responses because our setup compares (and finds heterogeneity in) the responses of the same insurer in differently regulated states.

(iv) Differences in competition. When an insurer wants to simultaneously increase rates across states, rates would increase faster in states where its demand is most inelastic. If low friction states are the least competitive and have the most inelastic demand (i.e. our friction measure and competition are positively correlated) then we would observe a greater increase in rates in low friction states relative to others. The evidence, however, is inconsistent with this concern. First, low friction states are as competitive as high and medium friction states, as proxied by the Herfindahl–Hirschman index (HHI) and the fraction of premiums sold by insurers that only operate in that state (single-state insurers).[26] Figure D.2 shows similar distribution of both measures, implying similar competitiveness across state types. Second, our spillover estimations include insurer $\times$ state fixed effects, which capture differences in insurers' market power across states. Third, the ZIP code analysis takes this idea further by adding even more granular geographic fixed effects to address the concern that market power of the same insurer could vary within a state across geographies.

(v) Differences in size of losses. An alternative explanation for the asymmetric rate spillovers may be differences in the size of losses across states. If losses are sufficiently small in low friction states, then there may be no spillovers from these states as rates may just adjust locally. In contrast, if high friction states typically suffer larger losses, then one would expect some of these losses to spillover to other states. While Figure D.3 indeed shows that losses per capita are slightly higher in high friction than in low friction states, two pieces of evidence are at odds with this alternative explanation.[27]

First, if spillovers are due to losses in high friction states being on average larger, then we should also observe insurers responding strongly to their own losses in high friction states. However, we see negligible responses to losses in these states (see Table 2), underscoring the role of regulatory frictions. Second, we re-estimate Equation (5) after excluding the low friction states that have low losses per capita such that the average losses per capita in low

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[26]The presence of single-state insurers makes states more competitive because they do not need to raise rates when multi-state insurers do.

[27]Table D.2 shows the relationship between the friction measure and several state and regulator characteristics. We only find a weak positive relation between the friction measure and climate risk, as proxied by a state's property damage per capita.

and high friction states are similar. Table D.3 shows that even when we focus on the low friction states that have comparable losses as the high friction states, there is still no spillover emanating from low friction states.

(vi) Shifts in reinsurance rates. Reinsurance rates typically rise after losses, in turn driving up insurance rates (Froot and O'Connell, 1999). A concern, therefore, may be that the asymmetric rate responses are driven by differential shifts in reinsurance rates. However, this explanation is inconsistent with the totality of our findings. On one hand, the results on same-state losses would suggest that losses in *low* friction states affect reinsurance rates more than losses in high friction states. As a result, we observe stronger response to same-state losses in low friction states. On the other hand, the results on out-of-state losses would suggest that losses in *high* friction states affect reinsurance rates more than losses in low friction states, which explains why only high friction losses spillover but not low friction losses. Thus, the reinsurance explanation cannot simultaneously rationalize all our empirical findings, while regulatory frictions can.

(vii) Bypassing regulation through strategic pricing. One reason why rates may be more sensitive to losses in low friction than in high friction states could be strategic initial pricing of contracts. Specifically, in response to regulation if insurers have a higher (lower) *initial* pricing in high (low) friction states, they would require fewer (more) *subsequent* rate increases. However, this possibility is unlikely. First, the ZIP code analysis shows that insurance rates are in fact lower and exhibit slower growth in bordering high friction ZIP codes than in low friction ZIP codes (Table 6 (a)). Second, note that this argument only applies to the response to same-state losses, but does not explain the asymmetric response to out-of-state losses.

5.2. Conditions Necessary to Rationalize Rate Responses

There are three key conditions necessary to rationalize our findings on insurers' rate responses. First, exits from high friction states should be unattractive. This is exactly what we find, as we later discuss in Section 6.2. Second, there should be some friction that prevents insurers' optimization problem from being separable across regions as otherwise shocks in one region would not spill over to the others (separability). Third, states should not be sufficiently competitive to counteract the spillovers (competition).

(i) Separability. One natural candidate to relax separability across regions is the presence of financing frictions (Koijen and Yogo, 2015, Ge, 2022). This can generate spillovers because price adjustments are a way to relax financial constraints through firms' internal capital markets. To understand whether it is the case, we ask if spillovers are larger for more

constrained insurers. To identify which insurers are financially constrained, we follow the methodology of Ge (2022) and consider the following measures of financial constraint: lagged net assets, RBC ratio, leverage ratio, and changes in leverage ratio. For each measure, an insurer is deemed constrained in each year relative to peers if the measure of constraint lies below the cross-sectional median.

Tables 9 and 10 provide some evidence for this channel. Exploiting the ZIP code analysis, we find that insurers that become more constrained by an out-of-state shock have a greater tendency to increase rates in low friction ZIP codes (Table 9). However, the heterogeneity in rate response across insurers is relatively less stark in the main analysis using rate filings (Table 10).[28] While these facts suggest that financing frictions have some role to play, we also find statistically and economically large spillovers for less constrained insurers. This suggests that while financing frictions could be one reason why insurers tend to cross-subsidize rates across unrelated geographies, it is not the only reason for it.

Another candidate is managerial incentives shaped by capital market pressure.[29] Since the profitability of insurers is subject to heavy scrutiny, large losses can induce insurers to myopically focus more on short-term profits (Stein, 1989). As a result, insurers may increase rates where they can easily do so (e.g., in low friction states) in order to cater to such pressure at the expense of long-term profitability. Similarly, an insurer operating with a short-term profit margin target (e.g., earnings target) or a slow-moving "habit" in profits may also forego long-term profits and increase rate across unrelated regions.[30] Consistent with capital market pressure, we find that the degree of rate spillovers is more pronounced for publicly traded companies (Table D.4). Similarly, business models may also give rise to rate spillovers. For example, mutual companies[31] have limited access to external capital and accumulate capital mainly through retained earnings, so they are likely more prone to average cost pricing than otherwise similar stock companies (Brown and Davis, 2009, Harrington and Niehaus, 2002). Consistent with this, we find that mutual insurers exhibit substantial degree of rate spillovers (Table D.4).

This lack of separability across states in the insurer's optimization problem can also help clarify why insurers did not increase rates in low friction states *before* losses occurred, even if they could have. To see this concretely, consider an insurer that maximizes a weighted

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[28]The divergence in our findings is likely a result of using a different sample of insurers and the size of the shock across the two analyses. The ZIP code analysis uses data on relatively fewer insurers and exploits larger shocks to examine the effect of regulation on rate spillovers.

[29]Another candidate to relax separability is cross-state learning. Since we do not find support for this mechanism (see the previous section), we omit discussing it again.

[30]We observe persistent emphasis on earnings target in insurers' earnings call transcripts (see e.g., Progressive's call transcripts in 2014).

[31]Mutuals are insurers owned by policyholders instead of stockholders.

sum of its short-term and long-term profits. This setup implies that in each period, the insurer is not necessarily at the static optimum maximizing current-period profits, but at the dynamic optimum maximizing both short- and long-term profits. Climate losses then induce the insurer to place more emphasis on short-term profits (e.g. due to financing frictions or capital market pressure), and it is thus forced to re-optimize by increasing rates and thereby getting closer to the static optimum price. Appendix F provides a model of insurance pricing that nests this mechanism and qualitatively matches our empirical results.

(ii) Competition. To understand how competition affects insurers' rate responses, we split the low friction states into two groups by the share of premiums sold by single-state insurers in the state. Table 11 shows that the spillover coefficients are 2.7 times greater for the low share (i.e. low competition) states than the high competition states. However, the coefficient is both statistically and economically significant even for high competition states. For example, the increase in rates in response to large out-of-state losses accounts for 43% (17%) of the increase experienced annually in low (high) competition states. Table D.5 shows similar patterns using other proxies of competition. These results suggest that while competition affects the degree of spillovers, even in the more competitive states, it appears not enough to prevent the spillovers. This could be because overall states are not sufficiently competitive. Indeed, Figure D.4 shows that the proportion of premiums sold by single-state insurers is relatively small (<10%).

Overall, our findings suggest that a combination of several economic forces may be generating the spillovers. However, fully identifying them is beyond the scope of the current paper. Our central point is that heterogeneous rate regulation results in asymmetric rate spillovers across states, which causes distortions in who bears climate risk. This point holds regardless of the precise mechanism that generates the spillovers in the first place.

6. Long-run Implications

In this section, we discuss the long-run implications of our findings, focusing on the following dimensions: (i) how rates and risk have become disjoint over the long-run, and (ii) how regulation has affected the availability of insurance. We also discuss the implications of having state-provided insurance (residual markets) for our findings.

6.1. Decoupling of Rates from Risk

We start by providing evidence that the regulatory landscape has led to a growing disconnect between rates and risk. First, granular rates data show that rates have become less reflective

of risks, especially in high friction states. Rate growth has also been slower (faster) in high (low) friction states compared to the growth in losses. Second, counterfactual experiments show that both strict regulation in high friction states and the spillovers to low friction states are quantitatively important in explaining the disconnect between rates and risks.

6.1.1. Evidence from ZIP code data

Figure 3 shows a binned scatter plot of ZIP code-level rates from QIS and expected losses for the various state types (Appendix E describes the construction of expected losses). Several striking patterns emerge.

First, insurance rates do not seem to accurately reflect risk in high friction states relative to low and medium friction states. In general, we expect insurers to charge higher rates in ZIP codes with higher expected losses. While this pattern holds true in low and medium friction states, rates and expected losses seem weakly correlated in high friction states. In fact, consistent with pooled pricing, price dispersion is significantly lower in high friction states. Second, for a given level of expected losses, rates are higher in low and medium friction states than in high friction states. These results are consistent with Panel (a) of Table 6 which shows that the average rate in high friction ZIP codes is 14% lower than the rate in low friction ZIP codes along state borders. Finally, rates appear least reflective of losses in high risk areas of high friction states where rates are well below losses.[32]

6.1.2. Evidence from long-run rates and losses

We next illustrate how rates have become disjoint from risks in the long-run. We begin by constructing a rate index for each state using the rate filings data. We first compute the average rate change across insurers for a given state-year, ΔRate_{st}.[33] We then compute the cumulative rate index for each state, $P_{sT} = \Pi_{t=2009}^{T}(1 + \Delta\text{Rate}_{st})$, with 2008 as the base year. Panel (a) of Figure 4 shows the evolution of average P_{sT} for high friction states relative to all other states. In the last 10 years, rates have grown 4 percentage points slower in the average high friction state relative to the other states.

The slower growth of rates in high friction states is surprising as these states tend to be more exposed to climate losses (see Figure D.3). Indeed, when we compare the growth in rates with growth in expected losses over the long run (see Figure B.3.1), we see that high friction states have experienced lower growth in rates compared to growth in expected losses.

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[32] As rates from QIS depict the supply schedule (see Section 4), this pattern need not imply that insurers are losing money on average in high friction states. In fact, Figure 2 shows that insurers on average remain profitable in high friction states.

[33] To compute ΔRate_{st}, we weight the rate changes received by insurers' market shares in the prior year, i.e. $\Delta\text{Rate}_{st} = \sum_i \text{Market Share}_{ist-1} \times \text{Rate}\Delta\text{Received}_{ist}$.

In contrast, low friction states have experienced higher growth in rates compared to growth in expected losses, suggesting long-run decoupling of rates and risk.

6.1.3. Counterfactual insurance rates

The decoupling of rates and risk may be coming from either rates being too low in high friction states due to strict regulation or from rates being too high in low friction states due to the spillovers. We next conduct two counterfactual experiments to assess the impact of the regulatory frictions and separately quantify the contribution of strict regulation and of the spillovers to the decoupling.

First, we ask what the rate changes in low and medium friction states would have been if the spillovers in these states (due to out-of-state losses) were similar in magnitude as in high friction states. To construct the counterfactual rate changes, we re-compute the rate changes for low and medium friction states by subtracting the additional spillover from actual rate changes, i.e. we subtract β^L and β^M (estimates from Table 4) times OSL. In doing so, we thereby impose that the sensitivity to out-of-state losses be at the same level for all state types, whereas previously the sensitivities were significantly higher for low and medium states (see Section 3.2). As a result, we shut down a significant portion of the rate growth in low and medium states that are due to out-of-state spillovers, which results in a lower rate growth for these states.

Second, we ask what the rate changes in high friction states would have been if the extent of regulation in these states were same as in the low and medium friction states. To this end, we scale-up the rate changes received for high friction states each year by multiplying by a factor of 1.252, which is the ratio of the average rate wedge in low and medium friction states to that of high friction states. In other words, we impose that a similar fraction of target rate changes are approved and the degree of regulatory friction be at the same level for all state types. This increases the rate growth in high friction states.

The effects of these two experiments are summarized in Panel (b) of Figure 4, which shows the evolution of the counterfactual rate indices. First, a comparison of the actual and counterfactual rate indices for low and medium friction states across the two panels shows that rates would have grown 10 percentage points (pp) slower if we were to eliminate the effects of additional spillovers in low and medium friction states.[34] Second, if we were to reduce the extent of regulation in high friction states, rates would have grown 13 pp more.[35] Thus, both strict regulation and the spillovers are quantitatively important in driving the decoupling of rates and risk. Overall, while actual rates have grown 4 pp slower in high

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[34]The counterfactual rate index would be 1.37 instead of the actual value of 1.47 in 2019.

[35]The counterfactual rate index would be 1.56 instead of the actual value of 1.43 in 2019.

friction states (Panel (a)), our estimates suggest that counterfactual rates would have instead grown 20 pp faster in high friction states relative to the other states (Panel (b)), which would be more in line with the differences in the underlying risk exposures across the state types.

6.2. Insurance Availability

It is conceivable that in response to regulation, insurers respond by fully exiting or by not renewing policies in high friction states. If so, rate regulation may have a detrimental effect on the availability of insurance for households, especially in states that are high friction, which are also relatively more exposed to climate risk. We examine two measures of exits: (i) hard exits (insurers fully stop selling insurance in a given state), and (ii) soft exits (insurers do not fully exit the state, but limit supply by terminating or not renewing contracts).

First, Table D.6 shows that hard exits are relatively rare and even more so among large insurers (the yearly likelihood is 0.17% for large vs. 0.44% for small insurers).[36] Second, we test if the tendency to exit is greater in high friction states. Because exits are rare, we collapse the data into a state $\times$ year panel. The outcome variable of interest is the fraction of insurers exiting a state (%$Exits$), defined as the total number of exits in a given state and year, divided by the total number of insurers in the state. Table 12 documents the main findings from estimating a cross-state regression of %$Exits$ on a dummy variable for high friction states. Column (1) shows that high friction states experience more exits than low or medium friction states. However, columns (2) and (3) show that high friction states experience more exits due to small insurers exiting rather than large ones. These results indicate that despite restrictive rate-setting frictions, larger insurers rarely choose to exit. Instead, they likely respond to the rate-setting frictions by adjusting rates on the intensive margin through cross-subsidization as the previous section shows.

Second, we examine the extent to which insurers cancel or stop renewing existing contracts. We collect data on the fraction of existing policies cancelled or not renewed (henceforth terminations) from the NAIC's Market Conduct Annual surveys, which are aggregated at the state-year level and available from the year 2014. Overall, only 3.3% of total policies are terminated per year, and while high friction states experience more terminations than low or medium friction states (Table 12, column (4)), the increase is modest at 20 bps.

There could be several reasons why exits are infrequent. First, insurers commonly bundle products by offering discounts or combining deductibles for consumers purchasing several

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[36]In measuring exits, we only want to capture exits from a particular state, so we require that an insurer exits a particular state but continues to operate in at least one other state. Note that we exclude insurers that have <0.05% market share as together they write a small fraction of total HO premiums but have the tendency to switch in and out of a state, which may lead to spurious findings.

types of insurance from the same insurer (NAIC, 2021). Therefore, the returns to selling HO insurance not only includes profits from this line but also future revenues from other lines (e.g., auto insurance). Second, insurers may be under regulatory pressure to not terminate policies. Narratives from insurers suggest that they indeed fear potential retaliation by regulators who sometimes respond by being overtly strict in other lines of businesses. Third, there could be high direct costs associated with exiting and re-entering the market (e.g., reapplying for state licenses, rehiring brokers, reestablishing relationship with regulators). Finally, operating across geographies may provide diversification benefits.

Taken together, the evidence suggests that while households in high friction states have started experiencing deterioration in insurance availability, overall exits and terminations are still modest in magnitude.[37]

6.3. The Role of Residual Markets

Our analysis so far has focused on the private HO insurance market. Another avenue for households to purchase HO insurance is the "residual market". Residual markets are state-organized insurance marketplace of last resort in which homeowners who are unable to obtain coverage directly from a private insurer can purchase insurance.[38] In this section we address two implications of residual markets for our findings.

