Homeowners Insurance and Housing Prices

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Abstract

How does the cost of insurance affect property values? We answer this question by constructing a dataset that combines detailed homeowners insurance data with property-level housing assessments and transactions in Florida. Importantly, we focus on the homeowners insurance provided by private insurers. To identify the causal effect of homeowners insurance prices on housing prices, we exploit a Florida statute that mandates auto insurers to participate in the homeowners insurance market if they offer homeowners coverage in other states. We construct a novel instrument that combines insurers' predetermined county exposure shares with insurer-year changes in their non-Florida business mix, isolating regulatory supply-driven variation in homeowners insurance prices. Our preferred IV estimates imply that a 10% increase in homeowners insurance prices lowers housing prices by roughly 6.5%. This effect is more pronounced in areas with a high prevalence of mortgage-financed buyers and limited insurer competition, though the presence of a public option moderates the effect.

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1 Introduction

In the US, homeowners insurance is a quasi-mandate for many homebuyers, as mortgage lenders require borrowers to maintain continuous coverage on their properties – approximately 97% of homeowners with mortgages maintain homeowners insurance (Larrimore et al. 2025). This requirement has become increasingly significant in light of rising climate risks, which have contributed to a sharp escalation in homeowners insurance costs (Insurance Information Institute 2022; Keys and Mulder 2024). However, despite the dominance of private insurers—who issue approximately 80–85% of homeowners insurance policies in the US—to the best of our knowledge, no empirical study has directly estimated the causal impact of private homeowners insurance prices on housing prices. A small but growing literature examines the relationship between property insurance and housing prices, but it focuses mostly on government-provided insurance, such as flood insurance (Ge et al. 2022; Georgic and Klaiber 2022) or residual homeowners insurance (Nyce et al. 2015).

Empirically estimating the causal effect of homeowners insurance on housing prices is challenging because observed insurance premiums are endogenous to housing prices and measured with noise.[1] To address these concerns, we leverage a unique regulation in Florida (Florida Statute §624.4055) that affects the supply of homeowners insurance but not local housing prices. In Florida, auto insurers that write homeowners insurance in states other than Florida are required to offer homeowners insurance coverage. This mandate forces certain insurers, whom we term "Mandated Entrants," into the homeowners insurance market. These firms tend to charge relatively high prices.[2] We construct a shift-share instrumental variable (IV) combining the predetermined share of mandated entrants to their time-varying homeowners insurance business *outside* of Florida. We find evidence that our IV addresses endogeneity, since the shifter reflects insurers' non-Florida portfolio strategy, which is likely orthogonal to local housing market conditions in Florida.[3] Regulations in other states suggest that this regulatory-supply approach is generalizable. For example, from 2019 to 2021, California required insurers to renew homeowners policies in areas affected by or adjacent to recent wildfires—an intervention that, like Florida's, alters insurer behavior and market pricing independently of local housing conditions.

[1]For instance, homes in high-risk areas may have lower prices due to climate risk. Conversely, these areas may also offer superior amenities, such as coastal views, which can drive up housing prices.

[2]We find that mandated entrants are financially stronger insurers than voluntary entrants, explaining why some homeowners still accept their policies despite the higher premiums. See detailed discussion in Appendix D.

[3]Our validation tests suggest that our instrument is uncorrelated with observable county demographics and, crucially, with unobserved local risk proxies, supporting the exclusion restriction. We further document that our instrument satisfies the relevance condition. We discuss the details of our IV regression strategy in Section 3.3.

Another empirical challenge is data. In this paper, we overcome this challenge by linking property-level housing data with private homeowners insurance data in Florida from 2011 to 2020.[4] Our housing data come from a comprehensive property tax assessment dataset encompassing all residential homes, with over 3.8 million individual house sales transactions. Our dataset includes granular details on private homeowners insurance market activity, segmented by insurance company, type of coverage, county, and quarter. The data include a measure of insured exposure, which is a key advantage of our identification and analysis.

We first document that the increase in observed insurance prices are associated with lower housing prices in our baseline OLS specification, which follows a hedonic pricing model (Rosen 1974). The relationship becomes somewhat more negative in repeat-sales specifications with property fixed effects (i.e., houses with at least two sales during the sample period).

We then turn to IV estimates that address potential attenuation and endogeneity in our OLS estimates. Our preferred IV specifications imply that a 1% increase in homeowners insurance prices reduces housing prices by about 0.65% in the full sample and 0.61% in the repeat-sales sample. Both results are supported by strong first-stage F-stats well above 100. We find evidence consistent with our OLS estimates being substantially attenuated—a pattern we trace specifically to county-quarter average premiums being noisy proxies for the marginal insurance-cost shock relevant to a given transaction, rather than to omitted variable bias, a distinction we establish through a formal decomposition following Ishimaru (2024). Additional diagnostic tests indicate that the IV-OLS gap is not explained by alternative premium definitions or by adding richer observable controls. Our estimates imply sizable consequences for local public finance. Applying the baseline IV elasticity to Florida's owner-occupied housing stock suggests that a 10% increase in homeowners insurance prices would reduce property values by roughly \$144 billion. At Florida's effective property tax rate of 0.71%, that translates to an annual property tax revenue loss of approximately \$1.0 billion. This is commensurate to about 3% of total statewide property tax revenues, with a present value approaching \$8 billion over a ten-year horizon.

Additional analyses suggest that the capitalization effect operates primarily through a financing channel. Price reductions are larger in areas with high volumes of new mortgage originations, suggesting that financing constraints bind at the point of purchase—an effect that does not bind for cash buyers. This financing channel is concentrated among owner-occupants with homestead exemptions rather than short-horizon investors, confirming that long-term consumption utility rather than speculative return drives the capitalization. The effect is moderated by risk perception. We find smaller housing price reductions in counties with higher perceived risk when homeowners insurance prices rise (Baldauf et al. 2020). In addition, limited private insurer competition amplifies the

[4]Throughout the paper, we focus on the most conventional homeowners insurance policy, insurance for owner-occupied dwelling properties (commonly referred to as HO-3 policy form). We exclude rental insurance or insurance policies for mobile homes or condominiums.

capitalization effect, while a larger presence of the public option, Citizens, moderates it. Nonetheless, the state's effort to offload Citizens policies back into the private market (i.e., Depopulation program) weakens that moderation, with direct implications for how regulators design public insurance interventions (Sastry et al. 2023).[5]

Finally, we assess the extensive-margin effect of homeowners insurance prices on housing markets. Using the number of homes transacted in a county-quarter to measure sale probability, we find that higher homeowners insurance prices reduce transaction activity: a 1% increase in homeowners insurance prices is associated with about a 0.3 percentage point decline in the probability of sale. This finding suggests that higher homeowners insurance costs not only affect housing prices but also dampen transaction volumes in the housing market.

1.1 Related Literature

Our findings contribute to the growing literature on insurance prices and real estate values. To the best of our knowledge, no study to date has empirically estimated the effect of private homeowners insurance on housing prices. Most existing literature examines the effect of public insurance, such as flood insurance (e.g., Gibson and Mullins 2020; Hino and Burke 2021; Bakkensen and Barrage 2022; Ge et al. 2022; Georgic and Klaiber 2022) or state-funded public homeowners insurance (e.g., Nyce et al. 2015), on housing prices. The scarcity of empirical research on private homeowners insurance market is mainly due to the lack of private homeowners insurance data. Nevertheless, the private homeowners insurance market is more economically integrated into property markets than the publicly funded flood insurance; the latter is mandated only for properties in designated flood zones, whereas the former is a requirement for all properties with mortgages. For example, only about 19% of housing units have flood insurance in Florida in 2019.[6] In addition, state-funded public homeowners insurance is only about 10% of total homeowners' insurance market in Florida in 2021.[7]

Our study complements recent work on flood insurance. Using the NFIP's risk-based repricing reform, Ge et al. (2022) find that flood insurance price increases lead to housing price declines through two channels: a direct cash-flow effect ("Subsidy-Cash-Flow") and an informational effect where higher premiums signal higher underlying risk ("Risk-Updating"). Our identification strategy, in contrast, isolates the pure financial cost channel because our price variation is driven by a regulatory supply shock in the private insurance market, which is plausibly orthogonal to the property market. This allows us to estimate the direct capitalization of insurance costs into housing values, unconfounded by the "risk-updating" signal that complicates flood insurance studies, consistent with Poterba's (1984) user cost framework.

[5] A broader set of heterogeneity tests also helps rule out narrower alternative explanations. The capitalization effect is not concentrated in coastal flood zones, in markets with less elastic housing supply, or among short-horizon investors, while it is somewhat stronger for homestead-exempt owner-occupants and, in the cross section, for properties with recent disaster experience.

[6] Statistics calculated by the National Association of Realtors, 2020. See FL Flood Insurance Report (2019).

[7] Based on Citizen's Homeowners Multi-peril market share in Florida reported in NAIC's 2021 Market Share Report.

In particular, we contribute to the literature on the capitalization of risk in housing prices and households' marginal willingness to pay for risk reduction (see Giglio et al. (2021) for a review). Several studies have examined how flood insurance, state-run public insurance, or incentivized programs affects housing values (e.g., Nyce et al. 2015; Bakkensen and Barrage 2022; Billings et al. 2022; Ge et al. 2022; Georgic and Klaiber 2022; Bellon et al. 2024). In addition, a developing literature documents that homeowners insurance costs are rising (e.g., Boomhower et al. 2024; Keys and Mulder 2024; Nowak et al. 2025) but they do not explore the effect of insurance prices on housing prices. Given the broader coverage, higher take-up rates, and significant role of private homeowners insurance in financing decisions compared to flood insurance, the lack of empirical evidence on its capitalization in housing prices represents a critical gap in the literature.[8] It is precisely this gap that we address in this study.

Finally, our study contributes to the literature on the interaction between public and private insurance markets. A combination of unique economic frictions and political desire for coverage availability has historically resulted in meaningful government involvement in insurance markets. While much of the academic research in this area has focused on health insurance markets (e.g., Cutler and Gruber 1996), a literature has also developed to examine interventions into property insurance markets. This has included evaluations of indirect intervention through public reinsurance programs (e.g., Brown et al. 2004; Solomon 2024), direct public interventions such as the aforementioned NFIP (e.g., Browne and Hoyt 2000; Kousky 2011) or residual markets (e.g., Nyce et al. 2015; Born et al. 2021). Our findings relating to Citizens and its role in shaping insurance availability and competition have important implications for regulators in how they design public property insurance interventions.

2 Data

2.1 Insurance Price Data

We collect quarterly county-level homeowners insurance data in Florida from the Quarterly Supplemental Report (QUASR) system from 2011 to 2020. Florida property insurers report quarterly county-level data on policies in force, total premiums written (i.e., direct premiums written), and exposures for each of the 67 counties where they write business. Insurers are also required to file information separately for different insurance policy types (e.g., homeowners insurance for owners occupying the houses, condominium owners, mobile homeowners, and tenants (rental properties)).[9] We focus on homeowners insurance for owner-occupied properties, "Personal Residential - Homeowners

[8] See NAIC (2022).

[9] For more details, see `http://www.leg.state.fl.us/statutes/index.cfm?App_mode=Display_Statute&URL=0600-0699/0627/Sections/0627.4133.html` (last access: June 1, 2024).

(Excl Tenant and Condo) - Owner Occupied," which corresponds to the commonly-used HO-3 homeowners insurance policy. QUASR maintains data prior to 2011, but we use data from 2011 because regulators required more granular reporting starting in 2011 that allows us to more accurately capture homeowners insurance prices.[10]

2.2 Property-level Housing Price Data

We collect property-level sales transaction data from the Name–Address–Legal (NAL) Files provided by the Florida Department of Revenue. Each county office in Florida collects property-level tax information annually, which includes detailed housing characteristics such as improvements to the houses, disaster experience, as well as information on the past two sales. Then, each county office submits tax rolls to the Department of Revenue. We use property-level information to create a panel of housing transactions. While tax rolls are reported annually, we can construct a sample of property sales using the sale date reported in the assessment data. To match our homeowners insurance data, we focus on single-family home transactions. We exclude transactions with prices less than $5,000 or more than $50 million, as well as those with recording errors (e.g., properties with year built after year sold). After data cleaning, our sample includes 3,897,806 single-family home property transactions from 2011 to 2020. Among these, 942,521 unique single-family homes had at least two transactions during the sample period, resulting in 2,202,829 repeat property-transaction observations.[11]

2.3 Other Data

We collect time-varying demographic and economic characteristics from the American Community Survey (ACS) 5-year estimates. These attributes include population, population density, unemployment rate, percent college, percent Black and Hispanic, median household income, percentage below the poverty line, median year of house construction, percentage of owner-occupied homes, and percent of owner-occupied housing with mortgage.

We use Home Mortgage Disclosure Act (HMDA) data as well as data from Fannie Mae and Freddie Mac to calculate the percent of government-sponsored enterprise (GSE) mortgages in each county in a given year.

[10]Prior to 2011, a wind-only policy was not separated from a homeowners insurance policy. The wind-only policy is a specific type of homeowners insurance policy in Florida, with limited coverage compared to the conventional homeowners insurance policy. Since 2018, data for a non-negligible number of insurers has been withheld from QUASR due to trade secret litigation. Consistent with Sastry et al. (2023) and Bellon et al. (2024), we test the robustness of our results by restricting the sample to 2011–2018 (see Section 3.4).

[11]We check the validity of our housing price dataset using the Federal Housing Finance Agency's housing price index (HPI) (FHFA 2022). We construct a comparable housing price index using the county tax assessment data (NAL-HPI). We compare NAL-HPI with FHFA's HPI and find they are highly correlated (correlation coefficient greater than 0.99 in both cases) as reported in Appendix Figures B1 (non-seasonal adjusted) and B2 (seasonal adjusted).

To measure disaster losses from hurricanes, we use county-quarter-level property damage loss estimates from the Spatial Hazard Events and Losses Database for the United States (SHELDUS v20.0; ASU 2023). We also use the publicly available hurricane loss estimates produced by Florida International University, the Florida Public Hurricane Loss Model; we use the county-level hurricane insured loss estimates for a typical Florida home (framed houses with $1,000 deductibles) in 2012.[12]

We also use risk scores from the National Risk Index (NRI), produced by the Federal Emergency Management Agency (FEMA). For an additional measure of risk perception, we use the Yale Climate Opinion Map 2016 (Howe et al. 2015). The Yale Climate data has been widely used in prior literature such as Bernstein et al. (2019) and Baldauf et al. (2020).

3 Homeowners Insurance Price and Housing Price

3.1 Descriptive Evidence

We begin by documenting descriptive evidence on the heterogeneous effects of homeowners insurance prices on housing prices in Florida. Figure 1 visualizes the average homeowners insurance price relative to the average housing price in 2019. Each county is colored based on its rank of the scaled homeowners insurance prices in deciles, with darker shades representing higher values. Several counties in north Florida report the lowest average homeowners insurance prices but the highest prices when scaled by housing value. This suggests that the relationship between insurance price and housing value is complex and influenced by additional factors. Homeowners are paying different prices for insurance per unit of housing value. Those in inland counties—potentially facing relatively lower disaster risk—are actually paying more. The relationships are similar if we were to scale using homeowners insured exposures instead of homeowners insurance prices, as reported in Figure B3.[13]

To further examine the relationship between insurance prices and housing values, we visualize the relative growth of homeowners insurance prices to housing prices. For each county, we calculate the change in housing prices (using the NAL-HPI index) and change in homeowners insurance prices, separately, from 2011 to 2020. Then, we identify counties that experienced higher homeowners insurance price growth than housing price growth. We then visualize these counties in Figure 2. The yellow-shaded counties experienced higher homeowners insurance price growth than housing price growth. These counties are mostly those with low hurricane loss estimates, such as north Florida, but also include southern counties with high hurricane loss estimates, such as the Tampa area and the Keys.

[12] We use the most recent publicly available estimates reported in 2019 (`https://fphlm.cs.fiu.edu/files/wind_certification/v7.0Submission/Submission_Document/`).

[13] Using the full sample period (2011 to 2020) we calculate, for each county, the unconditional correlation between housing prices (using the NAL-HPI index) and homeowners insurance prices. In Figure B4, we visualize the rank of the correlation coefficients with the darkest shade representing counties with positive correlation coefficients. The lighter the shade, the more negative the correlation coefficient. The unconditional correlation is highest in parts of northern Florida and it is the lowest in the southern part of Florida. Metropolitan areas such as Orlando, Jacksonville, and Fort Myers report negative correlations.

3.2 Conceptual Framework on Homeowners Insurance and Housing Prices

Any recurring cost of homeownership should be capitalized into housing values. In a user-cost framework (Poterba 1984), the price of a house reflects the present value of expected net housing services. Homeowners insurance enters the user cost as an ongoing expense required to maintain ownership (and, for mortgaged households, typically required by lenders). Holding other components of user cost fixed, an increase in homeowners insurance costs reduces the net service flow from owning a home. In equilibrium, this reduction lowers the willingness to pay for housing and therefore decreases transaction prices. Appendix A provides a formal discussion of how insurance costs shift the user cost and the implied capitalization logic.

To operationalize this capitalization channel empirically, we use Rosen's (1974) hedonic pricing approach. The method is a revealed preference approach that infers the value of characteristics in differentiated products, typically used in real estate markets (e.g., Smith et al. 1988; Chay and Greenstone 2005; Greenstone and Gallagher 2008). It decomposes a product (e.g., housing) into its constituent characteristics and estimates each contributory value. We extend the model to include homeowners insurance costs to specify an individual's utility function as a concave function of property characteristics and a composite good representing all other consumption:

$$U_{i(j)t} = U(c, X_i, N_j, \mathrm{HO}_{i(j)t}, \alpha) \tag{1}$$

In this framework, X_i represents property-specific characteristics of house i. N_j captures demographic and economic characteristics in county j. $\mathrm{HO}_{i(j)t}$ denotes homeowners insurance costs for house i at time t. Our implicit assumption is that most homeowners are required to maintain homeowners insurance due to mortgage lender requirements and, therefore, homeowners insurance costs enter the household's budget constraint. Households are utility-maximizing agents constrained by their budgets, and they differ in their preferences for housing attributes, α.

