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Insurers' Loss Portfolio Similarity and Climate Risk Insurance Cost: A Spatial Analysis of US Homeowners Insurance Market

Tao Sun

Department of Operations and Risk Management, Lingnan University, Tuen Mun, Hong Kong, China; taosun@ln.edu.hk

Abstract: This study examines the geographical spillover of the state-level average homeowners insurance cost for 48 US contiguous states. We estimate a panel spatial Durbin model with state and year fixed effect for data between 2001 and 2018. We found a significant positive spillover of average homeowners insurance cost as indicated by a large spatial autoregressive coefficient in the baseline model. We also found a positive relationship between underwriters' loss portfolio similarity and the average homeowners insurance cost. We conduct several robustness tests and show that the baseline results are robust if against potential biases due to heterogenous state-level insurance regulation, an alternatively defined spatial weighting matrix, and the usage of average homeowners cost for the dominant policy form (the HO3 policy). We also adopt the generalized spatial two-step least squares to mitigate the bias due to endogenous explanatory variables and find that the results are consistent with these reported for the baseline model.

Keywords: homeowners insurance; spatial autoregressive model; spillover; loss portfolio similarity

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1. Introduction

Home equity in primary residences is the largest asset on the balance sheets of US households in 2019, according to the 2019 Survey of Consumer Finances (Board of Governors of the Federal Reserve System 2020). Climate change imposes significant risks on the asset portfolios of US households because it can increase the frequency and/or the severity of weather-related natural disasters (e.g., wildfire, flooding, hurricane, etc.) that can severely damage houses. Homeowners insurance is a valuable risk management tool for US households to mitigate the negative impact of climate change on their wealth. For example, the wildfires in Greater Los Angeles that occurred in January 2025 could be one of the costliest US natural catastrophes, highlighting the vitally important role of insurance in mitigating climate risk.[1] There are few studies examining the strategic dependence on homeowners insurance costs among the segmented state-level markets.

In this paper, we examine whether there is a geographic dependence among the average homeowners insurance costs of different states. Insurance is regulated at the state level in the US. This means the price of homeowners insurance is regulated by the insurance department of each state separately and therefore, shall demonstrate little geographic dependence. Specifically, we focus on whether similar homeowners insurance underwriters' loss experience, as measured by their loss portfolio similarity, will affect the average homeowners insurance cost. Insurance functions on risk diversification. Under normal conditions, geographical diversification can help homeowners insurers to spread the losses of rare natural catastrophes among affected and unaffected regions and therefore

maintain a stable homeowners insurance cost. However, natural catastrophes have become more frequent and severe (in terms of total economic loss and the areas impacted) due to climate change, making geographical diversification less effective. This could be particularly true for large national homeowners insurance underwriters who reach geographical diversification limits.

We use the state-level average homeowners insurance premium per house as the average homeowners insurance cost due to the lack of policy-level data. To measure the geographic dependence among the state-level average homeowners insurance cost, we employ a panel spatial Durbin model. We choose this empirical specification based on the statistical tests against other alternative spatial models (e.g., spatial autoregressive or error model). We provide two main findings. First, we found that there is a statistically significant positive spatial correlation among the average homeowners insurance costs, suggesting a positive spillover and a strong feedback effect that magnifies the initial change in average homeowners insurance costs. For example, the estimated spatial autoregressive coefficient (ρ) in the baseline model is 0.76. This result suggests that a 1% increase in the average homeowners insurance cost will result in an initial increase in neighboring states' average homeowners insurance cost of 0.76%. This initial effect will be transmitted to other states and eventually back to the original state. The total effect will be larger than the initial effect (e.g., 0.76%) on the order of 3.17 (i.e., $\rho/(1-\rho) = 0.76/(1-0.76) = 3.17$). Second, we found that the state-level average homeowners insurers' loss portfolio similarity is positively related to the average homeowner insurance cost. We argue that the increasing level of average homeowners insurers' loss portfolio similarity may be viewed as the result of ineffective geographical diversification. The effectiveness of geographical diversification can arise because the number of states that homeowners insurers can diversify is fixed and because insurers' business strategies can result in overlapping in certain markets (e.g., large and profitable markets).

We conduct several robustness tests to ensure that our main results are valid against potential biases. First, we additionally control for the state-level insurance regulation and find that our main results are not affected, suggesting that our results are not driven by the different state-level insurance regulatory systems. Second, the average homeowners insurance cost used in the baseline analysis is constructed using all six forms of homeowners insurance policy (e.g., Dwelling Fire, HO1, HO2, HO3, HO5, and HO8). One may be concerned with potential measurement errors due to different policy forms. We estimate the average homeowners insurance cost by using a homogenous subsample (i.e., HO3 policy) and re-estimate the baseline model using binary and inverse distance-based spatial matrices separately. The results remain largely unchanged. Third, we replace the binary spatial weighting matrix used in the baseline model with an inverse distance-based spatial weighting matrix in the robustness test to account for more complicated geographical dependence structures among different states. We find that the estimated spatial correlation coefficient remains positive and statistically significant. Last, we utilize a generalized spatial two-stage least squares with instrumental variables to mitigate the potential endogeneity bias associated with covariates. We show that the estimated spillover effects using the generalized spatial two-stage least squares approach are consistent with the main results.

This study contributes to the academic literature in at least two ways. First, this study contributes to a fast-growing body of literature on climate change and household finance (see Canals-Cerdá and Roman (2021) for a review). Prior studies analyze the effects of climate-related natural disasters (e.g., hurricanes, floods) on the earnings losses of affected residents (e.g., Deryugina et al. 2018; Groen et al. 2020), increases in mortgage delinquency, foreclosure, or bankruptcies (e.g., Issler et al. 2020; Billings et al. 2022). Relatedly, Oh et al. (2021) show that state-level insurance regulation can have significant

impacts on the pricing of homeowners insurance. That is, homeowners insurers tend to raise rates more in states that are less regulated and when their out-of-state losses are high. Oh et al. (2021) argue that such a regulation arbitrage related to homeowners insurance pricing can lead to adverse selection in the homeowners insurance market in the long run because of the mispricing of climate risk. This study differs from Oh et al. (2021) in that we examine the geographic dependence of homeowners insurance costs and analyze the spillover effect due to the geographic dependence.

Second, this study contributes to a small strand of literature that examines the geographical dependence of loss experience of weather-related insurance (Woodard et al. 2012). We provide new evidence for a stronger geographic correlation among homeowners insurance costs and offer new explanations for such a dependence structure, i.e., ineffective diversification due to underwriters' loss portfolio similarity.

The rest of the paper is structured as follows: Section 2 provides a literature review and the development of testable hypotheses. Section 3 discusses the research design, the construction of average homeowners insurance cost, and the homeowners insurers' loss portfolio similarity, the sample data. Section 4 presents empirical results. Section 5 provides concluding remarks.