First, we show that residual markets also reflect only a mild deterioration in insurance availability, consistent with the evidence in Section 6.2. (i) The size of the homeowners' residual market is small relative to the private market, suggesting that most homeowners still access insurance through the private market. For example, 17 states do not have a residual market.[39] In addition, the amount of insurance coverage sold through the residual market is much smaller than that in the private market. Panel (a) of Figure D.5 shows that as of 2018 the amount of coverage sold via the residual market was less than 3% of the total coverage sold in the U.S. (ii) While the residual markets may be overall small, one implication of our findings is that the residual market would be larger in size in high friction states where insurers may be more likely to drop coverage or refuse to sell insurance altogether. Panel (b) of Figure D.5 tests this prediction by plotting the fraction of coverage sold via by the residual market against $Friction_s$. While the residual coverage is low in most

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[37]While exits have been rare so far, it is possible that if losses continue to increase and rates remain low we could see more insurers leaving high friction states. In fact, recent anecdotal evidence suggests rapid deterioration of insurance availability in California.

[38]These include Fair Access to Insurance Requirements plans, Beach and Windstorm plans, and Florida and Louisiana Citizens Property Insurance Corp plans. In most cases the liabilities are distributed among insurers licensed to do business in the state, except in the case of Citizens where it is borne by the state.

[39]Based on data reported by Property Insurance Plan Service Office (PIPSO).

states, it is indeed slightly higher in higher frictions states. Even so, the share of residual market exceeds 10% in only three states: in high friction North Carolina (20%), and in medium friction Massachusetts (15%) and Florida (13%).

Second, we argue against the possibility that residual markets are counteracting the decoupling of risk and rates in the private market. One concern is that if residual markets were sufficiently large and rates offered via this market accurately reflected underlying risks, then we may be overstating the degree of decoupling of rates from risk. However, this is unlikely to be the case given the small size of residual markets in most states. Given the size of the residual market, the rates offered via residual markets would need to be unrealistically high (low) to fully reverse the mispricing effects in high (low) friction states.[40]

Another concern is that households in low friction states may choose to switch to the residual market instead of paying the higher private market rates, implying that the private market rate would not be the effective market rate in most cases. However, this is unlikely for several reasons. (i) Empirically, low friction states have a very small residual market (Figure D.5), indicating that switching into the residual market is not prevalent in low friction states. (ii) Households in low friction states cannot just opt into the residual market because of high rates: they have to provide evidence that a number of insurers have *refused* to sell them insurance entirely at any rate (FIO, 2015). (iii) The typical contract offered via the residual market offers lower protection than the standard HO3 contract making it less than ideal given the requirements of mortgage lenders (FIO, 2015).

7. Conclusion

This paper studies the pricing of homeowners' insurance, a large and relatively under-studied market that is of growing importance given the significant rise in natural disasters in the last two decades. We show that insurance premiums (rates) are subject to extensive regulations at the state level in the United States. We quantify the extent of these rate-setting frictions in each individual state using novel data on the filings made by insurers to regulators. Then exploiting two different data sources and two different empirical designs, including state-border discontinuities, we show that (i) insurers are restricted in their ability to change rates in high friction states in response to losses; and (ii) they overcome the regulatory

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[40]Even if we focused on high friction North Carolina (NC), which has the largest residual market by coverage (20%), the rates offered via residual markets would need to be unrealistically high. For example, for average rates in NC to be as large as average rates in South Carolina (SC), which has comparable risk exposures, the rates offered via residual markets in NC would need to be 170% larger than the private market rate. Average rates reported by PIPSO suggest that in fact residual market rates are substantially below the private market rates in NC.

constraints by cross-subsidizing high friction states by raising rates in low friction states. Finally, we provide evidence that the combination of the two factors - strict regulation in high friction states and the rate spillovers - have led to a decoupling of insurance rates from the underlying risks in the long-run. Our estimates suggest that rates would have grown 20 percentage points faster in high friction states relative to the other states in a scenario where all the states were similarly regulated and the rate spillovers were absent.

Our findings point to distortions in how climate risk is shared across states, i.e. households in low friction states are disproportionately bearing the risks of households in high friction states. Our findings also question whether insurance rates can play a useful role in steering climate adaptation. In many insurance markets (e.g., health), consumers likely have an informational advantage over insurers. In HO insurance, however, the informational advantage is likely reversed: insurers have access to better technology, data, and models to forecast risks compared to households.[41] In that sense, insurance rates can both inform households about their local risks and provide incentives for the insured to take risk mitigation measures (e.g., by investing in disaster-resilient home features or migrating to a safer region). When rates no longer reflect risks, the informational role of insurance rates breaks down. Moreover, it also potentially gives rise to a moral hazard problem and ultimately prevents insurance rates from playing a critical role in risk mitigation. Anecdotal evidence also suggests that the availability of cheap insurance is one of the reasons why high risk areas have experienced disproportionate increase in construction and real estate development.[42] By making society less resilient to climate risk, such developments may exacerbate climate losses and cause substantial long-run damage to livelihoods.

Our findings also have implications for long-term insurance availability and for the stability of the insurance sector. Policymakers and academics view a healthy insurance sector as a front-line defense against climate risk and key for preserving financial stability (US Treasury, 2022, Scott et al., 2017, Krueger et al., 2020). However, over the long-run, rate-setting frictions could make insurers less prepared to deal with large losses and insurers may respond by exiting markets altogether or dropping important product features. 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. Our findings call into question the sustainability of the current regulatory system, especially in the face of the growing challenges posed by climate change.

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[41]Big data trends reverse the informational advantage towards insurers (Brunnermeier et al., 2021).

[42]See, e.g., the following news article from the Wall Street Journal (October 2020).

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Figure 1: Distribution of Rate Wedge

The figure shows the distribution of Rate Wedge, which is defined as the ratio of rate change received to the target rate change. The Y-axis shows the fraction of total rate filings. The data are from insurance product filings accessed through S&P MI for the period 2009 to 2019.
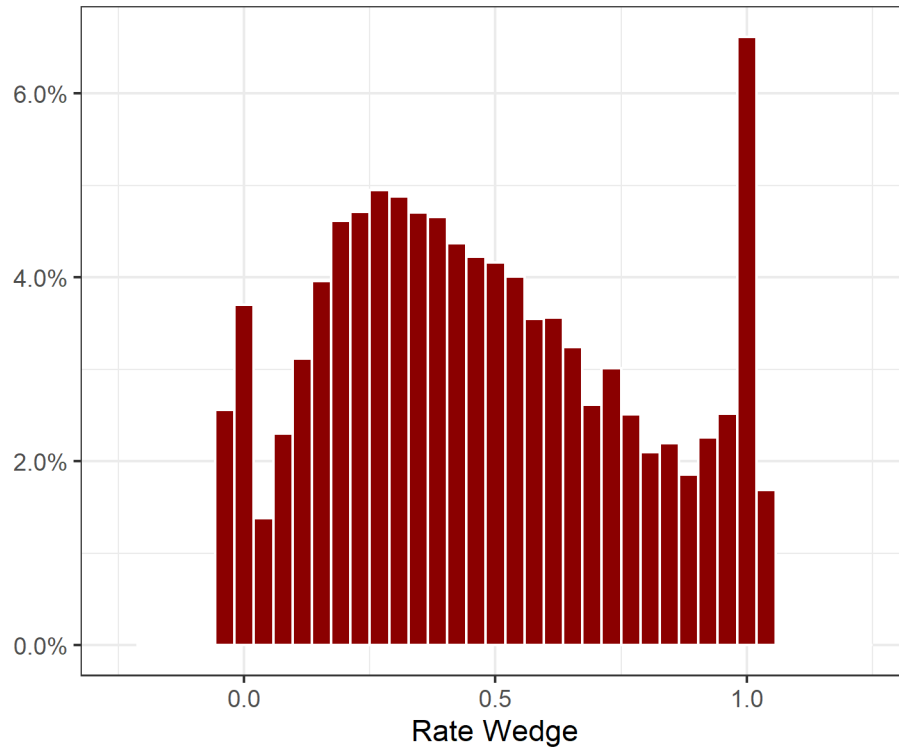
Figure 2: Insurers' profitability by state types

The figure shows the distribution of underwriting profitability. Underwriting profitability is defined as 1 - combined ratio. Combined ratio is a standard actuarial measure of insurers' underwriting profitability defined as the ratio of incurred losses and expenses to total premiums (see Insurance Information Institute (III)). First, for each insurer in each state, we collect direct simple combined ratio, which includes the following losses and expenses: direct incurred losses, direct defense and cost containment expenses incurred, commissions and brokerage expenses, taxes, and licenses and fees. These data are from insurers' regulatory filings S&P MI. Second, to get to the final combined ratio, as described in III, we add the following additional expenses: adjusting and other expenses incurred, other acquisition and field supervision expenses incurred, and general expenses incurred. Estimates are for the year 2019, and the graph plots high, medium, and low friction states separately. The error bars show the 95% confidence intervals.
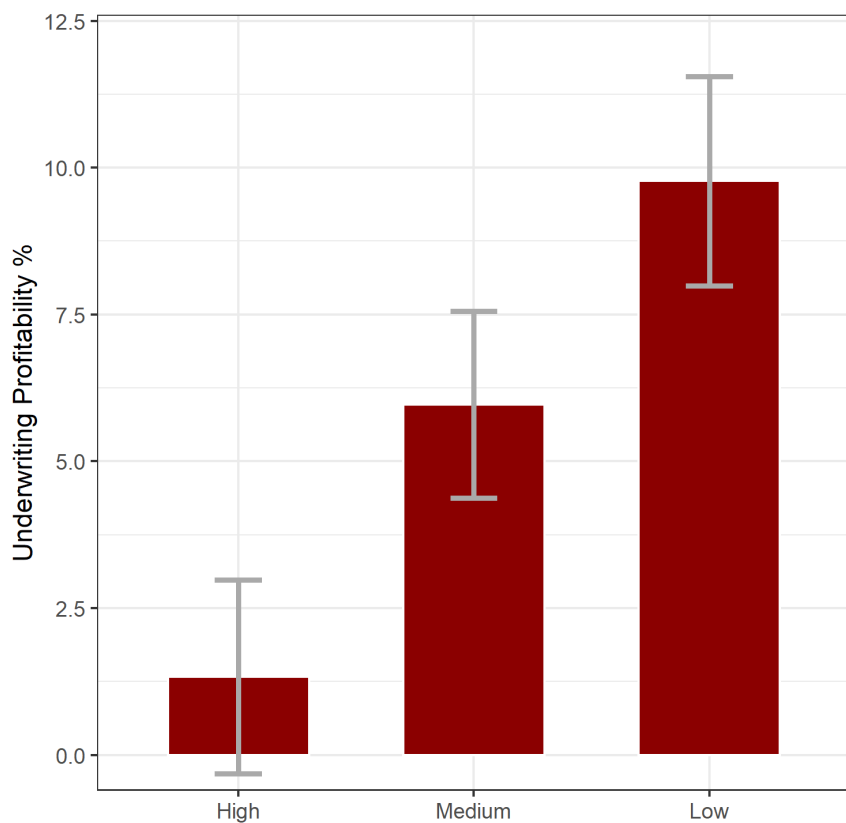
Figure 3: Decoupling of insurance rates from risk

The figure shows the binscatter of annual insurance rates and annual expected losses per housing unit at the ZIP code level across state types. The insurance rates are for the year 2019 obtained from QIS (accessed via insure.com) for a contract with $300,000 in coverage, $1000 deductible, and for a consumer with an excellent credit score. Rates are scaled by 0.75 to account for the average insurers' expense ratio, as reported by III. The construction of expected losses is detailed in Appendix E.

(a) High Friction
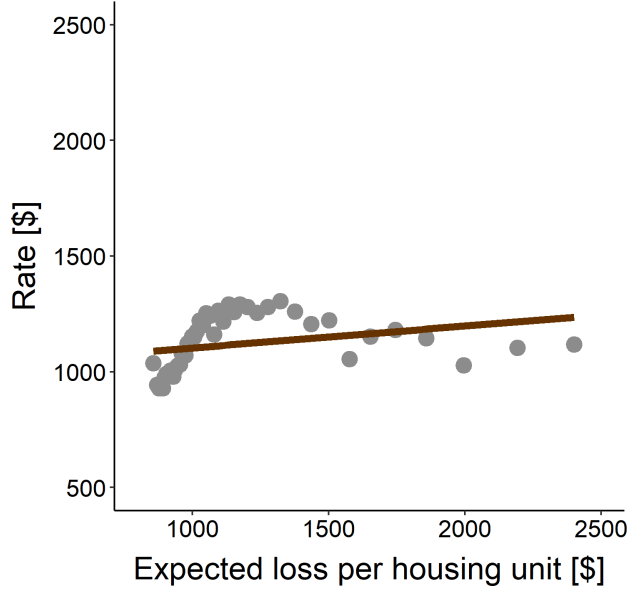
(b) Low and Medium Friction
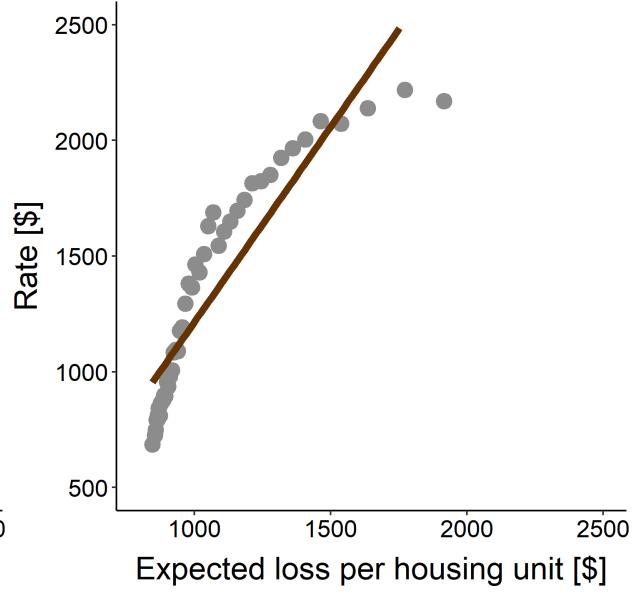
Figure 4: Long-run growth in insurance rates: actual and counterfactual

The figure shows the evolution of homeowners' rate indices for the different state types from 2008 to 2019. Refer to Section 6.1.2 for details on the construction of the indices. In Panel (a), we plot the actual rate indices. In panel (b) we plot the counterfactual rate indices for two scenarios. Red line shows counterfactual rates for high friction states in a scenario where high friction states were similarly regulated as low and medium friction states. Blue line shows counterfactual rates for low and medium friction states in a scenario where spillovers were similar in magnitude as in high friction states. The data are from insurance product filings accessed through S&P MI.

Panel (a): Actual rate growth
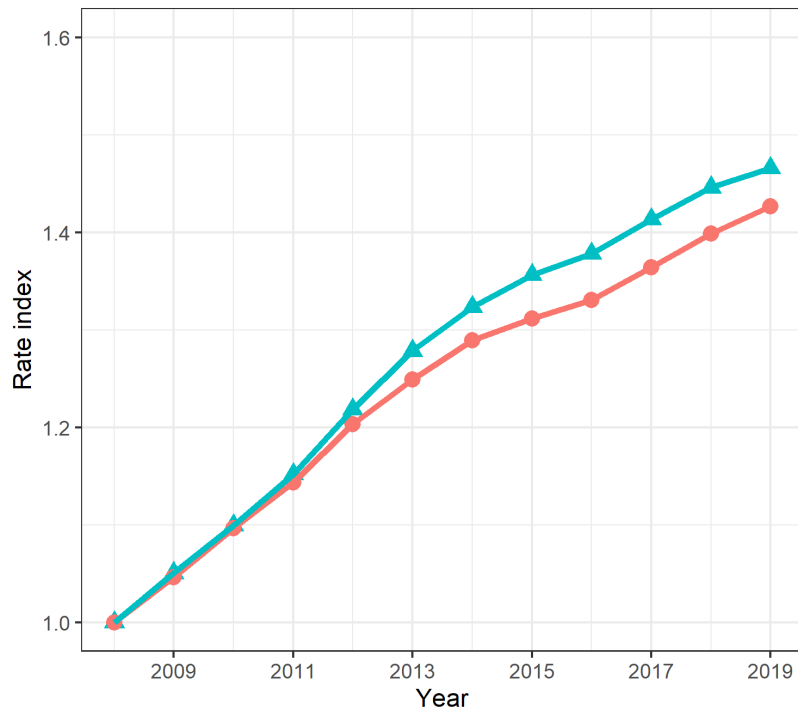
Panel (b): Counterfactual rate growth
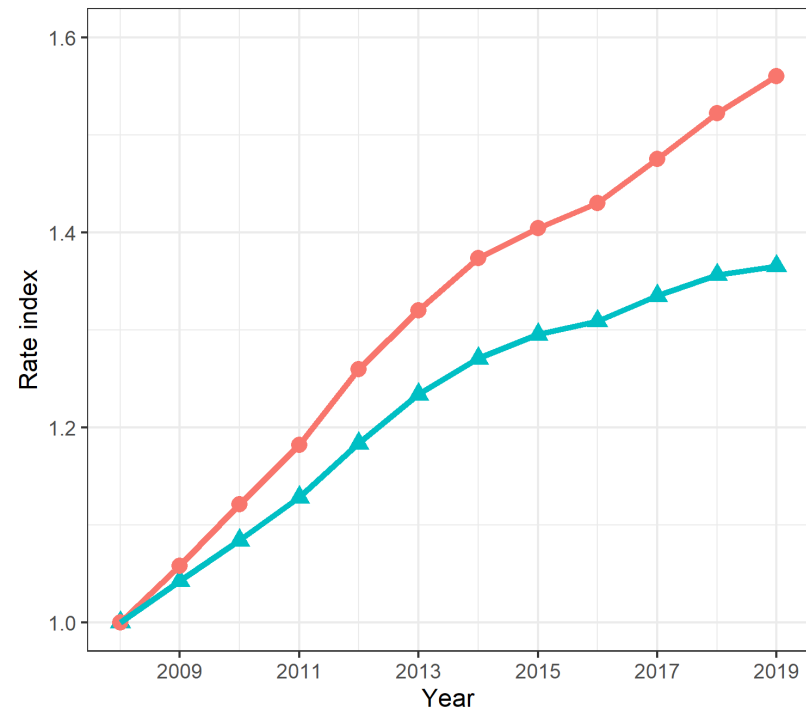
Table 1: Summary statistics

The table presents summary statistics. Variable descriptions are as follows. *Underwriting operations*: Premiums refer to the total amount of insurance sold. Losses refer to the total claims insurers pay to consumers if an insured event takes place. Loss ratio is the ratio of losses to premiums sold. These data are at an insurer × state × year level. We report statistics for the year 2019. *Financial statements*: We report loss ratio for non-homeowners' lines. Net assets is total assets of the insurer. RBC ratio is the ratio of total available capital to total required capital. Reinsurance ratio is the fraction of premiums reinsured. N states is the number of states insurers sell HO insurance in. These data are at an insurer × year level. We report statistics for the year 2019. *Rate filings*: Any Filings refers to whether an insurer filed for a rate change in a given state and year. RateΔTarget and RateΔReceived are the rate change targeted and received by an insurer in a given state and year. These two variables are populated only conditional on filing. These data are at an insurer × state × year level. We report statistics on the full sample from 2009 to 2019. These statistics pertain to our main sample as detailed in Appendix A.2.