Competition among buyers and sellers results in the hedonic equilibrium price schedule:

$$P_{i(j)t} = P_t(X_i, N_j, \mathrm{HO}_{i(j)t}) \tag{2}$$

Taking the derivative of the price function with respect to any of the observable attributes isolates the change in capitalized value associated with a marginal change in that attribute. This derivative reflects the implicit price of the attribute in equilibrium. Due to time-varying changes in hedonic equilibria, we interpret these effects as capitalized values that reflect the present market valuation of the attributes (Kuminoff and Pope 2014). The corresponding marginal effect is $\frac{\partial P}{\partial \mathrm{HO}} = \beta \frac{P}{\mathrm{HO}}$, and, evaluated at sample means, $\frac{\partial P}{\partial \mathrm{HO}} \approx \beta \frac{\bar{P}}{\overline{\mathrm{HO}}}$. In our log-log specification below, β is the elasticity of housing prices with respect to homeowners insurance costs.

3.2.1 OLS Regression

We estimate the following model specification:

$$\ln P_{i(j)t} = \beta \ln \mathrm{HO}_{jt} + X'_{it}\delta + N'_{jt}\lambda + \alpha_i + \alpha_t + \epsilon_{ijt} \tag{3}$$

In equation (3), $\ln P_{i(j)t}$ is the natural logarithm of the transaction price of house i (in county j) at time t. In the conceptual framework above, homeowners insurance costs are defined at the property level ($\mathrm{HO}_{i(j)t}$). Because we do not observe property-level premiums, we proxy for these costs using the county-quarter average homeowners insurance cost, HO_{jt}, and estimate its capitalization into transaction prices. Our key test variable, $\ln HO_{jt}$, is the natural logarithm of county-level average homeowner's insurance costs in county j, calculated as follows:

$$\mathrm{HO}_{jt} = \sum_k w_{kjt} \times \frac{\mathrm{DPW}_{kjt}}{\mathrm{PIF}_{kjt}} \tag{4}$$

where w_{kjt} is the share of private insurer k's insured property exposure to total insured property exposure of all private insurers combined in a given county j in a quarter t (we include all participating private insurers observed in QUASR to construct the variable), DPW_{kjt} is homeowners insurance direct premiums written by private insurer k in a county-quarter, and PIF_{kjt} is the number of private insurer k's homeowners insurance policies in force in a county-quarter.

The intuition behind our homeowners insurance price variable is that we measure property-exposure-adjusted average homeowners insurance price accounting for the homeowners insurers' participation that differs across county and time. It is crucial to account for both the insurers' market share and their differing property exposures, since insurance prices can differ for properties with the same housing attributes and housing prices depending on the insured loss exposure and the insurance company; the loss exposure is a function of both demand side factors (e.g., consumer choice on insurance coverage) and supply side factors (e.g., available coverage limits defined by insurers) in homeowners insurance markets.[14] This construct has an additional advantage, which is that we mitigate potential measurement error in QUASR driven by insurance companies with low coverage in a county.[15]

We control for a rich set of time-varying economic and demographic characteristics (N_{jt}) that are associated with housing and homeowners insurance price demand and supply in each county. These characteristics include demographic attributes (population, population density, unemployment rate, college attainment, the proportion of Black and Hispanic populations), income attributes

[14] An alternative measure would be to divide direct premiums written by insured property exposure; we would be calculating the unit price per loss exposure (i.e., insurance rates). Due to the non-linear relationship between the exposure and the price (e.g., a low-risk exposure is not priced significantly lower than a high-risk exposure), our preferred measure is the price per policy adjusted for the exposure.

[15] For example, insurance companies writing relatively few homeowners insurance policies for large properties will be accounted for more than those writing only a few number of policies for small properties. For robustness, we weight average homeowners insurance price by the total number of policies and find consistent results. In addition, we use un-weighted average homeowners insurance price and find large effect sizes. We report these results in Appendix Table B7.

(median household income, the percentage of households below the poverty line), and housing market attributes (median year of construction of homes, the percentage of owner-occupied homes, and the percentage of owner-occupied homes with a mortgage). We also include time-varying housing-level characteristics (X_{it}) that align with prior studies using similar datasets (e.g., Ihlanfeldt and Yang 2023). Specifically, we control for the total living area, square footage of the land area, property age, property age squared, an indicator that the property was renovated in the past five years, and indicators for structure quality (low, medium, or missing). In addition, we include location fixed effects (α_i) and year-by-month fixed effects (α_t).

We estimate equation (3) separately for the full sample, that includes all housing sales, and for a repeat-sales sample, which includes houses with at least two observed sales during our sample period. The location fixed effect, therefore, is zip code for the full sample and at the property level for the repeat-sales sample. The repeat-sales sample control for the unobserved time-invariant property characteristics (e.g., proximity to coastline), which can affect both homeowners insurance prices and housing prices. We cluster standard errors at the zip code level.

Our coefficient of interest, β, captures the relationship between changes in observed homeowners insurance prices on house prices using the full sample; in the repeat-sales sample, β captures the relationship between changes in observed homeowners insurance prices on house prices, holding constant unobservable time-invariant housing property amenities. The OLS specification estimates the correlation between homeowners insurance costs and housing prices, suggesting the extent to which these costs are capitalized into property values.

3.3 Instrumental Variable

The key concern for our estimate of β based on equation (3) is that observed homeowners insurance prices may be endogenous proxies for the true insurance-cost shock relevant to a housing transaction. On one hand, omitted local shocks, such as changes in property risk exposure or housing demand, may affect both homeowners insurance prices and house prices. On the other hand, county-quarter average homeowners insurance premiums are noisy measures of the marginal insurance-cost shock faced by a given buyer, which can attenuate OLS estimates toward zero. These concerns motivate our IV strategy, which isolates regulatory supply-driven variation in homeowners insurance prices that is plausibly orthogonal to local housing conditions.

3.3.1 Mandated Homeowners Insurers in Florida

Under Florida Statute §624.4055, insurers offering auto insurance in Florida must also offer homeowners insurance in Florida if they write homeowners insurance in other states, with an exception for auto insurers affiliated with a homeowners insurer writing in Florida.[16] After several insurers exited the Florida market due to the disaster losses arising from Hurricane Katrina, the statute was introduced in 2008, prior to the beginning of our sample period. A key aspect of the statute is that it mandates an auto insurer's participation in the homeowners insurance market by requiring them to "offer" policies, but without any related pricing restrictions.[17]

We find substantial differences in mandated insurer average observed prices compared to other insurers. In Figure 3, we report the observed average homeowners insurance price across counties in each year (premiums written divided by policies in force, from QUASR). We report prices separately based on an insurer's entry into the Florida market. "Existing" insurers offered homeowners insurance prior to 2007. "Voluntary Entrants" entered post-2007, but are deemed voluntary because they did not sell auto insurance in Florida when entering the homeowners insurance market. "Mandated Entrants" entered the market post-2007 and were required to offer homeowners insurance policies based on their Florida auto business. We find that the average homeowners insurance prices of mandated entrants are higher than either the existing or the voluntary entrants across the sample period.[18] We also find that the average prices of voluntary entrants are lower than those of existing insurers between 2012 and 2018.

A natural question is why homeowners would purchase policies from mandated entrants if those insurers charge higher premiums. We find evidence consistent with consumers' willingness to pay for low solvency risk. Prior literature shows that consumers are sensitive to insurer insolvency risk, so financially weaker insurers tend to compete by charging lower premiums (e.g., Sommer 1996; Cummins and Danzon 1997; Phillips et al. 1998; Froot 2007). We report the distribution for A.M. Best in Figure 4 Panel A and for Demotech in Panel B. A.M. Best is generally considered the market leader for insurer financial strength ratings while Demotech is somewhat newer with ratings that may

[16] The full statute is as follows: *Florida Statute § 624.4055 - Restrictions on existing private passenger automobile insurance.—No insurer writing private passenger automobile insurance in this state may continue to write such insurance if the insurer writes homeowners' insurance in another state but not in this state, unless the insurer writing private passenger automobile insurance in this state is affiliated with an insurer writing homeowners' insurance in this state.*

[17] We provide evidence that this statute significantly altered the composition of Florida's homeowners insurance market (Appendix Figure B5). Following the 2008 mandate, the market share of "No Auto" insurers grew substantially, from approximately 20% in early 2000s to 70% by 2014, indicating a significant shift in market structure. We face data limitations that prevent extending our main QUASR-based analysis further back in time. As discussed in Section 2, QUASR's reporting requirements do not differentiate between wind-only coverage in homeowners policies prior to 2011. We, therefore, use insurers' annual statutory statements to track data on auto insurance and homeowners insurance participation.

[18] We acknowledge that reported insurance prices only reflect the observed price of accepted homeowners insurance policies and would be a conservative comparison if the policies offered by mandated homeowners insurers are not accepted by policyholders due to excessive price.

contain noise (e.g., Sastry et al. 2023). For consumers who lack financial sophistication, these ratings represent the most straightforward signal of solvency. Even if consumers do not explicitly seek out ratings, these ratings likely are utilized by an insurance agent. We hypothesize that mandated entrants' stronger financial strength ratings justify homeowners' willingness to accept higher prices.

In Figure 4, higher prices from mandated entrants are consistent with those firms offering policies that are perceived as safer rather than simply more expensive. In Panel A, we observe that mandated insurers are more likely to have an A.M. Best rating and, when they do have Best ratings, they tend to be higher compared to non-mandated insurers. Turning to Panel B, non-mandated insurers are substantially more likely to have a Demotech rating, though mandated insurers tend to have higher Demotech ratings regardless. We confirm that mandated entrants are financially stronger than voluntary entrants along other dimensions. They are more profitable, less leveraged, and hold substantially more regulatory capital than non-mandated insurers (Appendix D).

3.3.2 Instrument Variable Construction

Leveraging the mandatory homeowners insurance market participation regulation in Florida, we construct an instrumental variable that captures the mandate pressure on homeowners insurance companies in a given county. The rationale behind our instrument is that, as documented previously, mandated homeowners insurers charge higher average homeowners insurance prices than homeowners insurers that do not participate in the auto insurance market.

Importantly, we account for mandated insurers' desire to avoid Florida's homeowners insurance market over other states. An earlier version of the mandate statute (the "Insurance Industry Accountability and Consumer Protection Act") refers to this behavior as "cherry picking." To capture firms that would have been "cherry picking," we construct a variable that measures how much an insurer is participating in homeowners insurance markets outside of Florida, relative to their participation in auto insurance markets. We construct *Non-FL Home Ratio*, which is the ratio of an insurer's premiums written in homeowners insurance in non-Florida states to the sum of premiums written in homeowners plus auto insurance in non-Florida states. We focus on the relative size of homeowners to auto insurance business given that these are the two largest personal lines insurance business (National Association of Insurance Commissioners 2025) and also because Florida's statute is based on insurers' participation in the auto insurance market. Our implicit assumption is that firms with higher *Non-FL Home Ratio* values would have had homeowners insurance as a more material part of their business than auto insurance in Florida, if not for concerns over natural disaster exposure in Florida.[19] Our construction of *Non-FL Home Ratio* is consistent with a host of recent studies that leverage an insurer's price or costs in other markets to instrument for its price in a market of interest (e.g., Koijen and Yogo 2015; Ge 2022; Ellis and Jaspersen 2025).

We multiply *Non-FL Home Ratio* with a mandate indicator variable: the indicator is equal to one for firms that enter the Florida homeowners insurance market post-2007 while also offering auto insurance in Florida, and zero otherwise. This multiplication captures the mandate pressure faced by these entrants—those that write homeowners insurance in other states but had previously avoided the Florida homeowners market. Because these firms also write auto insurance in Florida, which carries little catastrophe risk, their prior absence from the homeowners market reflects business risk considerations rather than regulatory barriers to operating in Florida. Specifically, our instrument (*Mandate IV*) for county j year t is calculated as:

$$\text{Mandate IV}_{jt} = \sum_{k \in j} I[\text{Mandated}_k] \times \left[\frac{\text{Non-FL Home}_{kt-1}}{(\text{Non-FL Auto} + \text{Non-FL Home})_{kt-1}} \right] \times w_{kj}^{t=0} \tag{5}$$

where the first component is the mandate indicator variable, the second component defines the previously-discussed *Non-FL Home Ratio*, and $w_{kj}^{t=0}$ is a mandate insurer k's initial share of the number of insurance policies in county j for the quarter measured when we first observe the insurer's market participation in each county. Homeowners insurance policies are annual, and therefore, we acknowledge that insurers may report different shares across quarters in a given year. Accordingly, we construct four quarter-specific initial shares for each county, corresponding to the insurer's market participation as first observed in each quarter. When calculating the insurer's share, we use the number of policies written by a mandated insurer k in the county. Equation (5) is therefore a shift-share style instrument in which $w_{kj}^{t=0}$ captures county exposure shares and the non-Florida business-mix term is the insurer-year shifter. This links our design to the quasi-experimental shift-share literature (Borusyak et al. 2022). A key concern in that literature is that nonrandom exposure shares can load on omitted county fundamentals through the predictable component of the instrument (Borusyak and Hull 2023). We therefore use predetermined shares, study the share and shifter components separately in Section 3.3.3, and report recentered-IV diagnostics in Section

[19] One concern is that by including all non-Florida states, we might not be accounting for differences in natural disaster risk across states. We checked the sensitivity of our results by limiting our calculation to non-Florida states that are i) catastrophe-prone (NAIC 2017) or ii) that reported high property losses from disasters. The results are consistent; this is not surprising given that many large states are catastrophe-prone (e.g., California, Texas) and many states also experienced disaster losses during our sample period. We, therefore, use the non-Florida states' measures as our instrument.

3.4.1. Using the initial share ensures that the variation in the instrument over time is not driven by changes in an insurer's market participation within a county.[20] Instead, the main source of variation comes from the time-varying, firm-level shifts in their non-Florida business mix, which is plausibly exogenous to local county-level housing market conditions.

A county-quarter with *Mandate IV* near zero has little exposure to insurers with the mandate pressure, whereas a county-quarter with *Mandate IV* closer to one has greater exposure to such insurers. We expect a county's homeowners insurance price to be higher if the county is written mostly by mandated insurers with high *Mandate IV* (i.e., insurers that could be looking to "cherry pick" were they not mandated to offer homeowners insurance).

3.3.3 Instrument Validity

We perform several tests to assess the validity of our instrument and whether it affects housing prices through insurance prices. To begin, we graphically depict the relevance of our instrument in Figure 5 Panel A. Specifically, this figure visualizes the first-stage relationship between our instrument on the horizontal axis (*Mandate IV*) and residualized (controlling for county and year-by-quarter effects) log homeowners insurance prices on the vertical axis. As expected, and consistent with our previous exploratory analysis, we observe a positive correlation between *Mandate IV* and homeowners insurance prices. This is consistent with the idea that mandated insurers offer more expensive policies, and counties with more mandated insurers report higher insurance prices, as discussed in Section 3.3.1 and Appendix D. This provides support for the relevance condition and indicates that the instrument operates through our hypothesized channel. Consistent with the instrument relevance reported in Figure 5 Panel A, Section 3.4 details our 2SLS results and the associated first-stage diagnostics, including F-statistics.

In Figure 5, Panel B, we examine the reduced-form relationship between our instrument (*Mandate IV*) and residualized (controlling for zip code and year-by-month effects) housing prices. We observe a negative correlation, suggesting that counties with more insurance offered by mandated insurers that also write homeowners insurance outside of Florida tend to report lower housing prices. Importantly, this reduced form pattern closely parallels the first stage relationship between the instrument and insurance prices, consistent with our hypothesis that the instrument affects house prices through insurance prices.

To further assess our identification strategy, we perform an instrument randomization test. We estimate county-quarter regressions where the dependent variable is either observed homeowners insurance prices, *ln(HO Price)*, or the instrument, *Mandate IV*. We standardize county characteristics so that the coefficient estimates are directly comparable across specifications. Table 2 indicates that observable county characteristics help explain homeowners insurance prices, but not the instrument. In column (1), unemployment and median income are positively correlated with *ln(HO Price)*,

[20] Our results are robust to using non-normalized initial shares and to fixing shares in 2006, two years before the mandate took effect, which further suggests that identification is driven by insurer-level shifts rather than endogenous changes in county exposure shares. To conserve space, we do not tabulate the results.

although the variables are not jointly significant. In column (2), county risk characteristics that are closely related to insurers' selection incentives are positively associated with homeowners insurance prices and are jointly significant. In contrast, columns (3) and (4) repeat the same specifications for *Mandate IV*. None of the coefficients are individually or jointly significant. This pattern supports the interpretation that the instrument is not systematically related to observable county fundamentals, including local risk measures that matter for insurer selection and pricing, even though those same fundamentals do help explain observed insurance prices.

Next, we separately examine the initial share and the shifter components of our IV. In Appendix Table B1, we find that mandated entrant initial market shares, a key component of our instrument that captures the regulatory shock, are not jointly correlated with these observable county characteristics. This evidence provides additional support for the interpretation that our instrument is not driven by systematic differences in observable county fundamentals. In Appendix Table B2, we examine the source of variation in our instrument's shifter component (i.e., the non-Florida homeowners/(homeowners+auto) direct premiums written ratio at the insurer group level). We regress this component on insurer financial and operational characteristics from NAIC annual statements. Across different specifications, the shifter is strongly predicted by insurers' size (*ln(Assets)*), reinsurance use (*Reinsurance Ratio*), product diversification (*Product HHI*), and risk-based capital (RBC) ratio, while the share of premiums from hurricane-prone states is statistically insignificant in all specifications. This collectively indicates that our instrument's shifter reflects insurers' national business portfolio composition rather than risk exposure tied to Florida (hurricane). While geographic concentration (*Geographic HHI*) is significant in the cross-sectional specifications, it becomes insignificant once we take into account insurer-specific unobservables through insurer fixed effects (column (3)), indicating that this correlation reflects differences across insurers rather than a time-varying confound.

