Homeowners Insurance and Housing Prices*

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Abstract

How costly is insurance for homeowners? We answer this question by constructing a novel dataset that combines detailed homeowners insurance data, including average insurance prices and policy cancellations (both overall and hurricane-related), with property-level housing assessments and transactions in Florida. To identify the causal effect of homeowners insurance prices on housing values, we exploit a Florida statute that mandates auto insurers to participate in the homeowners insurance market if they offer homeowners insurance in other states. This regulation leads to higher insurance prices by mandated insurers while remaining uncorrelated with local housing market conditions. We find that a 10% increase in homeowners insurance prices decreases housing prices by at least 1.4%. The effect of rising homeowners insurance prices is more pronounced among mortgage-financed buyers and owner-occupants, while smaller in counties with high perceived risk of future losses. Disaster experiences are not the primary driver, but hurricane-related insurance cancellations significantly reduce housing prices. Rising insurance prices also dampen housing market activity by reducing the probability of home sales. Together, our findings highlight the critical role of private homeowners insurance in shaping housing market dynamics, where both pricing and availability influence property values.

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1 Introduction

The U.S. homeowners insurance market was valued at $131.5 billion in 2022 and Florida has the highest homeowners insurance premium growth in the past 25 years among all states (Born and Karl 2022). The average homeowners insurance price in Florida is $4,231 in 2022, which is more than twice the national average, $1,544 (Born, Cole, and Nyce 2021; Carrillo, Telljohann, and Nyce 2022). Higher insurance prices could make houses less attractive to potential buyers through higher financing costs. However, the effect of homeowners insurance prices on housing prices may vary depending on homeowner characteristics, such as the absence of a mortgage or a strong preference for insurance coverage due to high risk aversion. The extent to which homeowners insurance prices are capitalized in house prices, therefore, is an empirical question.

In this study, we aim to identify the effect of private homeowners insurance prices on housing prices by leveraging detailed homeowners insurance information filed by insurers and property-level housing information in Florida from 2011 to 2020.[1] 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 on housing prices, such as flood insurance (e.g., Gibson and Mullins 2020; Bakkensen and Barrage 2022; Hino and Burke 2021; Georgic and Klaiber 2022; Ge, Lam, and Lewis 2022) or state-funded public homeowners insurance (e.g., Nyce et al. 2015). 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 important than the publicly funded flood insurance; the latter is

[1] 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). To be clear, we are excluding rental insurance or insurance policies for mobile homes or condominiums.

mandated only for properties in designated flood zones, whereas the former is a requirement for all properties with mortgages. Accordingly, only about 19% of housing units have flood insurance in Florida in 2019.[2] In addition, state-funded public homeowners insurance is only about 10% of total homeowners' insurance market in Florida in 2021.[3]

We construct a novel dataset that includes homeowners insurance prices as well as housing prices. For homeowners insurance, we utilize regulatory reporting of homeowners insurance price that includes comprehensive details on homeowners insurance premiums, the number of policies, insured exposures, cancellations, and non-renewals, segmented by individual insurance companies, line of business, county, and quarter in Florida from 2011 to 2020. The availability of homeowners insurance market data including the insured exposure is the key advantage of our analysis compared to the recent private homeowners insurance proxy calculated via mortgage escrow data (e.g., Keys and Mulder 2024; Sastry, Sen, and Tenekedjieva 2024; Ge, Johnson, and Tzur-Ilan 2024).[4] To measure house prices, we utilize a comprehensive property tax assessment dataset covering over 3.8 million individual housing transactions in Florida during the sample period.

We first report descriptive evidence of the relationship between homeowners insurance prices and housing prices. As expected, metropolitan areas such as Miami-Dade report the highest average housing prices and also the highest average homeowners insurance prices relative to more rural areas in Florida. The Miami-Dade area also reports the highest housing price increase as well as homeowners insurance price increase during our sample period. When we scale the average homeowners insurance price by housing prices in Miami-Dade, however, it is one of the lowest counties in Florida. Conversely,

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

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

[4] As noted by Keys and Mulder (2024), escrow data only provide a proxy for the homeowners insurance premiums paid by the homeowner, which is a function of both the risk of the home and the homeowners' choice on the insured exposure amount.

areas near Orlando and in northern Florida report much higher homeowners insurance prices scaled by housing prices. Overall, we find heterogeneity across counties in Florida on housing prices and homeowners insurance prices, that cannot be summarized simply based on the location characteristics.

Next, we perform our empirical analysis by examining the relationship between average homeowners insurance prices and house prices. We extend Rosen's hedonic pricing model (Rosen 1974) to estimate the capitalization effect of homeowners insurance prices on housing values. We use a sample of individual housing transactions and model specifications that include a rich set of time-varying property-level attributes and property fixed effects. Our ordinary least squares (OLS) estimates suggest that a one-percent increase in average homeowners insurance prices is associated with approximately 0.08-0.14 percent lower average housing prices.

An important aspect of our analysis is the direction of causality. On the one hand, homes in high-risk areas may have lower prices due to climate risks. On the other hand, homes in high-risk areas may also offer superior amenities, such as those found in coastal regions. In addition, if higher insurance costs reduce affordability, this could deter low-income buyers, potentially leading to an increase in house prices for market segments that cater to more affluent buyers seeking premium amenities. To address these issues, we leverage a regulation that mandates homeowners insurance market participation. In Florida, auto insurers that write homeowners insurance in states other than Florida are required to offer homeowners insurance coverage. We find that these mandated homeowners insurers' average homeowners insurance prices are larger than local homeowners insurers without auto insurance business in Florida; we exploit a granular insurer-county-quarter-level dataset to instrument the quarterly county-level average homeowners insurance prices using the percent market share of these mandated homeowners insurers.

Our instrumental variable (IV) estimates reveal a large effect of the homeowners insurance and housing price relationship than our ordinary least squares (OLS) estimates—we observe a 0.61-0.68 percent (p-value < 0.01) reduction in housing prices for a percent increase in homeowners insurance prices. To understand this difference, we follow Ishimaru (2024) and decompose the IV-OLS coefficient gap into three components: difference in weights on the covariates, difference in weights on the treatment levels, and difference in identified marginal effects that arises from endogeneity bias. We find that a significant portion of the gap is driven by marginal effect differences, suggesting that our IV estimates address potential endogeneity bias and that OLS estimates represent a conservative upper bound of the negative impact of homeowners insurance prices on housing prices.

What are potential explanations of the reduction in housing prices due to homeowners insurance price increase? We explore various mechanisms and alternative explanations. First, we conjecture that the mortgage lender's homeowners insurance requirement affects the extent to which home buyers respond to the rising homeowners insurance prices. Homeowners without financing restrictions, such as cash buyers, are less likely to adjust their housing valuations in response to higher insurance prices. In contrast, buyers relying on mortgages are directly impacted by rising insurance costs, as these costs are integrated into their overall financing constraints. To test this, we measure the prevalence of mortgage-financed purchases in each county and year using data on mortgage originations and the percentage of owner-occupied homes with a mortgage. Our findings indicate that the reduction in housing prices is significantly larger in counties with a high prevalence of mortgage-financed buyers compared to counties where cash buyers are more common.

Second, as a hurricane-prone state, Florida's vulnerability to natural disasters suggests that homebuyers' perceived risk influences how they value homeowners insurance. Buyers with higher perceived risk derive greater utility from homeowners insurance as part of their housing bundle, making them less responsive to increases in insurance costs. Conversely, buyers with lower perceived risk are more sensitive to changes in insurance prices, leading to larger reductions in their willingness to pay for housing. To proxy for perceived risk, we use three measures: FEMA's National Risk Index (NRI) scores, which capture expected annual losses and community resilience; and two variables derived from the Yale Climate Opinion Survey, reflecting beliefs about climate change and its perceived risks. Using these proxies, we find that counties with a higher prevalence of perceived risks experience smaller reductions in housing prices when homeowners insurance prices increase. This result underscores the role of risk perception in moderating the capitalization of insurance costs into housing prices.

Third, the negative relationship between homeowners insurance prices and housing prices could be influenced by disaster-related factors, as natural disasters may simultaneously increase insurance costs and reduce property values. To examine this possibility, we leverage a unique feature of the assessment data, which identifies properties affected by disasters in the past three years, and include an interaction term between instrumented homeowners insurance prices and a disaster indicator in our model. Our findings indicate that natural disasters do not significantly affect the relationship between homeowners insurance prices and housing prices, as the main coefficient on homeowners insurance prices remains stable. We further test this hypothesis using alternative proxies for disaster-related losses, including counties with high hurricane modeled losses (FPHLM) and counties with high per capita property losses (SHELDUS). The results consistently show that disaster experiences are not the primary driver of the observed relationship. Together with our risk perception explanations, our finding is consistent with Baldauf, Garlappi, and Yannelis (2020) that house prices are influenced only by people's perception of risk rather than by the risk itself.

We also compare how owner-occupants and investors, including flippers, respond to rising homeowners insurance costs. Owner-occupants, identified through properties with a Homestead Exemption, prioritize long-term housing utility and are therefore more sensitive to increases in insurance costs. Our findings suggest a notable reduction in property values for these buyers. In contrast, flippers who engage in quick sales are less sensitive to rising insurance costs, as their focus on short-term financial returns reduces the impact of such costs on their pricing decisions.

Importantly, we find evidence that insurance policy cancellations due to hurricanes reduce housing prices. Because we calculate insurance prices as total premiums divided by the number of policies in force, cancellations can directly affect this measure, especially in hurricane-prone Florida where supply-side challenges persist. We combine cancellations and non-renewals into a single measure and examine their impact on housing prices using OLS and 2SLS models. Our findings indicate that total cancellations are not significantly associated with housing prices; however, cancellations due to hurricanes exhibit a negative and statistically significant effect, with 2SLS results indicating that a 1 percent increase in hurricane-related cancellations leads to a 0.1 percent reduction in housing prices. This relationship is likely driven by supply shortages following natural disasters, as homeowners increase their demand for insurance while insurers face constraints on maintaining policies. These findings highlight the importance of supply-side factors in the insurance market and their influence on housing values, aligning with prior literature on post-disaster insurance demand (e.g., Michel-Kerjan and Kousky 2010; Gallagher 2014). Combined with our estimated effect of homeowners insurance prices on housing prices, this finding suggests that the availability of homeowners insurance also affects housing prices.

For the last step of our analysis, we aim to quantify the extensive margin of the effect of homeowners insurance prices on the housing market. Using the property tax assessment data, we calculate the number of homes transacted in a county-quarter to measure the probability of home sales. We find that a percent increase in homeowners insurance price reduces sales probability of homes by approximately 0.3 percentage point. This finding suggests that higher homeowners insurance costs not only influence housing prices but also dampen transaction volumes in the housing market. Given that the unconditional average probability of home sales is 1.6% in Florida, the estimated effect size explains about 18% of the housing sales probability in Florida.

Our findings contribute to the growing literature examining the effects of climate change on household finance, with a specific focus on property insurance markets. Existing literature on property insurance markets mainly focuses on the interaction between homeowners insurance and catastrophe risks (e.g., Cummins, Doherty, and Lo 2002; Grace, Klein, and Kleindorfer 2004; Born and Viscusi 2006; Born and Klimaszewski-Blettner 2013). A vast literature exists on public insurance such as flood insurance (e.g., Browne and Hoyt 2000; Bin, Kruse, and Landry 2008; Landry and Jahan-Parvar 2011; Kousky and Michel-Kerjan 2017; Collier et al. 2022; Mulder and Kousky 2023). A nascent literature focuses on the effect of regulation on the homeowners insurance market (e.g., Oh, Sen, and Tenekedjieva 2022; Eastman and Kim 2023; Sastry 2022), but do not examine its impact on housing market outcomes. We contribute to the growing literature on property insurance by documenting empirical evidence of the effect of private homeowners insurance on housing prices.