	N	Mean	SD	10th	25th	50th	75th	90th
Underwriting operations (2019):								
Premium (homeowners, $M)	1530	39.03	95.72	1.90	4.95	13.01	33.53	79.77
Loss (homeowners, $M)	1530	22.39	62.11	0.80	2.54	6.55	17.62	46.87
Loss ratio (homeowners)	1530	0.57	0.31	0.30	0.40	0.52	0.66	0.86
Financial statements (2019):								
Loss ratio (non-homeowners)	253	0.60	0.15	0.49	0.54	0.58	0.64	0.71
Net assets ($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
Rate filings (2009-2019):								
Any Filings	17980	0.70	0.46	0.00	0.00	1.00	1.00	1.00
RateΔTarget (%)	12563	15.60	15.97	0.00	5.20	11.70	21.44	35.59
RateΔReceived (%)	12563	5.85	5.55	0.00	2.03	5.00	8.70	12.86

Table 2: Rate responses to same-state losses

The table presents the results from estimating Equation (3). The dependent variables are: in column (1) whether a rate change is filed and in column (2) the rate change received by insurer i in state s and year t. The independent variable is Same-State Losses (SSL), i.e. losses experienced by an insurer in the state in which it has made the rate filing. SSLs are lagged one year and scaled by the lagged total premium sold in the filing state. The indicator variables Med_s and Low_s equal 1 if the filing state s is, correspondingly, a medium or a low friction state. All regressions control for log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and the percent of premiums reinsured for insurer i in year t. Column (2) also controls for the insurer's target rate change. The results pertain to our main sample as detailed in Appendix A.2 prior to the final exclusion of insurers selling in a single state. All regressions include insurer-year and filing state-year of submission fixed effects. Standard errors are shown in parentheses clustered at the state level.

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

	Any Filings$_{ist}$	Received$_{ist}$
	(1)	(2)
SSL$_{ist-1}$	−0.011	0.156
	(0.027)	(0.286)
SSL$_{ist-1}$ × Med$_s$	0.044	0.104
	(0.028)	(0.403)
SSL$_{ist-1}$ × Low$_s$	0.100***	0.688**
	(0.035)	(0.303)
E[LHS]	0.7	3.63
State type	All	All
Controls	Yes	Yes
State × Year Fixed Effects	Yes	Yes
Insurer × State Fixed Effects	Yes	Yes
Observations	19,308	19,308

Table 3: Asymmetric rate spillovers: filing decision

The table presents the results from estimating Equation (4). The dependent variable is whether a rate change is filed by insurer i in the filing state s and year t. The independent variable of interest is an insurer's "out-of-state" losses (OSL) in the prior year. To compute OSL, we sum an insurer's lagged losses in all the states it operates in other than the filing state s, which we scale by lagged total premiums sold in all states except s. The indicator variables Med_s and Low_s equal 1 if the filing state s is, correspondingly, a medium or a low friction state. The results pertain to our main sample as detailed in Appendix A.2. The panels in columns (1) and (5) include all states, while in columns (2), (3) and (4) are restricted to the filing state being a high, medium or low friction state. All regressions control for same state losses, log assets, log RBC ratio, loss ratio of all other (non-homeowners') lines of business, and the percent of premiums reinsured for insurer i in year t. All regressions include insurer-filing state and filing state-year of submission fixed effects. Standard errors are shown in parentheses, clustered at the state level.

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

	Any Filings$_{ist}$				
	(1)	(2)	(3)	(4)	(5)
OSL$_{ist-1}$	0.027*	−0.004	0.013	0.151***	−0.006
	(0.015)	(0.022)	(0.012)	(0.033)	(0.021)
OSL$_{ist-1}\times$ Med$_s$					0.019
					(0.025)
OSL$_{ist-1}\times$ Low$_s$					0.162***
					(0.041)
E[LHS]	0.7	0.7	0.8	0.7	0.7
State type	All	High	Medium	Low	All
Controls	Yes	Yes	Yes	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes	Yes	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,980	5,656	6,231	6,093	17,980

Table 4: Asymmetric rate spillovers: rate changes received

The table presents the results from estimating Equation (4). The dependent variable is the rate change received by insurer i in the filing state s and year t. The independent variable of interest is an insurer's "out-of-state" losses (OSL) in the prior year. To compute OSL, we sum an insurer's lagged losses in all the states it operates in other than the filing state s, which we scale by lagged total premiums sold in all states except s. The indicator variables Med_s and Low_s equal 1 if the filing state s is, correspondingly, a medium or low friction state. The results pertain to our main sample as detailed in Appendix A.2. The panels in columns (1) and (5) include all states, while in columns (2), (3) and (4) are restricted to the filing state being a high, medium or low friction state. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

	RateΔReceived$_{ist}$			
	(1)	(2)	(3)	(4)	(5)
OSL$_{ist-1}$	0.632**	0.085	0.758*	1.710***	0.075
	(0.236)	(0.208)	(0.362)	(0.543)	(0.205)
OSL$_{ist-1}\times$ Med$_s$					0.693*
					(0.402)
OSL$_{ist-1}\times$ Low$_s$					1.604***
					(0.559)
E[LHS]	3.7	3.4	4.5	3.3	3.7
State type	All	High	Medium	Low	All
Controls	Yes	Yes	Yes	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes	Yes	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,980	5,656	6,231	6,093	17,980

Table 5: Asymmetric rate spillovers: splitting out-of-state losses by state type

The table presents the results from estimating Equation (5), where out-of-state losses are split in three groups: high, medium, and low friction. The dependent variables are: in column (1) whether a rate change is filed and in column (2) the rate change received by insurer i in the filing state s and year t. The main independent variable is insurer's lagged "out-of-state" losses (OSL), which we split into losses coming from high (OSL^H), medium (OSL^M), low (OSL^L) friction states, scaled by total lagged out-of-state premiums from all states. The results pertain to our main sample as detailed in Appendix A.2. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

	Any Filings$_{ist}$	RateΔReceived$_{ist}$
	(1)	(2)
OSL^H_{ist-1}	0.222***	2.931***
	(0.057)	(0.752)
OSL^M_{ist-1}	0.275***	2.549***
	(0.067)	(0.632)
OSL^L_{ist-1}	0.055	0.680
	(0.148)	(2.326)
E[LHS]	0.7	3.3
State type	Low	Low
Controls	Yes	Yes
State × Year Fixed effects	Yes	Yes
Insurer × State Fixed effects	Yes	Yes
Observations	6,093	6,093

Table 6: Border discontinuity design: summary statistics and response to local shocks

Panel (a) presents summary statistics on the ZIP code-level insurance rates data. We report average insurance rates for high friction and low friction bordering ZIP codes for the 11 borders that share opposite regulatory classification. The data spans the period 2011 to 2020. Panel (b) presents the results from estimating Equation (6). The dependent variable is insurance rates (in logs) charged by insurer i in year t in ZIP code z, where the ZIP code belongs to a given state border pair b. Low_z is an indicator variable that takes the value of 1 for ZIP codes that are in a low friction state and 0 if in a high friction state. $Post_{bt}$ is an indicator variable that takes the value of 1 after the shock in a given border pair b and 0 before. Controls are as described before. Fixed effects are denoted at the bottom of the table. Standard errors are shown in parentheses, clustered at the ZIP code level.

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

(a) Summary statistics

	Low friction	High friction
Average insurance rate ($)	3,269	2,869
	(4.27)	(3.13)
Growth rate (2011 to 2020)	41%	33%

(b) Response to local shocks

	log(Insurance Rate$_{iz(\in b)t}$)		
	(1)	(2)	(3)
$Low_z \times Post_{bt}$	0.065***	0.053***	0.049***
	(0.008)	(0.008)	(0.006)
$Post_{bt}$	0.031***	0.031***	
	(0.008)	(0.007)	
Low_z	0.123***		
	(0.022)		
Controls	Yes	Yes	Yes
Insurer $\times$ Border Fixed effects	Yes	Yes	Yes
ZIP Code Fixed effects	No	Yes	Yes
Border $\times$ Year Fixed effects	No	No	Yes
Observations	18,883	18,883	18,883

Table 7: Border discontinuity design: response to out-of-state shocks

This table presents the results from estimating Equation (7). The dependent variable is insurance rates (in logs) charged by insurer i in year t in ZIP code z, where the ZIP code belongs to a given state border pair b. Low_z is an indicator variable that takes the value of 1 for ZIP codes that are in a low friction state and 0 if in a high friction state. $Post_{bt}$ is an indicator variable that takes the value of 1 after the shock in a given border pair b and 0 before. $Affected_{ie}$ ($= 1$) identifies insurers affected by the non-bordering out-of-state event e. Controls are as described before. Fixed effects are denoted at the bottom of the table. Standard errors are shown in parentheses, clustered at the ZIP code level.

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

	log(Insurance Rate$_{iz(\in b)t}$)				
	(1)	(2)	(3)	(4)	(5)
Low_z × $Post_{te}$ × $Affected_{ie}$	0.043***	0.033***	0.060***	0.058***	0.058***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Low_z × $Affected_{ie}$	−0.028***	−0.012*	−0.044***	−0.040***	
	(0.011)	(0.007)	(0.008)	(0.008)	
$Post_{te}$ × $Affected_{ie}$	0.006	−0.010**	−0.038***		
	(0.004)	(0.005)	(0.006)		
Low_z × $Post_{te}$	−0.014***	−0.020***			
	(0.003)	(0.003)			
$Post_{te}$	0.053***	0.085***			
	(0.003)	(0.002)			
Low_z	0.129***	0.106***			
	(0.037)	(0.017)			
$Affected_{ie}$	0.055***				
	(0.009)				
Controls	Yes	Yes	Yes	Yes	Yes
Border × Insurer × Event Fixed effects	No	Yes	Yes	Yes	No
Border × Year × Event Fixed effects	No	No	Yes	Yes	No
Insurer × Year × Event Fixed effects	No	No	No	Yes	Yes
ZIP × Insurer × Event Fixed effects	No	No	No	No	Yes
ZIP × Year × Event Fixed effects	No	No	No	No	Yes
Observations	295,560	295,560	295,560	295,560	295,560

Table 8: Product filings in response to out-of-state losses

The table presents the results from estimating Equation (4). The dependent variable is whether a rule change is filed by insurer i in the filing state s and year t. The independent variable of interest is an insurer's "out-of-state" losses (OSL) in the prior year. To compute OSL, we sum an insurer's lagged losses in all the states it operates in other than the filing state s, which we scale by lagged total premiums sold in all states except s. The indicator variables Med_s and Low_s equal 1 if the filing state s is, correspondingly, a medium or low friction state. The results pertain to our main sample as detailed in Appendix A.2. The panels in columns (1) and (5) include all states, while in columns (2), (3) and (4) are restricted to the filing state being a high, medium or low friction state. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

	Any Rule Filings$_{ist}$				
	(1)	(2)	(3)	(4)	(5)
OSL_{ist-1}	0.006	−0.007	0.001	0.051	−0.007
	(0.009)	(0.012)	(0.008)	(0.048)	(0.012)
$OSL_{ist-1} \times Med_s$					0.009
					(0.014)
$OSL_{ist-1} \times Low_s$					0.058
					(0.049)
E[LHS]	0.7	0.6	0.7	0.7	0.7
State type	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

Table 9: The role of financing frictions: evidence from border discontinuity design

This table shows the heterogeneity in response to out-of-state shocks by re-estimating Equation (7) for different subset of insurers. We split insurers by four different proxies of financial constraints (assets, RBC ratio, leverage, and changes in leverage) as described in Section 5. Using each proxy, we then split the *affected* insurers into two groups (as of the year of the shock), above and below median, to distinguish constrained from unconstrained insurers. For example, insurers with high (low) leverage are defined as constrained (unconstrained). For ease of comparison, we do not split the unaffected (control group) to ensure that the control group (unaffected) remains the same. All the main variables are as defined before. Fixed effects are denoted at the bottom of the table. Standard errors are shown in parentheses, clustered at the ZIP code level.

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

| | log(Insurance Rate$_{iz(\in b)t}$) | | | | | | | |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low$_z$ × Post$_{te}$ × Affected$_{ie}$	0.077***	−0.015	0.026***	0.094***	0.041***	0.071***	0.044***	0.088***
	(0.009)	(0.010)	(0.005)	(0.016)	(0.004)	(0.012)	(0.008)	(0.005)
Constrained Panel	No	Yes	No	Yes	No	Yes	No	Yes
Firm Constraint	Assets		RBC		Leverage		Δ Leverage	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer × Year × Event Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP × Insurer × Event Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP × Year × Event Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	274,979	246,179	264,955	256,203	260,727	260,431	264,273	256,885

Table 10: The role of financing frictions: evidence from rate filings

The table presents the results from estimating the following regression:

$$Y_{ist} = \left(\beta + \beta^M \times Med_s + \beta^L \times Low_s\right) \times OSL_{ist-1} +$$
$$+ \left(\beta_c + \beta_c^M \times Med_s + \beta_c^L \times Low_s\right) \times OSL_{ist-1} \times Constr_{it-1} + \theta X_{it} + \alpha_{is} + \alpha_{st} + \epsilon_{ist}.$$

Dependent variables are denoted at the top of the table. The independent variable of interest is an insurer's "out-of-state" losses (OSL) in the prior year. To compute OSL, we sum an insurer's lagged losses in all the states it operates in other than the filing state s, which we scale by lagged total premiums sold in all states except s. The indicator variables Med_s and Low_s equal 1 if the state s is, correspondingly, a medium or a low friction state. $Constr_{i,t-1}$ is 1 if insurer i is financially constrained according to the various metrics defined in Section 5, which are denoted at the bottom panel (assets, RBC, leverage, and changes in leverage). All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state and insurer level.