2. Related Literature and Hypothesis Development

Strategical interactions among the homeowners insurance costs of different states can arise for several reasons: yardstick competition, insurance mispricing, and insurance regulation arbitrage. The yardstick competition hypothesis proposed by Besley and Case (1995) suggests that voters within a jurisdiction overcome information asymmetry by using the information from other jurisdictions as a yardstick to determine the performance of their governors. As a result, the local politicians who are seeking votes will be forced to join a yardstick competition in which they care about what others are undertaking (i.e., local public expenditure, tax rate, etc.). Therefore, learning and imitation in the yardstick competition would lead to strategic interactions among different jurisdictions. The yardstick competition hypothesis has been extensively tested in economic literature (e.g., Case et al. 1993; Besley and Case 1995; Bivand and Szymanski 1997; Revelli and Tovmo 2007). See Brueckner (2003) for an early review. In the context of the homeowners insurance market, the cost and availability of homeowners insurance will be important for the households to manage risk. Therefore, homeowners insurance is subject to heavy regulation at the state level. State insurance regulators might use the costs in neighboring states as a benchmark in their decision-making process related to homeowners insurance rate approval.

Strategic spatial interaction of homeowners insurance costs can arise due to insurance mispricing and insurance regulation arbitrage. For example, Woodard et al. (2012) discovered a systematic geographically related loss experience in the Federal Crop Insurance program. They show that there is a positive spatial correlation among the average county-level loss ratios of the 12 main corn-producing states. They attribute such a spatial correlation to the crop insurance mispricing (e.g., biases related to loss cost ratio rate making and determination of guarantee based on actual production history) that leads to geographically inequitable loss experiences. Other than the bias in insurance rating, insurance regulation can also affect insurance pricing resulting in mispricing and cross-subsidization. Oh et al. (2021) examine the effect of state-level insurance regulation on homeowners insurance pricing. They propose an insurance regulatory pricing friction measure based on the discrepancy between insurers' requested rate and the approved rate for homeowners insurance. For example, a higher discrepancy would imply a higher level of regulatory friction. They show that rates have not adequately adjusted in response

to the growth in losses and that insurers have exploited the insurance regulation and cross-subsidized high-friction states by raising rates in low-friction states.

H1. *State-level average homeowners insurance costs are not spatially dependent.*

Another channel that can cause strategic interactions among average homeowners costs in different states is ineffective geographical diversification. It is well known that the insurance mechanism functions on effective risk diversification. Specifically, geographical diversification allows homeowners insurers to effectively diversify against location-specific perils (e.g., earthquakes and wildfires in California, and Atlantic hurricanes that will affect states on the east coast). As a result, the losses caused by rare natural disasters will only create a temporary shock to the insurance prices in the states impacted. Prior literature shows that the benefits of diversification can diminish due to capital market imperfections, fat-tailed loss distribution, and agency problems (Froot 2001; Imbragimov et al. 2008). Recent studies on diversification in financial markets suggest that the benefits of diversification can be limited if the number of assets that can be invested in is limited (Imbragimov et al. 2011), and that common asset holdings due to diversification can affect asset prices and exposures insurer to systemic risk (Girardi et al. 2021). Ineffective risk diversification could hamper the function of insurance (Imbragimov et al. 2008) and the broader financial markets (Imbragimov et al. 2011).

For large insurers that operate at the national level, the number of states that US homeowners insurance underwriters can diversify into is limited. Moreover, those large homeowners insurers' underwriting portfolios and loss portfolios tend to overlap in similar states (e.g., states with larger populations and better economic conditions) when they seek geographical diversification. Increasing levels of geographical diversification may also expose large homeowners insurance underwriters to climate-related perils in different regions. Due to the increased frequency and severity (i.e., total economic loss and impacted region) of climate crises caused by climate change, the supply of homeowners insurance coverage in a state could be more constrained if the top insurance underwriters suffer similar losses. As a result, the underwriters will raise the insurance rates at the same time, pushing up the average homeowners insurance costs. Moreover, if the rate increase cannot sufficiently cover the loss because the rates are regulated, homeowners insurers may choose to raise the rate in neighboring states or states that are less impacted. In short, the widespread impact of weather-related natural catastrophes may result in large homeowners insurers suffering huge losses all at once. This can lead to ineffective geographical diversification, which in turn causes rate increases in areas that are either directly or indirectly affected. The rate hikes could be more severe if the large underwriters within a state have more similar loss experiences. Therefore, we formulate the null hypothesis as follows:

H2. *State-level homeowners insurance underwriters' loss similarities are not associated with state-level average homeowners insurance cost.*

3. Empirical Methodologies and Sample Data

Section 3.1 presents the empirical model specification. Section 3.2 discusses the construction of state-level average homeowners insurance cost and coverage. Section 3.3 discusses the construction of state-level homeowners insurers' loss similarity index. Section 3.4 discusses the sample data and summary statistics.

3.1. Empirical Model Specification

We adopt a spatial regression model regression with state and year fixed effects. Let N and T denote the number of states and years in the panel data. The empirical model is specified as follows:

$$LNCOST_{s,t} = \alpha + \rho WLNCOST_{s,t} + X_{s,t-1}\beta + WX_{s,t-1}\theta + \gamma_t + \mu_s + \varepsilon_{s,t} \quad (1)$$

where $LNCOST_{s,t}$ denotes an $NT \times 1$ vector of the natural logarithm of the state-level average homeowners insurance cost in state s in year t and year $t-1$, respectively. We postpone the discussions of the construction of average homeowners insurance cost in Section 3.2. Parameter ρ denotes the spatial autoregressive parameter that measures the magnitude of correlation of spatially lagged dependent variable (e.g., *LNCOST*) across neighbor states. W denotes an $N \times N$ symmetric spatial weighting matrix for 48 US contiguous states, in which the element (i, j) equals $1/d_{ij}$ where d_{ij} denotes the distance between the state capitals of state i and j. $X_{s.t\ -\ 1}$ denotes an $N \times k$ matrix for k state-level regressors for state s in year $t-1$. *B and* θ is a $K \times 1$ vector of slope parameters of the state-level regressors. Furthermore, μ_s is a state-fixed effect, and γ_t is a year-fixed effect. Last, $\varepsilon_{s,t}$ represents the error terms that follow a Normal distribution.

The model specified in Equation (1) is known as the Spatial Durbin (SDM) model. SDM model provides a good starting point for testing spatial correlations because it nests many other spatial models. For example, the spatial autoregressive model is nested in the SDM when $\theta = 0$. By imposing the restriction that $\theta = -\rho\beta$, SDM becomes a spatial error model. Moreover, SDM will produce unbiased estimates even if the underlying data generating process is a spatial error model (LeSage and Pace 2009). In the empirical analysis, we will conduct formal statistical tests to determine the model's appropriateness against alternative models.

The spillover of the average homeowners insurance cost from neighbor states is modeled by including the spatially lagged dependent variable (i.e., $WLNCOST_{s,t}$). The estimated spatial autoregressive coefficient, ρ, is of particular interest because it represents a structural feedback effect that governs the process of arriving at a new equilibrium when the average homeowners insurance cost changes. For example, when the average homeowners insurance cost of state i changes, the influence of such a change on state i's direct neighboring states is captured by ρW, which causes reactions of neighboring states of direct neighbors of state i (i.e., ρW^2) and reactions to reactions (i.e., ρW^3, ρW^4, ρW^5, ...) in a geometric series sense. In a special case of an equally weighted spatial weighting matrix, the total effect of re-equilibration is determined by $\rho/(1-\rho)$ (Grieser et al. 2022).

