The Effect of Insurance Premiums on the Housing Market and Climate Risk Pricing

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Abstract

Climate change makes insurance more vital yet costly for households. We examine how insurance premiums affect the housing market. Using a 2013 flood insurance reform and a triple-difference design, we find that homes losing insurance subsidies experience a 2% price decline. Removing subsidies made home prices more sensitive to sea-level-rise risk, suggesting accelerated climate risk pricing. The price effect is not fully explained by the cash flows from subsidy reductions, suggesting market participants' increased perceptions of uninsured risks. Higher premiums reduce mortgage uptake as mandatory insurance becomes costlier and encourage the rebuilding of riskier homes.

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1 Introduction

As climate change intensifies disaster risks, home insurance has become ever more crucial for household financial resilience, but also increasingly expensive.[1] Insurance pricing, often distorted by subsidies and regulations, can skew risk perceptions and assessment, as well as delay the incorporation of risks into housing values. Consequently, the insurance market, both directly and through its effect on the housing market, can shape adaptation efforts, construction choices, and population migration, particularly in response to climate change-related risks.

We study how insurance premiums affect the housing market by analyzing a 2013 reform that phased out flood insurance subsidies for properties situated discontinuously around flood zone boundaries and construction year cutoffs. We find five key results. First, insurance prices pass through to home values. Properties facing the largest premium increases experience a 2% relative price decline. Second, removing insurance subsidies makes home prices more sensitive to *future* climate risk, measured by sea level rise exposure. Third, the observed house price effect is not fully explained by cash flows related to the subsidy reduction alone; we attribute the remainder to market's updated risk perception of uninsured damages. Fourth, higher premiums result in decreased mortgage uptake as mandatory insurance becomes costlier. Fifth, higher premiums encourage the rebuilding of treated homes, especially those facing greater flood risks.

This paper provides the first evidence establishing a direct link between insurance prices and climate risk pricing in real estate. The housing market provides an important setting to examine climate risks for several reasons. First, housing is directly exposed to natural disasters, with insurance serving as a critical hedge against these risks. Additionally, housing constitutes a large share of household wealth, accounting for 63% of non-pension wealth for the bottom 90% wealth group (Smith et al. 2021). Furthermore, due to the long-term nature of real estate, house prices reflect long-run expectations, offering valuable insights into how markets perceive and price future climate risks.

We use the flood insurance setting to study the effects of insurance premiums on the housing market. One reason is that flooding is an acute issue in the U.S., with 15 million homes (10% of the

[1]The average annual premium is $2,530 in 2023 in the U.S. and near $5,000 at the 90th percentile, according estimates by Keys and Mulder (2024).

total) currently exposed to flooding risk. Floods account for nine of the ten most costly disasters,[2] and this risk is expected to increase due to climate change.

Another reason for using the flood insurance setting is to address the identification challenge. A key challenge in studying the impact of insurance costs is isolating the effects of premiums from risk perception changes. In homeowners' insurance markets, premium changes often reflect insurers' updated risk expectations. Thus, it is difficult to separate the effect of the premium changes from that of risk updating. We address this challenge by exploiting an exogenous shock to pricing in the National Flood Insurance Program (NFIP), stemming from the 2013 Biggert-Waters rate reform.

The reform phased out subsidies for properties in NFIP-designated "High-Risk" areas built before local flood maps were created ("Pre-Map"). We refer to these High-Risk, Pre-Map homes as our treatment group and refer to all other homes as the control group. The reform aimed to gradually remove subsidies to align insurance rates with risk, without directly conveying any changes to the underlying physical risks. Physical risks and their perceptions should not have changed differently between the treatment and control groups at the time of the reform. This allows us to use the reform as a natural experiment to isolate the effect of insurance premiums.

Using the 2013 reform as an exogenous shock to insurance rates, we analyze housing market responses to the insurance rate shock. We use administrative flood insurance data and Zillow house transaction data from 2009 to 2018. Our main sample includes 4 million transactions. We estimate a triple-difference model with housing market outcomes as dependent variables. The key independent variable is a triple interaction term, *Pre-Map* $\times$ *High-Risk* $\times$ *Post-Reform*, where *Post-Reform* indicates 2013 and later.