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

	Any Filings$_{ist}$				RateΔReceived$_{ist}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OSL$_{ist-1}$	−0.009	−0.020	0.008	0.012	0.137	−0.027	−0.086	0.169
	(0.023)	(0.032)	(0.038)	(0.016)	(0.212)	(0.388)	(0.444)	(0.185)
OSL$_{ist-1}\times$ Med$_s$	0.017	0.040	0.035	0.003	0.616	0.824	0.790	0.529
	(0.025)	(0.037)	(0.040)	(0.019)	(0.443)	(0.566)	(0.530)	(0.363)
OSL$_{ist-1}\times$ Low$_s$	0.202***	0.128**	0.117**	0.165***	1.747**	1.327*	1.110*	1.779***
	(0.049)	(0.061)	(0.050)	(0.040)	(0.667)	(0.723)	(0.644)	(0.534)
OSL$_{ist-1}\times$ Constr$_{it-1}$	0.019	0.021	−0.016	−0.053***	−0.542	0.156	0.172	−0.273
	(0.054)	(0.030)	(0.034)	(0.018)	(0.488)	(0.411)	(0.419)	(0.295)
OSL$_{ist-1}\times$ Med$_s\times$ Constr$_{it-1}$	0.017	−0.030	−0.022	0.046***	0.654	−0.191	−0.101	0.510**
	(0.065)	(0.031)	(0.034)	(0.015)	(0.791)	(0.484)	(0.450)	(0.254)
OSL$_{ist-1}\times$ Low$_s\times$ Constr$_{it-1}$	−0.119*	0.039	0.060*	0.006	−0.018	0.325	0.769	−0.318
	(0.070)	(0.052)	(0.035)	(0.025)	(0.862)	(0.508)	(0.472)	(0.289)
E[LHS]	0.7	0.7	0.7	0.7	3.73	3.73	3.73	3.73
Firm Constraint	Assets	RBC	Leverage	ΔLeverage	Assets	RBC	Leverage	ΔLeverage
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,980	17,980	17,980	17,980	17,980	17,980	17,980	17,980

Table 11: The role of competition

The table presents the results from estimating Equation (4), where we split low friction states into two groups, above median (H) and below median (L), by the share of premiums sold by single-state insurers. As high and medium friction states are not split further, the control group remains the same as prior tables, i.e. all high and medium friction states. Dependent variables are denoted at the top of the table. The independent variable of interest is an insurer's "out-of-state" losses (OSL) in the prior year. To compute OSL, we sum an insurer's lagged losses in all the states it operates in other than the filing state s, which we scale by lagged total premiums sold in all states except s. The indicator variables Med_s and Low_s equal 1 if the state s is, correspondingly, a medium or a low friction state. The results pertain to our main sample as detailed in Appendix A.2. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

	Any Filings$_{ist}$		RateΔReceived$_{ist}$	
	(1)	(2)	(3)	(4)
OSL$_{ist-1}$	-0.005	-0.007	0.079	0.073
	(0.022)	(0.022)	(0.205)	(0.204)
OSL$_{ist-1}\times$ Med$_s$	0.019	0.019	0.691*	0.694*
	(0.025)	(0.024)	(0.403)	(0.402)
OSL$_{ist-1}\times$ Low$_s$	0.091**	0.250***	0.899*	2.435**
	(0.037)	(0.066)	(0.447)	(0.968)
Single State Insurers	H	L	H	L
Controls	Yes	Yes	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes	Yes	Yes
Observations	14,620	15,247	14,620	15,247

Table 12: Exits and contract terminations

The table presents the results from estimating the following regression: $Y_{st} = \beta High_s + X_s + \alpha_t + \epsilon_{st}$. The variable of interest $High_s$ is 1 for high friction states. The dependent variable in columns (1) to (3) is the percent of insurers in state s and year t that choose to exit the state. The years of observation are 2009 to 2019 and data source is S&P MI. The dependent variable in column (4) is the fraction of existing policies cancelled or not renewed. The data are from NAIC's Market Conduct Annual surveys, available from the year 2014. Column (1) shows all insurers, (2) shows large insurers (market share above 1%), and (3) shows small insurers. All regressions control for each state's 2019 median household income, percent of population that is black or Hispanic (S&P Geographic Intelligence), percent of the state's GDP from insurance (BEA), and average percentage of republican vote in the presidential elections of 2012, 2016 and 2020. We also control for the log sum of all HO insurers' net assets in each state and year and the average of all HO insurers' RBC ratio in each state and year (S&P MI). Standard errors are shown in parentheses, clustered at the state level.

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

	% Exits	% Exits (Large)	% Exits (Small)	Terminations
	(1)	(2)	(3)	(4)
High	0.108***	0.047	0.194*	0.201***
	(0.025)	(0.065)	(0.099)	(0.064)
E[LHS]	0.28	0.17	0.44	3.26
Insurer Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	510	510	509	290

Internet Appendix

"Pricing of Climate Risk Insurance:
Regulation and Cross-Subsidies"

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A. Data Construction

A.1. Rate Filings Data

We collect data on rate filings as follows. First, we focus only on the homeowners' lines of business in in the S&P MI database on Insurance Product filings (i.e, we exclude filings of other lines of business, e.g., auto insurance). Within all product filings, we focus attention on the filings which concern insurer's intention to change rates of its products (rate filings). From each rate filing, we extract the following variables: the insurer who initiated the request, the year in which the request was submitted (filing year), the state in which the request was submitted (filing state), the *target* rate change (RateΔTarget), the rate change received after regulators reviewed the request (RateΔReceived), and the date on which the request was decided (decision date). Using the filings, we construct an insurer-state-year panel of rate changes targeted and received. If an insurer files multiple times in the same year to the same state, we compute averages of the filings' observables. The U.S. has 51 separate insurance jurisdictions: the 50 states and D.C.. S&P MI reports that in their data, for 47 jurisdictions (henceforth states) we observe a full panel of filings for the years 2009 to 2019, i.e. we observe filings of all insurers that sell in these states for these years. For 3 states (Louisiana, Hawaii, and Texas) filings are available only starting in later years: Louisiana after 2015, Hawaii after 2012, and Texas after 2015. For these states, we include as many years of data as is available. We exclude Ohio as filings are incomplete (only available for a subset of insurers throughout the sample).

A.2. Sample Construction

To construct our main sample, we begin with all insurers who sold homeowners' insurance in any state at any point in time between 2009 and 2019 and construct an insurer-state-year panel on their underwriting operations, which is at insurer-state-year level, and financial observables, which is at insurer-year level. We restrict attention to insurers who are actively selling HO insurance in a state, i.e. to be included we require that an insurer must have written at least $100,000 in total premiums in each of the previous three years in a state. We also limit the sample to the largest 50 insurers by market share in any given state and year. We do so for the following reasons. (i) Small insurers typically make rate filings using external pricing agencies (e.g., Insurance Services Office). As pricing agencies make filings on behalf of several insurers at once, filing outcomes of small insurers are likely to be correlated leading us to over-weight similar outcomes. (ii) States with a large number of small firms are then not weighted more heavily. Note that the largest 50 insurers typically cover around 95% of the overall HO market share (see Figure D.6). This allows for a robust coverage of the HO market in our analysis. We merge this final panel with the insurer-state-year panel

on rate filings described above. The total number of observations in our final sample is 19,312. In the cross-subsidization regressions, we further restrict the panel to insurers who in a given year sell in at least two states. This results in a total of 17,980 observations.

B. Measurement of Rate-setting Frictions across U.S. States

B.1. Baseline Measurement and Robustness

This section provides details on how we construct the baseline regulatory rate-setting friction measure and provides several alternative constructions for robustness.

To construct the baseline measure, we make two main choices. First, we exclude filings from small insurers. We do so for several reasons. (i) Small insurers typically make rate filings using external pricing agencies (e.g., ISO). As pricing agencies make filings on behalf of several insurers at once, filing outcomes of small insurers are likely to be correlated leading us to over-weight similar outcomes. (ii) In contrast to large insurers who file almost every year, small insurers make infrequent filings (Table B.1.1). The decision of when to file is likely endogenous, but less worrisome in the case of large insurers as they make rate filings almost every year. (iii) Large insurers operate across a majority of U.S. states in contrast to small ones (Table B.1.1). This allows us to compute the average rate wedge using a similar composition of insurers in each state rather than a set of different insurers. Specifically, our measure uses filings of insurers with more than 1% market share in each state. This amounts to about 20 insurers in each state, together accounting for over 75% of the homeowners' market share. Second, we include the full sample of data from 2009 to 2019 to construct the baseline measure. We do so to incorporate the maximum available data for each state and because rate regulation is slow to change (see below).

Our classification of states into high, medium and low groups is not sensitive to these choices. First, we explore the relationship between the baseline measure and alternative measures constructed using a different number of insurers. We test if alternative constructions using different numbers of insurers significantly changes the classification. Specifically, we compute the alternative measure using the largest 30, 25, 15 or 10 insurers in each state. The results are shown in the first four rows of Table B.1.2. The correlation between the existing and alternative friction measures varies between 83% and 95% and only when we limit the sample to the largest 10 insurers do we see any states getting reclassified from high to low friction or vice versa (henceforth, major mis-classifications). This suggests that our friction metric is not sensitive to including a different number of insurers.

Second, we examine whether the baseline measure is robust to using different time periods. To test this, we check how the baseline metric compares relative to the ones estimated using the first part (2009-2013) and the second part (2014-2019) of the sample. The re-

sults are shown in the fifth and sixth rows of Table B.1.2. We see high levels of correlation (respectively, 81% and 74% for the early and late period metric), and very few major mis-classifications (2 for early and none for the late period metric). These results suggest that our measure is not sensitive alternative constructions using different time periods.

Table B.1.1: Insurer characteristics by market share

We compute each insurer's market share across all 51 U.S. jurisdictions by computing the fraction of all premium sold in 2019. We split the sample of insurers by whether their market share is below or above 1%. For each group, we report the average number of states they sell insurance in (column 1), likelihood of filing (number of years that insurers filed for a rate change across the states they operate in / total number of years in operation across all states) (column 2), and the average state rank by market share (column 3). In parentheses we show the standard errors of each mean.

N states an insurer sells homeowners	Yearly likelihood of filing	Average rank in state
Large insurers (market share >1%):		
33.9	0.8	18.5
(4.16)	(0.05)	(3.03)
Small insurers (market share ≤ 1%):		
7.1	0.6	75.4
(0.4)	(0.01)	(1.53)

Table B.1.2: Correlation between the baseline friction measure and alternative measures

Each row reports key statistics on the relationship between the baseline measure, $Friction_s$, as described in Equation (3) and an alternate friction measure computed using a different methodology. We report correlations and number of major re-classifications, where a state was majorly re-classified if it was high (low) friction under the baseline metric, and re-classified as low (high) friction under the alternate measure.

Method	Correlation with $Friction_s$	N major mis-classifications
Split panel by included insurers:		
largest 30	0.89	0
largest 25	0.95	0
largest 15	0.94	0
largest 10	0.83	3
Split panel by included years:		
2009-2013	0.82	2
2014-2019	0.74	0

B.2. Addressing Measurement Concerns: Insurer driven Heterogeneity in Rate Wedge

This section presents the results briefly discussed in Section 2.3. We present three main findings. First, we present the results on the predictive regressions to test if high friction today predicts lower future profitability. Second, we examine if the tendency to inflate targets is heterogeneous across state types. Third, we use a number of different methods to absorb insurer-driven variation (and construct alternative measures of rate-setting friction) to test whether the heterogeneity in rate wedge is driven by insurers' behavior.

B.2.1. Predictive regressions

In this section, we test whether the extent of rate-setting friction an insurer faces predicts its future profitability. If high friction was simply due to insurers inflating their target rates, then we would expect to see either no or even a positive relation with future profits. To test this, we run the following regression:

$$(\text{B.2.1}) \qquad \text{Underwriting Profit}_{ist} = \phi \text{Friction}_{ist-1} + \alpha_{is} + \alpha_{st} + Controls + \epsilon_{ist},$$

where Underwriting Profit$_{ist}$ = $1-$Loss Ratio$_{ist}$ for insurer i in state s in year t. Friction$_{ist-1}$ = $1-$Rate wedge$_{ist-1}$ measures how far from the rate target the received rate is for insurer i in state s in the prior year. We include insurer $\times$ state fixed effects (α_{is}) to exploit variation for the same insurer in the same state over time and state $\times$ year fixed effects (α_{st}) to absorb common state level shocks, e.g., a hurricane. The coefficient of interest ϕ measures the correlation between the extent of rate-setting frictions and future profitability. If insurers inflate targets, we would expect ϕ to be zero or even positive. In contrast, we find that ϕ is negative and statistically significant (Table B.2.1), implying that high values of friction today leads to lower future profitability for an insurer.

B.2.2. Is the tendency to inflate targets heterogeneous across state types?

We next show that the tendency to inflate does not differ across state types significantly. To test this, we examine whether RateΔTarget responds to realized losses differentially across state types. To this end, we run the following regression:

$$(\text{B.2.2}) \quad \text{Target}_{st} = \gamma SSL_{s,t-1} + \gamma^M SSL_{s,t-1} \times Med_s + \gamma^L SSL_{s,t-1} \times Low_s + \alpha_s + \alpha_i + \theta X_s t + \epsilon_{st}$$

where Target$_{st}$ is the premium-weighted cross-insurer average RateΔTarget$_{ist}$ at the state-year level. The independent variable is Same-State Losses (SSL), i.e. losses experienced in the state. SSLs are lagged one year and scaled by lagged total premium sold in the state. The indicator variables Med$_s$ and Low$_s$ equal 1 if the filing state s is, correspondingly, a medium or a low friction state. If the degree of target inflation is heterogeneous, we should observe

Table B.2.1: Rate Wedge predicts future losses

The table presents the results from estimating Equation (B.2.1). We start with our main sample as detailed in Appendix A.2 prior to the final exclusion of insurers selling in a single state and restrict attention to observations where a filing was observed. Standard errors are shown in parentheses, clustered at the state level. Note: *p<0.1; **p<0.05; ***p<0.01

	Underwriting profit$_{ist}$
Friction$_{ist-1}$	-0.009^{**}
	(0.004)
Controls	Yes
State $\times$ Year Fixed effects	Yes
Insurer $\times$ State Fixed effects	Yes
Observations	13,949

differential sensitivity to losses across states. However, Table B.2.2 shows that RateΔTarget responds to losses similarly across states, indicating that the degree of target inflation (to the extent it exists) is similar and therefore unlikely to be driving our classification of states.

Table B.2.2: Rate Target responds similarly across state types

The table presents the results from estimating Equation (B.2.2). The results pertain to our main sample as detailed in Appendix A.2 aggregated to the state-year level. Standard errors are shown in parentheses, clustered at the state level. Note: *p<0.1; **p<0.05; ***p<0.01

	Target$_{st}$		
	(1)	(2)	(3)
SSL$_{st-1}$	6.507^{***}	6.378^{***}	6.414^{***}
	(0.933)	(0.652)	(0.900)
SSL$_{st-1} \times$ Med$_s$	1.169	-1.704	-0.504
	(1.233)	(2.162)	(1.438)
SSL$_{st-1} \times$ Low$_s$	-1.462	1.009	-1.071
	(1.170)	(3.256)	(2.403)
Controls	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	No	Yes
Observations	533	533	533

B.2.3.   Alternative constructions absorbing sources of insurer driven variation

We next test whether the heterogeneity in rate wedge is driven by insurers' behavior (e.g., the tendency to inflate target rates). We construct three alternative friction measures to absorb insurer-driven variation and isolate the state regulators' effects more explicitly. Results are depicted in Table B.2.3. The high correlation between the baseline measure and the three alternatives suggest that our measure more likely reflects regulatory forces and not the strategic behavior of insurers. We describe the three approaches in more detail below.

- *Approach 1.* The first measure removes insurer specific variation by adding insurer $\times$ time fixed effects. Specifically, we run the regression $1 - RateWedge_{ist} = \alpha_{it} + \alpha_s + \epsilon_{ist}$ and use the coefficients on the state fixed effects to rank states, i.e. the new metric $Friction_s^{Alt(1)}$ contains the coefficients on α_s. The correlation between the baseline measure and $Friction_s^{Alt(1)}$ is 89% and only one state was majorly reclassified.

- *Approach 2.* Insurers' ability to inflate rates could depend on their market share in a state. To exclude this variation, first, we regress the rate wedge on insurer $\times$ time fixed effects *and* insurers' market share in each state: $1 - RateWedge_{ist} = \alpha_{it} + Mktshare_{ist} + \epsilon_{ist}$. Second, we construct a new measure as the average of the regression residuals for each state: $Friction_s^{Alt(2)} = E_{it}[\epsilon_{ist}]$. The correlation between our baseline friction measure and $Friction_s^{Alt(2)}$ is 91% and only two states were subject to a major reclassification.

- *Approach 3.* Another way to isolate insurers' strategic behavior is to compute the rate wedge with a target rate which can be "justified" only from an actuarial standpoint. To do so, we instrument RateΔTarget using past losses: $\text{Rate}\Delta\text{Target}_{ist} = LossRatio_{ist-1} + \alpha_{st} + \epsilon_{ist}$. Then, we use the predicted rate targets to construct an alternative rate wedge: $Friction_s^{Alt(3)} = 1 - E_{it}\left[\text{Rate}\Delta\text{Received}_{ist}/\widehat{\text{Rate}\Delta\text{Target}}_{ist}\right]$. The correlation between our baseline friction measure and $Friction_s^{Alt(3)}$ is 71% and only two states were subject to a major reclassification.

Table B.2.3: Correlation between the baseline friction measure and alternative measures

Each row reports the statistics on the relationship between the baseline measure, $Friction_s$, as described in Equation (3) and an alternate friction measure computed using a different methodology. We report correlations and number of major re-classifications, where a state was majorly re-classified if it was high (low) friction under the baseline metric, and re-classified as low (high) friction under each alternative.