The key independent variables are insurers' loss similarity (denoted by *STATE_LOSSSIM*). *STATE_LOSSSIM* is a state-level average cosine similarity index of homeowner insurance loss of large insurers whose market shares exceed 1%. We control for a set of factors that can affect the average homeowners insurance cost. That is, we control for the average homeowners insurance coverage (denoted by *AVG_COV*). The size of a state's homeowners insurance market is included, which is defined as the natural logarithm of total exposure (denoted by *SIZE*). Additionally, we control for a state's income (denoted by *INCOME*) which is defined as the natural logarithm of personal income per capita. We also include a state's average of state-level homeowners insurance loss ratios between years $t-1$, and $t-3$ (denoted by *STATE_LR*). The state-level direct loss ratio is defined as the total direct loss divided by the total direct premium written of homeowners insurance of a state. We detail the construction of average homeowners insurance coverage (*AVG_COV*), and insurers' loss similarity (*STATE_LOSSSIM*) in Sections 3.2 and 3.3, respectively. Lastly, to account

for the impact of natural catastrophes, and include a state-level property loss per capita (*DAMAGE*) using the data from SHELDUS.

Turning to the interpretation of explanatory variables, the marginal effect of the explanatory variable in Equation (1) will be different from that for the OLS model because the change in an explanatory variable can influence both the dependent variable in that state and the dependent variables in other states as well. Following LeSage and Pace (2009), we calculate the average direct, indirect, and total effect for explanatory variables included in Equation (1).[2]

3.2. Measure of Average Homeowners Insurance Cost and Coverage

Due to a lack of policy-level data, we used the data from the reports titled "Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/ Cooperative Unit Owner's Insurance" compiled by the National Association of Insurance Commissioners (NAIC) to construct the state-level annual average homeowners insurance cost and coverage. To construct the annual average homeowners insurance cost, we first aggregate premium and exposure (i.e., house-year) data for all six types of homeowners insurance policies (e.g., Dwelling Fire, HO-1, HO-2, HO-3, HO-5, and HO-8) in a state-year. Then, we calculate the state-level average homeowners insurance cost (*COST*) by dividing the total premium by total exposure. In the empirical analysis, the dependent variable (*LNCOST*) is defined as the natural logarithm of the state-level average homeowners insurance cost. We adjust for inflation using CPI with 2000 being the base year.

To measure the average homeowners insurance coverage, we utilize the insurance range data. For each type of homeowners insurance policy, NAIC classifies and reports the dollar amount of insurance coverage into eleven coverage ranges (i.e., 0 to 49,999, 50,000 to 74,999, 75,000 to 99,999, 100,000 to 124,999, 125,000 to 149,999, 150,000 to 174,999, 175,000 to 199,999, 200,000 to 299,999, 300,000 to 399,999, 400,000 to 499,999, and 500,000 and above). For each insurance coverage range under a certain type of homeowners insurance policy, the total insurance coverage is estimated at the midpoint coverage of the coverage range multiplied by the number of houses within that coverage range. For example, if a coverage range between 50,000 and 74,999 has 1000 houses, the average coverage is estimated as 62,499.5 (i.e., (50,000 + 74,999)/2) and the total insurance coverage for this insurance range is 62.4995 million (midpoint USD 62,499.5 $\times$1000 houses). We then aggregate across the eleven coverage ranges to obtain the total coverage and the total number of insured houses for a certain type of policy, and then further aggregate across six policy types to obtain the total coverage and the total number of insured houses in a state. Finally, we divide the homeowners insurance coverage aggregated at the state level by the total number of insured houses in the state to obtain the annual average homeowners insurance coverage per house (*AVG_COV*) in a state year.

3.3. Measure of Homeowners Insurers' Loss Portfolio Similarity

We use the firm-state level homeowners insurance direct loss data to empirically measure homeowner insurance underwriters' loss portfolio similarity. We first use the uncentered correlation or cosine similarity between all firm i, j pairings:

$$S_{i,j} = L_i L_j' / \sqrt{L_i L_i' \times L_j L_j'} \quad (2)$$

where L_i and L_j denote a 48 by 1 vector of direct loss of homeowners insurance of insurer i and j, respectively. This similarity measure has the properties that it equals one for firms whose loss vectors are identical, it equals zero for firms whose loss vectors are orthogonal, and it is bounded between 0 and 1 for all other pairs. In particular, this similarity measure

is closer to one when two firms' loss experiences are similar in both the size and the geographical distribution of losses.

To construct a state-level homeowners insurance underwriters' loss similarity, we first calculate the loss similarities for all pairs of large underwriters of homeowners insurance of a state. We define large homeowners insurance underwriters in a state as those whose direct premium is written relative to the state's total direct premium written for homeowners insurance is greater than 1%. We then calculate the state-level loss similarity by taking the average of all pairs of loss similarities. For example, we calculate 45 loss similarities if there are 10 large homeowners insurers in a state *i*. We then calculate the loss similarity of state *i* by averaging the 45 loss similarities among all pairings of 10 large homeowners insurers.

3.4. Sample Data and Summary Statistics

We utilized two main sources of data in this study. We obtained the firm-level (e.g., group-affiliated and non-group affiliated individual insurers) homeowners loss data from the NAIC annual statement to construct the homeowner insurance underwriters' loss similarities. We obtained the state-level homeowners insurance market data to estimate the average cost and coverage from NAIC reports titled "Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance". NAIC homeowners insurance market reports cover 50 states and the District of Columbia. We focus on the 48 contiguous states by removing Alaska, Hawaii, and the District of Columbia. The sample period is from 2000 to 2018. This choice is dictated by the availability of average homeowners insurance cost and coverage. Consequently, we have a balanced sample of 912 state-year observations. To mitigate the effects of extreme observations, we winsorize the continuous variables at the 1st and 99th percentile.

Table 1 presents the summary statistics. The dependent variable, *LNCOST*, has a mean of 6.708 (i.e., USD 818.93) and a standard deviation of 0.356. The 10th and 90th percentile of *LNCOST* are 6.255 (i.e., USD 520.61) and 7.199 (i.e., USD 1338.09), respectively. The key independent variable, *STATE_LOSSSIM*, has a mean of 0.363 and a standard deviation of 0.118.

Table 1. Summary Statistics.

Variable	Mean	Std Dev	p1	p10	p50	p90	p99
LNCOST	6.708	0.356	5.955	6.255	6.684	7.199	7.566
COVERAGE	218.980	81.559	102.307	132.524	199.398	315.199	538.920
LNEXPO	13.729	1.002	11.540	12.301	13.902	14.917	16.003
INCOME	10.547	0.221	10.079	10.260	10.547	10.836	11.081
STATE_LR	0.608	0.202	0.318	0.410	0.561	0.880	1.427
STATE_LOSSSIM	0.363	0.118	0.225	0.264	0.332	0.490	0.833
STATE_HHI	0.085	0.028	0.028	0.043	0.090	0.120	0.143
DAMAGE	41.438	118.249	0.106	0.810	7.780	81.710	911.778

This table reports the summary statistics. The dependent variable, *LNCOST*, is the natural logarithm of the average homeowners insurance cost that is defined as the total homeowners insurance premium written divided by the total loss exposures of a state. The key independent variable, *STATE_LOSSSIM*, is defined as the average of the cosine similarities of the homeowners insurance direct loss portfolio of 50 states and the District of Columbia among pairing of homeowners insurers with direct market shares exceeding 1%. Appendix A provides the definitions of variables.