On the household finance side, our study contributes to the growing literature on insurance prices and real estate values. 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 Beltrán, Maddison, and Elliott (2018) for a review). Several studies have examined how flood insurance or state-run public insurance affects housing values (e.g., Nyce et al. 2015; Bakkensen and Barrage 2022; Billings, Gallagher, and Ricketts 2022; Georgic and Klaiber 2022; Ge, Lam, and Lewis 2022). In addition, a developing literature documents the homeowners insurance costs are rising (e.g., Boomhower et al. 2024; Keys and Mulder 2024) 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.[5] It is precisely this gap that we address in this study.

With climate change risk, other parts of the U.S. may expect to experience a property market crisis similar to Florida. Our findings from the Florida market can shed light on the regulatory efforts put forth by federal and state governments. If rising insurance prices lead to decreased housing values, it could have a cascading effect on Florida's real estate market. Homeowners might find their properties devalued, which could lead, in extreme situations, to homeowners having negative equity (i.e., owing more on a mortgage than the home is worth). Additionally, potential buyers might be deterred from homeownership due to the combination of high insurance costs and the potential for decreased property value, leading to reduced demand and further devaluation.

[5] See NAIC (2022).

2 Background and Data

2.1 Florida's Homeowners Insurance Market

Florida is an important homeowners insurance market in the U.S. During the 2011 to 2020 period, about 9 to 10 percent of total premiums written in homeowners insurance policies nationwide (50 states and District of Columbia) came from Florida;[6] as a comparison, the share of housing units of Florida to the nationwide is 7% by the end of 2020 (U.S. Census Bureau). The average homeowners insurance prices in Florida are the highest in the U.S. (Born and Karl 2022).

The take-up rate for homeowners insurance in Florida is high. In our data, after merging county-level housing information from property tax assessment data to the total number of county-level homeowners insurance policies (see Section II.B for more details), we see that the average take-up rate for homeowners insurance is approximately 65% from 2011 to 2020 period.[7]

Homeowners insurance in Florida is provided by private insurance companies as well as a state-funded public insurance company, known as Citizens. Citizens is the insurance company of the last resort (i.e., a "residual" insurer). Only homeowners of risky homes who cannot purchase homeowners insurance from private insurance companies are eligible to purchase from Citizens. Insurance coverage provided by Citizens' homeowners insurance policies is similar to private homeowner insurance contracts, yet the average price of Citizens' homeowners insurance is approximately 15% higher than prices in the private market. Citizens is required by state law to charge actuarially sound rates to its policyholders, while complying with the state legislative and after being approved by the

[6] Authors' analysis based on NAIC Homeowners Reports from 2014 to 2023.

[7] We calculate the annual take-up rate as the ratio between the total number of homeowners insurance policies and the total number of single-family homes in the county tax rolls.

state's insurance commissioner.[8] The share of homeowners insurance provided by Citizens (measured using total exposures) on average from 2011 to 2020 is 6%, which varies during the period due to the Depopulation program; the share is the lowest in 2015 at 2.7% and it is the highest in 2011. Coverage is 8.6% by the end of 2020, the final year in our sample. The pattern is similar when we measure the share of Citizens using total premiums (price multiplied by policies in force), although the shares of total premiums are higher due to the higher price of homeowners insurance provided by Citizens; the share of total premiums written is the lowest in 2015 at 5% and the highest in 2011 at 20%, and it is 16% by the end of 2020.

2.2 Data

2.2.1 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, direct premiums written, and exposures for each of the 67 counties where they write business. Insurers also report detailed activity for each county-quarter, including the number of non-renewals, the number of non-renewals due to hurricanes, the number of cancellations, and the number of cancellations due to hurricanes. Both non-renewals and cancellations suggest a discontinuance of the insurance coverage with the current insurance company. The major difference is the timing of the cancellation. If the policy is canceled before the expiration

[8] See, https://www.citizensfla.com/-/20230329-citizens-board-approves-2023-rate-recommendations. (last access: May 24, 2024)

date, it is considered a “cancellation” and if the policy is canceled at the expiration date it is considered a “non-renewal.” 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 houses, “Personal Residential - Homeowners (Excl Tenant and Condo) - Owner Occupied,” which is the predominant type of residential homeowners insurance in Florida (28%) and is commensurate to the popular homeowners insurance policy in the U.S. (HO-3 policy).[10] QUASR maintains data prior to 2011, but we use data from 2011 because the reporting method was improved in 2011 to accurately capture homeowners insurance premiums.[11] We acknowledge that starting in 2014, a few insurers started not to report to the QUASR due to trade secret reasons (Dumm and Eckles 2022). Our results are robust when we limit our data to insurers who consistently report to QUASR throughout the sample period.

2.2.2 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 including improvements to the houses as well as the previous two sales information. Then, each county office submits tax rolls to the Florida Department of Revenue. We use property-level information from the Florida property tax roll to create panel data of housing transactions. While tax rolls are reported annually, we can construct

[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).

[10]The percentage is calculated when we consider all residential property types, including single family homes as well as condominiums. If we exclude condominium owners, homeowners insurance for owner occupied properties account for 35%.

[11]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.

a sample of property sales using the date of the sales reported in the assessment data. To match our homeowners insurance data, we create property-level sales transaction data for single-family homes. We exclude transactions with a price 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 engage in at least two transactions during the sample period, resulting in 2,202,829 property-transaction observations.

To maintain the consistency of our analysis of insurer data, which is at the county-quarter level, we construct a housing price index (NAL-HPI) at this same level using the sold properties. We verify our findings using the house price indices from the Federal Housing Finance Agency (FHFA 2022), which is only available at the annual frequency. We compare NAL-HPI with FHFA's HPI and find they are highly correlated (correlation coefficient greater than 0.99 in both cases).

2.2.3 Other Data

The time-varying demographic and economic characteristics are collected 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 the Home Mortgage Disclosure Act (HMDA) as well as data from Fannie Mae and Freddie Mac to calculate percent of government-sponsored enterprise (GSE) mortgages in each county in a given year. 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 the Floria 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 source of risk perception, we use the Yale Climate Opinion Maps 2016 (Howe et al. 2015). The Yale Climate data has been widely used in prior literature such as Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020).

3 Homeowners Insurance Price and Housing Price

3.1 Descriptive Evidence

We begin by documenting descriptive evidence of the heterogeneous effects of homeowners insurance prices on housing prices in Florida. In Figure 1, we plot the average housing prices (using property-level sales price) in each county throughout the 2011 to 2020 period (Figure 1.A) and the average homeowners insurance prices in each county during the same period (Figure 1.B). Each county is colored based on its rank in deciles, with darker shades representing higher values. Visually, we observe a similar pattern where areas near Miami-Dade report both the highest average housing prices as well as the highest average homeowners insurance prices. There are some counties where their rank of housing prices and homeowners insurance prices are the reverse, such as Osceola County right below the Orlando area, or Hendry County right next to Fort Myers. For details on the summary statistics of average homeowners insurance prices and housing prices, refer to Table 1.

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

Acknowledging the intuitive correlation that higher home values generally correspond with higher insurance prices, we further investigate the cost relative to home value. We calculate the average homeowners insurance price scaled by the average housing prices in 2019. Figure 2 visualizes the scaled homeowners insurance prices, showing the opposite pattern as compared to Figure 1.B. For example, several counties in northern Florida report the lowest average homeowners insurance prices but the highest prices when scaled by housing values. This suggests that the relationship between insurance prices and housing values 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.

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 3, 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.

To further explore the correlation between insurance prices and housing values, our last descriptive evidence aims to visualize separately the changes in housing prices and homeowners insurance prices from 2011 to 2020. For each county, we calculate the changes in housing prices (using the NAL-HPI index) and changes in homeowners insurance prices, separately, from 2011 to 2020. Then, we identify counties that experienced larger homeowners insurance price increases than housing price increases. We then visualize these counties in Figure 4. The yellow-shade counties experienced larger homeowners insurance price increases than housing price increases. These counties are mostly those with low hurricane loss estimates, such as northern Florida but also include southern counties with high hurricane loss estimates, such as Tampa area and the Key West. Together, Figures 1 to 4 suggest the complex relationship between insurance prices and housing values and heterogeneity of housing prices and homeowners insurance prices across time and areas in Florida.

3.2 Homeowners Insurance Costs Capitalization Model

The hedonic pricing method is a revealed preference approach that infers the value of characteristics in differentiated products, typically used in real estate markets (Rosen 1974). It decomposes a product into its constituent characteristics and estimates the contributory value of each. We extend the model to include homeowner's insurance costs to specify an individual's utility function as a concave function of property characteristics and a composite good representing all other consumption:

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

In this framework, X_i represents property-specific characteristics of house i. N_j captures demographic and economic characteristics in county j. HO_i denotes homeowner's insurance costs. Households are utility-maximizing agents constrained by their budgets, and they differ in their preferences for housing attributes, α.

Competition amongst buyers and sellers results the hedonic equilibrium price schedule:

$$P_{i,j} = P_{ij}(\beta, X_i, N_j, \mathrm{HO}_j) \tag{2}$$

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 derivate reflects the implicit price of the attribute in equilibrium. Due to time-varying changes in hedonic equilibria, these effects are interpreted as capitalized values that reflect the present market valuation of the attributes (Kuminoff and Pope 2014). For example, the effect of HO is given by: $\frac{\partial P_{ij}}{\partial \mathrm{HO}_j} = \beta \frac{\bar{P}}{\mathrm{HO}_j}$, where $\bar{P}$ is the average price.

This capitalization can also be rationalized in the well-established capital-theoretic model by Poterba (1984), which suggests a rational home buyer should equate the price of a house with the discounted value of future service. Intuitively, homeowners insurance is a key component of the housing services cost (see Appendix A for a detailed discussion).

We merge our county-quarter-level homeowners insurance price data with property-level transaction data that includes sales prices and various property characteristics. The benefit of this approach is that we can use a hedonic model to control for various observable housing attributes as well as a repeated-sale model to control for time-invariant location-specific attributes and housing attributes.[13]

3.2.1 OLS Regression

To empirically estimate the capitalization of homeowner's insurance costs, we specify the following double-logarithmic regression model:

$$\ln P_{i(j)t} = \beta \ln \mathrm{HO}_{i(j)t} + X_{it} + N_{jt} + \alpha_i + \alpha_t + \epsilon_{ijt} \tag{3}$$

[13]In a supplemental analysis, we find that our hedonic model using housing attributes with geographical area and calendar time (year by month) fixed effects yields more than 60% model fit to explain the sales price of the houses.

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. Our key test variable, $\ln HOi_{(j)t}$, 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 insured property exposure of private insurer k for 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 the 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 HO Price variable is that we measure the property exposure adjusted average homeowners insurance price accounting for the homeowners insurers' participation that differs across counties and time. It is crucial to account for both the insurers' market share and their differing property exposures, since insurance prices can be different 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) 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 the demand and supply of houses and homeowners insurance prices in each county. These characteristics include demographic attributes (population, population density, unemployment rate, college attainment, the proportion of Black and Hispanic populations, the percentage of people with health insurance), income attributes (median household income, the percentage of households below the poverty line), and housing market attributes (median housing value, median year of construction, the percentage of owner-occupied homes, the vacancy rate, and the percentage of owner-occupied homes with a mortgage). We also include 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, an indicator that the property's improvement quality is low, an indicator that the property's improvement quality is medium, and an indicator that the property's improvement quality information is missing. In addition, we include location (zip code or property) and time (e.g., year-by-month) fixed effects (α_i and α_t, respectively).

[14]If we were 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 with total number of policies and find consistent results. In addition, we use un-weighted average homeowners insurance and find large effect sizes. These results are reported in Appendix Table B3.

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 it is at the property level for the repeat-sales sample. Our preferred model is the repeat-sales sample as we can control for the unobserved amenity value of each property which can affect both homeowners insurance prices and housing prices. We cluster standard errors at the zip code level.[16] Our coefficient of interest, β, captures the relationship between changes in homeowners insurance prices on house prices. This specification allows us to quantify the extent to which homeowner's insurance costs are capitalized into housing prices.