Our model controls for the house size and granular fixed effects: zip-by-property age and area-by-year-by-number of bedrooms, where an area is defined by zip codes and latitudes and longitudes rounded to two decimal places (approximately 0.8 square miles). The latter fixed effects account for area-specific trends among homes of different sizes. Our identification strategy assumes that, conditional on controls, treated homes' price trajectories differ from controls only due to the reform. More precisely, given our triple difference setup, we assume that absent the reform, the difference between Pre-Map and Post-Map homes would trend similarly across High- and Low-Risk zones.

[2] See, https://www.cbsnews.com/news/15-million-homes-at-risk-of-flooding-new-data-from-first-street-foundation/.

Our analysis consists of seven parts. First, our analysis reveals that removing insurance subsidies led to a 2% decline in house prices for affected properties. The coefficient estimates for *Pre-Map* $\times$ *High-Risk* $\times$ *Post-Reform* are negative and statistically significant, aligning with the reform's larger premium increases for Pre-Map, High-Risk homes.

Second, we find that removing insurance subsidies makes house prices more sensitive to sea-level-rise risk. In contrast, we do not consistently observe increased house price sensitivity to short-term flood risk, as proxied by the First Street Foundation Flood Factor, storm surge risk, and other measures. These results indicate that removing insurance subsidies leads the market to incorporate long-term climate risks into home valuations, but not short-term risks that may have already been well understood and priced in.

Third, we consider the mechanisms through which insurance premiums affect house prices. We propose two potential mechanisms. First, the *Subsidy-Cash-Flow* operates through reduced subsidy payments, where house price declines reflect the net present value of lost subsidies. Second, the *Risk-Expectation* effect emerges when premium increases lead markets to reassess property risks. This update could occur through various channels. For example, before the reform, market participants may have underestimated flood risks due to subsidized insurance, consistent with rational inattention (Brown and Jeon 2024). These updated risk assessments affect home values through both higher expected future premiums and anticipated uninsured damages, as NFIP's $250,000 coverage cap leaves some rebuilding costs and land value unprotected.

Since we cannot observe expected future premiums, we instead examine whether the effect through uninsured damage expectations exists. Using 2009 local average flood insurance coverage, we divide our sample at the median into High-Coverage and Low-Coverage groups, where the High-Coverage sample has 1.3 times more coverage. Since premiums scale with coverage, a pure Subsidy-Cash-Flow effect would imply a proportional 1.3 times larger price effect in the High-Coverage sample. However, we find the price effect is three times larger, indicating the Risk-Expectation channel significantly influences house prices. Our estimates suggest the Risk-Expectation effect comprises 63% of the total price impact in High-Coverage subsample.

Fourth, we find that higher insurance premiums reduce mortgage uptake, potentially resulting in a higher concentration of disaster and house price risks among homeowners. Flood insurance is mandatory for High-Risk homes. Higher premiums effectively increase overall mortgage costs,

moving the equilibrium leftward on the mortgage demand curve. At the same time, higher premiums increase borrowers' debt-to-income ratios (as lenders incorporate these premiums into their calculations), shifting the mortgage supply curve to the left. Both effects would decrease mortgage uptake, reducing risk sharing between households and financial intermediaries.

Fifth, we find that High-Risk, Pre-Map homes show higher rebuilding probabilities following the reform, especially among properties facing elevated short-term flood risks. Three mechanisms could explain such behavior: (1) as subsidies for High-Risk, Pre-Map houses phase out, the financial advantages of maintaining Pre-Map status diminish; (2) higher insurance costs often lead to reduced coverage (Wagner 2022), increasing uninsured flood risk and potentially motivating resilience-focused rebuilding; (3) as previously discussed, house price effects partially reflect updated risk perceptions, which may prompt homeowners to enhance flood resilience through rebuilding.