Table 2 reports the linear correlation coefficients matrix. The correlation coefficient between *LNCOST* and *STATE_LOSSSIM* is 0.320, which is statistically significant at 1%. Moreover, a state's per capita personal income (*INCOME*), size of homeowners insurance market (*LNEXPO*), and average homeowners insurance coverage (*COVERAGE*) are positively correlated with *LNCOST*. The linear correlation coefficient between the state-level smoothed loss ratio (*STATE_LR*) and *LNCOST* is -0.024 (p-value > 0.10).

Table 2. Linear Correlation Coefficients Matrix.

		1	2	3	4	5	6	7
1	*LNCOST*	1						
2	*COVERAGE*	0.275 ***	1					
3	*LNEXPO*	0.246 ***	0.059 *	1				
4	*INCOME*	0.558 ***	0.629 ***	0.209 ***	1			
5	*STATE_LR*	−0.024	−0.197 ***	−0.027	−0.252 ***	1		
6	*STATE_LOSSSIM*	0.320 ***	0.099 ***	0.626 ***	0.143 ***	0.027	1	
7	*STATE_HHI*	−0.091 ***	−0.318 ***	−0.058 *	−0.535 ***	0.370 ***	−0.103 ***	
8	*DAMAGE*	0.128 ***	−0.056	−0.013	−0.077 **	0.298 ***	0.152 ***	0.109 ***

This table reports the linear correlation coefficients matrix. The dependent variable, *LNCOST*, is the natural logarithm of the average homeowners insurance cost that is defined as the total homeowners insurance premium written divided by the total loss exposures of a state. The key independent variable, *STATE_LOSSSIM*, is defined as the average of the cosine similarities of the homeowners insurance direct loss portfolio of 50 states and the District of Columbia among pairing of homeowners insurers with direct market shares exceeding 1%. Appendix A provides the definitions of variables. Symbols *, **, ***, represent the statistical significance at the 10%, 5%, and 1% levels.

4. Empirical Results

Section 4.1 presents the results for the baseline spatial regression model. Section 4.2 provides the results for additional analyses for insurance regulation, alternative spatial weighting matrix, and a homogenous subsample consisting of the HO3 policy. Section 4.3 provides the results for generalized spatial two-stage least squares.

4.1. Results of Baseline Spatial Regression Model

We begin the formal spatial regression analysis by first estimating a spatial Durbin model with state and year-fixed effects specified in Equation (1) using Maximum Likelihood Estimation.[3] Note that all right hand side variables are lagged by one year, which reduce the sample size to 864 state-year observations. Table 3 presents the results. We report the absolute *t*-statistics in parentheses. As shown in Table 1, Column 1, the estimated spatial autoregressive coefficient ρ is 0.76 (*t*-statistics = 37.61). This result provides strong evidence of a significant spatial correlation among the average homeowners insurance cost. This result indicates that a 1% increase in *LNCOST* will result in an initial increase in neighboring states' average homeowners insurance cost of 0.76%. This initial effect will be transmitted to other states and eventually back to the original state. As we discussed earlier, a larger ρ indicates a stronger spatial spillover effect and will magnify the feedback effects with a converging geometric sequence feature governed by ρ. Therefore, the total effect will be larger than the initial effect (e.g., 0.76%) on the order of 3.17 (i.e., $\rho/(1-\rho) = 0.76/(1-0.76) = 3.17$).

Turning to the effects of explanatory variables, Table 1, Column 1 shows that the coefficient of *STATE_LOSSSIM* is 0.149 (*t*-value = 2.438), suggesting that a state's homeowners insurance underwriters' direct loss portfolio similarity is significantly positively related to *LNCOST*. Similarly to the spillover effects caused by the change in dependent variable, a shift in *STATE_LOSSSIM* in a state will not only affect the average homeowners insurance cost of that state but also be transmitted to other states through paths specified in the spatial weighting matrix with transmission strengths governed by ρ. That is, a 1% increase in *STATE_LOSSSIM* will result in a 0.15% increase in *LNCOST* of such a state, which will in turn be transmitted to the direct neighboring state by a magnitude of 0.114% ($=\rho \times \beta = 0.15\% \times 0.76$). And the spillover continues with a geometric sequence feature (e.g., $\rho^2\beta$, $\rho^3\beta$, etc.) given the weight on each path is one in a binary spatial weighting matrix. Regarding other explanatory variables, Table 1, Column 1 shows that *INCOME* and *STATE_HHI* are significantly positively related to *LNCOST*, whereas *COVERAGE* is negatively correlated with *LNCOST*.

Table 3. Results of the Baseline Spatial Regression Model.

Dependent Variable:	***LNCOST***			
	1 Main	1a Direct Effect	1b Indirect Effect	1c Total Effect
ρ	0.756 ***			
	(37.607)			
COVERAGE	−0.000 ***	−0.000 ***	0.001 ***	0.001 ***
	(8.011)	(3.495)	(5.649)	(4.297)
LNEXPO	−0.021	−0.004	0.187 ***	0.184 **
	(1.544)	(0.238)	(2.591)	(2.195)
INCOME	0.247 ***	0.324 ***	0.757 ***	1.082 ***
	(4.345)	(6.263)	(5.345)	(7.342)
STATE_LR3	−0.002	0.013	0.160 **	0.173 **
	(0.114)	(0.917)	(2.162)	(2.142)
STATE_LOSSSIM	0.149 **	0.135 **	−0.153	−0.018
	(2.438)	(2.008)	(0.461)	(0.050)
STATE_HHI	1.348 ***	1.430 ***	0.697	2.127
	(4.388)	(4.415)	(0.520)	(1.439)
DAMAGE	−0.000	−0.000	0.000	0.000
	(0.629)	(0.161)	(0.537)	(0.451)
w.COVERAGE	0.001 ***			
	(9.346)			
w.LNEXPO	0.065 ***			
	(3.282)			
w.INCOME	0.017			
	(0.247)			
w.STATE_LR3	0.044 *			
	(1.913)			
w.STATE_LOSSSIM	−0.159 *			
	(1.696)			
w.STATE_HHI	−0.832 *			
	(1.796)			
w.DAMAGE	0.000			
	(0.744)			
Observations	864			
R-squared	0.424			
Number of States	48			
YEAR FE	YES			
STATE FE	YES			
Loglikelihood	1200.86			
LR test on $\rho = 0$	1414.24	(p-value = 0.000)		
LR test on $\theta = 0$	99.04	(p-value = 0.000)		
LR test on $\theta = -\rho\beta$	120.48	(p-value = 0.000)		

This table presents the results of the panel spatial Durbin model for the average homeowners insurance cost for 48 contiguous US states between 2000 and 2018. We use a binary weighting matrix in the estimation. The dependent variable is the natural logarithm of the state-level average homeowners insurance cost (*LNCOST*). The key independent variable is the state-level average homeowners insurers' cosine loss similarity (*STATE_LOSSSIM*). Appendix A provides the definition and construction of all variables. Note that all right-hand side variables are lagged by one year. Column 1 reports the estimated parameters and t-values in parentheses. Columns 1a to 1c report the average direct effect, indirect effect, and total effect of estimated parameters (LeSage and Pace 2009) and t-statistics in parenthesis. Symbols ***, **, and * denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Lastly, we perform likelihood ratio (LR) tests to examine whether the spatial Durbin model can be reduced to spatial lag or spatial error model. The p-value of the loglikelihood ratio (LR) test for the hypothesis $\rho = 0$ is less than 0.01, allowing us to reject the null hypothesis that there is no spatial correlation among average homeowners insurance costs. The p-values of the loglikelihood ratio (LR) tests for a null hypothesis $\theta = 0$ and $\theta = -\rho\beta$ are both less than 0.01, indicating that the spatial Durbin model may be properly applied to describe the relationship between state-level average homeowners insurance costs.