3.3 Instrumental Variable

The key concern for our estimate of β based on equation (3) is that variation in homeowners insurance prices over time may be correlated with variation in housing prices (driven, for example, by increased property risk exposure), even when controlling for for a wide range of observable characteristics. While our repeat-sales model mitigates bias by accounting for unobservable housing characteristics that influence housing prices, it may still be affected if changes in the underlying demand for homeowners insurance over time also impact housing prices simultaneously. To address this, we leverage a regulation unique to Florida's insurance market that influences the homeowners insurance market but does not directly affect housing prices. Using this regulation as an instrument, we estimate a two-stage least squares (2SLS) model.

[16]Results are robust 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.

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 writes homeowners insurance in other states, with an exception for auto insurers affiliated with a homeowners insurer writing in Florida.[17] The statute was first introduced in 2008, prior to the beginning of our sample period. A key aspect of the statute is that it mandates the auto insurer's participation in the homeowners insurance market without imposing minimum quantity requirements or price caps on their homeowners insurance offerings. These regulations has led these mandated homeowners insurers in Florida to price homeowners insurance higher than local Florida homeowners insurers.

Several factors contribute to this outcome. First, some of these mandated homeowners insurers have little experience writing homeowners in disaster-prone states like Florida despite their homeowners insurance business in other states, making their pricing less competitive. Second, even for those with experience in disaster-prone regions, such as Louisiana or through past operations in Florida, their decision to exit Florida's homeowners insurance market reflects strategic reluctance to compete on price. By charging higher homeowners insurance prices, ceteris paribus, these mandated homeowners insurers may limit their exposure to the Florida market while formally complying with the statute's requirements.

[17] 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.*

We begin by providing description evidence that the statute affected auto insurers in Florida. As shown in Appendix Figure B1, the number of auto insurers in Florida that also write homeowners insurance (including those writing homeowners insurance via affiliated insurers) shrunk in 2005 (post-Hurricane Katrina) and continues to decline until 2008.[18] However, the declining trend stopped in 2008, and the number of auto insurers also writing in homeowners insurance increased in 2009.

In Figure 5 Panel A, we report the distribution of homeowners insurers' market share in Florida separately for insurers that write auto insurance in Florida and those that do not ("No Auto"). Among the former, we further separate insurers based on whether the insurer writes auto insurance directly in Florida ("Writes Auto") or only through affiliates ("Writes Auto (Affliates)"). To assess the relationship between auto insurers' mandated participation in the homeowners insurance market, we examine both our sample period and earlier periods although we acknowledge that the homeowners insurance policies before 2011 include limited coverage policies (wind-only policies) as discussed in Data section.[19]

The share of homeowners insurance policies written by auto insurers exceeded 80% in 2000 but declined to approximately 70% in 2005-2006. By 2008, the share dropped to around 60%, continuing to decrease until 2014, when it reached 22%. Since the policies written by homeowners insurers are endogenous to the insurance price set by insurers, we next explore the average homeowners insurance price differences.

[18]These data on auto insurance and homeowners insurance participation come from insurers' annual statutory statements, and the homeowners insurance premium includes all types of homeowners insurance policies.

[19]We face several data limitations that do not allow us to perform our main analysis over a longer time series. Notably, QUASR's reporting requirements do not differentiate between wind-only coverage in homeowners policies. The inclusion of wind-only homeowners insurance policies prior to 2011 would bias down the average insurance prices due to the limited coverage of these policies.

In Figure 5 Panel B, we report the log average homeowners insurance price across counties, weighted by total insured property exposure, for each year. The prices are separated by insurers' auto insurance market participation. Because we observe insurers' auto insurance market participation at the annual-level, we use fourth-quarter homeowners insurance prices each year. We acknowledge that the insurance prices only contain the observed price of accepted homeowners insurance policies and would be biased down if the policies offered by mandated homeowners insurers that are higher than the observed prices are not accepted by policyholders.

We find that the average homeowners insurance prices are higher for those written by auto insurers (i.e., those mandated to offer these policies) compared to those written by homeowners insurers not writing auto insurance; the difference increases over time and peaks in 2020. Moreover, the average homeowners insurance prices of homeowners insurers not writing auto insurance and those affiliated with auto insurers that write in Florida are not as high as those writing auto insurance, and often lower than for insurers that do not offer auto insurance. Together, these trends highlight the pricing dynamics influenced by Florida's regulatory framework and the varying competitiveness of insurers across market segments.

3.3.2 Instrument Variable Construction

Leveraging auto insurers' mandated homeowners insurance market participation in Florida and the granular insurer-county-quarter-level homeowners insurance data reported in QUASR, we instrument the average homeowners insurance prices in a county-quarter with the average share of homeowners insurers' auto insurance participation. The rationale behind our instrument is that, as shown previsouly, mandated homeowners insurers charge higher homeowners insurance prices than homeowners insurers that do not participate in the auto insurance market. Consequently, counties with a higher proportion of homeowners insurance policies written by Florida auto insurers will exhibit higher average homeowners insurance prices.

We acknowledge that mandated homeowners insurer pricing in homeowners insurance market may adjust as they sell more homeowners insurance policies. To account for this, we calculate the relative share of homeowners insurance premiums to the combined total of homeowners insurance premiums and auto insurance premiums in Florida for each insurer, which we refer to as the "*FL Home/Auto share*." While our focus in this study is homeowners insurance for owner-occupied properties, the statute is broader and only refers to the participation in the "homeowners insurance market." To align with the statute, we use each insurer's annual statutory statements, which report total homeowners insurance premiums written (inclusive of all types of homeowners insurance) and private passenger insurance premiums written for auto insurance.

We link the insurer-year-level *FL Home/Auto share* variable to each insurer's participation in the owner-occupied insurance market in each county. We use the beginning-of-year *FL Home/Auto share* of each insurer, as insurers need to go through homeowners insurance price approval process before offering policies. Specifically, our instrument (*FL Home/Auto share*) takes the form of:

$$\text{FL Home/Auto share}_{jt} = \sum_{k} w_{kj}^{t=0} \times \frac{\text{Home}_{jt-1}}{\text{Auto}_{jt-1}} \tag{5}$$

where $w_{kj}^{t=0}$ is insurer i's initial share in county j, measured in the first quarter in our sample when we observe the insurer's market participation in each county. When calculating the individual insurer's share, we use the number of policies written by insurer i in the county.[20]

Using the initial share allows us to limit the influence of changes in an insurer's market participation within a county over time. Therefore, the main source of variation over time is each insurer's relative participation in the homeowners and auto insurance markets in Florida (at the beginning of the year). A homeowners insurer with *FL Home/Auto share* near zero writes predominantly auto insurance in Florida, whereas one with *FL Home/Auto share* of 1 writes only homeowners insurance. We expect a county's homeowners insurance price to be lower if the county is written mostly by insurers with high *FL Home/Auto share* (i.e., few auto insurers).

3.3.3 Validity of the Instrument

We graphically depict the relevance of the instrument in Figure 6 Panel A. We create nine bins of county-quarter observations defined as the absolute value of the instrument (*FL Home/Auto share*). There are no observations below 0.1, so the first bin includes observations with values below 0.2. The next eight bins each cover a 0.1 interval, with the eighth bin containing observations between 0.8 and 0.9 and the last bin including observations with values betwee 0.9 and 1). As expected, we find a negative relationship between the instrument and average insurance prices for the first three bins. The relationship become positive for county-quarters with a moderately high average

[20]To ensure that these weights sum to one, we normalize the initial shares ($w_{kj}^{t=0}$) by dividing each share by the total initial shares within the county. This adjustment ensures that the normalized shares sum to one within each county.

FL Home/Auto share between 0.6 and below 0.8. Importantly, we find that average insurance prices are lower for county-quarters written by insurers without much auto insurance coverage (e.g., bin 0.3) compared to county-quarters written by a low share of *FL Home/Auto share* (bin 0.6).

Our results are consistent if we estimate the relationship between *FL Home/Auto share* and average homeowners insurance prices while controlling for county fixed effects and year-quarter fixed effects, suggesting that the relationship is not driven by inherent differences across counties (Appendix Figure B2). We also formally test the relevance of the instrument in the first stage estimate of the 2SLS models and find that the F-stats are well above 100. We report full results including first-stage estimates in Table 2.

To establish causality using the instrument, it is important to show that the instrument meets exclusion restrictions, i.e., the instrument is as good as randomly assigned and does not affect the outcome variable (i.e., house prices) except through the first-stage channel (Angrist and Pischke 2009). While we cannot formally test the exclusion restrictions, we note that auto insurers' participation (and their pricing) in the homeowners insurance market is driven by the exogenous regulatory mandate that went into effect before the beginning of our sample period. We also find that while average homeowners insurance prices in each county-quarter are correlated with county characteristics such as income and unemployment, our instrument is not correlated with these characteristics (see Appendix Table B1).

Because the mandated homeowners insurers are required to offer coverage, our instrument captures a supply-side factor in the homeowners insurance market that affects insurance prices but not necessarily demand-side factors. We indirectly assess the assumption that our instrument affects the housing prices only through homeowners insurance prices, by estimating whether property risk exposures are correlated with our instrument.

We proxy property risk by calculating the average insured exposure in each county, which is the total insured exposure scaled by total premiums written in the county-quarter; the average insured exposure is jointly determined by policyholder coverage choices and property risk. Since some counties may be more vulnerable to disaster losses that could jointly affect insurer participation and insured exposure, we estimate the marginal effects of *FL Home/Auto share* bins (with bin 0.2 as the omitted reference group) on average insured exposures controlling for county and year-quarter fixed effects. We visualize the relationship in Figure 6 Panel B, which suggests that there is no statistically significant relationship between the instrument and property risk.

Lastly, we show that the instrument is correlated with the housing prices, which we report in Figure 6 Panel C. Average housing prices are the highest for county-quarters with a low *FL Home/Auto share* and decline as the share increases. Average housing prices are lowest for county-quarters with a low share of auto insurers (bin 0.9) and they are lower than county-quarters predominantly served by insurers without auto insurance participation (bin 1).

3.3.4 IV Regression

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

$$\ln \mathrm{HO}_{jt} = \gamma \text{FL Home/Auto share}_{jt} + N_{jt} + \alpha_j + \alpha_t + \epsilon_{jt} \tag{6}$$

where FL Home/Auto share$_{jt}$ is the instrumental variable. The second-stage equation estimates the impact of homeowners insurance on house prices:

$$\ln P_{i(j)t} = \beta \ln \widehat{\mathrm{HO}_{i(j)t}} + X_{it} + N_{jt} + \alpha_i + \alpha_t + \epsilon_{ijt} \tag{7}$$

where $\ln \widehat{\mathrm{HO}_{i(j)t}}$ are the predicted values from equation (6). 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 including first-stage estimates in Section 3.4 Results.

3.4 Results

Table 2 reports OLS and 2SLS estimates of the effects of homeowners insurance prices on housing prices, as well as first-stage estimates. Our preferred model is the 2SLS estimates using the repeat-sales sample, where the first-stage instruments $ln(HOPrice)$ with *FL Home/Auto share* (first-stage estimate includes time-varying control variables as well as the location and year-month fixed effects). We report OLS results for the full sample and the repeat sales sample in columns (1) and (2), respectively, as baseline estimates. The coefficient estimate on homeowners insurance prices are both negative, and the magnitude is larger in column (2) than that in column (1), at -0.125 (p-value = 0.086), implying that the association between homeowners insurance prices and housing prices becomes larger after controlling for unobservable property characteristics.

We report 2SLS results for the full sample and the repeat sales sample in columns (3) and (4), respectively. We find stronger effect sizes in both columns, at -0.555 and -0.6065 (both p-value < 0.01), than OLS estimates. The coefficients suggest that a percent increase in homeowners insurance prices reduces housing prices by 0.55 to 0.6 percent. The robust *Kleibergen-Paap* F-stats are 239.6 for the full sample and 118.8 for the repeat sample. Consistent with the expectation, the first-stage results indicate that the FL Home/Auto instrument is negatively associated with homeowners insurance prices.