Sixth, we find the effect of premiums on house prices varies with disclosure requirements and buyer type. The effect is larger in states requiring sellers to disclose High-Risk zone status, as buyers are more likely to factor premium increases into their valuations. Non-primary buyers also exhibit stronger price responses. One potential reason is that the reform mandates a larger premium increase for non-primary owners. Another potential reason is that these buyers tend to be more sophisticated investors, who are more likely to consider the premium increases when valuing treated homes.

Finally, we address potential alternative explanations for our main results on home prices. These explanations suggest that certain risks (e.g., sea level rise) may have intensified or become priced in around 2013, affecting High-Risk, Pre-Map houses more than other properties. We address these alternative explanations through several tests. First, we analyze homes located within 250 feet of boundaries between High- and Low-Risk zones, which reduces the difference in risks and their trends. We also examine properties built within three years of local map establishment to reduce age differences between Pre- and Post-Map homes. Additionally, we control for interactions between various hazard measures and our key treatment variables (*Hazard* $\times$ *Pre-Map* $\times$ *Post-Reform*, *Hazard* $\times$ *High-Risk* $\times$ *Post-Reform*, and *Hazard* $\times$ *Post-Reform*), where *Hazard* proxies for properties' exposure to five other measures of flooding risks, including sea level rise and First Street Foundation Flood Factor. If the alternative explanations were valid, the coefficient on *High-Risk* $\times$

Pre-Map × *Post-Reform* should decline in absolute magnitude towards zero with these controls. Our findings remain robust across all these tests, suggesting that alternative explanations are unlikely to drive our results.

This study contributes to several strands of literature. First, we contribute to the literature on insurance rates and home prices that has found mixed results. Gibson and Mullins (2020), Bakkensen and Barrage (2021), and Hino and Burke (2021b) find no significant impact of insurance rates on home prices. They also use the Biggert-Waters reform, but compare High-Risk with Low-Risk houses.[3] In contrast, we use a triple-difference methodology by exploiting the large premium increase for High-Risk, Pre-Map homes. Two recent studies, Georgic and Klaiber (2022) and Hennighausen et al. (2023), use a similar strategy and find a negative effect of flood insurance premiums on house values.[4]

We make several important contributions relative to these papers. (1) We highlight that when insurance rates better reflect underlying risk, the housing market is more likely to incorporate future long-term climate risk into current prices. (2) Our results indicate that the Risk-Expectation channel partly drives the house price effect of insurance rates. (3) We also uncover the important effect of insurance rates on buyer financing and rebuilding choices.

Second, we contribute to the literature on High-Risk flood zone location and house prices. Previous studies have yielded mixed results, with High-Risk zone home prices ranging from 76% lower to 61% higher than benchmarks (see a review by Beltrán et al. 2018).[5] The estimates in the literature also capture other differences other than insurance premiums across flood zones, such as FEMA's information on property riskiness and amenities associated with waterfront properties. We contribute to this literature by providing an estimate of the effect of premiums in isolation. We also connect to recent flood insurance research by Wagner (2022), Sastry (2021), Mulder (2021), Weill (2023), and Hu (2022). These papers abstract away from house prices, as their focus is different from ours. Our research complements their findings by explicitly examining the relationship

[3]However, Figure IA.1 in the Internet Appendix suggests that, on average, High-Risk houses did not experience a larger premium increase compared to Low-Risk houses until 2016, which makes it difficult to detect price effects in their difference-in-difference setting.

[4]Beyond flood insurance, Nyce et al. (2015) find a negative association between homeowners' insurance premiums and home value. However, homeowners' insurance premiums could be correlated with risks. Increased risks can also explain the reduction in home value, making it hard to infer the effect of insurance premiums.

[5]A few papers, including Gibson and Mullins (2020), Indaco et al. (2019), and Shr and Zipp (2019) find that houses see values decline when being added to High-Risk zones. However, Hino and Burke (2021a) find little effect on house prices when properties are added to High-Risk flood zones, especially when controlling for location-time fixed effects.

between flood insurance premiums and property values, adding to a more comprehensive understanding of the economic impacts of physical risks.