4.2. Results of the Robustness Tests

We perform several additional analyses to ensure the robustness of the results of the baseline SAR model. First, we consider the effect of insurance regulation. Homeowners insurance is subject to different state-level, rating laws with different levels of stringencies. For example, prior approval is the strictest rating law requiring that an insurer must obtain approval from the insurance department before implementing the new rates. In contrast, a few states adopted the "no file" system meaning that filing material only needs to be kept at the state insurance department for inspection. Between these two extremes, there are "use and file" and "file and use" systems. We augment the baseline SAR model specified in Equation (1) by including the interaction terms between *STATE_LOSSSIM* and several insurance regulation variables. The first variable, denoted by *NONREG*, is a dummy variable that equals 1 if a state does not adopt a prior approval system and 0 otherwise. We obtained the data from S&P MI Insurance Product Filing to determine a state's homeowners insurance rate law. Second, following Oh et al. (2021) report, we constructed a firm-state level insurance regulation friction measure that is defined as one minus the ratio of the homeowners insurance rate approved divided by the rate requested. A higher friction measure suggests a higher level of friction for homeowners insurance underwriters to adjust the rate. A state-level insurance friction measure is then calculated as the average of all firm-state-level insurance regulation friction measures between 2001 and 2018. We constructed a dummy variable, denoted by *LOWFRICTION*, that equals 1 a state's insurance friction measure is ranked below the 33rd percentile and 0 otherwise.

Table 4 reports the results for the augmented spatial Durbin model with state and year-fixed effects. First, the reported ρ coefficients are positive and statistically significant at the 1% level as shown in Table 4, Columns 1 and 2. The magnitudes of ρ coefficients are very close to the one (i.e., 0.756) reported in Table 3. Moreover, Table 4, Column 1 shows that the coefficient of the interaction term, *STATE_LOSSSIM* $\times$ *NONREG*, is 0.196 (t-statistics = 1.943), which is statistically significant at the 10% level. This result suggests that homeowners insurers' loss similarity is associated with higher average homeowners insurance costs in less regulated states. This might be due to easier adjustments of insurance rates in less regulated states. Furthermore, Table 4, Column 1 shows that the estimated coefficient of *STATE_LOSSSIM* $\times$ *LOWFRICTION* is 0.118, which is not statistically significant at the 10% level. In short, we found that the positive spillover among average homeowners insurance cost is driven by the inclusion of state-level insurance regulation variables and that insurance regulation can positively moderate the positive association between underwriters' loss portfolio similarity and the average homeowners insurance cost.

In the baseline model, the dependent variable *LNCOST* is constructed using all six types of homeowners insurance policies. One may be concerned that this measure could be subject to measurement errors because these homeowners policies can have very different policy features which will affect the coverage and cost. Our last robustness test is to re-estimate the baseline model using the average cost measure constructed for a relatively homogenous sample. Specifically, we estimate the average cost (denoted by *LNHO3COST*) and coverage (denoted by *HO3COVERAGE)* of the HO3 policy because it is the most popular homeowners policy among all sampled states. The HO3 policy accounts on average for 83% of the total homeowners insurance premium written during our sample period. We re-run the baseline SAR model with fixed effects and report the results in Table 5. The results are consistent with those reported for the baseline spatial Durbin model. The estimated ρ is 0.765 (t-value = 38.96) as shown in Table 5, Column 1. Moreover, the coefficients of *STATE_LOSSSIM* are positive and statistically significant at the 5% level.

Taken together, the results in Table 5 indicate that our results are not suffering from potential bias due to measurement errors in average homeowners insurance costs.

Table 4. Effect of State Insurance Regulation.

Dependent Variable:	***LNCOST***		***LNCOST***	
	1 Main		2	
ρ	0.756 ***		0.755 ***	
	(37.658)		(37.473)	
COVERAGE	−0.000 ***		−0.000 ***	
	(7.989)		(8.035)	
LNEXPO	−0.022		−0.022	
	(1.604)		(1.567)	
INCOME	0.245 ***		0.247 ***	
	(4.318)		(4.340)	
STATE_LR3	−0.002		−0.002	
	(0.178)		(0.124)	
STATE_LOSSSIM	0.041		0.100	
	(0.491)		(1.393)	
STATE_HHI	1.334 ***		1.362 ***	
	(4.341)		(4.413)	
DAMAGE	−0.000		−0.000	
	(0.292)		(0.837)	
STATE_LOSSSIM×NONREG	0.196*			
	(1.943)			
STATE_LOSSSIM×LOWFRICTION			0.118	
			(1.172)	
w.COVERAGE	0.001 ***		0.001 ***	
	(9.344)		(9.435)	
w.LNEXPO	0.066 ***		0.067 ***	
	(3.328)		(3.377)	
w.INCOME	0.019		0.013	
	(0.279)		(0.188)	
w.STATE_LR3	0.041 *		0.049 **	
	(1.771)		(2.084)	
w.STATE_LOSSSIM	−0.128		−0.213 **	
	(0.766)		(2.005)	
w.STATE_HHI	−0.773 *		−0.872*	
	(1.668)		(1.874)	
w.DAMAGE	0.000		0.000	
	(0.791)		(0.442)	
w.STATE_LOSSSIM×NONREG	−0.063			
	(0.303)			
w.STATE_LOSSSIM×LOWFRICTION			0.226	
			(1.110)	
Observations	864		864	
R-squared	0.424		0.448	
Number of States	48		48	
YEAR FE	YES		YES	
STATE FE	YES		YES	
Loglikelihood	1202.74		1202.24	
LR test on $\rho = 0$	1418.11	(p-value = 0.000)	1404.20	(p-value = 0.000)
LR test on $\theta = 0$	98.46	(p-value = 0.000)	100.59	(p-value = 0.000)
LR test on $\theta = -\rho\beta$	121.94	(p-value = 0.000)	121.53	(p-value = 0.000)

This table presents the results of the panel spatial Durbin model for the average homeowners insurance cost for 48 contiguous US states between 2000 and 2018. We use a binary weighting matrix in the estimation. The dependent variable is the natural logarithm of the state-level average homeowners insurance cost (*LNCOST*). The key independent variable is the state-level average homeowners insurers' cosine loss similarity (*STATE_LOSSSIM*). The variable *NONREG* is a dummy variable that equals 1 if a state does not adopt a prior approval system for homeowners insurance rate and 0 otherwise. The variable *LOWFRICTION* is a dummy variable that equals 1 if the state-level homeowners rate regulation friction falls into the first 33rd percentile and 0 otherwise. Appendix A provides the definition and construction of all variables. Note that all right-hand side variables are lagged by one year. We report *t*-statistics in parentheses. Symbols ***, **, and * denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5. Results for the HO3 Policy.