To explain the differences between our OLS and IV estimates, we apply the decomposition method developed by Ishimaru (2024), which decompose the IV-OLS gap into (1) the covariate weight difference, (2) the treatment-level weight difference, and (3) the endogeneity bias (or marginal effect difference). In our context, the covariate weight difference arises from heterogeneous impact of homeowners insurance prices on housing prices across observed economic and demographic attributes with different responses to the instrument. The treatment-level weight difference stems from nonlinear impact across homeowners insurance price levels with different sensitivity to the instrument, while the marginal effect difference corresponds to endogeneity bias associated with omitted unobserved variables. Comparing the coefficients between column (2) and column (4) in Table 2, we find that the IV-OLS gap of -0.528 (the difference between the OLS estimate of -0.082 and the IV estimate of -0.610) is primarily explained by the endogeneity bias (-0.339 or 64%) and the covariate weight difference (-0.187 or 35%), while the treatment-level weight difference contributes only 0.002 (0.3%). In other words, with the covariate weight difference components accounted for, the IV-identified effects are 0.339 lower than the OLS-identified effects.

As reported in Appendix Table B2, the results are similar when clustering standard errors at the county-level both for the first and the second stage estimates; the F-stats are larger than 20. We also find similar results with large effect sizes when using average homeowners insurance prices before weighting with insured loss exposures (Appendix Table B3).

3.5 Mechanisms and Alternative Explanations

The results thus far indicate that rising homeowners insurance price reduces housing prices. In this section, we examine potential mechanisms underlying this relationship and consider alternative explanations.

3.5.1 Mortgage Lender Requirement

The first explanation for the capitalization of homeowners insurance costs lies in the budgetary constraints imposed by mortgage lenders' requirement for continuous coverage. In the hedonic pricing framework discussed in Section 3.2, utility-maximizing households account for housing services costs, including homeowners insurance, when determining their willingness to pay for a property. For households financing their purchases through mortgages, homeowners insurance becomes a mandatory component of their budget constraint, directly influencing their utility function. Conversely, cash buyers are not bound by this requirement, and homeowners insurance costs may not factor into their utility maximization process.

Consider two prospective buyers bidding for the same house. Homeowner A is a cash buyer, while Homeowner B is reliant on mortgage financing. For Homeowner A, the cost of homeowners insurance does not enter their utility function and thus does not alter their bid. In contrast, for Homeowner B, an increase in homeowners insurance costs reduces the disposable income available for other consumption and limits the maximum bid they can offer under their budget constraint. This divergence in behavior reflects the role of homeowners insurance as a consumption good for mortgage-dependent buyers, consistent with Poterba's notion of housing as a bundle of services, including insurance, as discussed in Appendix A.

To empirically test this mechanism, we interact the homeowners insurance price variable with the proxy for areas with a high prevalence of type B homeowners (*High Mortg*):

$$\begin{aligned} \ln P_{i(j)t} = {} & \beta_1 \ln \mathrm{HO}_{i(j)t} \cdot \text{High Mortg}_{i(j)t} + \beta_2 \ln \mathrm{HO}_{i(j)t} \\ & + \beta_3 \text{High Mortg}_{i(j)t} + X_{it} + N_{jt} + \alpha_i + \alpha_t + \epsilon_{ijt} \end{aligned} \tag{8}$$

We do not observe the bidding process nor the potential bidders of a property. However, we proxy the prevalence of mortgage requirements in two complementary ways. First, we use the percentage of owner-occupied homes with a mortgage from the ACS data. This measure reflects the owner (i.e., seller) side 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 Mortg*). Because we include county fixed effects, the coefficient on the interaction term ($\ln HO_{i(j)t} \cdot High\ Mortg_{i(j)t}$) capture the changes in the homeowners insurance prices for counties that become highly prevalent with mortgaged homes on housing prices.

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

We report the results in Table 3, focusing on the preferred 2SLS model using the repeat sales sample (the results are consistent to using the full sample as in Appendix Table B4). Column (1) of Table 3 reports the results using the *Origination* variable, where we do not find a statistically significant coefficient on the interaction term. In columns (2) and (3), we report the results using the *High Origination* variables constructed with the number of properties and the value of properties, respectively. Both columns show similar results, in line with our expectation, that areas with a high prevalence of originations respond more to the increase in homeowners insurance prices than other areas. Compared to the estimate in Table 2 column (4), the effect sizes are 1.7x to 2x. We also find that areas with more originations (estimate on *High Origination*) are associated with higher average housing prices. We find consistent results using the full sample, as reported in Appendix Table B4.

3.5.2 Reservation Price of Homeowners Insurance

Florida's vulnerability to hurricanes suggests that expected future losses from natural disasters influence the utility households derive from homeowners insurance. In the hedonic framework, homeowners insurance is treated as a consumption good that contributes to the overall utility derived from housing services. Prospective homeowners with higher perceived risk of natural disasters are likely to place greater value on homeowners insurance as part of their housing bundle, consistent with Poterba's notion of housing as a composite of services. For these buyers, the utility derived from homeowners insurance is higher, leading to a more inelastic response to changes in insurance prices. Consequently, an increase in homeowners insurance costs is less likely to affect the price they are willing to pay for the property. Conversely, prospective buyers with lower perceived risk derive less utility from homeowners insurance and are more responsive to changes in its price. For these households, an increase in insurance costs reduces their willingness to pay for the property, resulting in a greater decrease in house prices.

Risk perception is not observed in our data. However, we explore two datasets (outlined in Section 2.2.3) to proxy for average risk perception in each county in Florida using three variables. The first variable is the risk score from the National Risk Index (NRI), produced by FEMA. The 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 as of 2022, 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 2013. The second variable 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. The variable, *Belief*, is calculated as the average percentage of affirmative responses to these questions. Since the Yale Survey is not well populated prior to 2013, for each county we take the average across the sample period from 2008 to 2021. Therefore, the *Belief* variable is time-invariant. We define a binary variable, *High Belief in Risk*, that equals one for counties with the top tercile of *Belief* value and zero otherwise.

The third variable 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. We construct a binary variable, *High Risk Perception*, similar to the way we construct the High Belief in Risk variable.

Using these three time-invariant variables, and we estimate the model with an interaction term of the prevalence of high risk perception:

$$\begin{aligned}\ln P_{i(j)t} = \beta_1 \ln \mathrm{HO}_{i(j)t} \cdot \text{High Risk}_{i(j)t} + \beta_2 \ln \mathrm{HO}_{i(j)t} \\ + \beta_3 \text{High Risk}_{i(j)t} + X_{it} + N_{jt} + \alpha_i + \alpha_t + \epsilon_{ijt}\end{aligned} \tag{9}$$

The results of 2SLS estimate of equation (9) on repeat sales sample are shown in Table 4. Across three columns, which differ in terms of the risk perception variable, we find consistent results showing that areas with high perceived risk report smaller reductions in housing prices for the homeowners insurance price increase.

3.5.3 Disaster experience

One concern with our results in Table 2 is that the estimated effect of homeowners insurance prices on housing prices could be a consequence of natural disasters. Prior studies document that areas suffering from natural disaster losses may experience a dual impact: reduced housing prices due to the damages incurred and increased homeowners insurance prices (e.g., Bernstein, Gustafson, and Lewis 2019; Bakkensen and Barrage 2022). In such scenarios, the relationship we identify might not directly reflect the impact of homeowners insurance prices but rather the underlying effect of natural disasters. Our assessment data includes an indicator of disaster and the year of the disaster. Therefore, we can identify, for each property-year, whether it was affected by a disaster. We test this alternative explanation by including the interaction term of the instrumented homeowners insurance price variable with the disaster indicator along with the disaster indicator variable. Specifically, for each property-year, we create an indicator variable (Disasteri(j)t) that equals one for houses that experienced disasters in the past three years identified by the county tax offices. Our model takes the form of:

$$\begin{aligned}\ln P_{i(j)t} &= \beta_1 \ln \mathrm{HO}_{i(j)t} \cdot \mathrm{Disaster}_{i(j)t} + \beta_2 \ln \mathrm{HO}_{i(j)t} \\ &\quad + \beta_3 \mathrm{Disaster}_{i(j)t} + X_{it} + N_{jt} + \alpha_i + \alpha_t + \epsilon_{ijt}\end{aligned} \tag{10}$$

If natural disaster losses do not affect the relationship between housing prices and homeowners insurance prices, the estimated coefficients on the interaction terms (β_1) would be zero. In the case where natural disaster losses are the sole determinants of housing prices, and insurance prices are capturing the effect of disaster losses rather than insurance costs, only Y would be negative, and both β and β_1 would be zero. These results would also suggest that the disaster losses do not provide new information on the property, and do not lead to immediate change in housing prices.

However, a statistically significant β_1 estimate would indicate the heterogenous effect of natural disaster losses and homeowners insurance prices on housing prices. For example, a negative β and positive β_1 suggest that disaster-affected properties with higher insurance prices have higher housing prices compared to properties without disaster losses and higher insurance prices; this would be indicative of either the premium placed on insured properties for disaster-prone areas or discount placed on insured properties for areas less likely to experience disasters. A negative β along with a negative β_1, however, would imply that disaster-affected properties with higher insurance prices see a larger reduction in housing values, highlighting the double-devaluation of houses due to disaster losses and increased insurance costs.

The results of 2SLS estimate of equation (10) on repeat sales sample are shown in Table 5 Column (1). We find that disasters do not affect housing prices. The coefficient estimate on homeowners insurance prices (ln(HO Price)) is -0.68 (p-value < 0.01), implying that our main estimate in Table 2 column (4) is close to the estimated effect among properties without recent disaster experiences. The disaster variable in NAL tracks the past three years, and hence may double-count the disaster experience if the property were sold within three years. We, therefore, explore two other variables that proxy for disaster experience. We identify counties with either high hurricane modeled losses (FPHLM) or natural disaster property losses per capita (SHELDUS), which are the top tercile counties. Hurricane modeled losses are time invariant, but the natural disaster property losses per capita varies each quarter. The results of replacing the Disaster variable with these two variables are reported in columns (2) and (3) of Table 5. Similar to column (1), we find that disaster is not driving our estimates. We find consistent results using the full sample, as reported in Appendix Table B5.

3.5.4 Investors and Flippers

In the context of Rosen's hedonic pricing model, property characteristics and buyer attributes interact to determine the equilibrium price schedule, reflecting the utility-maximizing decisions of households. Poterba's capital-theoretic framework further emphasizes that property values capitalize expectations about future housing services and associated costs. Investors and flippers introduce heterogeneity into this equilibrium by prioritizing financial returns over consumption utility, thereby altering the dynamics of price capitalization. For instance, properties with a *Homestead Exemption* typically indicate owner-occupants who derive utility from long-term housing services, aligning closely with the traditional hedonic pricing framework. In contrast, properties sold in a short period of time (e.g., within 12 months) suggest speculative behavior, where short-term financial gains take precedence over long-term utility considerations. By interacting these variables with homeowners insurance costs, we examine how different buyer profiles—investors or flippers versus owner-occupants—affect the capitalization of insurance costs into property values, shedding light on the role of buyer/seller heterogeneity.

In Table 6, we present results from interacting the instrumented homeowners insurance price variable with *Homestead Exemption*, a binary variable indicating properties with a homestead exemption, and *Quick Sale*, a binary variable identifying properties sold within the past 12 months. The results reveal a negative and statistically significant coefficient on the interaction term for *Homestead Exemption*, suggesting that owner-occupants are more sensitive to rising homeowners insurance costs, which reduce property values for these buyers. Conversely, the positive and significant coefficient on the interaction term for *Quick Sale* indicates that speculative buyers are less sensitive to insurance costs, potentially due to their emphasis on short-term financial returns rather than long-term consumption utility. These findings highlight the divergent effects of insurance price capitalization across buyer types, with owner-occupants bearing a larger burden of rising insurance costs compared to investors and flippers.