Finally, another potential concern is that our instrument is correlated with unobserved local risk factors, which would violate the exclusion restriction. For example, if mandated entrants systematically expand in higher risk counties, and those counties also experience weaker housing price trends due to risk exposure rather than changes in homeowners insurance prices, the instrument could pick up risk-driven price dynamics instead of variation operating through insurance price. We test this directly in Appendix Figure B6. This figure plots the marginal effects of our instrument (in deciles) on two key proxies for local risk: county-level insured exposure (Panel A) and hurricane loss estimates (Panel B). Across all deciles, we find no statistically significant relationship between *Mandate IV* and either risk measure.

3.3.4 IV Regression

To implement our instrumental variables approach, we estimate the following first-stage regression:

$$\ln \text{HO}_{jt} = \gamma \text{Mandate IV}_{jt} + N'_{jt}\lambda + \alpha_j + \alpha_t + \epsilon_{jt} \tag{6}$$

where Mandate IV_{jt} is the instrumental variable. The second-stage equation estimates the impact of homeowners insurance on house prices:

$$\ln P_{i(j)t} = \beta \ln \widehat{\text{HO}_{jt}} + X'_{it}\delta + N'_{jt}\lambda + \alpha_i + \alpha_t + \epsilon_{ijt} \tag{7}$$

where $\ln \widehat{\text{HO}_{jt}}$ are the predicted values from equation (6); all other terms and clustering are as in equation (3).[21] If the conditions for a valid instrumental variable are met, β captures the causal effect of homeowners insurance prices on housing market outcomes. We discuss the results of first-stage estimates in Section 3.4.

3.4 Baseline Results

Table 3 reports OLS and 2SLS estimates of the effects of homeowners insurance prices on housing prices, as well as first-stage estimates. Columns (1) and (2) present OLS estimates for the full sample and the repeat-sales sample, respectively. In both specifications, the coefficient on ln(*HO Price*) is negative; the estimate is larger in magnitude in the repeat-sales specification (column (2), −0.115), consistent with attenuation in the pooled cross-section when time-invariant property amenities are not fully controlled for (Appendix Table B3 reports the full set of coefficients).

Columns (3) and (4) report 2SLS estimates for the full and repeat-sales samples, respectively. The IV estimates are substantially larger in magnitude than the OLS estimates (−0.65 and −0.60), implying that a 1% increase in homeowners insurance prices reduces housing prices by roughly 0.60–0.65%.[22] The coefficients suggest that a percent increase in homeowners insurance prices reduces housing prices by 0.65 to 0.60 percent.[23] We discuss the magnitude of these effects in comparison to prior studies in Section 3.4.2. The robust *Kleibergen-Paap F*-stats are 127.980 for the full sample and 114.254 for the repeat-sales sample, suggesting a strong relevance of our instrument. Consistent with the expectation, the first-stage results indicate that the homeowners insurance mandate instrument is positively associated with homeowners insurance prices.

[21] Results are qualitatively similar to clustering at the county level, to two-way cluster by county and sale month, and to two-way cluster by zip code and sale month as shown in Table B4.

[22] We also find similar results with large effect sizes when using average homeowners insurance prices before weighting with insured loss exposures (Appendix Table B7). Additionally, when restricting the analysis to the 2011–2018 period to address potential QUASR data reporting issues, although the repeat-sales estimates are less precisely estimated, our main 2SLS coefficient estimate remains negative and statistically significant (Appendix Table B5).

[23] Our results are also robust to controlling for the potential property renovations, as reported in Appendix Table B6. For each property, we track the history of the properties' construction. We identify properties that report a significant renovation through the "Effective Year Built" variable in their property tax roll. We also identify properties that report an upgraded quality score in their property tax roll. Controlling for these variables and interacting them with the insurance price variable does not change our baseline estimate of the insurance price, as shown in Appendix Table B6.

3.4.1 Reconciling the Difference between OLS and IV Estimates

The IV estimates in Table 3 are substantially larger in magnitude than the corresponding OLS estimates. In our setting, we view this gap as arising primarily due to attenuation: county-quarter average homeowners insurance premiums are noisy proxies for the marginal insurance-cost shock relevant to a given transaction, whereas our instrument isolates a cleaner, regulatory supply-driven component of premium variation.[24] Progressively enriching the set of control variables only changes the OLS coefficient modestly (Appendix Table B8), and the accompanying Oster (2019) calculation yields $\delta = -0.79$ (with $R_{\max} = 1$), implying that unobservables would need to offset, rather than reinforce, the selection captured by observables to eliminate the controlled OLS estimate.[25] We also find that our IV is not driven by coastal or otherwise high-risk segments of the market (Appendix Table B9). The first stage is not concentrated solely in the most obviously high-risk geographies; if anything, it is strongest in recently-affected locations and in the low-loss tercile rather than the high-loss tercile.[26] Finally, the negative IV estimate is not fragile to moderate exclusion restriction violations. Following Conley et al. (2012), even allowing the instrument to directly effect house prices equal to 50% of the reduced form, the identified interval remains negative (Appendix Table B10).

A formal IV-OLS decomposition analysis following Ishimaru (2024) confirms that the marginal-effect component accounts for almost all of the observed gap, with the covariate-weight and treatment-level weight components near zero (Appendix Table B11). [27] This is consistent with the gap reflecting attenuation/endogeneity in OLS together with heterogeneity in the IV-identified margin, rather than simple reweighting on observables already in the model.

Furthermore, the IV estimates are likely not mechanically inflated by predictable components of the shift-share instrument. Using the Borusyak and Hull's (2023) recentered-instruments logic, we either add the expected instrument component (μ) as a control or replace the excluded instrument with its recentered counterpart under alternative exchangeability cells (Appendix Table B12). Across these specifications, the coefficient estimates remain negative. At the same time, the recentered specifications are much less precise and materially weaken the first stage relative to the baseline IV. We, therefore, interpret recentered IV results as diagnostics rather than preferred replacement estimators.

[24] The gap is also not driven by any particular definition of homeowners insurance premiums. Appendix Table B7 indicates that across alternative premium measures, OLS remains much closer to zero than 2SLS in both the full and repeat-sales samples. For example, in the full sample, the exposure-weighted premium measure yields OLS -0.080 and 2SLS -0.654, while the unweighted premium measure yields OLS -0.132 and 2SLS -1.101. Changing the premium proxy affects scale and precision, but it does not eliminate the large OLS–IV gap.

[25] We interpret the Oster (2019) proportional-selection result as suggestive rather than dispositive because it relies on proportional-selection assumptions and within-R^2 from fixed-effect regressions.

[26] Appendix Table B9 is descriptive rather than causal, but it is useful for assessing whether the IV is concentrated only in obvious high-risk coastal segments.

[27] The decomposition is performed using the Stata package `ivolsdec`, which is designed for discrete treatment variables. Since the theoretical framework in Ishimaru (2024) does not differentiate between continuous and discrete treatment variables, we transform our continuous homeowners insurance prices into discrete categories as basis functions. The results reported here use deciles, and the decomposition is qualitatively similar under coarser or finer categorizations.

3.4.2 Magnitude and Property Tax Implications

Our baseline IV estimates imply economically meaningful capitalization of homeowners insurance costs into house prices. Using the full-sample 2SLS estimate, a 1% increase in homeowners insurance prices reduces housing prices by about 0.65%. Because there is little prior work on private homeowners insurance and house prices, the closest comparison is Nyce et al. (2015), who report an OLS elasticity of −0.1039 for Miami-Dade County's residual market. Our estimate is materially larger in magnitude, which likely reflects differences in geography, insurance market segment, sample period, and identification strategy.

A helpful way to interpret this magnitude is through the user cost channel that underlies property tax capitalization. Like property taxes, homeowners insurance is a recurring expense that lowers the value of owning the property. The public finance literature therefore provides a natural comparison point: property taxes are generally capitalized into house prices, with estimates ranging from partial to near full capitalization (e.g., Oates 1969; Rosen and Fullerton 1977; Rosen 1982; Palmon and Smith 1998; Gallagher et al. 2013; Lutz 2015; Koster and Pinchbeck 2022; Gárate and Pennington-Cross 2023).

To benchmark our implied discount rate, we assume the price effect is valued as a perpetual change in annual user costs (Giglio et al. 2015). Using the mean homeowners insurance premium ($2,540) and mean house price ($179,872), a 10% premium increase ($254) combined with an approximate 6.5% price decline implies a discount rate of about 2.2%. This rate is below the 4.5% implied in Coven et al. (2024) for property taxes, which is plausible because property taxes fund valued local public goods that partially offset their burden, whereas homeowners insurance is a pure financial cost with no comparable consumption benefit beyond risk transfer.[28] This low rate is consistent with Giglio et al. (2021), who infer that very long-run housing cash flows are discounted at rates below 2.6%.

These calculations also imply sizable consequences for local public finance. Florida's owner-occupied housing stock is approximately $2.2 trillion; applying a 6.5% price decline implies an aggregate loss of roughly $144 billion.[29] Applying Florida's effective property tax rate of 0.71%, this implies an annual loss of roughly $1.0 billion in property tax revenue.[30] On a per-house basis, the average decline in value is about $19,100, with an associated annual tax loss of about $136.

[28] The corresponding benchmark from property tax studies can be higher for two reasons. First, property taxes finance local public goods, so the net price effect reflects both the tax burden and the value of amenities; when public goods are underprovided, additional spending can increase house prices. For example, Cellini et al. (2010) find that passing school facility bond referenda raises nearby house prices, consistent with positive capitalization of valued spending. Second, tax changes may be perceived as partly transitory because assessments, millage rates, and exemptions can adjust over time; expected reversals attenuate capitalization relative to a pure, permanent cost.

[29] Calculated by multiplying 7.5 million housing units (U.S. Census: Link) by the median home value ($292,768) estimated from our sample.

[30] Tax Foundation: Link.

These magnitudes are substantial. In fiscal year 2021, combined state and local general revenues totaled \$205 billion (\$9,389 per capita), of which property taxes accounted for \$1,624 per capita, or about 17% (roughly \$35 billion).[31] Our estimated annual loss of roughly \$1.0 billion therefore corresponds to about 3% of total property tax revenues. Because these revenues are generated by all property types (residential, commercial, and industrial), this 3% figure understates the proportional impact on the owner-occupied segment alone. Finally, we quantify the longer-run fiscal implications under Florida's "Save Our Homes" amendment, which caps annual assessment growth for homesteaded properties at the lesser of 3% or CPI.[32] Assuming a 7% discount rate and 3% annual property value growth, the present value of the recurring property tax loss is approximately \$4.4 billion over five years and \$8.0 billion over ten years.[33] These back-of-the-envelope calculations are illustrative rather than fiscal forecasts, but they suggest that insurance affordability can affect local public finance through the property-tax base.

3.5 Mechanisms

3.5.1 Mortgage Lender Requirement

The results so far indicate that higher homeowners insurance price reduces housing prices. We examine potential mechanisms underlying the relationship, beginning with mortgage financing constraints. In a user-cost framework (Poterba 1984) discussed in Section 3.2 and Appendix A, homeowners insurance is a non-discretionary component of the ongoing cost of ownership. For mortgage-financed buyers, lenders typically mandate continuous coverage, meaning higher insurance premiums mechanically increase the effective user cost and tighten affordability constraints. As a result, an increase in homeowners insurance costs reduces the maximum price a mortgaged-dependent buyer can bid, leading to greater capitalization into transaction prices. In contrast, cash buyers are not subject to lender insurance requirements and therefore may be less responsive to insurance price increases.

To illustrate this buyer-side constraint, consider two prospective bidders. For a cash buyer, homeowners insurance is an optional expense that may not strictly bind their budget. For a mortgage-dependent buyer, however, an increase in premiums reduces the disposable income available for debt service and limits the maximum bid they can offer under their lender-imposed credit constraints. This divergence reflects the role of insurance as a required consumption good for mortgaged buyers.

On the seller side, rising insurance costs may also influence the willingness to accept. For existing homeowners with a mortgage, higher premiums impose a financial burden that can increase the likelihood of default (Ge et al. 2024). In such cases, financially distressed sellers may be more inclined to accept lower offers to avoid foreclosure, further amplifying the negative effect of insurance costs on house prices.

[31] State Fiscal Briefs, Urban Institute: Link.

[32] Section 193.155, Florida Statutes (F.S.): Link.

[33] Computed as the present value of a growing annuity with a \$1.0 billion initial loss, 3% growth, and 7% discount rate over 5 and 10 years, respectively.

To empirically test this mechanism, we interact our homeowners insurance price variable with proxies for areas with a high prevalence of mortgage-dependent homeowners (*High Mortgage*):

$$\begin{aligned}\ln P_{i(j)t} = {} & \beta_1 \ln \widehat{\mathrm{HO}}_{jt} \cdot \text{High Mortgage}_{jt} + \beta_2 \ln \widehat{\mathrm{HO}}_{jt} \\ & + \beta_3 \text{High Mortgage}_{jt} + X'_{it}\delta + N'_{jt}\lambda + \alpha_i + \alpha_t + \epsilon_{ijt}\end{aligned} \tag{8}$$

We proxy for mortgage prevalence in two ways to distinguish between the seller and buyer sides of the market. First, we use ACS data on the percentage of owner-occupied homes with a mortgage. This measure reflects the owner (i.e., *seller*) by capturing the existing prevalence of mortgage financing among current homeowners in each county. In each year, we identify counties with a high percent (top tercile) of owner-occupied homes with a mortgage (*High Mortgage*). Because we include zip code fixed effects, the coefficient on the interaction term ($\ln HO_{jt} \cdot \textit{High Mortgage}_{jt}$) captures differential capitalization in areas with higher prevalence of mortgaged homes.

Second, we use property-level data from NAL and data on mortgage origination from HMDA to identify the percent of homes sold with mortgage originations. Compared to the ACS data, this measure more directly reflects the *buyer* side by capturing the prevalence of new homebuyers using mortgage financing. This buyer-focused measure provides a more accurate representation of active participants in the market, allowing us to examine the role of lender requirements during the bidding process. This approach further allows us to construct a granular census-tract variable to identify variation within counties. Similar to the *High Mortgage* variable, we identify census tracts with a high percent (top quartile) of mortgage originations in any given year (*High Origination*). We calculate the percent in two ways: number of properties and the value of properties.

We report the results in Table 4, focusing on the 2SLS models using the full sample (the results are generally consistent to using the repeat-sales sample, which we report in Appendix Table B13). Table 4, column (1) reports the results using the seller-side *High Mortgage* variable, where we do not find a statistically significant coefficient on the interaction term, suggesting that existing homeowners' leverage does not drive differential capitalization. In columns (2) and (3), we report results using the buyer-side *High Origination* variables constructed with the number of properties and the value of properties, respectively. Both columns report similar results that are in line with our expectation—areas with a high prevalence of mortgage originations respond more to the increase in homeowners insurance prices than other areas. The full effect in each column (-0.699 and -0.731) is more pronounced than our baseline estimate from Table 3. This finding supports the idea that the financial constraint mechanism imposed by mortgage lenders on new buyers is a key channel for the capitalization of insurance costs. We also find that areas with higher mortgage activity generally command higher average housing prices.

3.5.2 Reservation Price of Homeowners Insurance

Subjective beliefs regarding future disaster losses determine the marginal utility households derive from the homeowners insurance-housing bundle. Within the hedonic framework, insurance is a component of a composite housing good, providing utility by mitigating potential wealth shocks from climate-related events (Poterba 1984). Following Baldauf et al.'s (2020) logic, we posit that households with a higher perceived risk of natural disasters (i.e., "believers") place a higher valuation on insurance as a necessary hedge. For these buyers, the high reservation price for insurance makes their willingness to pay for the housing bundle less sensitive to premium fluctuations. Consequently, insurance price increases should have a smaller capitalization effect in high-risk-perception areas. In contrast, buyers with lower perceived risk derive less marginal utility from insurance and are more likely to view premiums as a pure friction, making their demand for housing more elastic with respect to insurance costs.

Since individual risk perception is unobservable, we construct three county-level proxies for risk salience using the data sources described in Section 2.3. The first variable is the risk score from the National Risk Index (NRI), produced by FEMA and used in the property insurance literature (Eastman and Kim 2023; Mulder and Kousky 2023). NRI scores incorporate expected annual losses as well as risk measures that reflect community-level resilience and social vulnerability (Zuzak et al. 2021). Although the data is a snapshot measure, the NRI captures elements of risk "perception," distinguishing it from measures like SHELDUS, which focus solely on historical loss data. We define a binary variable *High Risk Score* that equals one for counties in the top tercile of NRI scores and zero otherwise.