Method	Correlation with $Friction_s$	N major mis-classifications
$Friction_s^{Alt(1)}$	0.89	1
$Friction_s^{Alt(2)}$	0.91	2
$Friction_s^{Alt(3)}$	0.71	2

B.3. Addressing Measurement Concerns: Rate Wedge and Markups

Recognizing the operational difficulty involved in computing expected losses from limited samples, we attempt four different ways to compute the gap between the rate changes received and the changes in expected losses.

- *Approach 1.* We start by constructing an estimate of expected losses as the average state-level realized losses in the past N years where $N \in \{10, 11, 12, 13\}$. At the minimum, we require at least 10 years of data. Since our sample starts from 2009, the farthest we can go back is 13 years as data on insurer-level realized losses start from 1996. For each state, we then compute the average yearly percentage change in expected losses and subtract it from the average RateΔReceived for the corresponding state and year.

- *Approach 2.* We first compute average realized losses in each state for two separate periods: 1996 to 2008 and 2009 to 2019. We then compute the percentage change in the two averages from the 1996-2008 period to the 2009-2019 period. We subtract this quantity from the average rate growth during the 2009-2019 period, which is obtained by cumulating the yearly RateΔReceived$_{st}$ from 2009 to 2019 and dividing by 10.

- *Approach 3.* We compute the percentage change in losses from 2009 to 2019 for each insurer in each state. We then winsorize this quantity at the 5% level for each friction group and then average it across insurers to the state level. We subtract this quantity from the average rate growth during the 2009-2019 period, which is obtained by cumulating the yearly RateΔReceived$_{st}$ from 2009 to 2019 and dividing by 10.

- *Approach 4.* This approach is similar to *Approach 3.* except now the gap is computed first at the insurer level and then averaged to the state level. Specifically, we compute the percentage change in losses from 2009 to 2019 for each insurer in each state. We then winsorize this quantity at the 5% level for each friction group. We then subtract this quantity from the average RateΔReceived for the corresponding insurer-state during the 2009-2019 period. This quantity is then averaged to the state level.

Having computed the gap between the RateΔReceived and $\Delta\mathbb{E}[L]$ at the state level using the four approaches, we plot the average across high-friction and low-friction states in Figure B.3.1. It shows that for high friction states RateΔReceived has trailed $\Delta\mathbb{E}[L]$ on average, while in low friction states RateΔReceived has exceeded $\Delta\mathbb{E}[L]$ on average.[43] The results thus indicate that in high friction states, the regulator is likely forcing markups to fall rather than allowing it to rise. In low friction states, however, the regulator is likely allowing markups to rise. Together, these results mitigate concerns about potential misclassification of states due to the inability to directly observe shifts in expected losses.

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[43]This pattern need not imply that insurers are losing money on average in high friction states as additional information on the initial pricing of insurance is required to determine insurer profitability. In fact, Figure 2

Figure B.3.1: Average gap in RateΔReceived vs. $\Delta\mathbb{E}[L]$

The figure shows the average gap between RateΔReceived and $\Delta\mathbb{E}[L]$ for high and low friction states. We use four distinct ways of computing the gap for each state, as described above. The vertical lines show the 95% confidence intervals.
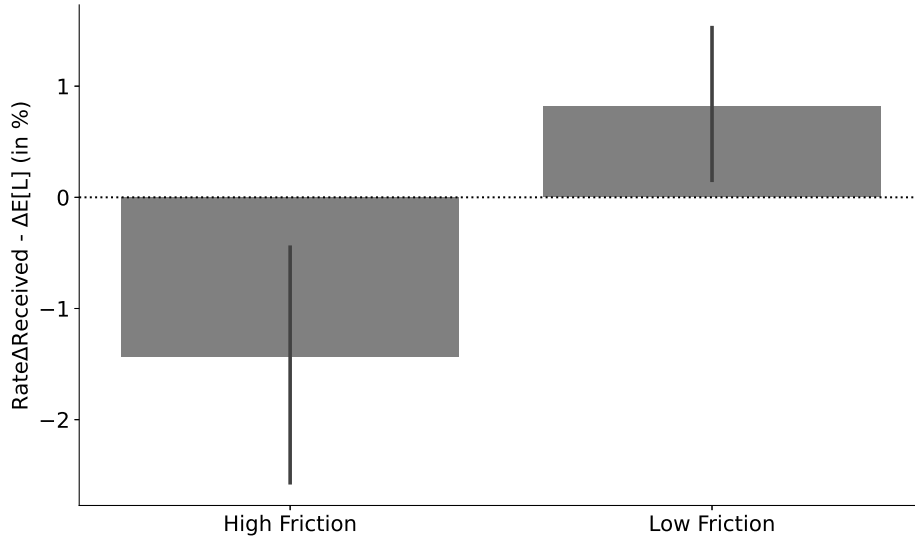
shows that insurers on average remain profitable in high friction states.

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

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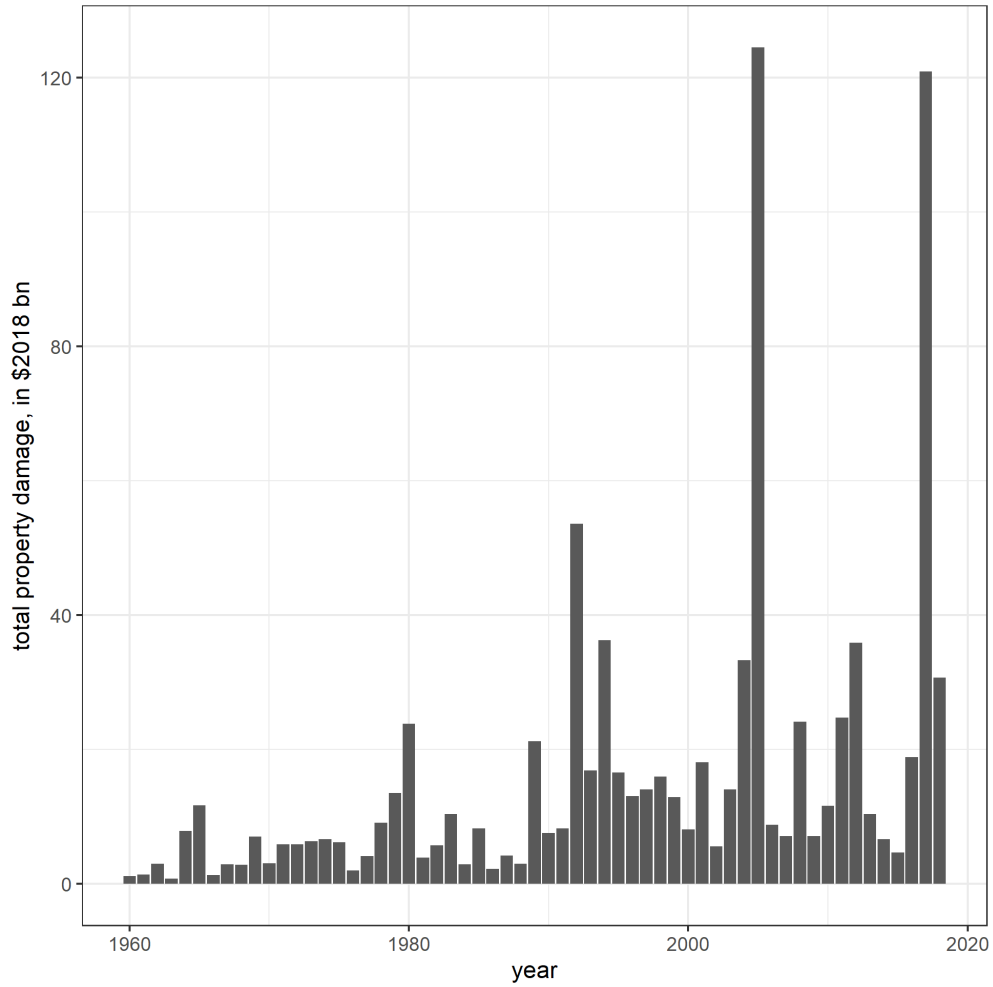
Figure C.2: Homeowners' insurance aggregate premia written

The figure shows the total homeowners' insurance premia written in the U.S. across all states between 1996 and 2019. The data are from S&P MI and the frequency is annual. Estimates are in billions of dollars.
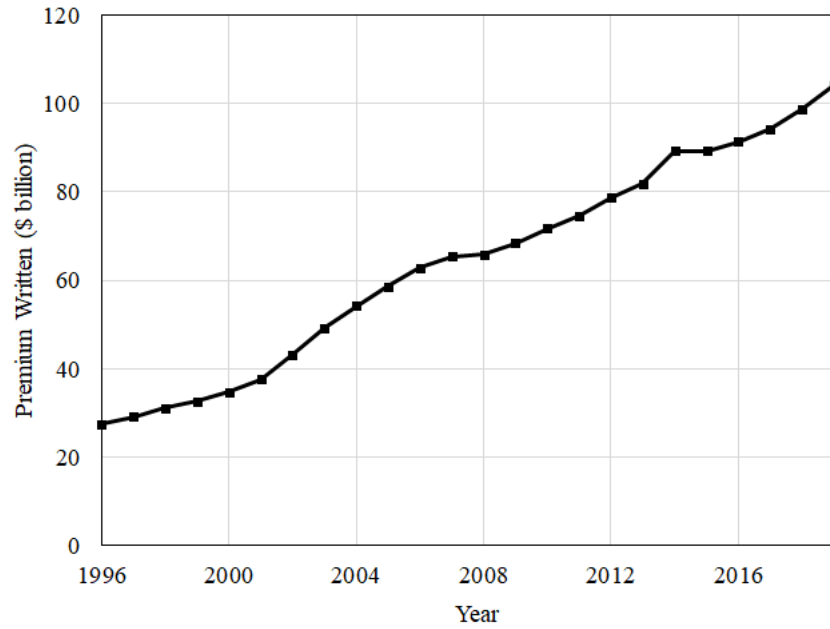
Figure C.3: Significance of homeowners' insurance for households

The figure shows average homeowners' insurance rate (left scale), average mortgage interest expenses (left scale), and insurance rates 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).

Figure C.4: California

Figure C.5: Oklahoma

Figure D.1: Product features by state types

Panel (a) shows the proportion of insured households that purchased HO3 policies through time for each state type. The denominator is insured households that purchase HO1, HO2, HO3, HO5, and HO8 contracts, i.e. all homeowners' contracts. Panel (b) shows the percentage growth in purchased coverage. Panel (c) shows the percentage growth in losses per insured home. Panel (d) shows the average fraction of claims closed without payment. Data in panels (a), (b) and (c) come from NAIC's *Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance.* For panel (c) data on losses also come from insurance statutory filings, accessed through S&P MI. Data on claims in panel (d) come from NAIC's Market Conduct Annual State Surveys. The start date for each graph is dictated by data availability.

(a) Contract types
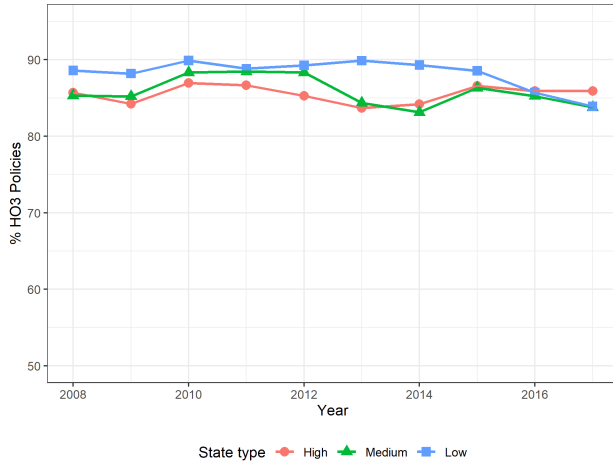
(b) Growth in insurance coverage

(c) Growth in losses per property
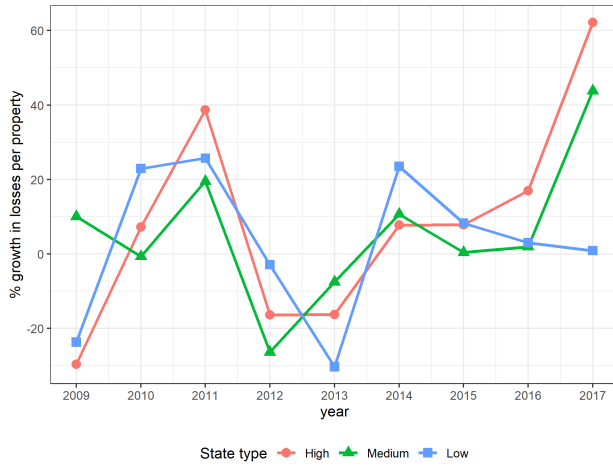
(d) Claims closed without payments
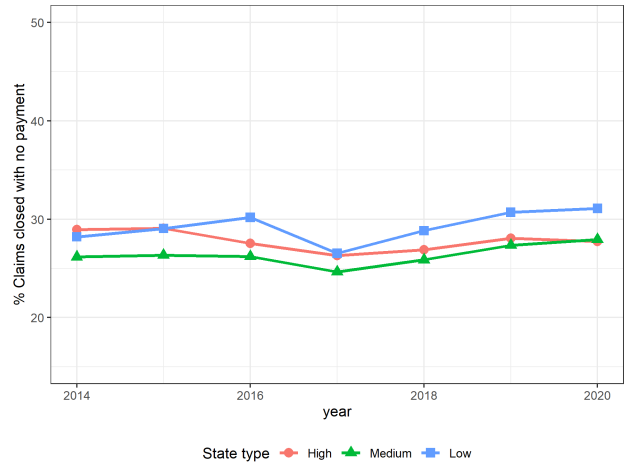
Figure D.2: Market competition by state types

This figure shows the distribution of two measures of competition for the different state types. Panel (a) shows the ratio of premiums sold by single-state insurers in each state. Panel (b) shows the Herfindahl–Hirschman index (HHI) in each state. The data are from insurance statutory filings accessed through S&P MI.

Panel (a): Fraction of premiums sold by single-state insurers
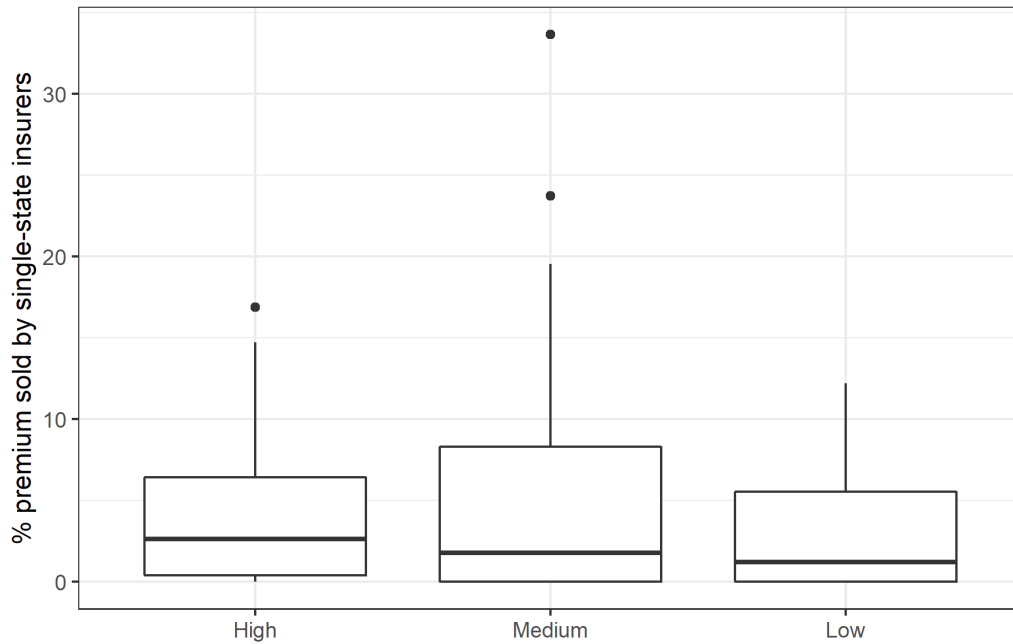
Panel (b): Herfindahl–Hirschman index (HHI)
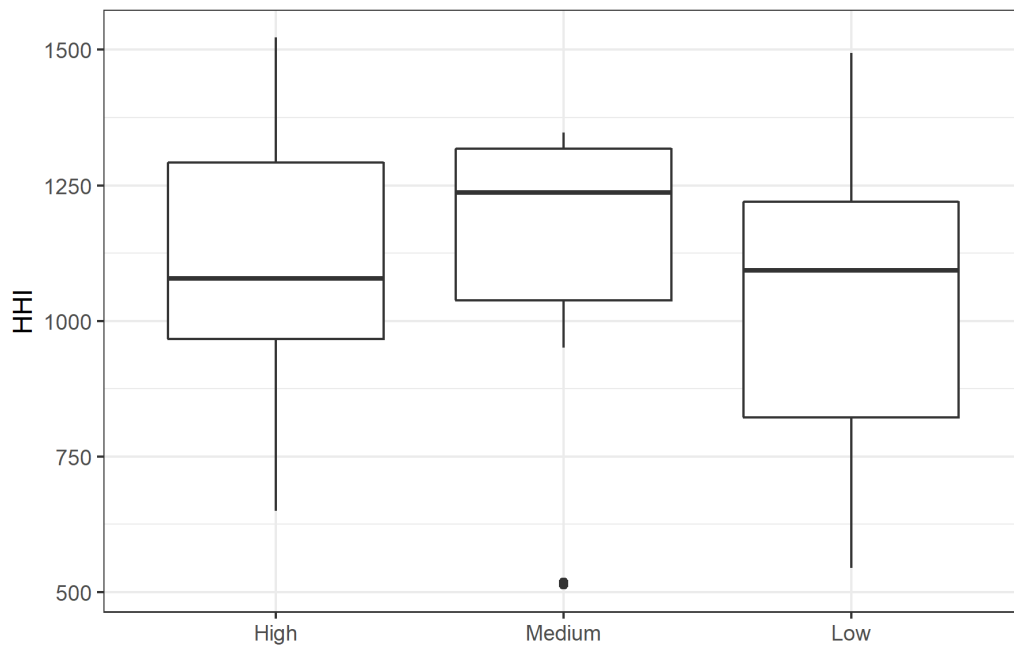
Figure D.3: Regulatory friction and climate losses