3.5.5 Insurance Policy Cancellations

Since insurance prices, HO_{jt}, are calculated by dividing total insurance premiums by the number of policies in force, this measure could be influenced by changes in either the numerator or the denominator. To delve deeper into the implications of insurance availability on housing prices (Sastry, Sen, and Tenekedjieva 2024), we explore the detailed insurance-related variables, especially in the context of Florida's frequent natural disasters and the supply-side challenges in the homeowners insurance market (e.g., Carrillo, Telljohann, and Nyce 2022). We are particularly interested in the relationship between homeowners insurance cancellations. As mentioned in section 2.2.1, we observe four different types of cancellations in QUASR reported by private insurers: non-renewals, non-renewals due to hurricanes, cancellations, and cancellations due to hurricanes. According to QUASR documentation, cancellations and non-renewals differ only based on the timing; a policy canceled before the expiration date is categorized as cancellation, and a policy canceled after the expiration date is categorized as non-renewal. In addition, either the insurance company or the policyholder can initiate policy cancellation or non-renewal. We, therefore, combine both non-renewals and cancellations to refer to cancellations. We create two measures of cancellations. We take the natural log of the number of cancellations for all policies as well as only for those related to hurricanes and estimate the following equation:

$$\ln P_{i(j)t} = \beta \ln \text{Cancellation}_{i(j)t} + X_{it} + N_{jt} + \alpha_i + \alpha_t + \epsilon_{ijt} \tag{11}$$

Equation (11) is the same as equation (3) except that we replace $\ln \text{HO}_{i(j)t}$ with $\ln \text{Cancellation}_{i(j)t}$. While we do not anticipate cancellations are subject to the same endogeneity issues as in our analyses of homeowners insurance prices, we are concerned that there is an omitted variable bias that explains insurance policy cancellations. For example, private insurers may refrain from writing in certain areas to efficiently pool risks in an idiosyncratic manner. We therefore run the analysis using both OLS and 2SLS using the same instrument as in Section 3.3. [21]

Figure B3 highlights the relevance of our instrumental variable in relation to policy cancellations. While total cancellations exhibit some irregularities, cancellations specifically attributed to hurricanes demonstrate strong relevance. The data suggest that areas with fewer auto insurers tend to experience a higher number of homeowners insurance cancellations following hurricanes. This pattern is likely influenced by regulatory mandates that suppress insurers' ability to cancel homeowners insurance policies.

[21] In unreported result, we also construct an alternaitve instrument by leveraging the Citizens depopulation program. We hypothesize that areas with high prevalence of policies that are part of the Citizens depopulation program could be indicative of areas that are more favorable to private insurers. We, therefore, instrument policy cancellations using the number of policies transferred from Citizens to the private insurers (i.e., Citizens depopulation program). The intuition is that the depopulation program activity is at the state level and therefore is not associated with local housing price changes. We find similar results using the state-level Citizens depopulation instrument.

In Table 7 columns (1)-(3), we report the OLS results using the repeat sales model. In column (1), the coefficient estimate on total policy cancellations is statistically insignificant. However, in column (2), we use a variable of policy cancellations that only include cancellations due to hurricanes, we find negative coefficients. The results is robust to county clustering in column (3). We report the 2SLS results in columns (4)-(6). We find a negative and statistically significant coefficient on the policy cancellations due to hurricanes. We find a larger economic magnitude in the instrumental variable regression model, suggesting that a percent increase in policy cancellations due to hurricanes reduces the housing prices by 0.1 percent (p-value = 0.025).

Since homeowners demand homeowners insurance more after natural disasters, the equilibrium homeowners insurance price increases when more policies are canceled after hurricanes (supply shortage), leading to lower housing values. The existing empirical literature on insurance demand suggests that the demand for property insurance increases after natural disasters (e.g., Michel-Kerjan and Kousky 2010; Gallagher 2014). The results reported in Table 7, therefore, indicate that insurance supply issues play a role in the relationship between insurance prices and housing prices that we document in Tables 2.

4 Homeowners Insurance Price and Housing Sales

Thus far, we have documented evidence that increasing homeowners insurance prices reduces housing prices (i.e., intensive margin). Our final empirical analysis aims to provide evidence on the extensive margin on the housing market by investigating the relationship between homeowners insurance prices and the likelihood of housing transactions. If homeowners are accounting for the financing cost of homeowners insurance prices that lead to housing price reduction, we would also expect homeowners to be less likely to purchase homes with increasing homeowners insurance prices. Using tax assessment data that including 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:

$$\%Sale_{jt} = \beta \ln \mathrm{HO}_{jt} + N_{jt} + \alpha_j + \alpha_t + \epsilon_{jt} \tag{12}$$

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

To the best of our knowledge, we are the first to examine the effect of private homeowners insurance on housing prices. Homeowners insurance is the major financial contract that helps homeowners finance various financial losses arising from property damage and liability exposure. While it is the most important insurance for homeowners, the vast literature focuses on public insurers such as flood insurance and state-run public insurance programs. Our rich dataset that 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.

We develop a novel instrument based on Florida's unique regulatory framework, which mandates auto insurers to participate in the homeowners insurance market if they offer such coverage in other states. This regulation creates exogenous variation in homeowners insurance prices driven by supply-side constraints unrelated to local housing market conditions. By exploiting this variation, our instrumental variable approach yields estimates that effectively address potential endogeneity concerns, providing a more accurate assessment of the causal effect of homeowners insurance prices on housing values.

We document compelling evidence that higher homeowners insurance price reduces housing prices, and the effect is different for mortgaged homes or homes with natural disaster losses. Our results are robust to using both house price indices and individual housing transactions, to including a comprehensive location-specific or property-specific fixed effects, and to including a rich set of time-varying locational and housing attributes.

We identify key mechanisms driving this relationship. Mortgage lenders' insurance requirements amplify the negative impact of insurance price increases on housing values in areas with a high prevalence of mortgaged buyers. 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. Importantly, our results suggest that the observed relationship is not driven by disaster-related losses but reflects broader dynamics in the homeowners insurance market, including supply-side constraints and pricing strategies. Additionally, we document significant effects of policy cancellations, particularly those caused by hurricanes, on housing prices. Our analysis shows that hurricane-related cancellations exacerbate the negative impact of rising insurance costs on property values, likely due to increased insurance demand and constrained supply in the aftermath of disasters. These findings highlight the critical role of insurance availability in shaping housing market outcomes and underscore the broader implications of supply-side dynamics in the homeowners insurance market. Our analysis also reveals implications for housing market liquidity, as higher insurance prices reduce the probability of housing transactions.

As climate change exacerbates risks in disaster-prone areas, our findings offer timely insights into the potential ripple effects of rising insurance costs on property values and market activity. Further analysis tying insurance market supply and housing prices can shape the direction of the regulations. If insurance companies are increasing prices due to the lack of reinsurance availability or increased financing costs, then interventions could focus on expanding reinsurance options or providing state-backed reinsurance pools (e.g., the Florida Hurricane Catastrophe Fund). Conversely, if housing values are affected by perceptions of risk rather than actual insurance costs, strategies like public education campaigns or infrastructure improvements to mitigate natural disaster losses could be more effective.

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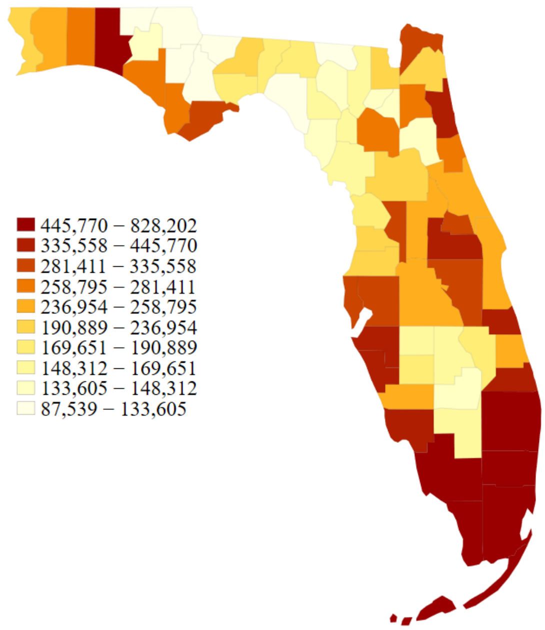
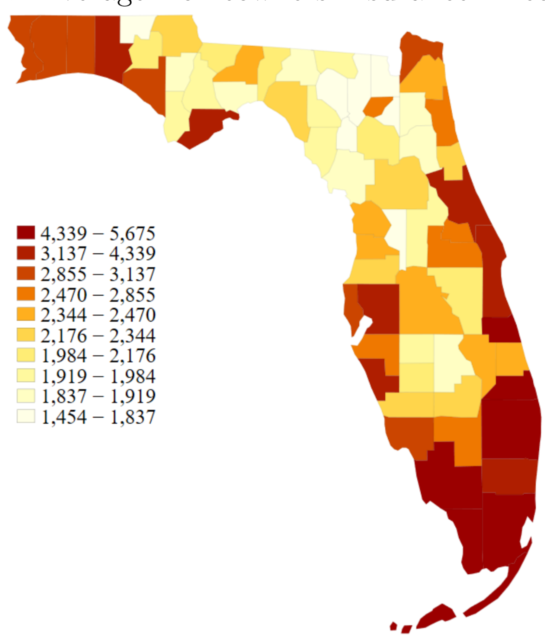
Figure 1: Florida Housing Values and HO Premiums by County

A. Average Housing Prices

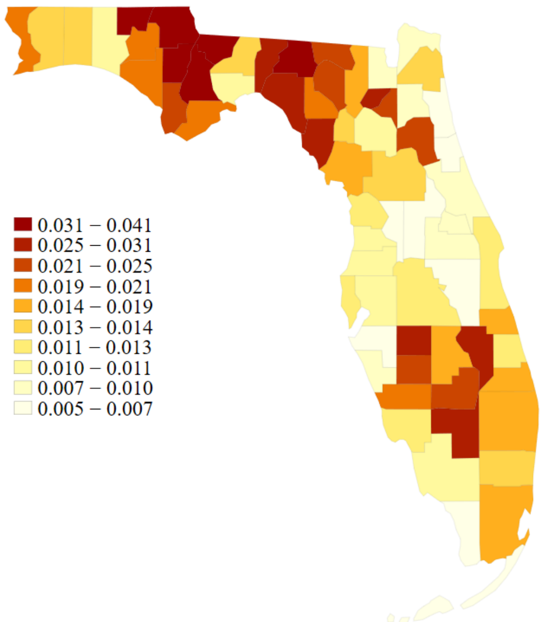


B. Average Homeowners Insurance Price



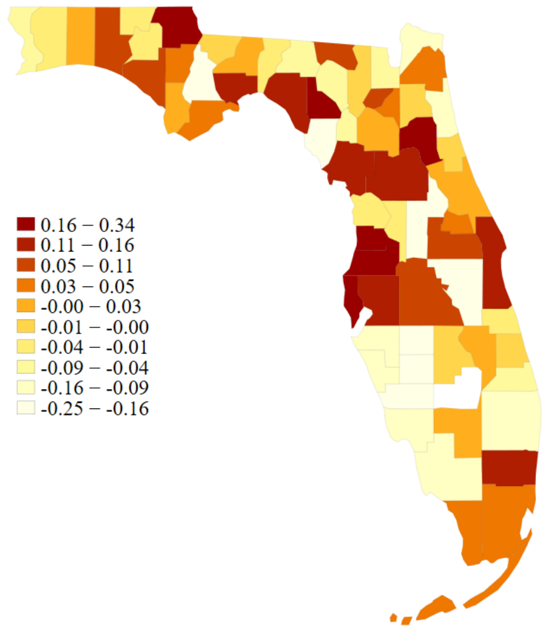
Source: NAL for housing prices and QUASR for homeowners insurance prices.
Notes: Panel A. reports average sale price for homes in each Florida county. Panel B. reports average annual homeowners insurance premiums in each Florida county. Reported data are from 2019.