The second and third variables are derived from the Yale Climate Opinion Map 2015 (Howe et al. 2015). Specifically, *Belief* is calculated as the average percentage of affirmative responses to these questions. We then define a binary variable, *High Belief in Risk*, that equals one for counties with the top tercile of *Belief* value and zero otherwise. Similarly, *High Risk Perception*, based on questions under the category of "risk perceptions," is similar to the way we construct the *High Belief in Risk* variable.[34]

Using these three time-invariant variables, we estimate our model with an interaction term measuring the prevalence of high risk perception similar to equation 8. Table 5 reports the 2SLS estimates, with repeat-sales results provided in Appendix Table B14. The findings support our hypothesis across all three specifications. While the baseline effect of insurance prices remains negative and significant, the interaction term (β_1) is positive and statistically significant. This suggests that the negative capitalization of insurance costs is significantly attenuated in areas with

[34] *Belief* is based on responses to questions about (a) whether climate change is happening; (b) whether it is human-caused; (c) whether there is scientific consensus; and (d) whether they believe they will be personally affected. *High Risk Perception* is based on questions under the category of "risk perceptions," including (a) whether they are worried about global warming; (b) whether they believe that global warming will harm plants and animals; (c) whether they believe that global warming will harm future generations; (d) whether they believe that global warming will harm people in developing countries; (e) whether they believe that global warming will harm people in the US; (f) whether they believe that global warming is already harming people in the US; and (g) whether they have personally experienced the effects of global warming.

high perceived risk. Specifically, the positive interaction term partially offsets the main effect, indicating that "high-risk" buyers are willing to absorb a larger share of insurance cost increases to maintain coverage. This finding provides empirical support for the belief-based capitalization channel documented by Baldauf et al. (2020), where subjective risk perceptions act as a primary moderator in how climate-related costs are integrated into asset prices.

3.5.3 Competition and Residual Market

The third mechanism we explore is how homeowners insurance supply frictions are capitalized into residential properties. In theory, private insurers gain pricing power in counties with low insurer competition. However, in Florida, supply is bifurcated between private insurers and the state-sponsored residual market, Citizens Property Insurance Corporation ("Citizens"). Although Citizen's primary purpose is to insure residual risks, its market share has expanded significantly in Florida (Born et al. 2021). Homeowners typically migrate to Citizens when private insurers either withdraw (i.e., availability failure) or charge excessive prices (i.e., affordability failure). In areas with limited supply from private insurers, Citizens creates a non-linear "price-ceiling" effect. Because high-risk, high-premium properties shift to the public option, average private homeowners insurance prices in these areas appear artificially suppressed. Consequently, while the true cost of insurance is internalized by the buyer, the resulting decline in housing prices may appear moderated in our private insurance market data.

Conversely, the Citizens Depopulation program introduces a countervailing force. Private insurers "take out" lower-risk policies from Citizens at rates below the public level but often above existing private averages. This potentially increases average private insurance prices. Furthermore, while "take-out" insurers increase nominal competition, they often carry higher insolvency risk (Sastry et al. 2023). This pushes mortgage-dependent buyers—who require coverage for financing—toward lower-rated, lower-cost providers. In low-competition counties with high depopulation activity, we conjecture that this necessity-driven sorting further exacerbates the downward pressure on housing prices.

We formally test these proposed competition and residual market effects. To begin, we identify counties with low competition among private homeowners insurers. We use a predetermined measure of low competition using each county's Herfindahl-Hirshleifer Index (HHI) measured at the beginning of our sample (2011 Q1).[35] We measure the HHI of private homeowners insurers using the number of policies written, since premiums will inaccurately capture price, not the quantity. We proxy low competition by identifying top tercile counties in terms of predetermined HHI. Then, we interact our homeowners insurance price variable with the low competition indicator *(Low Competition)*, similar to equation 8.

[35]The cross-sectional distribution of HHI is stable. Of the counties in the top tercile in 2011 Q1, 75% remain in the top tercile through the end of the sample. Furthermore, a regression of current HHI on 2011 Q1 values (including year-quarter fixed effects) yields a coefficient of 0.60 ($t = 8.88$), indicating significant path dependency in insurer concentration.

We report the results in Table 6 column (1).[36] As expected, we find a statistically significant and negative coefficient on β_1 and β_2. The combined effect of homeowners insurance prices on housing prices in low competition areas is -1.107, which is larger than our baseline estimate in Table 3.

Next, we test the effects of Citizen's growing market share. In Table 6 column (2), we fully interact the insurance price variables, ($\ln \widehat{HO}$ and $\ln \widehat{HO} \cdot$ *Low Comp.*), with an indicator, *High Citizens*, which identifies the top tercile counties in terms of new policies written by Citizens in each year-quarter. In each quarter, we calculate the number of new Citizens policies in a county relative to total new Citizens policies in the state.[37] We report the results in Table 6 column (2). As hypothesized, we find the moderating effect of Citizens' presence in low competition counties. The magnitude of the coefficient estimate on ($\ln \widehat{HO} \cdot$ *Low Comp.*) is larger than in column (1), while the coefficient estimate on the triple interaction term ($\ln \widehat{HO} \cdot$ *Low Comp.* $\cdot$ *High Citizens*) is statistically significant and positive (0.18). We also find that the moderating effect of Citizens is not observed in counties with sufficient competition, as the coefficient estimate on ($\ln \widehat{HO} \cdot$ *High Citizens*) is not statistically significantly different from zero (p-value = 0.65). It is important to note that the moderating effects of Citizens do not imply that the homebuyers' capitalization of insurance cost is smaller; it is simply not captured through our private homeowners insurance prices. As documented by Nyce et al. (2015), Citizens' prices are also negatively associated with housing prices.

Our third test examines the effect of Citizens' depopulation. To isolate the effect of Citizens' depopulation from the growing presence of Citizens, we calculate the share of beginning-of-quarter Citizens' policies transferred to private insurers (i.e., depopulation). The tercile category indicator (*High Depop*) identifies counties with high depopulation share in each year-quarter. We are primarily interested in counties with low competition and high depopulation activity. Therefore, we fully interact *High Depop* with insurance price variables ($\ln \widehat{HO}$ *and* $\ln \widehat{HO} \cdot$ *Low Comp.*). We report the results in Table 6 column (3). As predicted, the sign of the coefficient estimate on the triple interaction term ($\ln \widehat{HO} \cdot$ *Low Comp.* $\cdot$ *High Depop*) is negative and statistically significant at -0.11 (p-value = 0.086). The combined effect of high Citizens depopulation in low competition counties is statistically significant and negative (-1.136). In comparison to the estimates in columns (1) and (2), the results imply that low competition and high depopulation reverse the moderating effects of Citizens in areas with limited availability. In counties with sufficient competition, we do not find a statistically significant effect of depopulation, and the effect size is small (0.0023, p-value = 0.90).

[36] Our results are consistent using the repeat transaction sample, which we report in Appendix Table B15.

[37] We use the number of policies because the insured exposure for new Citizens policies is not reported in our data; we also believe the number of policies will sufficiently capture the presence of Citizens. Our results are similar if we rank counties by the share of new Citizens policies relative to total policies written in the county. This measure, however, is endogenous to the private market participation in the county. Our preferred measure, therefore, is the relative share of the total in the state.

3.6 Alternative Explanations

3.6.1 Disaster experience

A potential threat to our identification strategy is that the estimated effect of insurance premiums could be confounded by the direct impact of natural disasters. Prior research suggests that disaster-stricken areas may experience a dual shock: a decline in property values due to both physical damage and a spike in insurance premiums (Bernstein et al. 2019; Bakkensen and Barrage 2022). In such a scenario, insurance costs might proxy for the underlying disaster shock rather than exerting an independent effect on prices. If this was the case, we would expect the effect of homeowners insurance prices on housing prices to be statistically indistinguishable from zero once we control for the disaster losses. However, if disaster experience leads to "double-devaluation," disaster-affected properties suffer a disproportionate price decline due to the compounding effect of physical risk and rising insurance costs. To examine these hypotheses, we leverage a unique feature of our dataset: property-level disaster indicators from the NAL assessment data. While most prior studies rely on aggregate, county-level proxies for disaster exposure (e.g., SHELDUS or FEMA disaster declarations), our data allow us to identify with high precision whether a specific structure was flagged by county tax offices as having sustained damage in the preceding three years. This granular identification enables us to disentangle the physical impact of a disaster from the broader insurance supply shock.

We find evidence of "double-devaluation," which we report in Table 7 column (1). The reduction of housing prices due to increasing homeowners insurance prices is larger for properties with past disaster experience; when controlling for time-invariant property-specific characteristics using a repeat-sales model, however, we do not find differences in properties with and without disaster experiences (Appendix Table B16 Column (1)). Importantly, properties without disaster experience also experience a similar reduction of housing prices due to increasing homeowners insurance prices. [38]

3.6.2 Flood Zones

Standard homeowners insurance policies do not cover flood damage, which is primarily insured through the National Flood Insurance Program (NFIP). A large literature documents capitalization of flood risk and NFIP premiums into housing values (e.g., Harrison et al. 2001; Bin and Kruse 2006; Bin et al. 2008; Ge et al. 2024; Georgic and Klaiber 2022). This work, however, is inherently concentrated in designated flood zones (only about 19% of Florida homes had flood coverage in 2019, see Section 1), whereas homeowners insurance is a near universal requirement for mortgage financed transactions across the entire housing stock.

[38] We also test the sensitivity of our disaster variable by using natural disaster property losses (SHELDUS) and hurricane modeled losses (FPHLM) instead, and find consistent results. These findings imply that insurance costs exert an independent economic influence on housing prices that is not merely a mechanical artifact of disaster losses.

We use flood zones to clarify the incremental contribution of our analysis and to test whether the capitalization of private homeowners insurance costs differs in locations where flood insurance is more salient. Using the NFIP flood map, we define an indicator for coastal flood zones (V or VE).[39] We then augment our baseline model by interacting this flood zone indicator with ln(*HO Price*).

Table 7 column (2) indicates that flood zone status does not materially change the sensitivity of house prices to private homeowners insurance prices. The interaction term is small and statistically indistinguishable from zero, and the coefficient on ln(*HO Price*) remains essentially unchanged relative to our baseline estimates. This finding suggests that coastal flood zone status does not materially alter how private homeowners insurance premiums are capitalized into house prices. One interpretation is that flood insurance coverage and pricing are heterogeneous even among exposed homes, consistent with evidence of incomplete take-up and uneven responses to flood risk (e.g., Bin et al. 2008; Kousky 2010, 2011; Atreya and Czajkowski 2019; de Koning et al. 2019). This test is not designed to estimate the capitalization of NFIP premiums directly. Rather, it implies that the private homeowners insurance channel we identify operates broadly across the mortgaged housing market, complementing the flood insurance literature that focuses on a subset of properties.[40].

In the repeat sales specification with property fixed effects, the estimated sensitivity to homeowners insurance prices is more negative for coastal flood zone properties (Appendix Table B16 column (2)). For these homes, insurance related costs may increase more sharply over time, consistent with evidence of rising NFIP pricing and flood risk salience (Georgic and Klaiber 2022; Ge et al. 2024). Importantly, the baseline effect of homeowners insurance prices remains close to our main estimates, indicating that homeowners insurance is a distinct cost, independent of and not eroded by the specific risks associated with flood zone designation.

3.6.3 Housing Supply Elasticity

Capitalization of recurring costs could be affected by housing supply elasticity (Baum-Snow and Han 2023). When supply is fixed, increases in user costs must be fully absorbed by lower property values (Lutz 2015). Conversely, in markets with highly elastic supply, developers can theoretically adjust the quantity of housing (e.g., by slowing construction), which should mitigate the negative impact on prices. We test whether supply constraints explain heterogeneity in capitalization using housing supply elasticity estimates from Baum-Snow and Han (2023), aggregated to the county level for all 67 Florida counties via a weighted average of occupied housing units in 2000. This measure best captures the extensive margin of supply (new units) while accounting for unobserved heterogeneity across metropolitan areas.[41] We do not find differences in insurance price capitalization

[39] We use the 2023 NFIP map. As pointed out by Sastry (2022), we acknowledge that properties' designation of flood risk levels can vary over time. We, therefore, focus on the coastal flood risk identifier, which remained stable throughout the sample period.

[40] Results are similar when we use the broader Special Flood Hazard Area definition

[41] We define *High Elasticity* as an indicator equal to one if a county's weighted average elasticity exceeds the sample median. The housing unit's elasticity is estimated via the quadratic Finite Mixture Model (FMM) based on 2001 tract characteristics. We also use alternative linear IV estimates from Saiz (2010), separately based on 2001 and 2011 data. Our results are consistent.

into property values that are driven by housing supply elasticity (Table 7 column (3)). This finding suggests that insurance cost capitalization is not driven by long-run supply adjustments. Instead, the capitalization we observe is consistent with immediate demand-side constraints. Because insurance premiums are a non-discretionary component of mortgage qualification, they bind immediately for buyers regardless of developer responses, so the "financing channel" likely overrides the "quantity adjustment channel." Our results are also consistent in the repeat-sales sample, as reported in Appendix Table B16.

3.6.4 Homeowners and Investors

Capitalization of recurring costs depends on the buyer's horizon and the nature of the utility derived from the asset. In Rosen's (1974) hedonic framework, property values reflect the equilibrium between a household's consumption utility and the associated cost of ownership. Poterba (1984) further posits that for owner-occupants, insurance premiums are a direct component of the user-cost of housing services. In contrast, institutional investors or "flippers" prioritize short-term financial returns and capital gains over long-term consumption utility. Consequently, we expect owner-occupants to be more sensitive to supply-driven insurance shocks, as these costs directly impair their long-term affordability and net utility. We find that owner-occupants bear a statistically larger burden from rising insurance costs. We use Florida's *Homestead Exemption*, which is restricted to primary residences, as a proxy for owner-occupant. The homeowners claiming homestead exemption report a larger reduction in housing prices due to increasing homeowners insurance prices, as reported in Table 7 column (4). In contrast, we find no evidence that short-term investors respond differently to insurance prices than the baseline. We proxy for speculative investors using a *Quick Sale* indicator for properties resold within 12 months, following Bayer et al. (2021). This finding is consistent with speculative investors' focus on short-term financial returns rather than long-term consumption utility (column (5)). Our results are consistent in repeat-sale model estimates (Appendix Table B16 Columns (4) and (5)).

4 Homeowners Insurance Price and Housing Sales

Thus far, we have documented evidence that increasing homeowners insurance prices reduces housing prices (i.e., the intensive margin). Our final empirical analysis investigates the extensive margin by studying the relationship between homeowners insurance prices and the likelihood of housing transactions. If households internalize rising insurance costs when deciding whether to buy, we would also expect completed sales to fall as homeowners insurance becomes more expensive. To the extent higher insurance costs cause some transactions to fail before closing, the estimates below may understate the full extensive-margin effect because our data only observe completed sales.

Using tax assessment data that includes all single-family homes, both sold and unsold, we construct a measure of property sales probability for each county-quarter. The outcome variable is the county-quarter-level property sales probability (in decimals). We estimate the following OLS model:

$$\%Sale_{jt} = \beta \ln \mathrm{HO}_{jt} + N_{jt} + \alpha_j + \alpha_t + \epsilon_{jt} \tag{9}$$

where $\%Sale_{jt}$ is the percent of homes sold in county j quarter t. We report the results in Table 8, with the columns differing in terms of the control variables included in the regression models. Across columns, we find that increases in homeowners insurance prices are associated with lower housing transaction volume, suggesting that home buyers are responding to the financing costs of homeowners insurance. The unconditional average probability of home sales in our sample is 0.016 (1.6%), suggesting that our estimated effect of homeowners insurance price account for approximately 18% (0.003/.016) of the housing sales probability.

5 Conclusion

Homeowners insurance is the key financial contract that helps homeowners finance various financial losses arising from property damage and liability exposure. While it is the most material insurance for homeowners, the existing literature at the intersection of insurance and residential real estate focuses on public insurers such as the NFIP or state-run public insurance programs. To the best of our knowledge, we are the first to examine the effect of private homeowners insurance on housing prices. Our rich dataset which identifies property-level characteristics, as well as variations in private homeowners insurance across time and counties in Florida, allows us to explore various aspects of homeowners insurance and their effects on housing prices.

Using detailed insurer-county-quarter homeowners insurance data linked to property-level housing transactions, we first find that higher homeowners insurance prices is associated with lower house values. To identify a causal effect, we exploit a Florida regulation that requires certain auto insurers to participate in the homeowners insurance market if they offer homeowners coverage in other states. Our instrument combines predetermined county exposure to these mandated entrants with insurer-year changes in their non-Florida business mix, generating a shift-share style source of regulatory supply-driven variation in homeowners insurance prices. The validation tests and additional diagnostics indicate that observed county-quarter premiums are noisy and endogenous proxies for the marginal insurance-cost shock relevant to a housing transaction, while the IV more cleanly isolates the supply-driven component of premium variation. Our preferred IV estimates imply that a 10% increase in homeowners insurance prices lowers housing prices by roughly 6.5%, and also reduces housing market activity on the extensive margin.

We also shed light on the mechanisms through which homeowners insurance prices are capitalized into housing values. The effect is larger in areas with more mortgage-financed buyers, consistent with insurance costs tightening borrowing constraints at the point of purchase. Moreover, the effect of insurance prices is moderated by homeowners' risk perceptions; in counties with higher perceived risk, housing prices are less sensitive to insurance cost changes. Finally, limited private insurer competition amplifies the capitalization effect, while a larger Citizens presence moderates it; depopulation of Citizens policies back into the private market weakens that moderation.[42]

Overall, our findings indicate that private homeowners insurance is an important channel through which climate-related financial pressures affect housing markets. As insurance costs continue to rise in disaster-prone regions, these pressures are likely to spill over not only into house values and transaction activity, but also into local public finance through the property-tax base. Our back-of-the-envelope calculations imply that a 10% increase in homeowners insurance prices could reduce Florida owner-occupied housing wealth by roughly $144 billion and annual property tax revenues by about $1.0 billion. More broadly, the interaction between insurance-market supply and housing-market outcomes is likely to become increasingly important for both researchers and policymakers in climate-vulnerable areas.

[42] But we caution readers that such moderation is a result of a shift of residual risks from the private market to the public market and not necessarily indicates that homeowners' costs are reduced.