Dependent Variable:	***LNHO3COST***			
	1 Main	1a Direct Effect	1b Indirect Effect	1c Total Effect
ρ	0.765 ***			
	(38.960)			
HO3COVERAGE	−0.000 ***	−0.000 ***	0.002 ***	0.001 ***
	(8.066)	(3.428)	(5.558)	(4.251)
LNEXPO	−0.036 ***	−0.020	0.180 **	0.160 *
	(2.668)	(1.201)	(2.447)	(1.886)
INCOME	0.197 ***	0.281 ***	0.832 ***	1.113 ***
	(3.562)	(5.551)	(5.769)	(7.386)
STATE_LR3	−0.010	0.006	0.173 **	0.179 **
	(0.742)	(0.428)	(2.316)	(2.193)
STATE_LOSSSIM	0.137 **	0.133 **	−0.041	0.092
	(2.301)	(2.018)	(0.122)	(0.247)
STATE_HHI	1.570 ***	1.657 ***	0.753	2.410
	(5.252)	(5.223)	(0.556)	(1.612)
DAMAGE	−0.000	−0.000	0.000	−0.000
	(1.004)	(0.705)	(0.007)	(0.101)
w.HO3COVERAGE	0.001 ***			
	(9.369)			
w.LNEXPO	0.073 ***			
	(3.763)			
w.INCOME	0.065			
	(0.962)			
w.STATE_LR3	0.053 **			
	(2.329)			
w.STATE_LOSSSIM	−0.120			
	(1.321)			
w.STATE_HHI	−1.007 **			
	(2.227)			
w.DAMAGE	0.000			
	(0.342)			
Observations	864			
R-squared	0.394			
Number of States	48			
YEAR FE	YES			
STATE FE	YES			
Loglikelihood	1221.43			
LR test on $\rho = 0$	1517.90	(p-value = 0.000)		
LR test on $\theta = 0$	105.06	(p-value = 0.000)		
LR test on $\theta = -\rho\beta$	124.66	(p-value = 0.000)		

This table presents the results of the panel spatial Durbin model for the average HO3 policy cost for 48 contiguous US states between 2000 and 2018. Panels A binary spatial weighting matrix is used in estimation. The dependent variable is the natural logarithm of the state-level average HO3 policy cost (*LNHO3COST*). The key independent variable is the state-level average homeowners insurers' cosine loss similarity (*STATE_LOSSSIM*). Appendix A provides the definition and construction of all variables. Note that all right-hand side variables are lagged by one year. Column 1 reports the estimated parameters and t-statistics in parentheses. Columns 1a to 1c report the average direct effect, indirect effect, and total effect of estimated parameters (LeSage and Pace 2009) and t-values in parenthesis. Symbols ***, **, and * denote the statistical significance at the 10%, 5%, and 1% level, respectively.

The spatial weighting matrix determines the complex spatial dependence structure. We conducted a robustness test by using an alternatively defined spatial matrix to capture a more intricate dependence structure among states. We replaced the binary spatial weighting matrix with an inverse distance-based spatial weighting matrix. W denotes an $N \times N$ symmetric spatial weighting matrix for 48 US contiguous states, in which the element (i, j) equals $1/d_{ij}$ where d_{ij} denotes the distance between the state capitals of states i and j. We obtained the distance between the state capitals of 48 contiguous states from the NBER City Distance Database.[4] The key difference between the binary spatial weighting matrix and the inverse distance-based spatial weighting matrix is that a pairing of two states that are not immediate neighbors (e.g., Maine and Pennsylvania) will receive a non-zero weight (proportional to the inverse distance between state capitals) rather than 0 in the inverse distance based spatial weighting matrix. As a result, the dependence structure under the

inverse distance-based weighting matrix is much more complicated than that specified in the binary weighting matrix.

Table 6 reports the results for the spatial Durbin model using an inverse distance-based weighting matrix. In general, the results are very similar to those reported in Table 3. The estimated ρ coefficient is 0.834 (t-statistics = 27.60), suggesting a very strong spatial correlation among the *LNCOST* of states. The estimated coefficient of *STATE_LOSSSIM* is 0.146 (t-statistics = 2.07), which is comparable to that reported in Table 3. Lastly, Table 6, Columns 1a and 1b show that the indirect effect of *STATE_LOSSSIM* is much larger than the direct effect, which is also consistent with those reported for the baseline model.[5] In short, the results of the baseline spatial Durbin model still hold if we use a distance-based weighting matrix to model the dependence structure among 48 contiguous states.

Table 6. Results for the Inverse Distance based Weighting Matrix.

Dependent Variable:	*LNCOST*			
	1 Main	1a Direct Effect	1b Indirect Effect	1c Total Effect
ρ	0.834 ***			
	(27.596)			
COVERAGE	−0.000 **	−0.000	0.002 **	0.002 **
	(2.551)	(1.222)	(2.181)	(2.043)
LNEXPO	−0.013	0.000	0.651 **	0.651 **
	(0.751)	(0.024)	(2.496)	(2.438)
INCOME	0.478 ***	0.482 ***	−0.130	0.352
	(7.322)	(7.752)	(0.215)	(0.573)
STATE_LR3	0.020	0.024	0.172	0.196
	(1.271)	(1.441)	(0.513)	(0.573)
STATE_LOSSSIM	0.146 **	0.117	−1.373	−1.256
	(2.074)	(1.591)	(1.035)	(0.926)
STATE_HHI	1.888 ***	1.869 ***	−1.387	0.482
	(6.507)	(4.825)	(0.153)	(0.051)
DAMAGE	−0.000	0.000	0.001	0.001
	(0.366)	(0.107)	(0.797)	(0.781)
w.COVERAGE	0.001 ***			
	(2.754)			
w.LNEXPO	0.119 **			
	(2.470)			
w.INCOME	−0.419 ***			
	(3.443)			
w.STATE_LR3	0.013			
	(0.213)			
w.STATE_LOSSSIM	−0.365 *			
	(1.657)			
w.STATE_HHI	−1.826			
	(1.207)			
w.DAMAGE	0.000			
	(0.857)			
Observations	864			
R-squared	0.521			
Number of States	48			
YEAR FE	YES			
STATE FE	YES			
Loglikelihood	1068.04			
LR test on $\rho = 0$	761.51	(p-value = 0.000)		
LR test on $\theta = 0$	14.66	(p-value = 0.023)		
LR test on $\theta = -\rho\beta$	24.35	(p-value = 0.001)		

This table presents the results of the panel spatial Durbin model for the average homeowners insurance cost for 48 contiguous US states between 2000 and 2018. We use an inverse distance-based weighting matrix. The distance between two states is defined as the distance between the state capitals. The dependent variable is the natural logarithm of the state-level average homeowners insurance cost (*LNCOST*). The key independent variable is the state-level average homeowners insurers' cosine loss similarity (*STATE_LOSSSIM*). Appendix A provides the definition and construction of all variables. Note that all right-hand side variables are lagged by one year. Column 1 reports the estimated parameters and t-statistics in parentheses. Columns 1a to 1c report the average direct effect, indirect effect, and total effect of estimated parameters (LeSage and Pace 2009) and t-statistics in parenthesis. Symbols ***, **, and * denote the statistical significance at the 10%, 5%, and 1% level, respectively.