Figure 2: County-Level Homeowners Insurance Price Scaled by House Prices



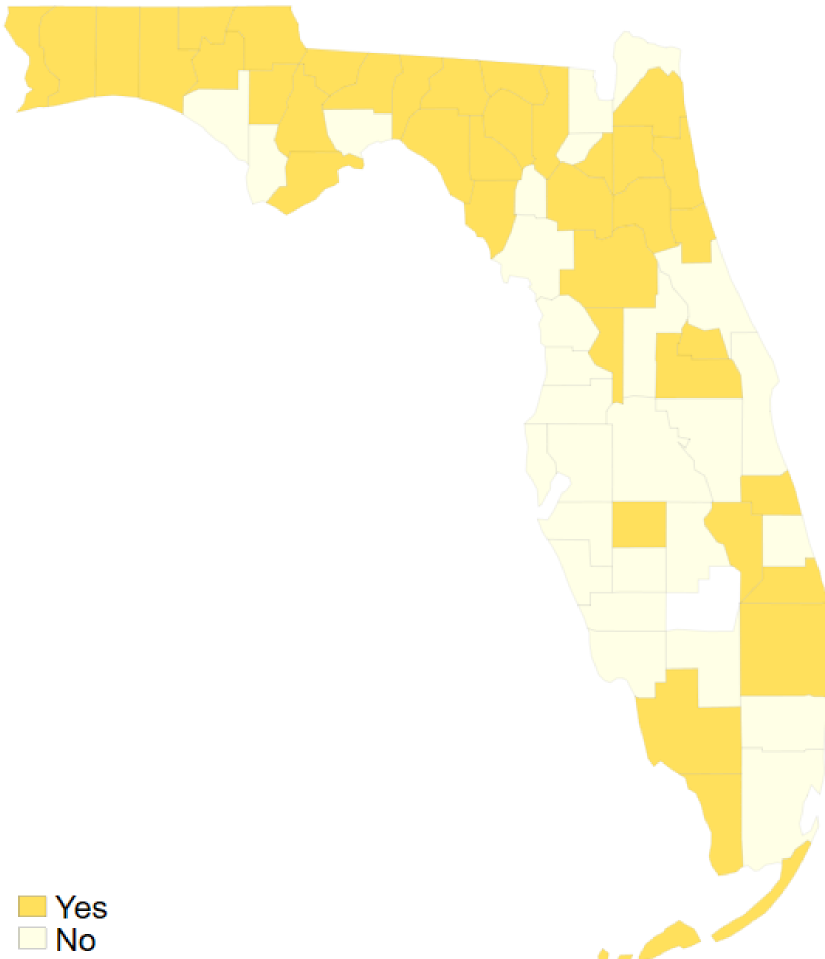
Source: NAL for housing prices and QUASR for homeowners insurance prices.
Notes: This figure reports the average ratio of homeowners insurance prices to average home price for each Florida county reported in 2019.

Figure 3: Correlation Coefficient between Changes in Homeowners Insurance Prices and Changes in House Prices



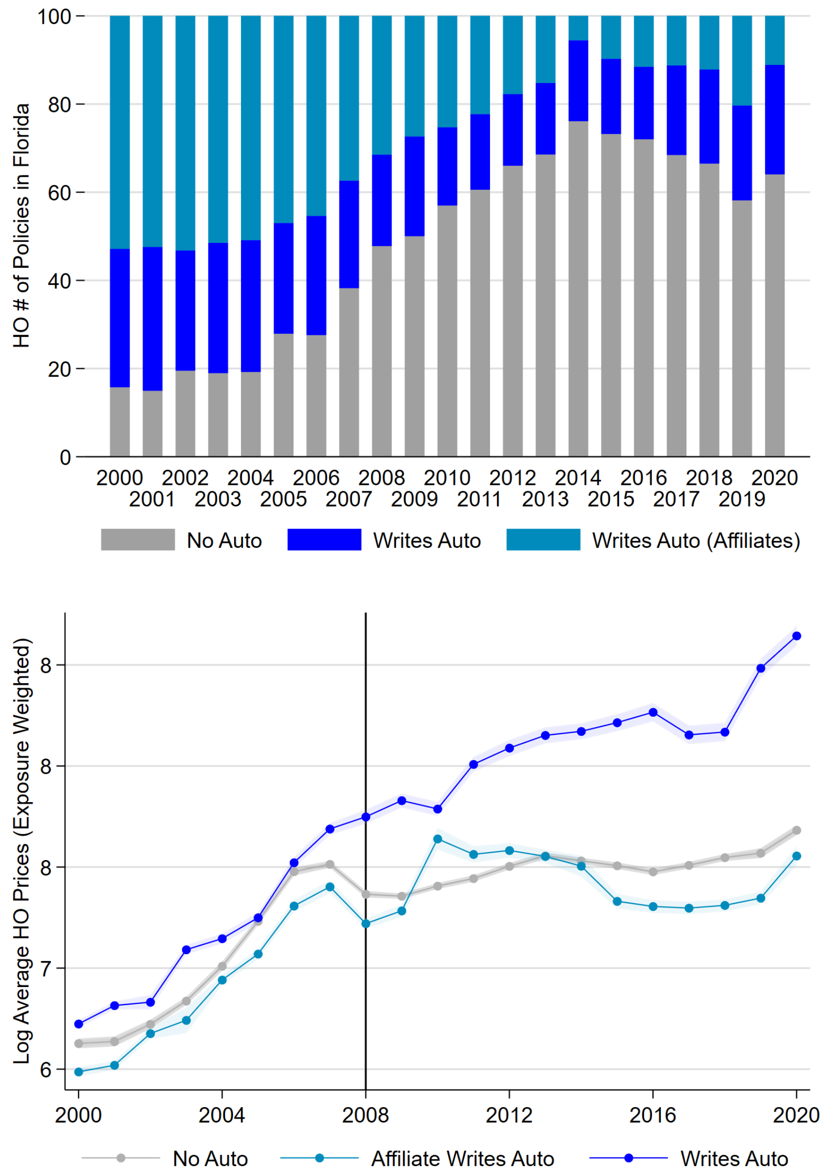
Source: NAL for housing price index (HPI) and QUASR for homeowners insurance prices.
Notes: This figure reports the correlation between changes in the housing prices, measured by the NAL-HPI, and changes in homeowners insurance prices.

Figure 4: Changes in Homeowners Insurance Prices and Changes in House Prices by County



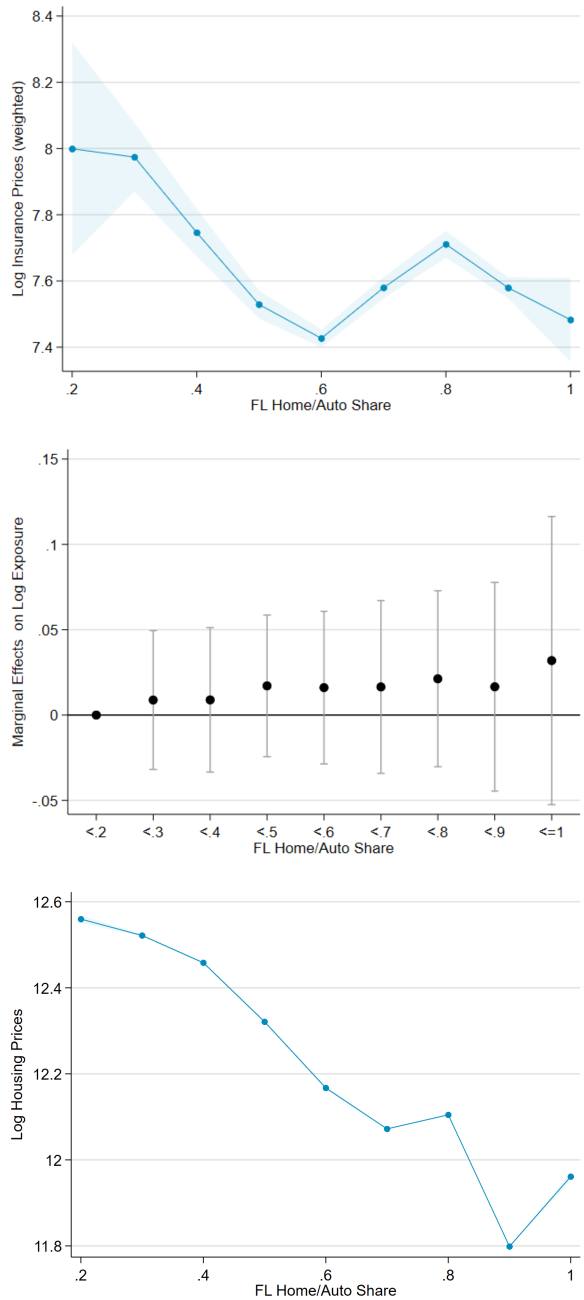
Source: NAL for housing price index (HPI) and QUASR for homeowners insurance prices.
Notes: This figure reports the intersection between changes in house prices (measured by the NAL-HPI) and changes in homeowners insurance price measured at the county level. Counties shaded in dark yellow experienced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

Figure 5: Florida Homeowners Insurance Market Trend



Notes: The top figure reports the market share based on the number of homeowners insurance policies offered in Florida by each insurer's auto insurance business. We identify auto insurance offerings using the State Pages in the NAIC annual statements. "Writes auto (affiliates)" only include insurers who do not directly write auto insurance in Florida, but have affiliates that write auto insurance in Florida. The bottom figure reports the natural log of the average homeowners insurance price (weighted by exposure) at the county-year level using 4^{th} quarter homeowners insurance prices. We separately report prices, as in the top figure, for firms that write no auto insurance, directly write auto insurance, and have affiliates that write auto insurance in Florida.

Figure 6: Homeowners Insurance Price Instrument Relevance



Notes: The top left figure reports estimates for an OLS model where the dependent variable is the natural log of each county's total premiums scaled total insured exposure (estimated using county-quarter observations). The top right figure reports estimates for an OLS model where the dependent variable in the total exposure divided by total county direct premiums written (county-quarter observations). The bottom figure reports the mean value of the natural log of housing prices on the vertical axis (property-level observations). The horizontal axis for all 3 figures is the weighted average share of auto insurance business to auto plus homeowners business in each county-quarter. We create 10 bins in increments of 0.1 (i.e., 1 indicates county-quarters with a weighted average share of auto insurance business larger than 0.9 and less than or equal to 1). No county-quarter reported weighted average shares below or equal to 0.1, so we omit that bin. We use the number of policies in force for homeowners insurers in each county-quarter to calculate weights.

Table 1: Summary Statistics

	Mean	SD	P1	P25	P50	P75	P99
ln(Housing 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
% Health Insurance	0.84	0.04	0.70	0.82	0.85	0.87	0.92
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	1986	5.75	1975	1983	1986	1990	2002
% Owner Occupied	0.68	0.08	0.52	0.61	0.69	0.73	0.90
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. *ln(HO Price)* is the natural log of the average homeowners insurance premium, where the average premiums are weighted by total insurance exposures. *ln(Population)* is the natural log of the county population. *ln(Density)* is the natural log of the population density. *Unemployment* is the unemployment percent. *% College* is the percent of the population with at least a bachelors degree. *% Black/Hispanic* is the percent of the population that is either black or Hispanic. *% Health Insurance* is the percent of the population that reports having health insurance. *ln(Median Income)* is the natural log of the median household income. *% Poverty* is the percent of the population below the poverty line. *Median Year Built* is the median year a house in each county was built. *% Owner Occupied* is the percent of houses that are owner occupied. *Living Area* is the reported living area in square feet. *Land Area* is the reported land area in square feet. *Home Age* is the reported age of the home. *Renovated* is a binary variable equal to 1 if a home has been renovated in the past five years and 0 otherwise. *Improvement Quality Low* is a binary variable equal to 1 if the home has received improvements of low quality and 0 otherwise. *Improvement Quality Mid* is a binary variable equal to 1 if the home has received improvements of medium quality and 0 otherwise. *Improvement Quality Missing* is a binary variable equal to 1 if the home is missing the improvement quality variable and 0 otherwise.