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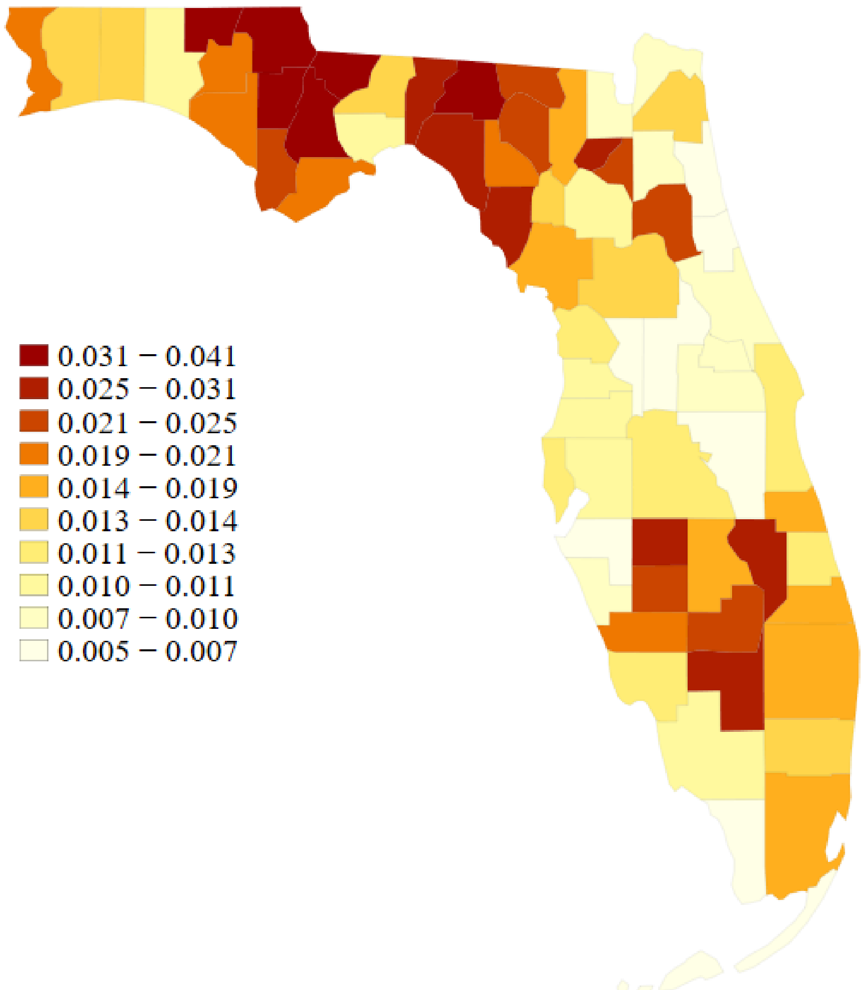
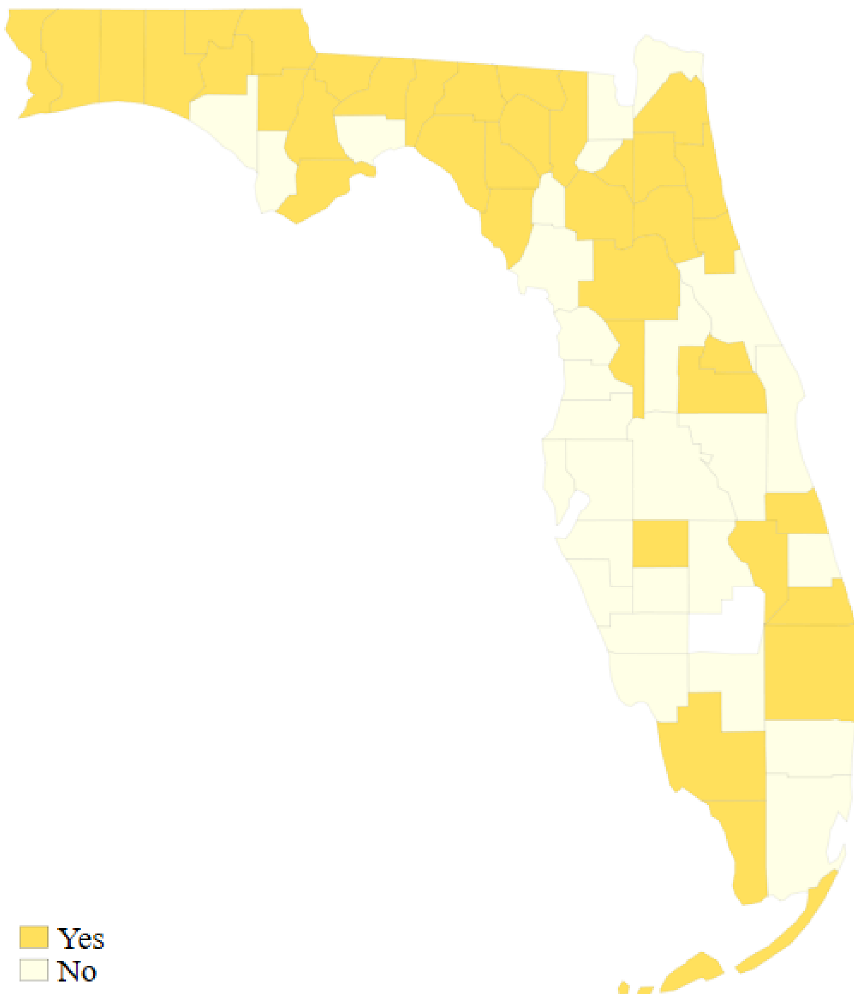
Figure 1: County-Level Homeowners Insurance Price Scaled by House Prices



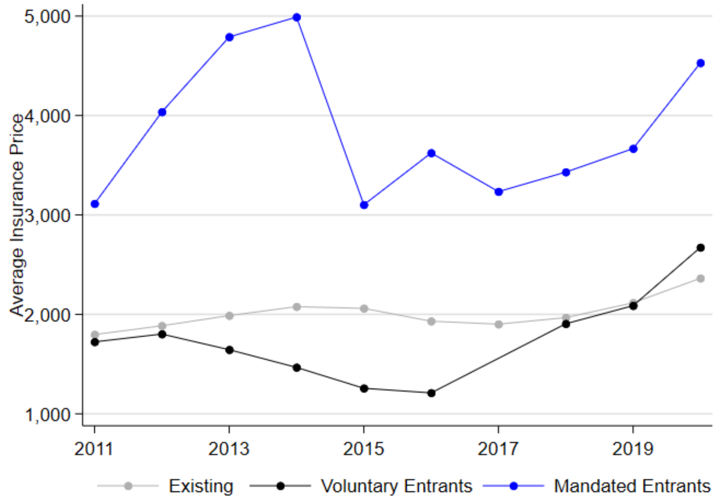
Source: NAL for housing prices and QUASR for homeowners insurance prices.
Notes: This figure reports the average ratio of homeowners insurance prices to housing sales prices for each Florida county in 2019.

Figure 2: Changes in Homeowners Insurance Prices and Changes in House Prices by County



Source: NAL for housing price and QUASR for homeowners insurance prices.
Notes: This figure reports the relationship between changes in house sales prices and changes in homeowners insurance prices at the county level. Counties shaded in dark yellow experienced larger increases in homeowners insurance prices relative to increases in housing prices across our sample period (2011 to 2020). Counties shaded in light yellow experienced larger increases in housing prices relative to homeowners insurance prices.

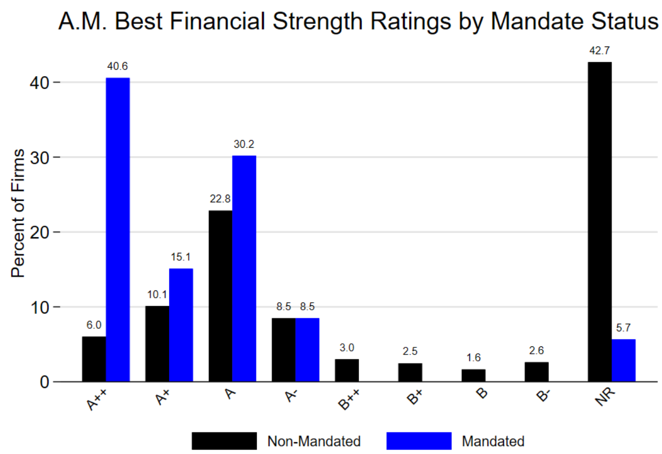
Figure 3: Florida Homeowners Insurance Price



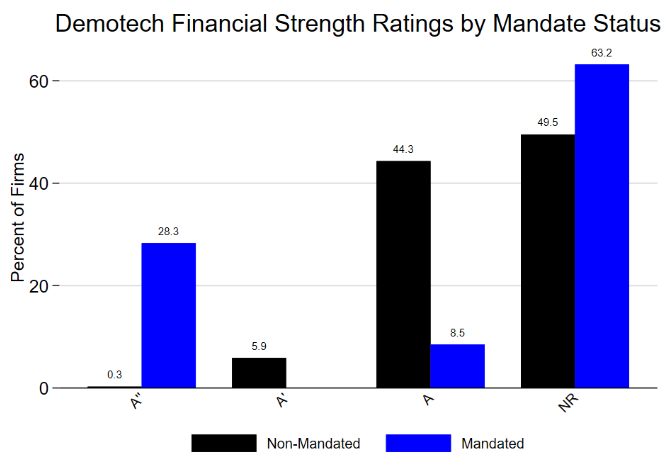
Notes: The figure shows the average natural log of the average homeowners insurance price. We separately report average prices for insurers that enter Florida's homeowners insurance market due to the mandate after 2007 (Mandated Entrants), that enter voluntarily after 2007 (Voluntary Entrants), and that were existing insurers in 2007 (Existing). We identify insurance companies' entrants to Florida's homeowners insurance market (i.e., positive premiums written) using the State pages of the NAIC annual statements. Average insurance prices in homeowners insurance policies come from QUASR.

Figure 4: Florida Property Insurer Financial Strength Ratings

A. A.M. Best



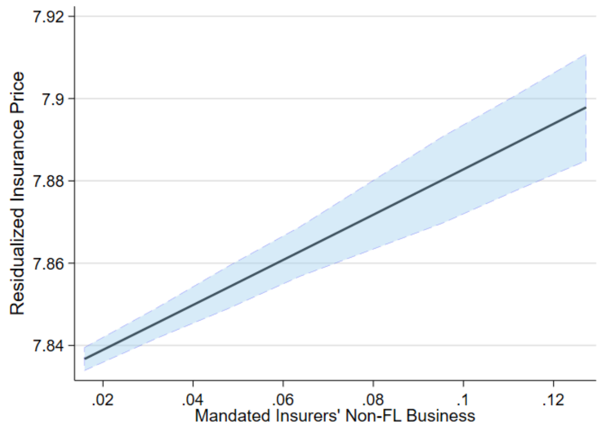
B. Demotech



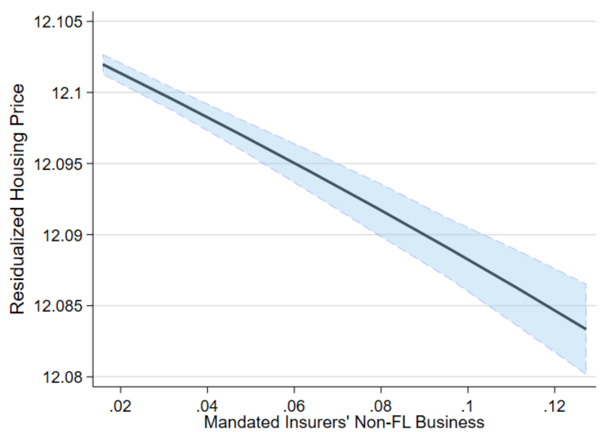
Notes: Panel A reports the distribution of A.M. Best financial strength ratings for non-mandated (in black) and mandated (in blue) insurers in our sample. Panel B reports the distribution of Demotech financial stability ratings for non-mandated (in black) and mandated (blue) insurers in our sample.

Figure 5: Homeowners Insurance Price Instrument Validity

A. Relevance - Insurance Prices



B. Reduced Form - Housing Prices



Notes: Panel A shows the relationship between the instrument (mandated insurers' Non-FL home to auto business ratios) and the homeowners insurance prices, a local linear version of our first stage. We estimate local linear regression of the average natural log of homeowners insurance prices (weighted by insured exposure) on the instrument, estimated from the 1st to 99th percentiles of the instrument - we have residualized out the county and year-by-quarter effects. Shaded areas represent 95% confidence interval. The regressions are weighted by each county-quarter's number of housing sales. Panel B shows the reduced-form relationship between the instrument and the outcome variable (housing prices). We show a local linear regression of average natural log of housing prices on the instrument, along with 95% confidence interval, estimated from the 1st to 99th percentiles of the instrument. Consistent with our second stage estimates, we have residualized out the zip code and year-by-month effects.

Table 1: Summary Statistics

	Mean	SD	P1	P25	P50	P75	P99
ln(Sale Price)	12.10	0.91	9.55	11.64	12.18	12.62	14.46
ln(HO Price)	7.84	0.50	6.98	7.46	7.73	8.16	9.25
ln(Population)	13.28	0.95	10.59	12.67	13.33	14.09	14.81
ln(Density)	6.46	0.88	3.97	5.86	6.55	7.19	8.16
Unemployment	0.09	0.03	0.04	0.06	0.08	0.11	0.15
% College	0.59	0.06	0.42	0.55	0.60	0.62	0.73
% Black/Hispanic	0.15	0.08	0.05	0.09	0.13	0.19	0.31
ln(Median Income)	10.73	0.12	10.42	10.66	10.74	10.80	11.05
% Poverty	0.11	0.03	0.05	0.09	0.10	0.12	0.17
Median Year Built	1,986.13	5.75	1,975.00	1,983.00	1,986.00	1,990.00	2,002.00
% Owner Occupied	0.68	0.08	0.52	0.61	0.69	0.73	0.90
% Mortgage	0.60	0.08	0.41	0.53	0.59	0.67	0.77
Living Area	2,149.69	1,195.24	784.00	1,470.00	1,934.00	2,535.00	5,822.00
Land Square Feet ($000)	16.36	603.38	0.00	6.10	8.70	11.81	184.73
Home Age	28.29	21.95	0.00	11.00	25.00	43.00	90.00
Renovated	0.02	0.13	0.00	0.00	0.00	0.00	1.00
Improvement Quality Low	0.16	0.36	0.00	0.00	0.00	0.00	1.00
Improvement Quality Mid	0.52	0.50	0.00	0.00	1.00	1.00	1.00
Improvement Quality Missing	0.05	0.22	0.00	0.00	0.00	0.00	1.00
Observations	3,897,806						

Note: This table reports summary statistics for our sample from 2011 to 2020. *ln(Housing Sale Price)* is the natural log of the sale price of each property. See Appendix C for definitions of the variables.

Table 2: Instrument Randomization Test

Dependent Variable :	ln(HO Price)		Instrument	
	(1)	(2)	(3)	(4)
ln(Population)	-1.2977		-2.9815	
	(1.8383)		(12.7694)	
ln(Density)	1.6454		3.3280	
	(1.9532)		(12.4327)	
Unemployment	0.7750*		-0.6021	
	(0.4446)		(1.2124)	
% College	-0.1521		-1.8205	
	(0.4234)		(1.4592)	
% Black/Hispanic	0.0629		-7.2015	
	(0.8401)		(6.8180)	
ln(Median Income)	0.3950**		0.2892	
	(0.1951)		(0.5782)	
% Poverty	0.1518		0.3348	
	(0.3381)		(1.6040)	
Median Year Built	-0.0029		-0.0095	
	(0.0055)		(0.0429)	
% Owner Occupied	-0.0524		0.1988	
	(0.3520)		(1.5363)	
% Mortgage	-0.0450		-0.3859	
	(0.2480)		(0.9747)	
High FPHLM		0.3912***		0.1178
		(0.0928)		(0.1461)
High Risk Score		0.2622***		0.0151
		(0.0942)		(0.1389)
High Risk Perception		0.0984		0.1427
		(0.1017)		(0.1672)
County FE	✓		✓	
Year-Quarter FE	✓	✓	✓	✓
Observations	2,680	2,680	2,680	2,680
Joint F-test p-value	0.330	0.000	0.233	0.790

Note: This table reports results of the instrument randomization test. We estimate OLS regressions where the dependent variable is the natural log of homeowners insurance prices in columns (1) and (2) and standardized instrument in columns (3) and (4). Observations are at the county-year-quarter level. Columns (1) and (3) include time-varying county characteristic variables; we include county fixed effects and year-by-quarter fixed effects in these regressions. Columns (2) and (4) include time-invaryring county characteristic variables; we include year-by-quarter fixed effects in these regressions. The Joint F-test p-value reported at the bottom is from F-tests of joint significance of the variables. Standard errors are clustered at the county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Housing Sales Price in Florida Using Property-Level Transactions

	OLS		2SLS	
	All	Repeat	All	Repeat
Panel A. Estimate on *ln(Housing Sales Price)*				
	(1)	(2)	(3)	(4)
ln(HO Price)	-0.0796*	-0.1150*	-0.6536***	-0.6059**
	(0.0435)	(0.0689)	(0.1615)	(0.2823)
First-stage KP F-stat			127.980	114.254
Census Attributes	✓	✓	✓	✓
Housing Attributes	✓	✓	✓	✓
Parcel FE		✓		✓
ZIP FE	✓		✓	
Year-Month FE	✓	✓	✓	✓
Observations	3,897,806	2,202,829	3,897,806	2,202,829
Panel B. First Stage Results on *ln(HO Price)*				
Mandate IV			0.3767***	0.2989***
			(0.0333)	(0.0280)

Note: This table reports results of estimating the natural log of the sale price of each property, *ln(Housing Sales Price)*. *ln(HO Price)* is the natural log of weighted average county-level homeowners insurance prices, using total insurance exposure as the weight. Columns (1) and (2) report results from estimating equation (3) and columns (3) and (4) report results from estimating the two-stage least squares as outlined in equation (6) and (7).. Results reported in columns (1) and (3) are based on the full sample and those reported in columns (2) and (4) are generated from our repeat-sales sample. We report the first stage results from estimating equation (6) using the instrument in Panel B. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Housing Sales Price in Florida—Mortgage Requirement