4.3. Results for GS2SLS

There is a possibility that the baseline model could be subject to endogeneity bias. For example, the explanatory variables could be endogenous. To tackle such an endogeneity issue, we adopted a generalized spatial two-stage least squares (GS2SLS) (Kelejian and Prucha 1998, 2010). This three-step procedure proceeds as follows. In the first step, a

two-stage least squares regression model is estimated by using explanatory variables, and spatially lagged explanatory variables (i.e., X, WX, W^2X) as a set of instrumental variables. That is, regressing WY on X, WX, W^2X, and using the fitted values as instruments for WY. In the second step, the autoregressive parameter in the disturbance is estimated using the residuals from the first step. In the third step, the estimate of the autoregressive disturbance is used to perform a spatial Cochrane–Orcutt transformation of the data and estimate the spatial autoregressive coefficient (ρ) and coefficients of explanatory variables (β). This procedure generates consistent and asymptotically efficient estimates under the assumption that the explanatory variables are exogenously related to the dependent variable (Kelejian and Prucha 1998).

Table 7, Panels A and B report the results for the spatial Durbin model using binary weighting matrix and inverse distance weight matrix, respectively. We separately estimate the GS2SLS using *LNCOST* and *LNHO3COST* as the dependent variable in Table 7, Columns 1 and 2. The estimate ρ coefficients are positive and statistically significant at the 1% level as shown in Table 7, Columns 1 and 2, indicating a strong positive geographical spillover of average homeowners insurance cost. Moreover, Table 7 Columns 1 and 2 confirm that there is a significant positive association between *STATE_LOSSSIM* and *LNCOST* and *LNHO3COST* because the reported coefficients of *STATE_LOSSSIM* are positive with *p*-values that are less than 0.01. Furthermore, the results reported in Table 7, Panel B are largely in line with those reported in Table 7, Panel A. In summary, the results of GS2SLS assure that the results of the baseline SAR model with fixed effects are robust against bias caused by endogenous or omitted explanatory variables.

Table 7. Results for GS2SLS.

	Panel A: Binary Weighting Matrix		**Panel B: Inverse Distance Weighting Matrix**	
Dependent Variable:	*LNCOST*	*LNHO3COST*	*LNCOST*	*LNHO3COST*
	1	2	3	4
ρ	0.864 ***	0.903 ***	0.789 ***	0.816 ***
	(18.924)	(20.302)	(18.955)	(20.247)
COVERAGE	−0.000 ***		−0.000 **	
	(6.232)		(2.471)	
HO3COVERAGE		−0.000 ***		−0.000 **
		(6.260)		(2.174)
LNEXPO	−0.008	−0.015	0.005	−0.001
	(0.647)	(1.266)	(0.314)	(0.042)
INCOME	0.316 ***	0.265 ***	0.426 ***	0.395 ***
	(5.274)	(4.539)	(7.528)	(7.204)
STATE_LR	0.002	−0.003	0.013	0.008
	(0.159)	(0.249)	(0.800)	(0.529)
STATE_LOSSSIM	0.221 ***	0.233 ***	0.191 ***	0.200 ***
	(4.042)	(4.392)	(2.817)	(3.031)
STATE_HHI	1.196 ***	1.272 ***	2.021 ***	2.223 ***
	(5.200)	(5.684)	(6.991)	(7.897)
DAMAGE	−0.000	−0.000	−0.000	−0.000
	(0.847)	(1.427)	(0.279)	(0.889)
Constant	−2.414 ***	−2.053 ***	−3.361 ***	−3.155 ***
	(5.994)	(5.194)	(8.668)	(8.380)
Observations	864	864	864	864
YEAR FE	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES
F-test of 1st stage regression	1861.23 (p-value = 0.000)	1965.46 (p-value = 0.000)	1224.54 (p-value = 0.000)	1300.70 (p-value = 0.000)

This table presents the results of generalized spatial two-stage least squares (GS2SLS) (Kelejian and Prucha 1998, 2010) for 48 contiguous US states between 2000 and 2018. Panels A and B report the results when a binary spatial weighting matrix and an inverse distance based spatial weighting matrix is used in estimation. The dependent variable in Columns 1 and 3 is the natural logarithm of the state-level average homeowners insurance cost (*LNCOST*). The dependent variable in Columns 2 and 4 is the natural logarithm of the state-level average HO3 cost (*LNHO3COST*). The key independent variable is the state-level average homeowners insurers' cosine loss similarity (*STATE_LOSSSIM*). Appendix A provides the definition and construction of all variables. Note that all right-hand side variables are lagged by one year. We report *t*-statistics in parentheses. Symbols ***, **, and * denote the statistical significance at the 10%, 5%, and 1% level, respectively.

5. Conclusions

In this study, we examine the spatial dependence among the average homeowners insurance costs of 48 US contiguous states. Using a panel spatial autoregressive model, we detect a statistically significant positive spillover effect in the average homeowners insurance cost, with estimates indicating that the initial sensitivity of a state's average homeowners insurance cost to neighboring states' average homeowners insurance cost is on the order of 0.77. Moreover, we examine the relationship between homeowners insurers' loss portfolio similarity and the average homeowners insurance cost. We found a positive association between homeowners insurance underwriters' loss portfolio similarity and the average homeowners insurance cost. Such a positive association becomes stronger in states where homeowners insurance is less regulated.

We conducted several tests to ensure the robustness of the baseline regression results. We show that the positive spatial spillover effect remains largely unchanged when we control for the state-level insurance regulation stringency and homeowners insurance rate regulation friction. Moreover, we found that the baseline results still hold when we use a different spatial weighting matrix with a more intricate dependence structure. Furthermore, we re-estimated the baseline model using a homogenous homeowners insurance policy (i.e., the HO3 policy) and found that our main results are not affected by using an alternatively defined average homeowners insurance cost. Lastly, to mitigate the concerns about the potential endogeneity problems, we adopted a GS2SLS with instrumental variables. The results are consistent with the baseline regression results, assuring the robustness of the main results.