The figure shows $Friction_s$, estimated as in Equation (2), and the average climate losses per capita over the period 2009 to 2019. The data on climate losses are from SHELDUS and refer to damages to properties. We exclude losses from flood as flood losses are not covered by homeowners' insurance. Climate losses are inflation adjusted and are shown in 2018 dollars. The blue line is a fitted line from the following linear regression: log Property per cap$_s = \alpha + \beta$Friction$_s + \epsilon_s$.
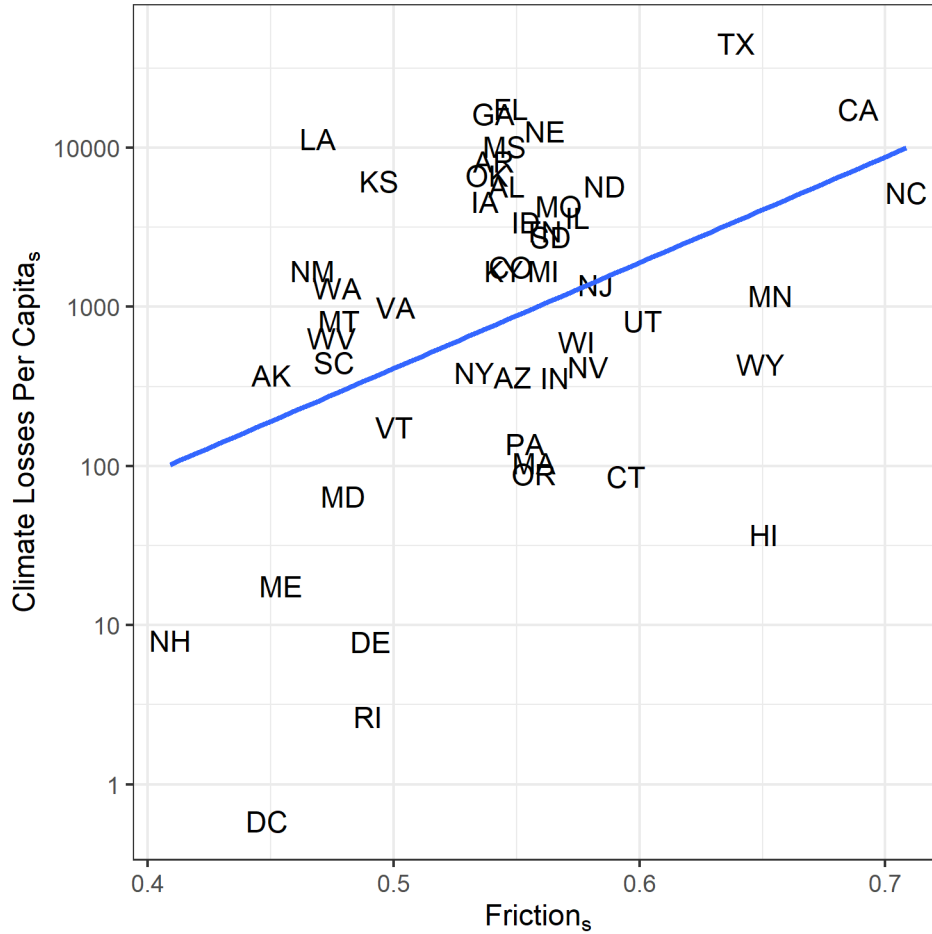
Figure D.4: Fraction of premiums sold by single-state insurers

The figure shows the fraction of premiums sold by single-state insurers relative to insurers that sell in two or more states in any given year. Data are from insurance statutory filings accessed through S&P MI.
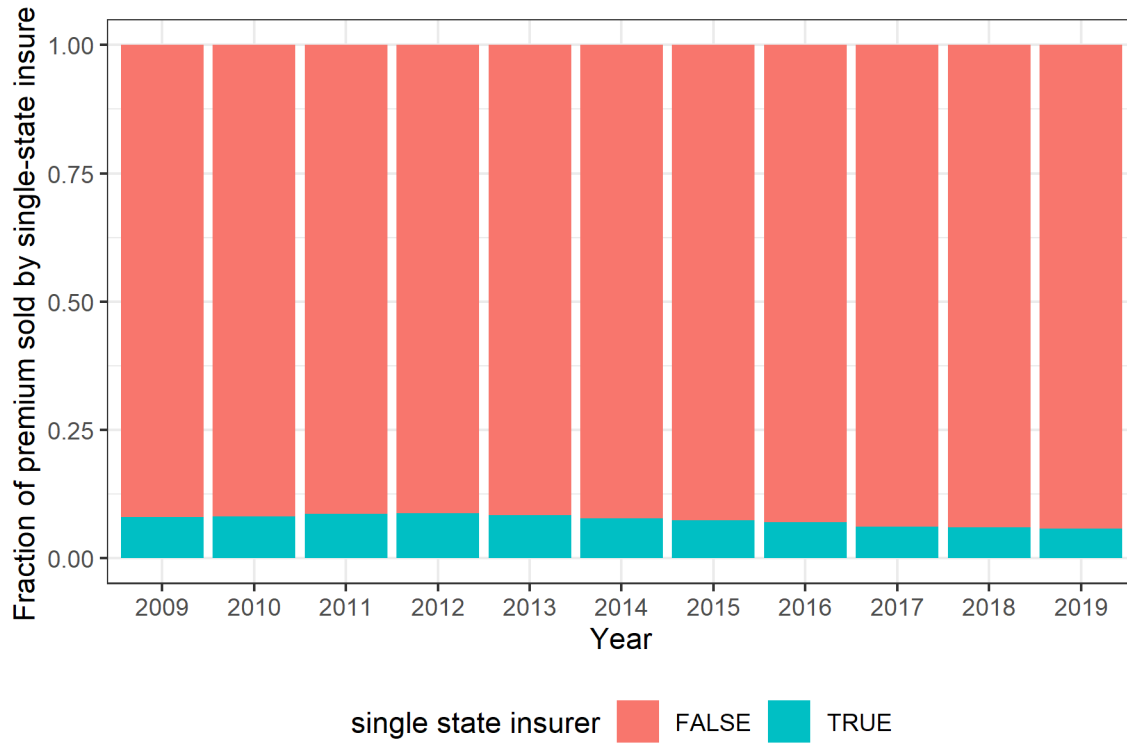
Figure D.5: Role of residual markets

Panel (a) shows the total insurance coverage (in $ billions) written via the residual market plotted against the coverage written via the private homeowners' market for the period 2008 to 2018. Residual market data are from PIPSO and private market data are from NAIC's Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/ Cooperative Unit Owner's Insurance Report. Panel (b) shows the fraction of total coverage written in residual market in 2018 plotted against our measure of regulatory friction ($Friction_s$). Only states that have a residual market are shown. Start and end dates are dictated by data availability.

(a) Size of private vs. residual insurance markets
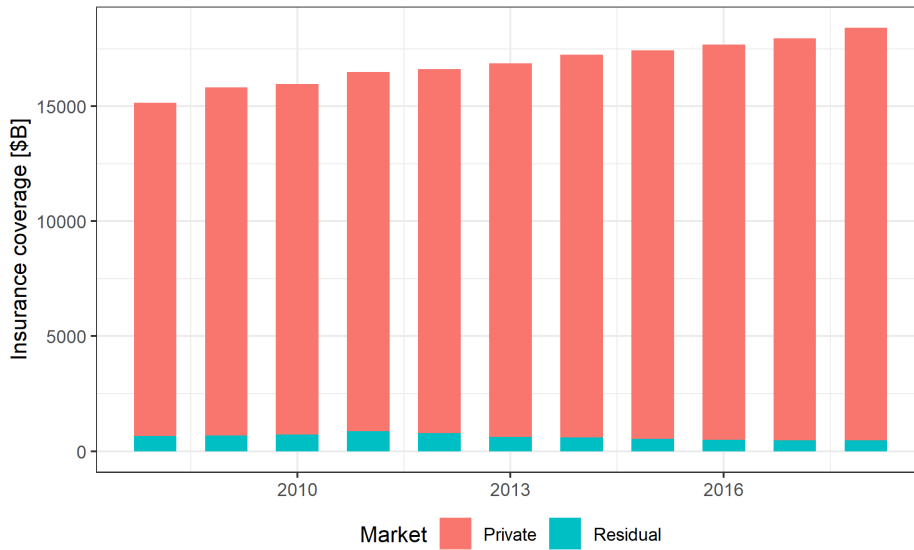
(b) Regulation and size of the residual market

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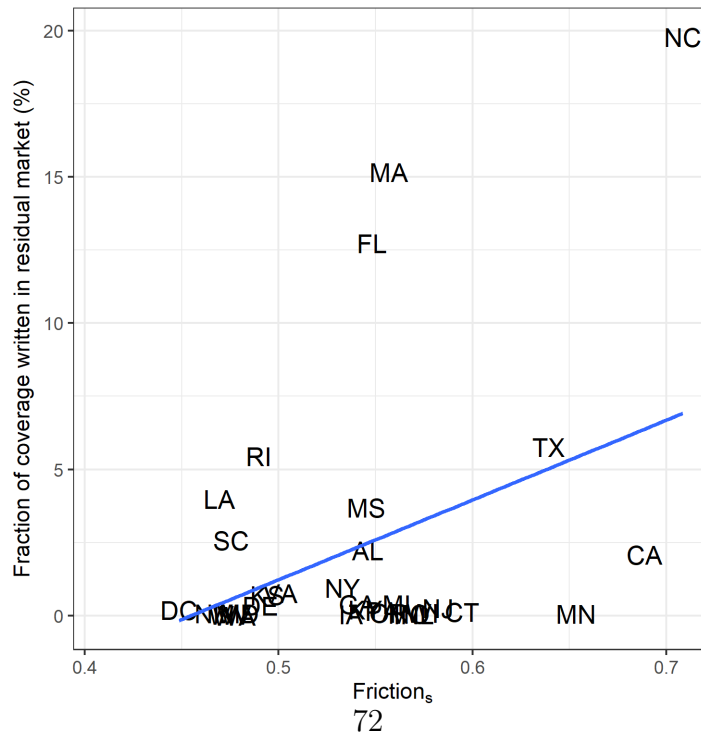
Figure D.6: Market concentration

The figure shows the distribution of market share by insurer size. Market share is computed as premium sold by the largest "n" insurers divided by total premium sold in a state 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. The data are from insurance statutory filings accessed through S&P MI.
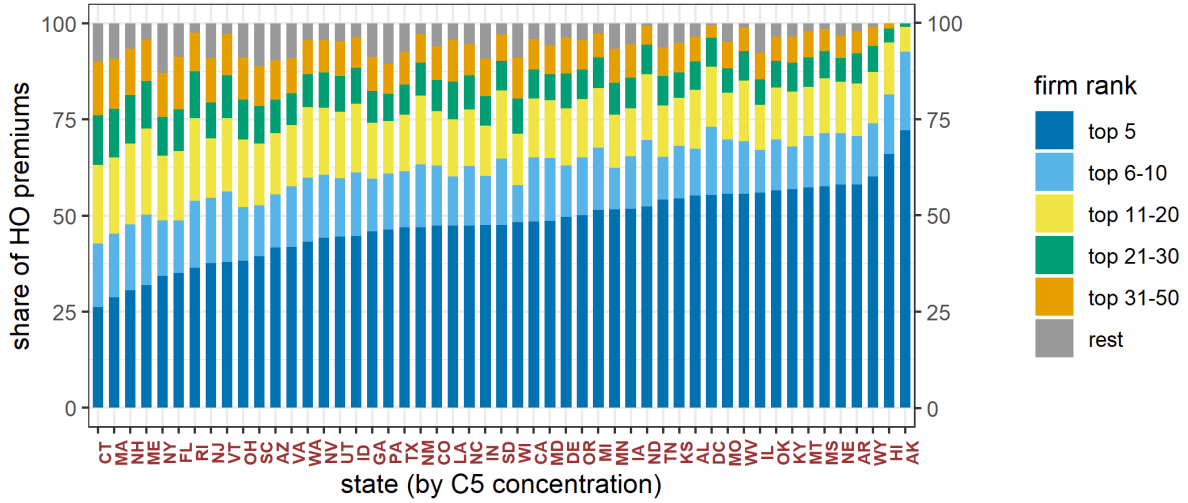
Table D.1: Learning about risks

Panel (a) lists the classification of U.S. states into geographical regions. The classification is provided by S&P MI. Panel (b) presents the results from estimating Equation (4). Dependent variables are denoted at the top of the table. The main independent variable is insurer's "out-of-zone" losses (OZL) in the prior year. To compute OZL, we sum an insurer's losses occurring outside (i) the filing state s and (ii) the same geographical region of s. We scale the lagged losses by lagged total premiums sold in the corresponding states. The indicator variables Med_s and Low_s equal 1 if the state s is, correspondingly, a medium or low friction state. The results pertain to our main sample as detailed in Appendix A.2. Furthermore, we require that each insurer sells in at least one non-neighboring state and the total premiums sold outside its zone is over \$100,000. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

(a) Classification of geographical zones

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

(b) Learning about risks: response to out-of-zone losses

	Any Filings$_{ist}$	RateΔReceived$_{ist}$
	(1)	(2)
OZL$_{ist-1}$	0.034	0.393
	(0.034)	(0.270)
OZL$_{ist-1}\times$ Med$_s$	−0.007	0.987**
	(0.049)	(0.473)
OZL$_{ist-1}\times$ Low$_s$	0.142**	1.373*
	(0.062)	(0.724)
E[LHS]	0.4	0.4
Controls	Yes	Yes
State × Year Fixed effects	Yes	Yes
Insurer × State Fixed effects	Yes	Yes
Observations	15,796	15,796

Table D.2: Regulator characteristics and rate-setting friction

The table shows results from estimating the following regression: $Friction_s = \alpha + \beta X_s + \epsilon_s$. The covariates are as follows. In column (1) log budget of the state's department of insurance averaged over 2009 to 2019; in column (2) log number of employees of the state's department of insurance averaged over 2009 to 2019; in column (3) whether the department of insurance is led by an elected or not elected (appointed) regulator (all three variables are sourced from NAIC's Insurance Department Resources Report); in column (4) log total amount of premiums sold for HO insurance in each state (from S&P MI); in column (5) each state's 2019 median household income; in column (6) percent of population that is minority (Black or Hispanic) (the last two from S&P Geographic Intelligence); in column (7) percent of the state's GDP attributed to the insurance sector (from BEA); in column (8) log property damage per capita between 2009 and 2019 (from SHELDUS); in column (9) the average percentage of republican vote in the presidential elections of 2012, 2016 and 2020; in column (10) all nine variables together.