	(1)	(2)	(3)
ln(HO Price)	-0.7047***	-0.5767***	-0.6119***
	(0.1738)	(0.1546)	(0.1574)
High Mortgage	-0.4415		
	(0.6815)		
ln(HO Price)×High Mortgage	0.0711		
	(0.0892)		
High New Mortgage		1.0395***	
		(0.2440)	
ln(HO Price)×High New Mortgage		-0.1226***	
		(0.0306)	
High New Mortgage (Value)			0.9887***
			(0.2882)
ln(HO Price)×High New Mortgage (Value)			-0.1192***
			(0.0366)
Full Effect of High Mortgage	-0.634***	-0.699***	-0.731***
First-stage KP F-stat	73.988	63.729	64.464
Census Attributes	✓	✓	✓
Housing Attributes	✓	✓	✓
ZIP FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Observations	3,897,806	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating the natural log of the sale price of each property, *ln(Housing Sales Price)* using equation (8). *ln(HO Price)* is the natural log of weighted average county-level homeowners insurance prices, using total insurance exposure as the weight. *High Mortgage* is a binary variable equal to one if a county is in the top quartile of percent of mortgaged properties and zero otherwise. *High New Mortgage* is a binary variable equal to one if, in a given year, a census tract is in the top quartile of percent of new mortgage originations and zero otherwise. *High New Mortgage (Value)* is a binary variable equal to one if, in a given year, a census tract is in the top quartile of percent of new mortgage originations' values and zero otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Housing Sales Price in Florida—Reservation Price

	(1)	(2)	(3)
ln(HO Price)	-0.5009***	-0.7922***	-1.3762***
	(0.1559)	(0.2066)	(0.3927)
ln(HO Price)×High Risk Score	0.1280**		
	(0.0634)		
ln(HO Price)×High Belief in Risk		0.1277**	
		(0.0587)	
ln(HO Price)×High Risk Perception			0.4648***
			(0.1708)
Full Effect of Risk	-0.373**	-0.664***	-0.911***
First-stage KP F-stat	47.705	66.163	9.698
Census Attributes	✓	✓	✓
Housing Attributes	✓	✓	✓
ZIP FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Observations	3,897,806	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating the natural log of the sale price of each property, *ln(Housing Sales Price)* using equation (**??**). *ln(HO Price)* is the natural log of weighted average county-level homeowners insurance prices, using total insurance exposure as the weight. *High Risk Score* is a binary variable that is equal to one for counties in the top tercile of NRI scores and zero otherwise. *High Belief in Risk* is a binary variable that is equal to one for counties in the top tercile of belief in climate change (Yale Climate Survey) and zero otherwise. *High Risk Perception* is a binary variable that is equal to one for counties in the top tercile of perception that climate change will impact them (Yale Climate Survey) and zero otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Housing Sales Price in Florida—Competition and Citizens

	(1)	(2)	(3)
ln(HO Price)	-0.6564***	-0.6809***	-0.6658***
	(0.1645)	(0.1856)	(0.1772)
Low Comp.	3.0749***	3.5885***	3.2224***
	(1.0482)	(1.3097)	(1.0988)
ln(HO Price)×Low Comp.	-0.4503***	-0.5152***	-0.4702***
	(0.1468)	(0.1809)	(0.1536)
High Citizen		0.1001	
		(0.2431)	
ln(HO Price)×High Citizen		-0.0143	
		(0.0311)	
Low Comp.×High Citizen		-1.4413**	
		(0.6078)	
ln(HO Price)×Low Comp.×High Citizen		0.1837**	
		(0.0801)	
High Depop			-0.0128
			(0.1286)
ln(HO Price)×High Depop			0.0023
			(0.0166)
Low Comp.×High Depop			0.8151*
			(0.4795)
ln(HO Price)×Low Comp.×High Depop			-0.1100*
			(0.0640)
Full Effects of Low Comp.	-1.107***	-1.196***	-1.136***
First-stage KP F-stat	61.455	35.097	30.601
Census Attributes	✓	✓	✓
Housing Attributes	✓	✓	✓
ZIP FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Observations	3,897,806	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating the natural log of the sale price of each property, *ln(Housing Sales Price)* using equation (8). *ln(HO Price)* is the natural log of weighted average county-level homeowners insurance prices, using total insurance exposure as the weight. *Low Comp.* is a binary variable equal to one if a county is in the top tercile in terms of predetermined private insurer HHI and zero otherwise. *High Citizen* is a binary variable equal to one if, in a given year-quarter, a county is in the top tercile in terms of the share of policies transferred from private insurers to Citizens and zero otherwise. *High Depop* is a binary variable equal to one if, in a given year-quarter, a county is in the top tercile in terms of the share of policies transferred from Citizens to private (depopulation participation) and zero otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Alternative Explanations Results

X =	Disaster	Flood Zone	Elasticity	Homestead	Quick Sale
	(1)	(2)	(3)	(4)	(5)
ln(HO Price)	-0.6659***	-0.6538***	-0.5255***	-0.5180***	-0.6514***
	(0.1634)	(0.1623)	(0.1332)	(0.1647)	(0.1620)
X	3.2238***	0.5158	-0.0314	0.7854***	-0.1111
	(0.8660)	(1.4730)	(1.2443)	(0.1068)	(0.1070)
X×*ln(HOPrice)*	-0.4054***	0.0110	0.0757	-0.0935***	0.0146
	(0.1099)	(0.1868)	(0.1545)	(0.0136)	(0.0136)
First-stage KP F-stat	62.790	63.354	57.571	62.682	63.711
Census Attributes	✓	✓	✓	✓	✓
Housing Attributes	✓	✓	✓	✓	✓
ZIP FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Observations	3,897,806	3,826,623	3,412,476	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating the natural log of the sale price of each property, *ln(Housing Sales Price)*. *ln(HO Price)* is the natural log of weighted average county-level homeowners insurance prices, using total insurance exposure as the weight. In each column we set **X** equal to a variable that represents proxy for a potential alternative explanation for our results that we then interact with *ln(HO Price)*. In column (1) *Disaster* is a binary variable equal to one if a property reported having a disaster in the NAL dataset over the past 3 years and zero otherwise. In column (2) *Flood Zone* is an indicator that equals one for properties that are designated as coastal flood zone (V or VE) and zero otherwise. In column (3) *Elasticity* is a binary variable equal to one if the county's weighted average elasticity—aggregated from tract-level estimates in Baum-Snow and Han (2023) using 2000 occupied housing units as weights—is above the sample median. This uses an elasticity measure estimated via a quadratic Finite Mixture Model (FMM) based on 2001 tract characteristics. In column (4) *Homestead* is a binary variable equal to one if a property has filed for a homestead exemption and zero otherwise. In column (5) *Quick Sale* is a binary variable equal to one if a property previously sold over the past 12 months and zero otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Homeowners Insurance Price and Housing Sale Probabilities

	(1)	(2)	(3)	(4)
ln(HO Price)	-0.0036**	-0.0034**	-0.0034**	-0.0036**
	(0.0015)	(0.0016)	(0.0015)	(0.0014)
ln(Population)		-0.0014	-0.0329	-0.0319
		(0.0523)	(0.0491)	(0.0493)
ln(Density)		-0.0047	0.0264	0.0247
		(0.0538)	(0.0506)	(0.0510)
Unemployment		0.0085	0.0098	0.0089
		(0.0080)	(0.0076)	(0.0079)
% College		0.0042	-0.0031	-0.0047
		(0.0073)	(0.0072)	(0.0073)
% Black/Hispanic		-0.0016	-0.0152	-0.0138
		(0.0190)	(0.0186)	(0.0186)
Median Year Built			0.0001	0.0001
			(0.0001)	(0.0001)
% Owner Occupied			0.0011	0.0008
			(0.0057)	(0.0057)
% Mortgage			0.0155**	0.0153**
			(0.0063)	(0.0062)
ln(Median Income)				0.0030
				(0.0024)
% Poverty				0.0045
				(0.0049)
Year-Quarter FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Observations	2,680	2,680	2,680	2,680

Note: This table reports OLS regression results from equation (9). The dependent variable is *Pr(Sale)*, which is the county-level probability that a house is sold. *ln(HO Price)* is the natural log of average county-level homeowners insurance prices. Standard errors are clustered at county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A Homeowners Insurance Price and Housing Price based on Poterba's Capital-Theoretic Model

This appendix extends Poterba (1984)'s classic capital-theoretic model of the owner-occupied house prices to incorporate homeowner's insurance price. The main takeaway is that if homeowner's insurance is a significant portion of the user cost of housing services, an increase in insurance costs raises the overall cost of owning housing relative to its benefits. This makes housing less attractive as an asset, reducing demand for ownership. In equilibrium, lower demand pushes down house prices to restore balance in the market.

In Poterba (1984)'s classic capital-theoretic model of the owner-occupied house prices, a rational home buyer should equate the price of a house with the discounted value of future service stream.

1. Housing Services Demand and Supply

On the demand side, the desired quantity of housing services HS^d is a function of the real rental price R of these services.

$$HS^d = f(R), \quad f_R < 0.$$

As the rental price increases, the quantity of housing services demanded decreases.

On the supply side, the flow of supply of services HS is produced by the stock of housing structures H according to a production relationship,

$$HS^s = h(H).$$

The stock of houses is fixed in the short run.

The equilibrium rental price R is determined where the quantity of housing services demanded equals the quantity supplied,

$$HS^d = HS^s.$$

Substituting the production relationship gives

$$R = R(h(H)), \quad R' < 0.$$

The negative slope of the inverse demand function reflects diminishing marginal utility for housing services.

2. User Cost of Housing Services

Homeowners make decisions by equalizing the marginal benefit and marginal cost of housing services:

$$R(H) = Q \cdot W,$$

where Q is the real price of housing structures, and W is per-unit user cost of housing services.

The user cost (W) includes several components:

$$W = \delta + \kappa + (1-\theta)(i+\mu) - \pi_H,$$

where δ represents the depreciation rate, κ denotes maintenance costs as a fraction of current value, μ is the property tax rate, θ is the marginal income tax rate, i is nominal interest rate, and π_H represents the expected real house price appreciation.

When we include homeowner's insurance costs (γ) as a component of the user cost:

$$W = \delta + \kappa + (1-\theta)(i+\mu) - \pi_H + \gamma,$$

where γ is annual cost of homeowner's insurance, expressed as either a percentage of the house's real price (Q) or as a fixed cost. By adding γ to W, the per-unit user cost of housing increases.

3. Asset-Market Equilibrium

Relates house price (Q) to the discounted value of future net service flows. The equilibrium prices satisfy:

$$Q = -R(H) + vQ,$$

where v is after-tax cost of ownership, which includes depreciation, taxes, interest rates, and expected price changes.

$$v = \delta + \kappa + (1-\theta)(i+\mu) - \pi_H + \gamma.$$

Alternatively, the equilibrium can be expressed as the present value of future net service flows:

$$Q(t) = \int_t^\infty S(z) e^{-\int_t^z [(1-\theta)i - \pi]\, dz}\, dz,$$

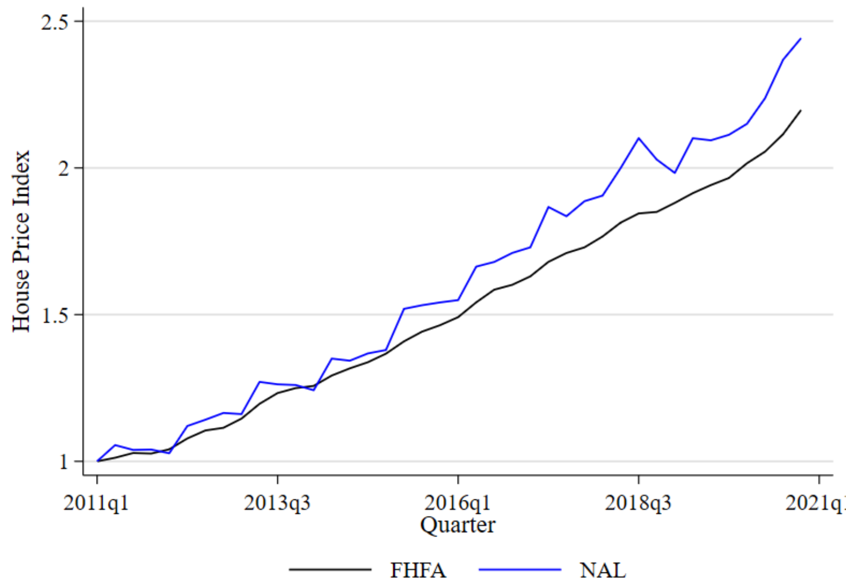
where $S(z)$ is net service value, calculated as real rental income minus costs (taxes, maintenance, and depreciation):

$$S(z) = R(H) - (\delta + \kappa + \mu + \gamma)Q.$$

The inclusion of homeowner's insurance costs raises the overall per-unit cost of housing services, making ownership more expensive. Higher insurance costs reduce the net service value, $S(z)$, leading to lower discounted future service flows and, ultimately, lower equilibrium housing prices.

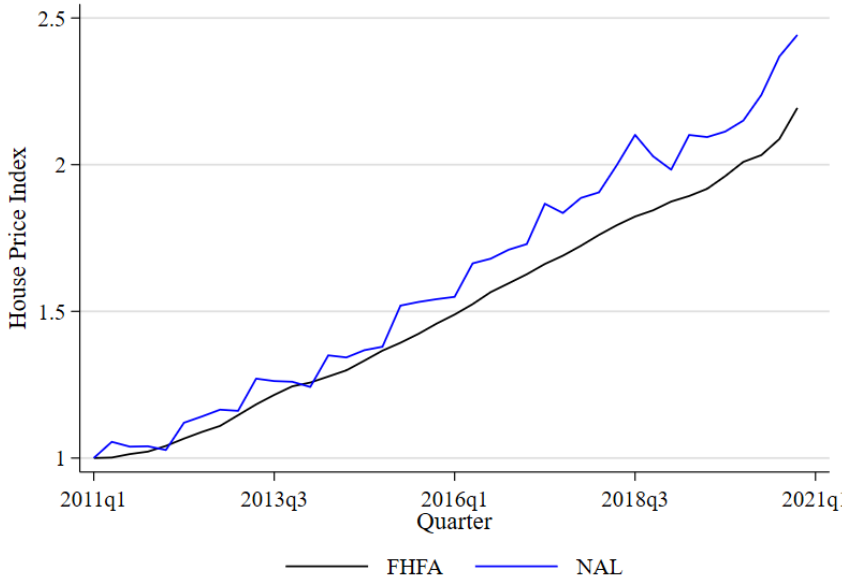
B Supplemental Figures and Tables

Figure B1: Time-Series Comparison between FHFA-HPI and NAL-HPI (Non-Seasonal Adjusted)



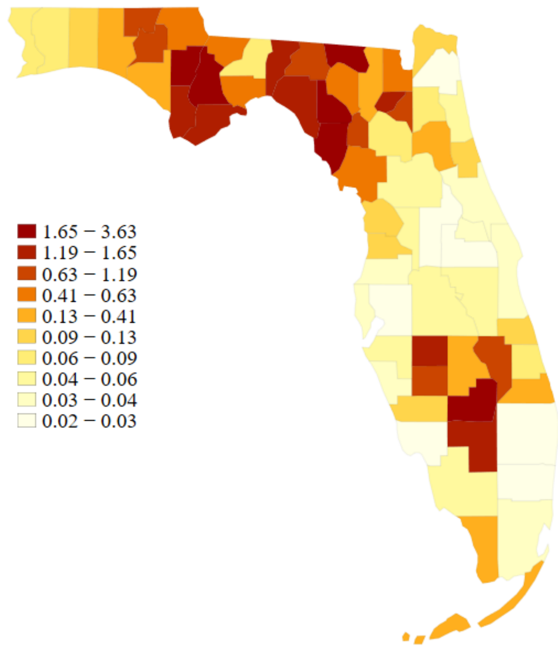
Source: FHFA and NAL for housing price indicies (HPI).
Notes: This figure reports the time-series index value for the housing prices in Florida using either FHFA index (black line) or our construction of the NAL index (blue line) using property-level transaction prices. We do not perform a seasonal adjustment in this figure.

Figure B2: Time-Series Comparison between FHFA-HPI and NAL-HPI (Seasonal Adjusted)



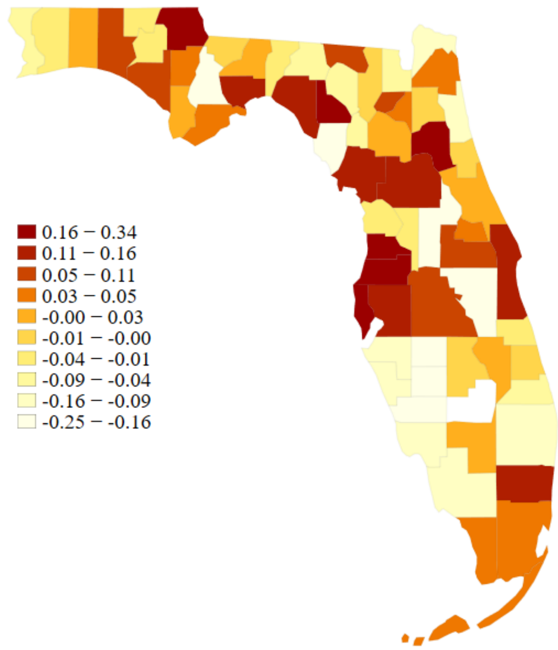
Source: FHFA and NAL for housing price indicies (HPI).
Notes: This figure reports the time-series index value for the housing prices in Florida using either FHFA index (black line) or our construction of the NAL index (blue line) using property-level transaction prices. We perform a seasonal adjustment in this figure.