Table 2: 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)	-0.0822*	-0.1402*	-0.6103***	-0.6806***
	(0.0437)	(0.0732)	(0.1018)	(0.1567)
First-stage KP F-stat			226.906	120.050
Demographics	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes
Housing Market	Yes	Yes	Yes	Yes
Housing Attributes	Yes	Yes	Yes	Yes
Parcel FE	No	Yes	No	Yes
ZIP FE	Yes	No	Yes	No
Year-Month FE	Yes	Yes	Yes	Yes
Within R^2	0.308	0.011	0.305	0.007
N	3,897,806	2,202,829	3,897,806	2,202,829
Panel B. First Stage Results on *ln(HO Price)*				
FL Home/Auto			-0.5763***	-0.5458***
			(0.0383)	(0.0498)

Note: This table reports OLS and 2SLS regression results from estimating equation (3). The dependent variable in Panel A, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Results reported in columns (2) and (4) are generated from our repeat-sales sample. Estimates in columns (3) and (4) instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). We report first stage estimates of our instrument in Panel B. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Housing Sales Price in Florida—Mortgage Requirement

	Repeat Sales		
	(1)	(2)	(3)
ln(HO Price)	-0.8317***	-0.7454***	-0.7564***
	(0.2454)	(0.1792)	(0.1674)
High Mortgage	1.3692		
	(1.1409)		
ln(HO Price)×High Mortgage	-0.1754		
	(0.1437)		
High Origination		3.6899***	
		(0.7953)	
ln(HO Price)×High Origination		-0.4565***	
		(0.1001)	
High Origination (Value)			2.3583**
			(1.0484)
ln(HO Price)×High Origination (Value)			-0.2919**
			(0.1334)
Full Effect of High Origination	-1.007***	-1.202***	-1.048***
First-stage KP F-stat	9.909	50.376	19.187
Within R^2	0.002	-0.007	0.002
N	2,202,829	2,202,829	2,202,829

Note: This table reports 2SLS regression results from estimating equation (8) on our repeat-sales sample and interacting our variable of interest, *ln(HO Price)*, with proxies for mortgage prevalence. The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Estimates instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). *High Mortgage* is a binary variable equal to 1 if a county is in the top tercile of percent of mortgaged properties and 0 otherwise. *High Origination* is a binary variable equal to 1 if a county is in the top quartile of percent of new mortgage originations and 0 otherwise. *High Origination (Value)* is is a binary variable equal to 1 if a county is in the top quartile of percent value of new mortgage originations and 0 otherwise. 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—Reservation Price

	Repeat Sales		
	(1)	(2)	(3)
ln(HO Price)	-0.9694***	-0.7466***	-0.6612***
	(0.1825)	(0.1506)	(0.1561)
ln(HO Price)×High Risk Score	0.3251***		
	(0.0911)		
ln(HO Price)×High Belief in Risk		0.1499**	
		(0.0733)	
ln(HO Price)×High Risk Perception			0.2071***
			(0.0783)
Full Effect of Risk	-0.644***	-0.597***	-0.454***
First-stage KP F-stat	62.821	49.955	68.386
Within R^2	0.007	0.008	0.009
N	2,202,829	2,202,829	2,202,829

Note: This table reports 2SLS regression results from estimating equation (9) on our repeat-sales sample and interacting our variable of interest, *ln(HO Price)*, with proxies for home buyer reservation price. The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Estimates instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). *High Risk Score* is a binary variable equal to 1 if a county is above the XXth percentile of of FEMA's NRI and 0 otherwise. *High Belief in Risk* is ... *High Risk Perception* is... 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—Disaster

	Repeat Sales		
	(1)	(2)	(3)
ln(HO Price)	-0.6842***	-0.7076***	-0.6892***
	(0.1553)	(0.2042)	(0.1539)
Disaster	0.3993		
	(3.8897)		
ln(HO Price)×*Disaster*	-0.0599		
	(0.4970)		
ln(HO Price)×*High Model Loss*		0.0299	
		(0.0784)	
Prop. Loss Top Tercile			-0.1308
			(0.4249)
ln(HO Price)×*Prop. Loss Top Tercile*			0.0127
			(0.0553)
First-stage KP F-stat	2.448	58.276	60.213
Within R^2	0.008	0.007	0.008
N	2,202,829	2,202,829	2,202,829

Note: This table reports 2SLS regression results from estimating equation (10) on our repeat-sales sample and interacting our variable of interest, *ln(HO Price)*, with proxies for disaster exposure. The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Estimates instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). *Disaster* is a binary variable equal to 1 if a property reported having a disaster in the NAL dataset over the past 3 years and 0 otherwise. *High Model Loss* is a binary variable equal to 1 if a property is in a county in the top tercile of FPHLM projected losses and 0 otherwise. *Prop. Loss Top Tercile* is a binary variable equal to 1 if a county is in the top tercile of reported property losses over the past 5 years and 0 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—Homestead/Quick Sales

	Homestead		Sales within 12 months	
	All	Repeat	All	Repeat
	(1)	(2)	(3)	(4)
ln(HO Price)	-0.5040***	-0.2748	-0.6510***	-0.6764***
	(0.1070)	(0.1685)	(0.1039)	(0.1561)
Homestead Exemption	2.1731***	5.8048***		
	(0.3256)	(0.7530)		
ln(HO Price)×Homestead Exemption	-0.2702***	-0.7550***		
	(0.0414)	(0.0961)		
Quick Sale			-6.4792***	-8.2222***
			(1.0656)	(2.1868)
ln(HO Price)×Quick Sale			0.8266***	1.0804***
			(0.1359)	(0.2793)
Full Effects of Homestead/Quick Sales	-0.774***	-1.030***	0.176	0.404
First-stage KP F-stat	83.791	57.690	24.880	10.329
Within R^2	0.301	-0.056	0.273	-0.128
N	3,897,806	2,202,850	3,897,806	2,202,850

Note: This table reports 2SLS regression results from estimating equation (1). The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Results reported in columns (2) and (4) are generated from our repeat-sales sample. Estimates instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). *Homestead Exemption* is a binary variable equal to 1 if a property has filed for a homestead exemption and 0 otherwise. *Quick Sale* is a binary variable equal to 1 if a property previously sold over the past 12 months and 0 otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Homeowners Insurance Cancellations and Housing Sale Price in Florida

	OLS			2SLS		
	SE Cluster: Zip		County	Zip		County
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Nonrenew/Cancel)	-0.0151			1.3369*		
	(0.0151)			(0.7890)		
ln(Nonrenew/Cancel Hurricane)		-0.0185***	-0.0185***		-0.1008***	-0.1008**
		(0.0031)	(0.0045)		(0.0248)	(0.0414)
First-stage KP F-stat				5.437	55.505	8.340
Within R^2	0.011	0.012	0.012	-0.114	-0.005	-0.005
N	2,202,829	2,202,829	2,202,829	2,202,829	2,202,829	2,202,829

Note: This table reports OLS and 2SLS regression results from estimating equation (11). *ln(Nonrenew/Cancel)* is the natural log of 1 plus the number of cancellations and nonrenewals in a county. *ln(Nonrenew/Cancel Hurricane)* is the natural log of 1 plus the number of cancellations and nonrenewals in a county attributed to hurricanes. All results are generated from our repeat-sales sample. Estimates in columns (3), (4), and (5) instrument for nonrenewals and cancellations using the average share of insurance policies written by mandated homeowners insurers. Standard errors are clustered at the zip code level in columns (1), (2), (4), and (5) and at the county level in columns (3) and (6). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Homeowners Insurance Price and Housing Sale Probabilities

	(1)	(2)	(3)	(4)
ln(HO Price)	-0.0036**	-0.0030*	-0.0032**	-0.0025*
	(0.0015)	(0.0015)	(0.0015)	(0.0014)
ln(Population)		-0.0225	-0.0188	-0.0283
		(0.0496)	(0.0498)	(0.0514)
ln(Density)		0.0159	0.0116	0.0258
		(0.0514)	(0.0517)	(0.0518)
Unemployment		0.0042	0.0051	0.0017
		(0.0085)	(0.0089)	(0.0085)
% College		0.0036	0.0019	0.0084
		(0.0068)	(0.0071)	(0.0075)
% Black/Hispanic		-0.0067	-0.0046	-0.0021
		(0.0187)	(0.0188)	(0.0194)
% Health Insurance		-0.0158**	-0.0149**	-0.0145**
		(0.0066)	(0.0065)	(0.0066)
ln(Median Income)			0.0022	0.0030
			(0.0024)	(0.0022)
% Poverty			0.0003	0.0036
			(0.0045)	(0.0044)
ln(Median Housing Value)				-0.0045**
				(0.0019)
Median Year Built				0.0001
				(0.0001)
% Owner Occupied				-0.0019
				(0.0052)
% Vacant				0.0075
				(0.0051)
Year-Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Adj. R^2	0.857	0.859	0.859	0.862
N	2,680	2,680	2,680	2,680

Note: This table reports ordinary least squares regression results from equation (12). 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 premiums, where the average premiums are weighted by total insurance exposures. Refer to Table 1 for definitions of the other variables. 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:

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

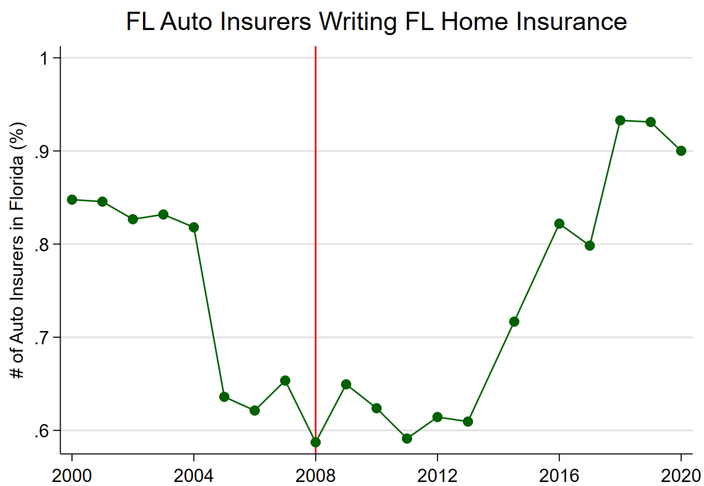
where $S(z)$ is net service value, calculated as real rental income minus costs (taxes, maintenance, and depreciation):

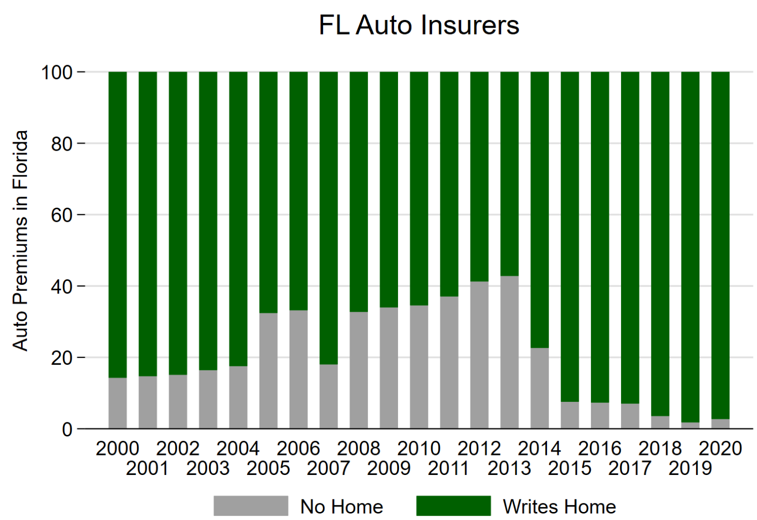
$$S(z) = R(H) - (\delta + \kappa + \mu + \gamma)Q.$$