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

	$Friction_s$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log budget	0.017*									0.002
	(0.010)									(0.033)
Log staff size		0.017								−0.013
		(0.011)								(0.029)
Is commissioner elected?			0.005							−0.006
			(0.022)							(0.023)
Log premium				0.019**						0.014
				(0.008)						(0.017)
Median HH income					0.0003					0.002
					(0.001)					(0.001)
% Minority						0.0002				−0.0003
						(0.001)				(0.001)
% GDP from insurance							−0.001			0.001
							(0.005)			(0.005)
Log Prop. Damage Per Cap								0.010***		0.013*
								(0.004)		(0.007)
% Republican									0.069	−0.007
									(0.088)	(0.169)
Constant	0.254	0.461***	0.542***	0.272**	0.521***	0.538***	0.547***	0.478***	0.508***	0.186
	(0.172)	(0.054)	(0.010)	(0.115)	(0.054)	(0.018)	(0.017)	(0.025)	(0.046)	(0.381)
E[LHS]	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Observations	50	50	50	50	50	50	50	50	50	50
R^2	0.056	0.047	0.001	0.104	0.004	0.002	0.002	0.135	0.013	0.237

Table D.3: Differences in size of losses

The table presents the results from re-estimating Equation (5), where out-of-state losses are split in three groups: high, medium, and low friction. In computing out-of-state losses, we exclude the low friction states that have low losses per capita so that the average losses per capita in low and high friction states are statistically similar. We denote the new out-of-state losses from low friction states as $OSL^{L'}$. The construction of OSL^H and OSL^M is same as before. The dependent variables are: in column (1) whether a rate change is filed and in column (2) rate change received by insurer i in the filing state s and year t. The results pertain to our main sample as detailed in Appendix A.2. Note that insurers who sell no premiums in the included low friction states get dropped from the regression. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

	Any Filings$_{ist}$	RateΔReceived$_{ist}$
	(1)	(2)
OSL^H_{ist-1}	0.200***	3.054***
	(0.066)	(0.928)
OSL^M_{ist-1}	0.277***	2.868***
	(0.088)	(0.701)
$OSL^{L'}_{ist-1}$	−0.139	1.394
	(0.277)	(3.497)
E[LHS]	0.7	3.4
State type	Low	Low
Controls	Yes	Yes
State × Year Fixed effects	Yes	Yes
Insurer × State Fixed effects	Yes	Yes
Observations	5,056	5,056

Table D.4: The role of ownership structure: evidence from rate filings

The table shows results from estimating $Y_{ist} = \beta_1 OSL_{ist-1} + \beta_2 OSL_{ist-1} \times Insurer\ type_i + Controls + \alpha_{is} + \alpha_{st} + \epsilon_{ist}$., The dependent variables are denoted at the top of the table and the main independent variable OSL is as defined before. *Insurer type* refers to an insurer's ownership structure, which are of three types: mutual, public-stock, and private-stock. The indicator $Stock_i$ is 1 if insurer i is a public-stock or a private-stock. The indicator Publicly Held$_i$ is 1 if insurer i is a public-stock (i.e., the insurer's equity is publicly traded). The results pertain to our main sample as detailed in Appendix A.2. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

	Any Filings$_{ist}$	RateΔReceived$_{ist}$
	(1)	(2)
OSL_{ist-1}	0.192***	2.043***
	(0.048)	(0.571)
$OSL_{ist-1} \times$ Stock$_i$	-0.284***	-1.752***
	(0.049)	(0.446)
$OSL_{ist-1} \times$ Stock$_i \times$ Publicly Held$_i$	0.642***	3.679***
	(0.031)	(0.446)
State type	Low	Low
Controls	Yes	Yes
State $\times$ Year Fixed effects	Yes	Yes
Insurer $\times$ State Fixed effects	Yes	Yes
Observations	6,093	6,093

Table D.5: The role of competition: additional measures of competition

The table presents the results from estimating Equation (4), where we split the low friction states into two groups, above median (H) and below median (L), by the level of concentration in each market, estimated using either HHI index (HHI) or the fraction of premiums sold by the largest five insurers (C5). As high and medium friction states are not split further, the control group remains the same as prior tables, i.e. all high and medium friction states. Dependent variables are denoted at the top of the table. The independent variable of interest is an insurer's "out-of-state" losses (OSL) in the prior year. To compute OSL, we sum an insurer's lagged losses in all the states it operates in other than the filing state s, which we scale by lagged total premiums sold in all states except s. The indicator variables Med_s and Low_s equal 1 if the state s is, correspondingly, a medium or a low friction state. The results pertain to our main sample as detailed in Appendix A.2. All regressions include fixed effects and controls as in Table 3. Standard errors are shown in parentheses, clustered at the state level.

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

	Any Filings$_{ist}$				RateΔ Received$_{ist}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OSL_{ist-1}	−0.006	−0.006	−0.006	−0.006	0.080	0.070	0.077	0.074
	(0.022)	(0.022)	(0.022)	(0.022)	(0.204)	(0.205)	(0.205)	(0.204)
$\text{OSL}_{ist-1} \times \text{Med}_s$	0.019	0.019	0.019	0.019	0.691*	0.694*	0.694*	0.692*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.404)	(0.401)	(0.404)	(0.401)
$\text{OSL}_{ist-1} \times \text{Low}_s$	0.228***	0.116**	0.175**	0.152***	2.278***	1.091	1.723**	1.491**
	(0.057)	(0.048)	(0.071)	(0.040)	(0.735)	(0.686)	(0.813)	(0.679)
Concentration	H	L	H	L	H	L	H	L
Measure	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

Table D.6: Summary statistics: insurer exits

The table reports summary statistics on insurer exits. We report the number and fraction of insurers that exit a state, defined as the total number of exits in a given state and year divided by the total number of insurers in the state. In measuring exits, we only want to capture exits from a particular state, so we require that an insurer exits a particular state but continues to operate in at least one other state. Large insurers have more than 1% market share in a state and small insurers have less than 1% market share in a state. We exclude insurers that have less than 0.5% market share in any given state. Columns (1) and (2) include all states. Columns (3) and (4), (5) and (6), (7) and (8) focus on correspondingly, high, medium, low friction states.

Market share	All States		High		Medium		Low	
	N exits	% Exited	N exits	% Exited	N exits	% Exited	N exits	% Exited
Large	16	0.17	4	0.18	4	0.12	8	0.22
Small	26	0.44	13	0.64	8	0.43	5	0.23

E. Constructing ZIP Code Level Expected Losses

To form estimates of expected losses per housing unit at the ZIP code level used in Section 6.1, we measure expected *climate* losses and *non-climate* losses separately and add them to construct the final estimates. The non-climate losses are added in order to appropriately compare premiums and losses.

Climate losses. To measure expected *climate* losses at the ZIP code level, we use data from FEMA. The FEMA data confers two major advantages compared to other data sources, e.g., realized losses from insurers' filings. First, it readily provides estimates of expected losses for each of the 18 natural hazards by computing separately the value of the property exposed to a natural hazard occurrence, the probability of such occurrence, and the percentage of value expected to be lost in case of such occurrence. Second, the estimates are available for each ZIP code, thus providing the level of granularity necessary for our analysis.

We first take FEMA's expected loss estimates ("Expected Annual Loss for Building Value"), which measure the average annual expected economic loss to buildings due to natural hazards. We exclude from it losses arising from floods ("Expected Annual Loss - Building Value" for Riverine and Coastal Floods). FEMA losses are available at the census tract level. We aggregate these losses up to the ZIP code level using census tract to ZIP code mapping provided by the U.S. Census. Specifically, for each ZIP, we sum the losses arising within its underlying census tracts. If a census tract belongs to multiple ZIP codes, we apportion the census tract losses to the ZIP codes in proportion to the fraction of housing units of the census tract that belonged to a particular ZIP code. We next divide the expected climate losses in each ZIP code by the number of housing units to get the average climate losses per housing unit. We first collect the total number of owner-occupied housing units with outstanding mortgages at the census tract level from the S&P Geographic Intelligence database. We follow the same procedure as described above to aggregate the census tract estimates to the ZIP code level.

Non-climate losses. We next estimate expected *non-climate* losses (per housing unit) that insurers incur in selling HO insurance. Non-climate losses are not available at a ZIP code level. To form estimates of non-climate losses we regress insurers' total losses in 2019, which are available at a state level, on FEMA's climate losses aggregated to the state level. We use the intercept of this regression to quantify the non-climate portion of the losses in dollars and scale the losses by the number of housing units. Finally, we add the climate and non climate losses per housing unit to get an estimate of the total expected losses for each housing unit. Because our estimate of non-climate losses are constant across geographies, adding it does not affect the cross-geography relationship between premiums and total losses but just affects the levels.

F. A Model of Insurer Pricing with Regulatory Frictions

In this section, we present a model of insurance pricing with regulatory frictions. The model, which extends the standard insurance supply framework, describes how regulation leads to asymmetric cross-subsidization documented in the earlier sections.

An insurer operates in two regions $R \in \{H, L\}$ that differ in the level of exposure to climate risk with H and L denoting high and low exposure. There are two regulators, one in each region. We denote the expected climate losses in each region as V_H and V_L, where $V_H > V_L > 0$. The insurer chooses the *target* price in each region, denoted as P_R. The target price once chosen is subject to regulatory approval in its respective region. The regulator in region R chooses $g_R \in [0, 1]$ i.e. the the proportion of target price that should be approved for the insurer in region R. Thus, post regulatory approval, the final price in region R charged by the insurer is $g_R P_R$.

F.1. The Regulator's Problem

The key objective of state insurance regulators is balancing the needs of "insurance affordability against availability and insurance company solvency".[44] To capture this trade-off, we assume that the regulator's objective is given by

$$(\text{F.1}) \qquad \max_{g_R} \quad g_R V_R^\gamma - g_R^\psi \left(\frac{P_R}{V_R} \right)$$

where $\gamma, \psi > 0$. The first term in the objective captures the regulator's desire to keep g_R high so that the insurer does not exit the state (i.e. maintain insurance availability). The incentive is stronger when the expected climate loss is high (V_R^γ), with γ controlling the degree of sensitivity. The second term captures the regulator's dislike for high markups (i.e. keep insurance affordable). Thus, when the target price deviates from the underlying losses (P_R/V_R), the regulator seeks to reduce prices by lowering g_R, with the parameter ψ controlling how aggressively the regulator reacts to the given markup.

The first order condition to the regulator's problem yields the optimal proportion of target price to be approved, given as

$$(\text{F.2}) \qquad g_R = \psi^{\frac{1}{1-\psi}} P_R^{\frac{1}{1-\psi}} V_R^{\frac{-\gamma-1}{1-\psi}}.$$

First, note that g_R is decreasing in P_R as long as ψ is sufficiently large. In other words, the discount $1 - g_R$ is greater when the target price P_R is higher, holding the underlying risk V_R fixed. Second, the relation between g_R and V_R cannot be immediately gleaned from

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[44]See the 2020 NAIC minutes of the Property and Casualty Insurance Committee meeting (NAIC, 2020).

Equation (F.2) as P_R also depends on V_R in the insurer's problem. We revisit this question after fully solving the insurer's problem.

F.2. The Insurer's Problem

We consider an insurer problem of the general form

$$(F.3) \qquad \max_P \quad \Pi(P) + \Phi F(P)$$

where $\Pi(P)$ is current period profit that depends on vector of prices P. Importantly, the second term $F(P)$ is an object that is decreasing in $\Pi(P)$ and captures the trade-off in the insurer's objective. Finally, Φ captures the relative weight on each part of the objective.

This setup is quite general and encompasses a wide range of objective functions commonly featured in the literature. First, in the face of risk-based capital requirements, insurers may sacrifice current economic profits in order to relax current or future leverage constraints (Koijen and Yogo, 2015). With a similar financing friction, a firm with a sticky customer base also faces a trade-off between current profits and current market share (Gilchrist et al., 2017). Second, as the profitability of insurers is subject to heavy scrutiny, large losses can induce insurers to myopically focus more on short-term profits (Stein, 1989). In a similar vein, an insurer may also operate with a short-term profit margin target or exhibit a slow-moving "habit" in profits and care about performance today relative to its history rather than just the level of profits today. Overall, our general statement of the insurer's problem nests all these mechanisms.

For tractability, we let $F(P)$ be equal to current-period revenues.[45] There is naturally an inverse relation between profits and revenues: lowering price relative to profit-maximizing price reduces current-period profits, but it is also an investment in the future through higher market share today. Revenue also has a natural place in the insurer's objective since insurance markets feature significant search and switching costs (Schlesinger and Von der Schulenburg, 1991, Honka, 2014) and thus current market share is an important determinant of future profitability (Klemperer, 1995). In addition, insurers commonly bundle products by offering discounts or combine deductibles for consumers purchasing several types of insurance from the same insurer (NAIC, 2021). The aforementioned considerations therefore incentivize insurers to lower its price to increase revenue today.

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[45]Evidence consistent with this assumption can be found in earnings call of insurance companies. For example, Allstate in a 2010 Q2 earnings call said, "We don't want to grow the business and throw profitability out the door. And so it's a balancing act and it changes from quarter-to-quarter. Our long-term goal though is, obviously, to grow market share in the Property Casualty business and we've talked about all the ways in which we're trying to do that."

F.2.1. Insurer Pricing without Regulatory Friction

We first lay out the insurer's problem in the absence of regulatory friction. Here we recover the standard pricing formula with market power: price is set to equate marginal revenue using the "effective" marginal cost, which depends on the relative weight between profit versus revenue maximization. We then add introduce regulatory friction into the insurer's problem and solve for the optimal price and its sensitivity to losses.

As the insurer's profit in region R is $(P_R - V_R) Q_R$ and revenue $P_R Q_R$, the maximization problem can be written as the following:

$$(F.4) \qquad \max_{P_H, P_L} \quad (P_H - V_H) Q_H + (P_L - V_L) Q_L + (\Phi - 1)(P_H Q_H + P_L Q_L)$$

where $\Phi > 1$ and is assumed to depend on V_H and V_L. In this setup, Φ represents the relative weight the insurer places on maximizing current revenue as opposed to maximizing contemporaneous profits.[46] To highlight the role of regulatory frictions, we assume the insurer faces the same demand curve in each region, $Q_H = Q_L = Q$, where

$$(F.5) \qquad \epsilon = -\frac{\partial \log Q}{\partial \log P} > 1$$

is the elasticity of demand.

We further assume that the sensitivity of relative weights to climate losses is proportional to the level of climate risk in each region. In other words, the shift from revenue to profits is more pronounced with respect to losses from high-risk areas than to those from low-risk areas:

$$(F.6) \qquad \frac{\partial \Phi}{\partial V_R} \propto -V_R \quad \Rightarrow \quad \frac{\partial \Phi}{\partial V_H} < \frac{\partial \Phi}{\partial V_L} < 0$$

For example, if climate losses in riskier regions receive more nationwide coverage and the attention of investors, then the incentive to manage short-term profits for the manager shift more in response to losses in riskier regions than to those in less risky regions.

Taking the first-order condition of (F.4) with respect to P_R yields:

$$(F.7) \qquad P_R^0 \left(1 - \frac{1}{\epsilon}\right) = \frac{V_R}{\Phi}$$

where the superscript in P_R^0 denotes the fact that the price expression is obtained in the absence of regulatory friction. V_R/Φ denotes the "effective" marginal cost to the insurer: as

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[46]We scale V_R to be sufficiently greater than Φ such that $\frac{V_R}{\Phi} \frac{\partial \Phi}{\partial V_R} < -\gamma$. For example, the interpretation of Φ as weights (and hence between 1 and 2) and the interpretation of V_R as expected dollar losses from climate events in region R is consistent with this assumption.

greater weight is given to revenue maximization, the insurer prices as if the marginal cost is lower.

When $\Phi = 1$, i.e. when the insurer only maximizes profits, then expression (F.7) reduces to the standard pricing formula with market power. Since we assume Φ to be greater than 1, the target price is lower when the insurer also cares about the total revenue.

F.2.2. Insurer Pricing with Regulatory Friction

We now consider the general case in which the insurer is choosing the target price in the presence of regulatory friction. Importantly, because g_R depends on P_R, the insurer internalizes the impact that its choice of P_R will have on the regulatory outcome.

The insurer's maximization problem is then given by:

$$(F.8) \qquad \max_{P_H, P_L} \quad (g_H P_H - V_H) Q_H + (g_L P_L - V_L) Q_L + (\Phi - 1)(g_H P_H Q_H + g_L P_L Q_L)$$

Taking the first-order condition of (F.8) with respect to P_R yields:

$$(F.9) \qquad g_R P_R \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon} \right) = \frac{V_R}{\Phi}$$

Equation (F.9) echoes the intuition in Equation (F.7) – the insurer once again equates marginal revenue with the "effective" marginal cost, now taking into account the regulatory decision and an adjusted markup.

By substituting in (F.2), the expression for g_R, we can further solve for the insurer's target price decision P_R. Proposition 1 summarizes these results:

Proposition 1. *For region $R \in \{H, L\}$, the insurer's target price P_R is given as*

$$(F.10) \qquad P_R = K \Phi^{-\frac{\psi-1}{\psi-2}} V_R^{\frac{\psi-2-\gamma}{\psi-2}}$$

where

$$K = \psi^{\frac{1}{\psi-2}} \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon} \right)^{-\frac{\psi-1}{\psi-2}}$$

Furthermore, assuming that ψ is sufficiently greater than γ such that $\psi > 2 + \gamma$, $\frac{\partial g_R P_R}{\partial V_R} > 0$ and $\frac{\partial P_R}{\partial V_R} > 0$.

Next, we re-visit the relationship between regulatory friction and the level of underlying losses, which is summarized in Corollary 1.

Corollary 1. *Regulatory friction in a given region is increasing in the expected climate losses in the same region, i.e. $\partial g_R / \partial V_R < 0$.*

Corollary 1 says that regulatory friction is greater in regions with greater climate losses, which we documented earlier in data. As shown in (F.2), g_R depends on both P_R and V_R. While the direct dependence of g_R on V_R implies that g_R may be decreasing in V_R, the indirect dependence of g_R on V_R through P_R implies that g_R may actually be increasing in V_R. In the end, the total relationship between g_R and V_R depends on the relative magnitude of these two forces. As ψ is sufficiently greater than γ, the first effect dominates and $\partial g_R / \partial V_R$ is therefore negative.