Figure B3: County-Level Homeowners Insurance Price Scaled by Insured Exposures



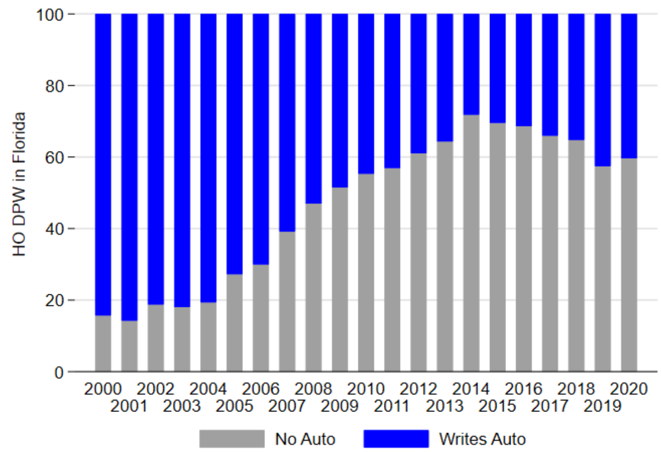
Source: NAL for housing prices and QUASR for homeowners insurance prices.
Notes: This figure reports the average ratio of homeowners insurance prices to average insured exposures for homeowners insurance (measured in $10,000 of exposure) for each Florida county reported in 2019.

Figure B4: Correlation Coefficient between Changes in Homeowners Insurance Prices and Changes in House Prices



Source: NAL for housing price and QUASR for homeowners insurance prices.
Notes: This figure reports the correlation between changes in housing prices, measured by our county-quarter-level housing price index using property-level transaction prices (NAL-HPI), and changes in homeowners insurance prices.

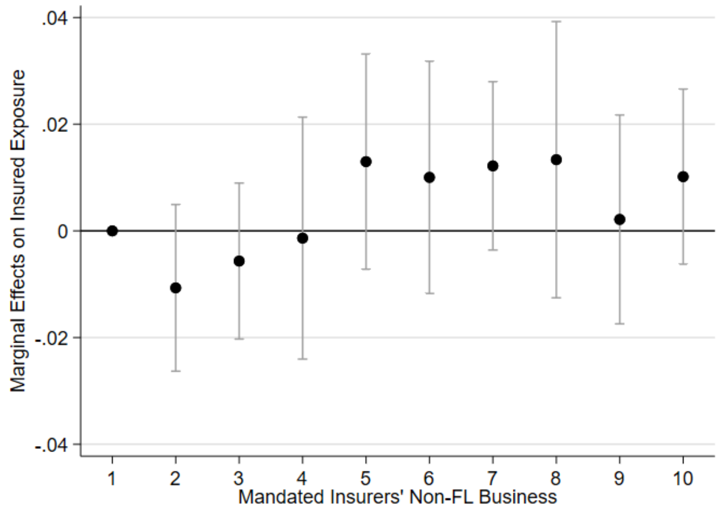
Figure B5: Florida Homeowners Insurance Market Share Trend



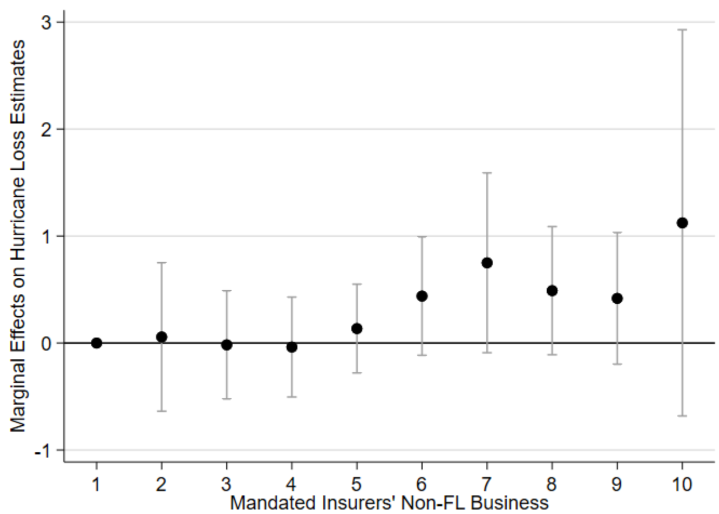
Notes: The figure reports the market share of the homeowners insurance in Florida (based on total direct premiums written). "No Auto" includes homeowners insurance companies that do not write auto insurance in Florida in a given year. "Writes auto" includes homeowners insurance companies that write auto insurance in Florida in a given year, including those that indirectly write auto insurance in Florida through their affiliated insurers. Data for insurance company types (auto insurance premiums) and homeowners insurance premiums are from the State Pages of the NAIC annual statements.

Figure B6: Instrument Exclusion Tests

A. Insured Exposure



B. Hurricane Loss Estimates



Notes: Panel A reports the marginal effects of the instrument on insured exposures of homeowners insurance. We estimate OLS regressions of the natural logarithm value of insured exposure on the deciles of the instrument, which include county and year-by-quarter fixed effects. Deciles of the instrument are created separately in each year-quarter. Standard errors are clustered at the county. We weight each county-quarter observation by the number of sales transactions. Panel B reports the marginal effects of the instrument on the hurricane loss cost estimate from FPHLM. The estimation model is the same as in Panel A, with only the outcome variable being different.

Table B1: Mandated Insurers' Entrance Randomization Test

Dependent Variable :	Mandated Entrants' Initial Share	
	(1)	(2)
ln(Population)	4.5054	
	(7.1835)	
ln(Density)	-3.9048	
	(6.7702)	
Unemployment	-0.0846	
	(0.2879)	
% College	0.1440	
	(0.5900)	
% Black/Hispanic	-1.5920	
	(1.1181)	
ln(Median Income)	0.0375	
	(0.0752)	
% Poverty	0.1257	
	(0.0815)	
Median Year Built	-0.0008	
	(0.0041)	
% Owner Occupied	0.0039	
	(0.2587)	
% Mortgage	-0.3265	
	(0.2305)	
High FPHLM		0.0115
		(0.0101)
High Risk Score		-0.0255
		(0.0234)
High Risk Perception		0.0177
		(0.0113)
County FE	✓	
Year-Quarter FE	✓	✓
Insurer FE	✓	✓
Observations	127,092	127,092
Joint F-test p-value	0.761	0.316

Note: This table reports results of the mandated entrants' randomization test. We estimate OLS regressions where the dependent variable is pre-determined initial share of mandated entrants in columns (1) and (2). We standardize the share. Observations are at the insurer(insurance group)-county-year-quarter level. Column (1) includes time-varying county characteristic variables and column (2) includes time-invaryring county characteristic variables. The Joint F-test p-value reported at the bottom is from F-tests of joint significance of the variables. Standard errors are clustered at the county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Prediction Model for the Instrument Shifter: Standardized Explanatory Variables

	(1) OLS	(2) OLS + Year FE	(3) Insurer + Year FE
ln(Assets)	-0.0217**	-0.0252***	0.0385***
	(0.0085)	(0.0086)	(0.0147)
Surplus / Assets	0.0300***	0.0274***	-0.0033
	(0.0088)	(0.0089)	(0.0045)
Liabilities / Surplus	-0.0092**	-0.0084*	-0.0004
	(0.0045)	(0.0045)	(0.0021)
Reinsurance Ratio	0.0195***	0.0189***	0.0119***
	(0.0064)	(0.0064)	(0.0042)
Product HHI (NPW)	-0.2426***	-0.2448***	-0.0807***
	(0.0086)	(0.0087)	(0.0128)
Geographic HHI	0.0522***	0.0526***	-0.0005
	(0.0073)	(0.0073)	(0.0080)
Hurricane State Premium %	-0.0028	-0.0030	0.0152
	(0.0073)	(0.0073)	(0.0100)
Long-Tail Proportion (NPW)	0.0337***	0.0325***	0.0143
	(0.0060)	(0.0060)	(0.0118)
RBC Ratio	0.0001	0.0002	0.0008***
	(0.0015)	(0.0014)	(0.0002)
Loss Ratio	-0.0035	-0.0033	0.0002
	(0.0034)	(0.0034)	(0.0013)
Return on Assets	-0.0067*	-0.0059	-0.0020
	(0.0039)	(0.0040)	(0.0016)
Year FE		✓	✓
Insurer FE			✓
R^2	0.400	0.403	0.912
Observations	20,984	20,984	20,821

Note: This table reports regression results of estimating the instrument's shifter component—the non-Florida homeowners/(homeowners+auto) direct premiums written ratio at the insurer group level—on insurer financial and operational characteristics from NAIC annual statements. "Insurer" refers to the insurance group for firms that belong to a group and a single insurer for firms that do not belong to a group. All continuous explanatory variables are standardized to mean zero and standard deviation one using the common prediction sample, so the coefficients represent the change in the shifter from a one-standard-deviation increase in the regressor. Column (1) estimates an OLS model. Column (2) estimates an OLS model with year fixed effects. Column (3) adds insurer fixed effects to exploit within-insurer time variation. Surplus / Assets is statutory insurance capital scaled by assets. Liabilities / Surplus is the leverage ratio. Reinsurance Ratio is ceded premiums relative to direct premiums. Product HHI is the Herfindahl-Hirschman Index of net premiums written across lines of business. Geographic HHI is the concentration of premiums across states. Hurricane State Premium % is the share of premiums written in hurricane-exposed states. Long-Tail Proportion is the share of net premiums written in long-tail lines. RBC Ratio is risk-based capital relative to the authorized control level. Loss Ratio is the insurer loss ratio from the annual statement. Return on Assets is net income scaled by assets. The unit of observation is insurer-year. Standard errors are clustered at the insurer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Housing Sales Price in Florida Using Property-Level Transactions—Full Model

	OLS		2SLS	
	All	Repeat	All	Repeat
Panel A. Estimate on *ln(Housing Sales Price)*				
	(1)	(2)	(3)	(4)
ln(HO Price)	-0.0796*	-0.1150*	-0.6536***	-0.6059**
	(0.0435)	(0.0689)	(0.1615)	(0.2823)
Living Area	0.0003***	0.0000***	0.0003***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Living Area Squared	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Land Square Feet ($000)	0.0000	-0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Home Age	-0.0085***	-0.0136***	-0.0084***	-0.0134***
	(0.0006)	(0.0023)	(0.0006)	(0.0023)
Home Age Squared	0.0000***	0.0000	0.0000***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Renovated	0.0601***	0.0069	0.0685***	0.0097
	(0.0172)	(0.0163)	(0.0170)	(0.0166)
Improvement Quality Low	-0.3273***	-0.0743***	-0.3251***	-0.0760***
	(0.0184)	(0.0212)	(0.0185)	(0.0221)
Improvement Quality Mid	-0.1678***	-0.0481***	-0.1681***	-0.0542***
	(0.0108)	(0.0161)	(0.0109)	(0.0177)
Improvement Quality Missing	-0.0353**	0.1795***	-0.0364**	0.1827***
	(0.0158)	(0.0272)	(0.0159)	(0.0269)
ln(Population)	-0.1955**	-10.2619*	-0.0680	-12.5827**
	(0.0778)	(6.0253)	(0.0922)	(5.9434)
ln(Density)	-0.0224	9.8518	-0.1519	12.4077**
	(0.1333)	(6.0031)	(0.1638)	(6.0065)
Unemployment	-0.8886*	-1.5138*	0.2189	-0.4778
	(0.5353)	(0.7770)	(0.6459)	(0.9606)
% College	0.4441	-0.4844	0.1356	-1.1505
	(0.4100)	(0.7443)	(0.5054)	(0.8162)
% Black/Hispanic	1.7841***	1.6180	1.0609	0.4394
	(0.5885)	(1.5791)	(0.7221)	(1.7669)
ln(Median Income)	0.1237	0.0692	1.1710***	0.7861*
	(0.1867)	(0.2516)	(0.3509)	(0.4479)
% Poverty	-0.5034	-0.3847	-0.0606	-0.3612
	(0.4728)	(0.6792)	(0.4726)	(0.6633)
Median Year Built	-0.0029	0.0022	-0.0077	-0.0009
	(0.0045)	(0.0076)	(0.0058)	(0.0080)
% Owner Occupied	-0.9144***	-2.1054***	-2.0801***	-2.9949***
	(0.2778)	(0.5648)	(0.4503)	(0.8089)
% Mortgage	-0.0777	-0.3114	-0.9038***	-1.0364*
	(0.2380)	(0.5392)	(0.3502)	(0.5731)
First-stage KP F-stat			127.980	114.254
Census Attributes	✓	✓	✓	✓
Housing Attributes	✓	✓	✓	✓
Parcel FE		✓		✓
ZIP FE	✓		✓	
Year-Month FE	✓	✓	✓	✓
Observations	3,897,806	2,202,829	3,897,806	2,202,829
Panel B. First Stage Results on *ln(HO Price)*				
Mandate IV			0.3767***	0.2989***
			(0.0333)	(0.0280)

Note: This table reports coefficient estimates for models estimated in Table 3. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Housing Sales Price in Florida, Alternative SE Cluster

	OLS		2SLS	
	All	Repeat	All	Repeat
Panel A. County Cluster				
	(1)	(2)	(3)	(4)
ln(HO Price)	-0.0796	-0.1150	-0.6536***	-0.6059
	(0.0766)	(0.1091)	(0.2261)	(0.4235)
First-stage KP F-stat			7.994	8.510
Census Attributes	✓	✓	✓	✓
Housing Attributes	✓	✓	✓	✓
Parcel FE		✓		✓
ZIP FE	✓		✓	
Year-Month FE	✓	✓	✓	✓
Observations	3,897,806	2,202,829	3,897,806	2,202,829
Panel B. County-Year Quarter Cluster				
	(1)	(2)	(3)	(4)
ln(HO Price)	-0.0796	-0.1150	-0.6536***	-0.6059
	(0.0802)	(0.1100)	(0.1776)	(0.3686)
First-stage KP F-stat			31.095	12.965
Census Attributes	✓	✓	✓	✓
Housing Attributes	✓	✓	✓	✓
Parcel FE		✓		✓
ZIP FE	✓		✓	
Year-Month FE	✓	✓	✓	✓
Observations	3,897,806	2,202,829	3,897,806	2,202,829

Note: This table reports results from estimating models in Table 3, except standard errors are clustered at the county in Panel A and they are clustered at the county-by-year-quarter in Panel B. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Housing Sales Price in Florida Using Property-Level Transactions (2011-2018)

	OLS		2SLS	
	All	Repeat	All	Repeat
Panel A. Estimate on *ln(Housing Sales Price)*				
	(1)	(2)	(3)	(4)
ln(HO Price)	0.1301**	0.1559	-0.5099**	-0.7035
	(0.0662)	(0.1169)	(0.2209)	(0.4816)
First-stage KP F-stat			110.860	82.764
Census Attributes	✓	✓	✓	✓
Housing Attributes	✓	✓	✓	✓
Parcel FE		✓		✓
ZIP FE	✓		✓	
Year-Month FE	✓	✓	✓	✓
Observations	3,038,357	1,554,174	3,038,357	1,554,174
Panel B. First Stage Results on *ln(HO Price)*				
Mandate IV			0.2839***	0.2127***
			(0.0270)	(0.0234)

Note: This table reports results from estimating models in Table 3 on a subsample of 2011 - 2018 period. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Housing Sales Price in Florida— Renovations

	Effective Year Built	Quality Upgrade
	(1)	(2)
ln(HO Price)	-0.6545***	-0.6564***
	(0.1616)	(0.1615)
Renovation	0.3044	
	(0.4219)	
ln(HO Price)×Renovation	-0.0298	
	(0.0532)	
Renovation		-3.7598***
		(0.7799)
ln(HO Price)×Renovation		0.4736***
		(0.0981)
Full Effects of Renovation	-0.684***	-0.183
First-stage KP F-stat	64.164	63.983
Census Attributes	✓	✓
Housing Attributes	✓	✓
ZIP FE	✓	✓
Year-Month FE	✓	✓
Observations	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating the natural log of the sale price of each property, *ln(Housing Sales Price)*, by extending equation (7) to include interactions with renovation indicators. *ln(HO Price)* is the instrumented natural log of weighted average county-level homeowners insurance prices. *Renovation* in column (1) is an indicator equal to one if the property reports a new effective year built during the sample period and zero otherwise. *Renovation* in column (2) is an indicator equal to one if the property reports an upgraded quality during the sample period and zero otherwise. All specifications include the full set of property and neighborhood controls, as well as ZIP code and year-quarter fixed effects. Standard errors are clustered at the ZIP code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B7: OLS–IV Gap Across Alternative Premium Measures

Measure	OLS	2SLS	KP F-stat
Panel A. ZIP FE / full sample			
Weighted average premium	-0.0796	-0.6536	128.0
	(0.0435)	(0.1615)	
Unweighted average premium	-0.1322	-1.1014	117.7
	(0.0650)	(0.2704)	
Premium / exposures	-0.0002	-0.4130	27.4
	(0.0032)	(0.1089)	
Panel B. Property FE / repeat-sales sample			
Weighted average premium	-0.1150	-0.6059	114.3
	(0.0689)	(0.2823)	
Unweighted average premium	-0.1611	-1.0463	87.9
	(0.1016)	(0.4834)	
Premium / exposures	0.0090	-0.4221	20.1
	(0.0058)	(0.2074)	

Note: This table reports the OLS and 2SLS coefficient on the log homeowners insurance price under alternative premium definitions. The baseline measure in the main text is the insured-exposure-weighted average premium. Across these alternative definitions, OLS remains much closer to zero than 2SLS in both the full and repeat-sales samples. Standard errors are in parentheses.