Our results have important policy implications. First, the uncovered positive spatial spillover of average homeowners insurance costs suggests that the climate-related crisis can have greater impacts on the homeowners insurance rates outside the impacted region. Second, one contributing factor to the positive spillover effect is the homeowners insurers' loss portfolio similarity. Because of the natural limit of geographical diversification and the increased scope of climate risk, the performance of homeowners insurers' geographical diversification could be less effective in hedging climate risk, pushing the cost of homeowners insurance coverage for consumers. To balance the affordability and availability of homeowners insurance coverage, the primary homeowners insurance underwriters may consider mitigating the losses caused by climate risk through risk transfer. One potential solution could be a combination of private and public insurance to mitigate inefficient geographical diversification. Historically, when the loss associated with peril is so large that such a risk (e.g., terrorism risk) becomes uninsurable in the private insurance market, public insurance can supplement the private insurance market through risk transfer. For instance, after the 11 September 2001 attacks, the US Congress enacted the Terrorism Risk Insurance Act (TRIA) which provides shared public and private compensation for insured losses resulting from acts of terrorism in 2002. TRIA was signed into law by President George W. Bush on 26 November 2002. Since 2002, TRIA has been renewed and extended multiple times, and it remains in effect today. A similar mechanism can be arranged for mitigating climate risk., e.g., a reinsurance program for mega loss caused by climate risk in which the government serves as the climate risk reinsurer of last resort.

There are several caveats to this study. First, our analysis is based on state-level data because of a lack of policy-level data. It would be interesting to conduct the analysis using data from more granular levels (i.e., policy-level). Second, while we make a step forward to understanding the geographical spillover of insurance rate hikes in homeowners insurance market, the exogeneity of the explanatory variable is less well established because the covariates in predicting the outcome variable are often affected by neighboring state variables. Therefore, this preliminary evidence shall be interpreted with caution.

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Data Availability Statement: Requests to access the datasets should be directed to the data vendor directly.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Variable Definitions

Variable	Definitions
LNCOST	It is defined as the natural logarithm of the state-level average homeowners insurance cost, which is defined as the total premium divided by the total loss exposure of a state. The total premium and total loss exposures are calculated for six types of homeowners insurance policy forms (dwelling fire, HO1, HO2, HO3, HO5, and HO8) for a state year. We adjust for inflation using CPI with 2000 being the base year. *Source:* NAIC, own calculation.
COVERAGE	It is a state-level annual average homeowner insurance coverage amount per house. This variable is calculated by dividing the total insurance coverage by the total number of houses. The total insurance coverage is aggregated for six types of homeowners insurance policies: dwelling fire, HO-1, HO-2, HO-3, HO-5, and HO-8. For each type of homeowners insurance policies, there are eleven insurance ranges (i.e., 0 to 49,999, 50,000 to 74,999, 75,000 to 99,999, 100,000 to 124,999, 125,000 to 149,999, 150,000 to 174,999, 175,000 to 199,999, 200,000 to 299,999, 300,000 to 399,999, 400,000 to 499,999, and 500,000 and above). We use the midpoint of a given insurance range as the estimated homeowners insurance amount per house for the respective range. The total amount of insurance coverage for a given insurance range is calculated by multiplying the estimated insurance amount per house by the number of houses in such a range. We sum the total insurance coverage (houses) for each type of homeowners insurance policy to calculate the total amount of insurance coverage (houses) for all insurance ranges. The total insurance coverage (houses) for a state is then aggregated by adding up the total insurance coverage (houses) of all six types of homeowners insurance policies. *Source:* NAIC, own calculation.
LNEXPO	It is the natural logarithm of the state-level annual total loss exposures. *Source:* NAIC.
INCOME	It is the natural logarithm of the state-level personal income per capita. Source: BEA.
STATE_LR	It is the average of a state's homeowners insurance direct loss ratios between years t-2 and t. The direct loss ratio is calculated as total direct loss divided by total premium written. Source: NAIC, own calculation.
STATE_LOSSSIM	It is the average of the cosine similarities of homeowners insurance loss portfolios of homeowners insurance underwriters with a direct market share exceeding 1% of a state. We first calculate cosine similarity between a paring of insurers and then aggregate at the state level by averaging the cosine similarities of all possible pairings. *Source:* NAIC, own calculation.
STATE_HHI	It is the state-level Herfindal Hershman index for the homeowners insurance market. It is the sum of the squares of market shares in terms of the direct premium of all operating homeowners insurance underwriters of a state. Source: NAIC, own calculation.
DAMAGE	It is defined as the per capita property loss of a state year. Source: SHELDUS, own calculation.

Variable	Definitions
LNHO3COST	It is defined as the natural logarithm of the state-level average homeowners insurance cost, which is defined as the total premium divided by the total loss exposure of a state. The total premium and total loss exposures are calculated for HO-3 policies of a state. *Source:* NAIC, own calculation.
HO3COVERAGE	It is a state-level annual average homeowner insurance coverage amount for HO3 policies. This variable is calculated by dividing the total insurance coverage by the total number of houses of HO-3 policies. *Source:* NAIC, own calculation.
NONREG	It is a dummy variable defined as 1 if a state does not adopt a prior approval system for homeowners insurance rating and 0 otherwise. *Source:* S&P MI Product Filing.
FRICTION	It is defined as 2 if a state is ranked in the lower 33rd percentile of state-level average homeowners insurance rate friction score, 0 if a state is ranked in the upper 33rd percentile, and 1 otherwise. The state-level average homeowners insurance rate friction score is calculated in two steps. First, following Oh et al. (2021), we calculate the firm-state-year level homeowners insurance friction as one minus the rate approved divided by the rate requested. Second, we aggregate the state-level average homeowners insurance rate friction score by averaging all firm-year scores between 2001 and 2018. *Source:* S&P MI Product Filing, own calculation.
OWFRICTION	It is defined as 1 if a state is ranked in the lower 33rd percentile of state-level average homeowners insurance rate friction score, and 0 otherwise. The state-level average homeowners insurance rate friction score is calculated in two steps. First, following Oh et al. (2021), we calculate the firm-state-year level homeowners insurance friction as one minus the rate approved divided by the rate requested. Second, we aggregate the state-level average homeowners insurance rate friction score by averaging all firm-year scores between 2001 and 2018. *Source:* S&P MI Product Filing, own calculation.

Notes

1 See https://www.latimes.com/business/story/2025-01-09/loss-from-wildfires-could-surpass-50-billion (accessed on 1 Febuary 2025).

2 Note that the SAR model can be represented as $E(Y) = [1 - \rho W]^{-1} E[X\beta]$. The partial derivative matrix of *E(Y)* with respect to kth explanatory variable captures the effect of kth explanatory variable. In particular, every diagonal term represents a direct effect and every off-diagonal term represents an indirect effect (LeSage and Pace 2009). Therefore, the average direct effect and indirect effect are calculated as the average of diagonal terms and off-diagonal terms, respectively.

3 As a preliminary analysis, we estimate a linear regression model with state and year fixed effects and conduct Moran I's test for the residuals. The test result allows us to reject the null hypothesis that there is no spatial correlation among residuals.

4 We use the 2010 version data obtained from https://www.nber.org/research/data/city-distance-database-place-distance-database (accessed on 10 November 2022).

5 Note that the strength for spillover is much more complicated when using a inverse distance based weighting matrix. For example, the change in state i's average cost ($\Delta(LNCOST_i)$) will lead to the change in direct neighboring state j's average cost by $\rho(1/d_{ij})\Delta(LNCOST_i)$ and indirect effect to state k's average cost by $\rho^2(1/d_{ij})\,(1/d_{jk})\Delta(LNCOST_i)$, when state k is two steps away from state i.

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