In addition, the model also allows us to examine the extent to which regulatory friction leads to inflated target prices by insurers:

Corollary 2. *For region $R \in \{H, L\}$, $g_R P_R < P_R^0 \lessgtr P_R$.*

Corollary 2 has two parts. The first inequality says that the final price to consumers in a world with regulatory friction ($g_R P_R$), which we observe, is less than the final price to consumers in a *counterfactual* world with no regulatory friction (P_R^0). This is true because the regulator is sufficiently concerned about the deviation of prices from losses, compared to its considerations about insurer exits. Therefore, when the insurer chooses a target price P_R that is much greater relative to expected losses V_R, the regulator further decreases the proportion granted.

The second inequality then says that the final target price of the insurer in a world with regulatory friction (P_R) may or may not be greater than that in a counterfactual world with no regulatory friction (P_R^0). This is because the regulator's approval function is known to the insurer, and the insurer internalizes the regulatory decision when making its target price decision. The final target price in the presence of a regulator therefore depends on γ and ψ, which govern the regulator's objective.

F.3.   Cross-Subsidization in Response to Climate Losses

We now establish how the insurer's pricing decision depend on climate losses from *other* regions. First, proposition 2 establishes the relationship between the target price in a given region to losses in another region:

Proposition 2. *For region $R \in \{H, L\}$, P_R is increasing in V_{-R}.*

Proposition 2 establishes that price in a given region responds positively to increases in expected losses in *another* region. The loss – even if it occurs in another state – induces a greater focus on current-period profits, which induces the insurer to raise the target price P_R even in a region not directly affected by losses. The next proposition describes how regulatory friction reinforces the degree of cross-subsidization.

Proposition 3. *Regulatory friction leads to asymmetric cross-subsidization, i.e.*

$$\frac{\partial P_L/\partial V_H}{\partial P_H/\partial V_L} > \frac{\partial P_L^0/\partial V_H}{\partial P_H^0/\partial V_L} = 1.$$

Finally, Proposition 3 establishes that in the presence of regulatory friction, the magnitude of the price response to the other region's losses now depends on whether the other region is high-risk or low-risk. In the case without a regulator, the relative magnitudes of the price response are the same and therefore $\frac{\partial P_L^0/\partial V_H}{\partial P_H^0/\partial V_L} = 1$. However, with the regulator, the insurer is then penalized in the form of a lower g_R if it chooses to increase P_R without a proportional increase in V_R. As Corollary 1 indicates, this penalization is greater in region H than in L, and therefore the price response is more muted in region H, resulting in an asymmetric cross-subsidization behavior of insurers.

F.4. Model Proofs

The Regulator's Problem The first-order condition with respect to g_R implies,

$$V_R^{\gamma} = \psi g_R^{\psi-1} P_R V_R^{-1}$$

Rearranging,

$$g_R^{1-\psi} = \psi P_R V_R^{-\gamma-1}$$

Therefore,

$$g_R = \psi^{\frac{1}{1-\psi}} P_R^{\frac{1}{1-\psi}} V_R^{\frac{-\gamma-1}{1-\psi}}$$

□

Proof of Proposition 1 Since g_R now depends on P_R, there are additional terms to consider. Taking the first-order condition of the objective in (F.8) with respect to P_R:

$$\frac{\partial}{\partial P_R}\left[\underbrace{(g_R P_R - V_R)Q_R}_{(1)} + \underbrace{(\Phi - 1)g_R P_R Q_R}_{(2)}\right]$$

Differentiating (1) with respect to P_R:

$$\frac{\partial}{\partial P_R}\left[(g_R P_R - V_R)Q_R\right]$$
$$= \frac{\partial g_R}{\partial P_R}P_R Q_R + g_R Q_R + (g_R P_R - V_R)\frac{\partial Q_R}{\partial P_R}$$

Differentiating (2) with respect to P_R:

$$\frac{\partial}{\partial P_R}\left[(\Phi-1)\, g_R P_R Q_R\right]$$

$$= (\Phi-1)\left[\frac{\partial g_R}{\partial P_R}P_R Q_R + g_R Q_R + g_R P_R\frac{\partial Q_R}{\partial P_R}\right]$$

Combining the derivatives of (1) and (2), we have:

$$\frac{\partial}{\partial P_R}\left[\underbrace{(g_R P_R - V_R)\,Q_R}_{(1)} + \underbrace{(\Phi-1)\,g_R P_R Q_R}_{(2)}\right]$$

$$= \frac{\partial g_R}{\partial P_R}P_R Q_R + g_R Q_R + (g_R P_R - V_R)\frac{\partial Q_R}{\partial P_R}$$

$$+ (\Phi-1)\left[\frac{\partial g_R}{\partial P_R}P_R Q_R + g_R Q_R + g_R P_R\frac{\partial Q_R}{\partial P_R}\right]$$

$$= \Phi\frac{\partial g_R}{\partial P_R}P_R Q_R + \Phi g_R Q_R + \Phi g_R P_R\frac{\partial Q_R}{\partial P_R} - V_R\frac{\partial Q_R}{\partial P_R} = 0$$

Dividing both sides by $\partial Q_R/\partial P_R$:

$$\Phi\frac{\partial g_R}{\partial P_R}P_R Q_R\frac{\partial P_R}{\partial Q_R} + \Phi g_R Q_R\frac{\partial P_R}{\partial Q_R} + \Phi g_R P_R - V_R = 0$$

$$-\Phi\frac{\partial g_R}{\partial P_R}P_R^2\underbrace{\left(-\frac{Q_R}{P_R}\frac{\partial P_R}{\partial Q_R}\right)}_{1/\epsilon} - \Phi g_R P_R\underbrace{\left(-\frac{Q_R}{P_R}\frac{\partial P_R}{\partial Q_R}\right)}_{1/\epsilon} + \Phi g_R P_R - V_R = 0$$

Rearranging:

$$\Phi g_R P_R\left(1 - \frac{1}{\epsilon}\right) = V_R + \frac{\Phi}{\epsilon}\frac{\partial g_R}{\partial P_R}P_R^2$$

(F.11)
$$g_R P_R\left(1 - \frac{1}{\epsilon}\right) = \frac{V_R}{\Phi} + \frac{1}{\epsilon}\frac{\partial g_R}{\partial P_R}P_R^2$$

Note that since $g_R = \psi^{\frac{1}{1-\psi}}P_R^{\frac{1}{1-\psi}}V_R^{\frac{-\gamma-1}{1-\psi}}$, we have

$$\frac{\partial g_R}{\partial P_R} = \frac{1}{1-\psi}\psi^{\frac{1}{1-\psi}}P_R^{\frac{1}{1-\psi}-1}V_R^{\frac{-\gamma-1}{1-\psi}} \Rightarrow \frac{\partial g_R}{\partial P_R}P_R = \frac{1}{1-\psi}g_R$$

Substituting into (F.11) yields,

$$g_R P_R \left(1 - \frac{1}{\epsilon}\right) = \frac{V_R}{\Phi} + \frac{1/(1-\psi)}{\epsilon} g_R P_R$$

or

(F.12)
$$g_R P_R \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right) = \frac{V_R}{\Phi}$$

Further substituting into (F.12) the expression for $g_R P_R$,

$$\psi^{\frac{1}{1-\psi}} P_R^{\frac{1}{1-\psi}+1} V_R^{\frac{-\gamma-1}{1-\psi}} \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right) = \frac{V_R}{\Phi}$$

Rearranging,

$$P_R^{\frac{2-\psi}{1-\psi}} = \psi^{\frac{1}{\psi-1}} \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right)^{-1} \frac{V_R^{1+\frac{\gamma+1}{1-\psi}}}{\Phi}$$

Exponentiating both sides by $\frac{1-\psi}{2-\psi}$:

$$P_R = \psi^{\frac{1}{\psi-1}\frac{1-\psi}{2-\psi}} \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right)^{-\frac{1-\psi}{2-\psi}} \Phi^{-\frac{1-\psi}{2-\psi}} V_R^{\frac{2+\gamma-\psi}{1-\psi}\frac{1-\psi}{2-\psi}}$$

$$= \psi^{\frac{1}{\psi-2}} \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right)^{-\frac{\psi-1}{\psi-2}} \Phi^{-\frac{\psi-1}{\psi-2}} V_R^{\frac{\psi-2-\gamma}{\psi-2}}$$

Simplifying,

$$P_R = K \Phi^{-\frac{\psi-1}{\psi-2}} V_R^{\frac{\psi-2-\gamma}{\psi-2}}$$

where

$$K = \psi^{\frac{1}{\psi-2}} \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right)^{-\frac{\psi-1}{\psi-2}} > 0$$

And from (F.12), the price after the regulatory decision is

$$g_R P_R = \frac{V_R}{\Phi} \left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right)^{-1}$$

Differentiating ([F.10](#)) with respect to V_R, we obtain:

$$
\begin{aligned}
\frac{\partial P_R}{\partial V_R} &= K \frac{\partial P_R}{\partial V_R} \left[\Phi^{-\frac{\psi-1}{\psi-2}} V_R^{\frac{\psi-2-\gamma}{\psi-2}} \right] \\
&= A \left[\left(-\frac{\psi-1}{\psi-2} \right) \Phi^{-\frac{\psi-1}{\psi-2}-1} \frac{\partial \Phi}{\partial V_R} V_R^{\frac{\psi-2-\gamma}{\psi-2}} + \Phi^{-\frac{\psi-1}{\psi-2}} \frac{\psi-2-\gamma}{\psi-2} V_R^{\frac{\psi-2-\gamma}{\psi-2}-1} \right] \\
&= \underbrace{\frac{A}{\psi-2} \Phi^{-\frac{\psi-1}{\psi-2}-1} V_R^{\frac{\psi-2-\gamma}{\psi-2}-1}}_{>0} \left[\underbrace{-(\psi-1) \frac{\partial \Phi}{\partial V_R} V_R}_{>0} + \underbrace{\Phi \frac{\psi-2-\gamma}{\psi-2}}_{>0} \right] \\
&> 0
\end{aligned}
$$

where the inequality follows from the fact that $\partial \Phi / \partial V_R < 0$ and $\psi > 2 + \gamma$.

Proof of Corollary 1   Recall that we had

$$
P_R = K \Phi^{-\frac{\psi-1}{\psi-2}} V_R^{\frac{\psi-2-\gamma}{\psi-2}}
$$

$$
g_R = \psi^{\frac{1}{1-\psi}} P_R^{\frac{1}{1-\psi}} V_R^{\frac{-\gamma-1}{1-\psi}}
$$

Combining the two expressions, we have:

$$
\begin{aligned}
g_R &= \psi^{\frac{1}{1-\psi}} \left(K \Phi^{-\frac{\psi-1}{\psi-2}} V_R^{\frac{\psi-2-\gamma}{\psi-2}} \right)^{\frac{1}{1-\psi}} V_R^{\frac{-\gamma-1}{1-\psi}} \\
&= (\psi K)^{\frac{1}{1-\psi}} \Phi^{-\frac{\psi-1}{\psi-2} \frac{1}{1-\psi}} V_R^{\frac{\psi-2-\gamma}{\psi-2} \frac{1}{1-\psi}} V_R^{\frac{-\gamma-1}{1-\psi}} \\
&= (\psi K)^{\frac{1}{1-\psi}} \Phi^{\frac{1}{\psi-2}} V_R^{\frac{1}{1-\psi} \left(1 - \frac{\gamma}{\psi-2} - \gamma - 1 \right)} \\
&= (\psi K)^{\frac{1}{1-\psi}} \Phi^{\frac{1}{\psi-2}} V_R^{\frac{1}{1-\psi} \left(-\frac{\gamma}{\psi-2} - \gamma \right)}
\end{aligned}
$$

Differentiating g_R with respect to V_R,

$$
\begin{aligned}
\frac{\partial g_R}{\partial V_R} &= (\psi K)^{\frac{1}{1-\psi}} \frac{\partial}{\partial V_R} \left[\Phi^{\frac{1}{\psi-2}} V_R^{\frac{1}{1-\psi} \left(-\frac{\gamma}{\psi-2} - \gamma \right)} \right] \\
&= (\psi K)^{\frac{1}{1-\psi}} \left[\frac{1}{\psi-2} \Phi^{\frac{1}{\psi-2}-1} V_R^{\frac{1}{1-\psi} \left(-\frac{\gamma}{\psi-2} - \gamma \right)} \frac{\partial \Phi}{\partial V_R} + \Phi^{\frac{1}{\psi-2}} \frac{1}{1-\psi} \left(-\frac{\gamma}{\psi-2} - \gamma \right) V_R^{\frac{1}{1-\psi} \left(-\frac{\gamma}{\psi-2} - \gamma \right)-1} \right] \\
&= (\psi K)^{\frac{1}{1-\psi}} \Phi^{\frac{1}{\psi-2}-1} V_R^{\frac{1}{1-\psi} \left(-\frac{\gamma}{\psi-2} - \gamma \right)-1} \left[\underbrace{\frac{1}{\psi-2} V_R \frac{\partial \Phi}{\partial V_R}}_{<0} + \underbrace{\frac{1}{1-\psi}}_{<0} \underbrace{\left(-\frac{\gamma}{\psi-2} - \gamma \right)}_{<0} \Phi \right]
\end{aligned}
$$

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Recall that we scaled V_R such that

$$\frac{V_R}{\Phi}\frac{\partial \Phi}{\partial V_R} < -\gamma$$

which implies that the term inside the square brackets is less than zero. Therefore, the proof is complete. $\square$

Proof of Corollary 2 We first show that $g_R P_R < P_R^0$. This is trivial since:

$$g_R P_R = \frac{V_R}{\Phi}\left(1 - \frac{1}{\epsilon} - \frac{1/(1-\psi)}{\epsilon}\right)^{-1}$$
$$< \frac{V_R}{\Phi}\left(1 - \frac{1}{\epsilon}\right)^{-1} = P_R^0$$

Next, to show $P_R^0 < P_R$, consider the ratio P_R/P_R^0:

$$\frac{P_R}{P_R^0} = \frac{K\Phi^{-\frac{\psi-1}{\psi-2}}V_R^{\frac{\psi-2-\gamma}{\psi-2}}}{\frac{V_R}{\Phi}\left(1-\frac{1}{\epsilon}\right)^{-1}}$$
$$= K\left(1 - \frac{1}{\epsilon}\right)\Phi^{1-\frac{\psi-1}{\psi-2}}V_R^{\frac{\psi-2-\gamma}{\psi-2}-1}$$
$$= K\left(1 - \frac{1}{\epsilon}\right)\Phi^{-\frac{1}{\psi-2}}V_R^{-\frac{\gamma}{\psi-2}}$$
$$\lesseqqgtr 1$$

where the last inequality depends on the magnitude of $K, \epsilon, \gamma, \psi, \Phi$, and V_R. $\square$

Proof of Proposition 2 Differentiating (F.10), reproduced below,

$$P_R = K\Phi^{-\frac{\psi-1}{\psi-2}}V_R^{\frac{\psi-2-\gamma}{\psi-2}}$$

with respect to V_{-R}, we obtain:

$$\frac{\partial P_R}{\partial V_{-R}} = \underbrace{KV_R^{\frac{\psi-2-\gamma}{\psi-2}}}_{>0}\underbrace{\left(-\frac{\psi-1}{\psi-2}\right)}_{<0}\underbrace{\Phi^{-\frac{\psi-1}{\psi-2}-1}}_{>0}\underbrace{\frac{\partial \Phi}{\partial V_{-R}}}_{<0}$$

Note that $\partial \Phi/\partial V_{-R} < 0$ and $\psi > 2$, it follows immediately that $\partial P_R/\partial V_{-R} > 0$. $\square$

Proof of Proposition 3 The ratio of cross-derivatives can be computed as:

$$\frac{\partial P_L/\partial V_H}{\partial P_H/\partial V_L} = \left(\frac{V_L}{V_H}\right)^{\frac{\psi-2-\gamma}{\psi-2}}\left(\frac{\partial \Phi/\partial V_H}{\partial \Phi/\partial V_L}\right)$$

$$= \left(\frac{V_L}{V_H}\right)^{1-\frac{\gamma}{\psi-2}}\left(\frac{\partial \Phi/\partial V_H}{\partial \Phi/\partial V_L}\right)$$

$$= \left(\frac{V_L}{V_H}\right)\left(\frac{V_H}{V_L}\right)^{\frac{\gamma}{\psi-2}}\left(\frac{\partial \Phi/\partial V_H}{\partial \Phi/\partial V_L}\right)$$

$$= \frac{\partial P_L^0/\partial V_H}{\partial P_H^0/\partial V_L}\left(\frac{V_H}{V_L}\right)^{\frac{\gamma}{\psi-2}} > \frac{\partial P_L^0/\partial V_H}{\partial P_H^0/\partial V_L}$$

where the last inequality holds since $\gamma > 0$ and $\psi > 2$. So the presence of regulatory friction leads to asymmetric cross-subsidization. $\square$