Table B8: OLS Coefficient Stability and Selection on Unobservables

	OLS				2SLS
	(1)	(2)	(3)	(4)	(5)
ln(HO Price)	-0.0347	-0.0693*	-0.0796*	-0.1223***	-0.6536***
	(0.0439)	(0.0411)	(0.0435)	(0.0392)	(0.1615)
First-stage KP F-stat					127.980
Housing Attributes		✓	✓	✓	✓
Census Attributes			✓	✓	✓
Risk Controls				✓	
ZIP FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Observations	3,897,806	3,897,806	3,897,806	3,826,624	3,897,806

Note: This table reports OLS estimates of the effect of homeowners insurance prices on housing sale prices with progressively richer control sets. Column (1) includes only zip code and year-month fixed effects with no additional controls. Columns (2) through (4) sequentially add housing attributes, census attributes, and risk controls. Due to the time-invariant nature of the risk controls, the number of observations in column (4) is smaller than in the full sample. Column (5) reports the main 2SLS estimate for comparison. Using the Oster (2019) framework, we find that the proportional selection on unobservables (δ) between the column (1) and column (3) models is -0.79 (with $R_{\max} = 1$). Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B9: Complier Profile Diagnostics

Group	Sample Share	First Stage	2SLS	KP F-stat
Panel A. Recent exposure and flood-risk markers				
Affected in prior 3 years = No	0.982	0.3751	-0.6680	129.3
Affected in prior 3 years = Yes	0.018	0.5701	-0.3186	26.3
Floodzone2 = No	0.789	0.3586	-0.6648	132.2
Floodzone2 = Yes	0.211	0.4582	-0.4688	79.2
SFHA = No	0.819	0.3542	-0.6583	128.0
SFHA = Yes	0.181	0.5091	-0.4003	93.9
Panel B. FPHLM loss-cost groups				
Low loss-cost tercile	0.361	0.5675	-0.5287	57.5
Middle loss-cost tercile	0.325	0.3436	-1.0048	36.6
High loss-cost tercile	0.314	0.0804	-1.1310	61.5

Note: This table reports 2SLS regression results using different subsamples in each row, as defined in the "Group" column. The first-stage slope and 2SLS coefficient are estimated separately within each subgroup using the full-sample ZIP FE specification in equation (7).

Table B10: Plausibly Exogenous Bounds for the Baseline IV

	Point IV	95% CI	10%	25%	50%
Baseline controls	-0.6536	[-0.9701, -0.3372]	[-1.0393, -0.2754]	[-1.1438, -0.1819]	[-1.3196, -0.0241]

Note: This table reports plausibly exogenous bounds for the IV estimates following Conley et al. (2012). The "10%" column reports the estimated bounds allowing for a direct effect of the instrument on the outcome of up to 10% of the instrument's total effect on the outcome (the reduced form); the "25%" and "50%" columns scale the allowance proportionally. Even allowing a direct effect equal to 50% of the reduced form leaves the implied interval negative.

Table B11: Decomposing the OLS–IV Gap

Specification	N	OLS	2SLS	Gap	Δ_{CW}	Δ_{TW}	Δ_{ME}
Main model	3,897,806	-0.0796	-0.6536	-0.5740	-0.0129	0.0133	-0.5744
Risk control model	3,826,624	-0.1223	-0.6493	-0.5270	0.0159	-0.0024	-0.5405

Note: This table reports the Ishimaru (2024) decomposition of the OLS–IV gap for the full sample in the first row (Main model). Δ_{CW} is the covariate-weight difference, Δ_{TW} is the treatment-level weight difference, and Δ_{ME} is the marginal-effect difference. In the second row (Risk control model), we decompose the OLS–IV gap after including time-invariant risk controls. The number of observations is smaller in the second row because the risk controls reduce the sample.

Table B12: Recentered-IV Diagnostics for the Linear Shift-Share Instrument

	Original	IV + μ Mand.-yr	RC IV Mand.-yr	IV + μ Year	RC IV Year
Panel A. ZIP FE / full sample					
ln(HO Price)	-0.6536	-0.8413	-0.9299	-1.3319	-1.5294
	(0.1615)	(0.6260)	(0.9192)	(0.9660)	(1.3524)
KP F-stat	128.0	89.6	17.0	32.3	20.4
Panel B. Property FE / repeat-sales sample					
ln(HO Price)	-0.6059	-2.0643	-2.6316	-3.5488	-3.9171
	(0.2823)	(1.9566)	(2.9384)	(3.1075)	(4.1665)
KP F-stat	114.3	84.8	15.8	8.7	23.4

Note: This table applies the recentered-instruments logic of Borusyak and Hull (2023) to the linear shift-share instrument actually used in the baseline regressions. Columns (2) and (4) add the expected instrument μ as an additional control under alternative exchangeability cells. Columns (3) and (5) replace the excluded instrument with the corresponding BH-recentered version. The recentered specifications remain negative but are much less precise and have weaker first stages than the original IV. We therefore interpret them as validity diagnostics rather than preferred replacement estimators. Standard errors are clustered at the zip code level.

Table B13: Housing Sales Price in Florida—Mortgage Requirement, Repeat Transactions

	2SLS	2SLS	2SLS
	(1)	(2)	(3)
ln(HO Price)	-0.6699**	-0.5423*	-0.5826**
	(0.2777)	(0.2787)	(0.2798)
High Mortgage	-1.0661		
	(1.0373)		
ln(HO Price)×High Mortgage	0.1407		
	(0.1354)		
High New Mortgage		1.1803***	
		(0.3636)	
ln(HO Price)×High New Mortgage		-0.1403***	
		(0.0458)	
High New Mortgage (Value)			0.3482
			(0.4122)
ln(HO Price)×High New Mortgage (Value)			-0.0362
			(0.0523)
Full Effect of High Mortgage	-0.529*	-0.683**	-0.619**
First-stage KP F-stat	64.237	55.776	58.129
Census Attributes	✓	✓	✓
Housing Attributes	✓	✓	✓
Parcel FE	✓	✓	✓
ZIP FE			
Year-Month FE	✓	✓	✓
Observations	2,202,829	2,202,829	2,202,829

Note: This table reports results from estimating models in Table 4 using the repeat-sales sample. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B14: Housing Sales Price in Florida—Reservation Price, Repeat Transactions

	2SLS	2SLS	2SLS
	(1)	(2)	(3)
ln(HO Price)	-1.3558**	-1.2037***	-1.2072***
	(0.5360)	(0.3672)	(0.3792)
ln(HO Price)×High Risk Score	0.6629**		
	(0.3123)		
ln(HO Price)×High Belief in Risk		0.5593***	
		(0.1874)	
ln(HO Price)×High Risk Perception			0.6109***
			(0.2015)
Full Effect of Risk	-0.693**	-0.644**	-0.596**
First-stage KP F-stat	50.269	44.829	46.677
Census Attributes	✓	✓	✓
Housing Attributes	✓	✓	✓
Parcel FE	✓	✓	✓
ZIP FE			
Year-Month FE	✓	✓	✓
Observations	2,202,829	2,202,829	2,202,829

Note: This table reports results from estimating models in Table 5 using the repeat-sales sample. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B15: Housing Sales Price in Florida—Competition and Citizens, Repeat Transactions

	(1)	(2)	(3)
ln(HO Price)	-0.6285**	-0.6509**	-0.6271**
	(0.2816)	(0.2976)	(0.2794)
ln(HO Price)×Low Comp.	-0.6402***	-0.5379**	-0.6506**
	(0.2433)	(0.2607)	(0.2536)
ln(HO Price)×High Citizen		-0.0030	
		(0.0038)	
ln(HO Price)×Low Comp.×High Citizen		0.0058	
		(0.0055)	
ln(HO Price)×High Depop			0.0014
			(0.0012)
ln(HO Price)×Low Comp.×High Depop			-0.0052
			(0.0041)
Full Effects of Low Comp.	-1.269***	-1.189***	-1.278***
First-stage KP F-stat	56.950	27.827	28.374
Census Attributes	✓	✓	✓
Housing Attributes	✓	✓	✓
Parcel FE	✓	✓	✓
ZIP FE			
Year-Month FE	✓	✓	✓
Observations	2,202,829	2,202,829	2,202,829

Note: This table reports results from estimating models in Table 6 using the repeat-sales sample. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B16: Alternative Explanations Results, Repeat Transactions

X =	Disaster	Flood Zone	Elasticity	Homestead	Quick Sale
	(1)	(2)	(3)	(4)	(5)
ln(HO Price)	-0.6050**	-0.6303**	-0.4964*	-0.4722	-0.4421
	(0.2821)	(0.2851)	(0.2817)	(0.3162)	(0.2833)
X	0.7602			0.3159	0.2078
	(0.9366)			(0.2250)	(0.2502)
X×*ln(HOPrice)*	-0.1056	-0.5025**	0.2901	-0.0570**	0.0056
	(0.1182)	(0.2420)	(0.1984)	(0.0287)	(0.0323)
First-stage KP F-stat	57.295	56.887	53.765	55.213	57.692
Census Attributes	✓	✓	✓	✓	✓
Housing Attributes	✓	✓	✓	✓	✓
Parcel FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Observations	2,202,829	2,173,702	1,951,741	2,202,829	2,202,829

Note: This table reports 2SLS regression results from estimating the natural log of the sale price of each property, *ln(Housing Sales Price)*. *ln(HO Price)* is the natural log of weighted average county-level homeowners insurance prices, using total insurance exposure as the weight. In each column we set **X** equal to a variable that represents proxy for a potential alternative explanation for our results that we then interact with *ln(HO Price)*. In column (1) *Disaster* is a binary variable equal to one if a property reported having a disaster in the NAL dataset over the past 3 years and zero otherwise. In column (2) *Flood Zone* is an indicator that equals one for properties that are designated as coastal flood zone (V or VE) and zero otherwise. In column (3) *Elasticity* is a binary variable equal to one if the county's weighted average elasticity—aggregated from tract-level estimates in Baum-Snow and Han (2023) using 2000 occupied housing units as weights—is above the sample median. This uses an elasticity measure estimated via a quadratic Finite Mixture Model (FMM) based on 2001 tract characteristics. In column (4) *Homestead* is a binary variable equal to one if a property has filed for a homestead exemption and zero otherwise. In column (5) *Quick Sale* is a binary variable equal to one if a property previously sold over the past 12 months and zero otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Variable Definitions

Variable	Definition (Data Source)
ln(HO Price)$_{j,t}$	The natural log of county-quarter level homeowners insurance price (direct premiums written divided by policies in force) weighted by exposure (QUASR).
ln(Housing Sale Price)$_{i,t}$	The natural log of a property's sale price (NAL).
ln(Population)	The natural log of a county's population (ACS).
ln(Density)	The natural log of a county's population density (ACS).
Unemployment	The unemployment rate in a county-quarter (ACS).
% College	The percent of a county's population with at least a bachelors degree (ACS).
% Black/Hispanic	The percent of a county's population that reports being either black or Hispanic (ACS).
% Health Insurance	The percent of a county's population that reports having health insurance (ACS).
ln(Median Income)	The median income reported in each county (ACS).
% Poverty	The percent of each county that is below the poverty line (ACS).
Median Year Built	The median year a house in each county was built (NAL).
% Owner Occupied	The percent of households in each county that are owner occupied (ACS).
Living Area	The reported living area for a property in square feet (NAL).
Land Square Feet	The reported land area for a property in square feet (NAL).
Home Age	The age of a property in years (NAL).
Renovated	A binary variable equal to one if a property has been renovated in the past 5 years and zero otherwise (NAL).
Improvement Quality Low	A binary variable equal to one if a home is reported to have received low quality improvements and zero otherwise (NAL).

D Mandated Entrants and their Credit Ratings

We document pricing behavior in the Florida homeowners insurance market from the mandated entrant insurers in our sample. Specifically, they appear to set higher prices compared to existing Florida insurers or voluntary entrants (i.e., non-mandated insurers). Since we can only observe accepted prices and not price offers, this implies that the higher prices set by the mandated entrants are accepted by some consumers. Given the relative homogeneity of homeowners insurance policies, the acceptance of these higher prices requires additional explanation; we therefore investigate the factors that drive homeowners to select mandated entrants.

Prior theoretical and empirical literature on P/C insurance markets finds that consumers are risk-sensitive. Consequently, insurers with higher insolvency risk tend to charge lower prices (e.g., Sommer 1996; Cummins and Danzon 1997; Phillips et al. 1998; Froot 2007). All else equal, an insurance policy with a higher probability of nonperformance (i.e., the insurer can not pay a covered claim due to insolvency) will be less valuable.

While the existing studies tend to use proxies for insurer insolvency risk, there are two natural channels that could steer consumers, who potentially lack the financial literacy to evaluate an insurer's financial strength, to understand the value of a more stable, though expensive, insurance company. First, ratings agencies provide a third-party evaluation of an insurer's financial strength that can serve as an easily comprehensible signal to consumers. Epermanis and Harrington (2006) find evidence consistent with prior studies (e.g., Sommer 1996; Phillips et al. 1998) when using ratings as a proxy for financial strength—premiums decline for insurers that receive a financial strength rating downgrade. Second, insurance is often purchased through an agent who is likely in a better position to evaluate financial strength to a consumer. Cookson et al. (2024) find that because coverage limits are "difficult to estimate without the input of insurance agents," consumers rely heavily on agent recommendations. This reliance implies that agents act as essential intermediaries who translate complex data, like financial strength ratings, into actionable advice

We, therefore, hypothesize that financial strength ratings of mandated entrants justify homeowners' willingness to accept their higher priced homeowners insurance policies. A.M. Best has historically been the most prominent rating agency for U.S. insurers—Doherty et al. (2012) note that they acted as a "monopoly" for many decades. In addition to A.M. Best ratings, we also examine Demotech ratings which play an important role in the Florida insurance market. Demotech is a relatively newer rating agency that provides the lone rating for many Florida Homeowners insurers. Sastry et al. (2023) find evidence that Demotech standards for a given rating level are lower than A.M. Best. We provide descriptive statistics on the rating characteristics of our sample insurance companies based on whether they are a mandated entrant or not.

First, we provide a summary of the distribution of ratings for our sample insurance companies, separately reported by mandated and non-mandated status. As shown in Appendix Table D1, mandated insurers are more likely to have an A.M. Best rating than non-mandated insurers (5.7% mandated versus 42.7% non-mandated do not have a Best Rating). Among the insurers that do have ratings, the distribution of ratings is higher for the mandated insurers. For the top three rating categories ("A++," "A+," and "A") the mandated entrants have proportionally more firms. Turning to Demotech ratings, Appendix Table D2, the mandated entrants tend to be less likely to have a Demotech rating (63.2% versus 49.5%). As highlighted by Sastry et al. (2023), it is important for homeowners insurers to maintain at least some financial strength rating so that they can insurer properties backed by government-sponsored enterprises' (GSE) loans. Within the distribution of Demotech ratings, the mandated insurers, again, tend to be more highly rated relative to the non-mandated insurers.

Table D1: **A.M. Best Ratings**

Rating	*Mandated*	*Non-Mandated*
A++	40.6%	6.0%
A+	15.1%	10.1%
A	30.2%	22.9%
A-	8.5%	8.5%
B++	0.0%	3.0%
B+	0.0%	2.5%
B	0.0%	1.6%
B-	0.0%	2.6%
F	0.0%	0.1%
None	5.7%	42.7%

Table D2: **Demotech Ratings**

Rating	*Mandated*	*Non-Mandated*
A"	28.3%	0.3%
A'	0.0%	5.9%
A	8.5%	44.3%
None	63.2%	49.5%

We next perform univariate tests to more fully understand differences in ratings and financial strength between our sample of mandated and non-mandated insurers. We report the results in Appendix Table D3. Overall, the tests are consistent with our observations when looking at the ratings distribution across mandated and non-mandated insurers. Mandated insurers are statistically significantly more likely to have an A.M. Best rating, while they are less likely to have a Demotech rating. If they do have a Demotech rating, it is unlikely to be a mandated insurer's only rating (only 5.66% of sample firms). Overall, our examination of the ratings (and, implicitly, the financial strength) of mandated versus non-mandated insurers suggests that the mandated entrants are financially stronger firms. Based on prior theoretical and empirical literature examining the link between financial strength and P/C insurance pricing (e.g., Sommer 1996; Epermanis and Harrington 2006), this is a potential explanation for why consumers are willing to pay higher prices for homeowners insurance from the mandated insurers.

The existence of two options for rating agencies may indicate that firms can potentially "shop" for ratings, which would make ratings a noisy signal for insurer financial strength. Accordingly, we also examine some select financial characteristics to further understand differences between mandated and non-mandated insurers. We report tests of univariate differences between these two groups in Appendix Table D4 for measures of firm size (natural log of assets), profitability (return on assets), leverage (liabilities divided by surplus), and regulatory capital (risk-based capital ratios). We observe that mandated insurers are statistically significantly more profitable, less leveraged, and have stronger risk-based capital ratios. We do not find a statistical difference in firm size, which could be driven by larger national insurer groups establishing small, Florida-specific subsidiaries (sometimes referred to as "pup" companies). Overall, these results are consistent with our findings for ratings, where mandated insurers appear to be financially stronger.

Table D3: **Univariate Differences**

Mandated	*Non-Mandated*	*Difference*
A. Have an A.M. Best Rating?		
94.34%	57.32%	37.02%***
B. Have a Demotech Rating?		
36.79%	50.48%	-13.69%***
C. Only have an A.M. Best Rating?		
63.21%	46.92%	16.29%***
D. Only have a Demotech Rating?		
5.66%	39.67%	-34.01%***
E. Rated by both A.M. Best and Demotech?		
31.13%	10.81%	20.32%***

Table D4: **Univariate Differences**

	Mandated	*Non-Mandated*	*Difference*
ln(Assets)	19.64	19.44	0.20
ROA	0.03	0.01	0.02**
Liab./Surplus	1.20	1.65	-0.45***
RBC Ratio	70.09	32.13	37.97***