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

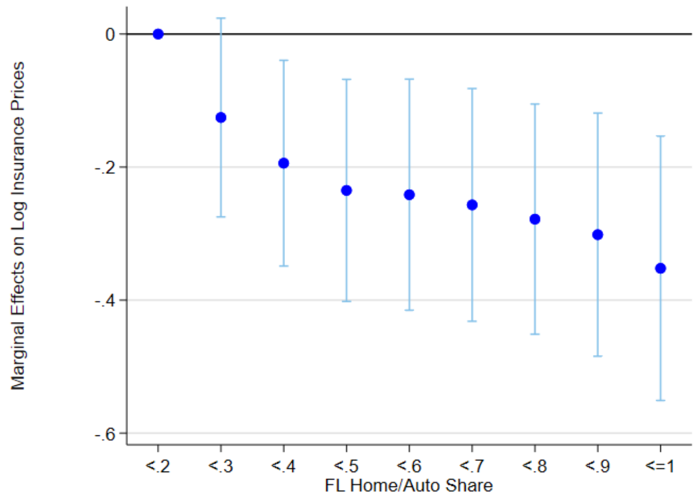
Figure B1: Florida Auto Insurers' Homeowners Insurance Participation





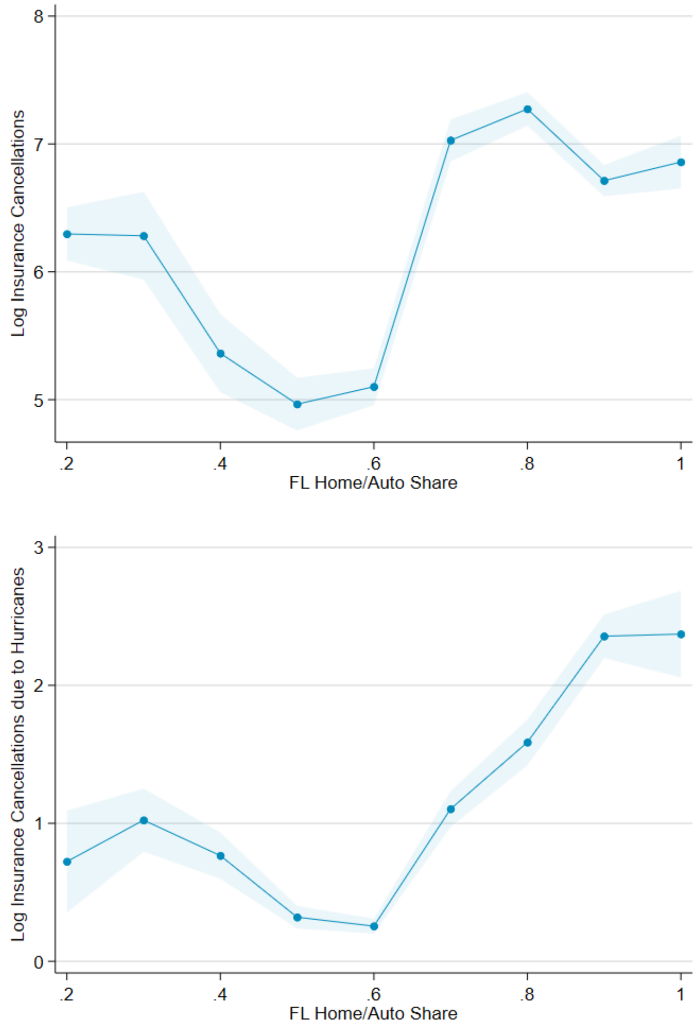
Notes: The top figure reports the number of insurers in Florida that write both auto insurance and homeowners insurance as a share of all insurers writing auto insurance across our sample period. We define a firm as writing a line if they report positive direct premiums written in private passenger or homeowners using data from the NAIC's annual statutory filing State Pages. The bottom figure reports the business mix (measured using direct premiums written) between auto insurance and homeowners insurance for Florida insurers, conditional on writing auto insurance in Florida.

Figure B2: Instrument Relevance, marginal effects including county and year-quarter FEs



Notes: This figure reports the marginal effect of our *FL Home/Auto* bins (in increments of 0.1) where the 0.2 bin is the omitted reference group. The dependent variable is the natural log of homeowners insurance price at the county-quarter-level. The model also includes county and year-quarter fixed effects. Standard errors are clustered at the county. The bars represent 95% confidence intervals.

Figure B3: Insurance Cancellations and the Instrument



Notes: The top figure reports the average natural log of 1 plus the number of cancellations across bins of our *FL Home/Auto* bins (increasing in increments of 0.1). The bottom figure reports the natural log of 1 plus the number of cancellations due to hurricanes across bins of our *FL Home/Auto* bins (increasing in increments of 0.1).

Table B1: Instrument Randomization Test

Dependent Variable :	ln(HO Price)		IV FL Home/Auto	
	(1)	(2)	(3)	(4)
ln(Population)	-1.8488	-1.2730	0.7738	1.5037
	(1.8584)	(1.8263)	(1.2733)	(1.5765)
ln(Density)	2.3067	1.6122	-1.1013	-1.8111
	(1.9708)	(1.9383)	(1.3258)	(1.6285)
Unemployment	0.7110*	0.7693*	-0.0603	0.0981
	(0.3946)	(0.4418)	(0.2869)	(0.3153)
% College	0.0950	-0.1785	-0.2716	-0.1276
	(0.3422)	(0.4175)	(0.3127)	(0.3315)
% Black/Hispanic	-0.2962	0.0487	0.6316	0.8022
	(0.8212)	(0.8447)	(0.5785)	(0.6118)
ln(Median Income)		0.4047**		-0.0811
		(0.1937)		(0.1412)
% Poverty		0.1524		-0.3834
		(0.3379)		(0.2393)
% Owner Occupied		-0.0674		-0.2760
		(0.3498)		(0.2240)
% Mortgage		-0.0527		-0.2164
		(0.2497)		(0.2444)
County FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Within R^2	0.048	0.076	0.044	0.060
N	2,680	2,680	2,680	2,680

Note: This table reports OLS estimates. The dependent variable is the natural log of homeowners insurance prices in columns (1) and (2) and our instrument, *FL Home/Auto*, in columns (3) and (4). Observations are at the county-quarter level. Standard errors are clustered at the county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Housing Sales Price in Florida, County SE Cluster

	OLS		2SLS	
	All	Repeat	All	Repeat
	(1)	(2)	(3)	(4)
ln(HO Price)	-0.0822	-0.1402	-0.6103***	-0.6806***
	(0.0738)	(0.1068)	(0.1998)	(0.2520)
First-stage KP F-stat			19.308	19.705
Within R^2	0.308	0.011	0.305	0.007
N	3,897,806	2,202,829	3,897,806	2,202,829

Note: This table reports OLS and 2SLS regression results from estimating equation (3). The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Results reported in columns (2) and (4) are generated from our repeat-sales sample. Estimates in columns (3) and (4) instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). Standard errors are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Housing Sales Price in Florida, unweighted HO Price

	OLS		2SLS	
	All	Repeat	All	Repeat
	(1)	(2)	(3)	(4)
ln(HO Price)	-0.1363**	-0.1960*	-1.1810***	-1.3167***
	(0.0673)	(0.1053)	(0.1991)	(0.3082)
First-stage KP F-stat			130.799	72.503
Within R^2	0.308	0.011	0.303	0.003
N	3,897,806	2,202,829	3,897,806	2,202,829

Note: This table reports OLS and 2SLS regression results from estimating equation (3). The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, but we do not weight by exposure. Results reported in columns (2) and (4) are generated from our repeat-sales sample. Estimates in columns (3) and (4) instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). 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—Mortgage Requirement, All Transactions

	Any Sales		
	(1)	(2)	(3)
ln(HO Price)	-0.7178***	-0.6860***	-0.7023***
	(0.1320)	(0.1188)	(0.1157)
High Mortgage	1.0778*		
	(0.6522)		
ln(HO Price)×High Mortgage	-0.1409*		
	(0.0821)		
High New Mortgage		3.0529***	
		(0.6174)	
ln(HO Price)×High New Mortgage		-0.3772***	
		(0.0780)	
High New Mortgage (Value)			2.7170***
			(0.7850)
ln(HO Price)×High New Mortgage (Value)			-0.3400***
			(0.1002)
Full Effect of High Mortgage	-0.859***	-1.063***	-1.042***
First-stage KP F-stat	22.867	65.265	26.754
Within R^2	0.302	0.296	0.299
N	3,897,806	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating equation (1) on our full sample and interacting our variable of interest, *ln(HO Price)*, with proxies for mortgage prevalence. The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Estimates instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). *High Mortgage* is a binary variable equal to 1 if a county is in the top tercile of percent of mortgaged properties and 0 otherwise. *High Origination* is a binary variable equal to 1 if a county is in the top quartile of percent of new mortgage originations and 0 otherwise. *High Origination (Value)* is is a binary variable equal to 1 if a county is in the top quartile of percent value of mortgage originations and 0 otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Housing Sales Price in Florida—Reservation Price, , All Transactions

	Any Sales		
	(1)	(2)	(3)
ln(HO Price)	-0.6359***	-0.6952***	-0.5724***
	(0.1277)	(0.1367)	(0.1795)
ln(HO Price)×High Risk Score	-0.1752***		
	(0.0629)		
ln(HO Price)×High Belief in Risk		-0.2506**	
		(0.1120)	
ln(HO Price)×High Risk Perception			-0.5395***
			(0.2073)
Full Effect of Risk	-0.811***	-0.946***	-1.112***
First-stage KP F-stat	9.169	3.260	5.131
Within R^2	0.296	0.295	0.274
N	3,897,806	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating equation (1) on our full sample and interacting our variable of interest, *ln(HO Price)*, with proxies for home buyer reservation price. The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Estimates instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). *High Risk Score* is a binary variable equal to 1 if a county is above the XXth percentile of of FEMA's NRI and 0 otherwise. *High Belief in Risk* is ... *High Risk Perception* is... 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—Disaster, All Transactions

	Any Sales		
	(1)	(2)	(3)
ln(HO Price)	-0.5021***	-0.5551***	-0.6076***
	(0.1142)	(0.1542)	(0.1042)
Disaster	23.6001*		
	(13.4506)		
ln(HO Price)×Disaster	-3.0090*		
	(1.7090)		
ln(HO Price)×High Model Loss		-0.0668	
		(0.0840)	
Prop. Loss Top Tercile			0.0496
			(0.3341)
ln(HO Price)×Prop. Loss Top Tercile			-0.0082
			(0.0432)
First-stage KP F-stat	1.682	8.826	113.492
Within R^2	0.280	0.305	0.305
N	3,897,806	3,897,806	3,897,806

Note: This table reports 2SLS regression results from estimating equation (1) on our full sample and interacting our variable of interest, *ln(HO Price)*, with proxies for disaster exposure. The dependent variable, *ln(Housing Sales Price)*, is the natural log of the sale price of each property. *ln(HO Price)* is the natural log of average county-level homeowners insurance premiums, where the average premiums are weighted by total insurance exposures. Estimates instrument for homeowners insurance premiums using the weighted average share of homeowners to auto insurance Florida (*FL Home/Auto*). *Disaster* is a binary variable equal to 1 if a property reported having a disaster in the NAL dataset over the past 3 years and 0 otherwise. *High Model Loss* is a binary variable equal to 1 if a property is in a county in the top tercile of FPHLM projected losses and 0 otherwise. *Prop. Loss Top Tercile* is a binary variable equal to 1 if a county is in the top tercile of reported property losses over the past 5 years and 0 otherwise. Standard errors are clustered at the zip code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.