Third, we make a significant contribution to the literature on climate change and real estate. As climate change intensifies, disasters such as flooding pose an increasingly significant threat. Insurance remains the only financial tool households use to hedge against disaster risk. However, Stroebel and Wurgler (2021) find that 42% of survey respondents think the insurance market does not adequately price for climate risks. We shed light on how climate risks can be incorporated into home values through insurance pricing. Bernstein et al. (2019), Baldauf et al. (2020), and Keys and Mulder (2020) show price and liquidity reductions for homes facing sea-level-rise risk. Fairweather et al. (2024) study the effect of providing house-specific flood risk information on the housing market. We provide evidence that insurance premiums can be an important channel through which long-term climate risks are incorporated into current asset prices.[6]

While our study focuses on flood insurance, its implications extend beyond this specific context. Our results have broader relevance for the effect of other insurance premiums (e.g., homeowners, commercial) on asset values. Premiums in these markets have been, and will likely continue, increasing in areas most affected by climate change, such as homeowners insurance in California or hurricane-exposed areas (Keys and Mulder 2024).[7] Moreover, if climate change increases the systemic risk of disasters, insurance rates may increase across a wider geographic spectrum. Our results indicate that household and business assets exposed to climate change can suffer significant price depreciation through the channel of rising insurance premiums. Consequently, fairly priced insurance can accelerate climate adaptation by discouraging further development and migration into climate-vulnerable regions.

[6]Murfin and Spiegel (2020) do not find a discount when comparing homes with more or less regional historical sea level rise exposure, though their design is broader in geographic scope and effects may be attenuated due to migration patterns as observed by Bernstein et al. (2022). Other related papers in this area include Giglio et al. (2021), and Issler et al. (2020). Relatedly, Chay and Greenstone (2005), Greenstone and Gallagher (2008), and Currie et al. (2015) study the effects of air pollution and toxic emissions on the housing market.

[7]Relatedly, Ge et al. (2024) examine the causal effect of rising home insurance premiums on mortgage outcomes, and Sastry et al. (2024) investigate the effect on home insurance coverage gap. Van der Straten (2023) studies the macrofinancial implications of climate change and adaptation, with insurance built into the model. Sastry et al. (2023) analyze the effect of exits of large insurers and entry of vulnerable, small insurers. Jung et al. (2023) estimate insurers' exposure to climate risk.

2 Institutional Background

2.1 The National Flood Insurance Program

The National Flood Insurance Program (NFIP), established by the National Flood Insurance Act of 1968, operates under FEMA with two primary objectives: mitigating future flood damage and protecting property owners.[8] As the dominant flood insurer with over 95% market share (Kousky et al., 2018), NFIP fills a critical gap as standard homeowners' insurance policies typically exclude flood damages.

NFIP provides coverage across all 50 states and Puerto Rico. Except for properties in suspended NFIP communities (less than 0.4% of US properties), virtually all homeowners can obtain NFIP insurance. From 2009 to 2018, NFIP annually underwrote 4.5 million flood policies, representing $3.5 billion in premia and $1.4 trillion in coverage.

Flood Insurance Rate Map: Each NFIP community (typically a town or city) has its own Flood Insurance Rate Map (FIRM), mostly established between 1975 and 1990. Properties built before local FIRM implementation are designated Pre-Map (Pre-FIRM), while those built after are Post-Map. For maps established before 1975, all houses built prior to 1975 qualify as Pre-Map (Georgic and Klaiber, 2022).

High-Risk Zones: NFIP designates Special Flood Hazard Areas (SFHA) as zones with annual flood probability of one percent or higher, labeled as "A", "AE", "AH", "AO", "V", "OPEN WATER", "D", and "IN". We classify these as High-Risk zones and all others as Low-Risk zones. High-Risk and Low-Risk zones follow separate standardized insurance pricing schedules during our sample period.[9]

Homeowners in High-Risk zones with federally backed mortgages must purchase flood insurance, a requirement often extended to other residential mortgages by lenders. Prior to 2016, flood insurance premium payments for High-Risk homes are escrowed by mortgage lenders as a common practice. Since 2016, this has become a legal requirement.[10]

[8] See https://www.fema.gov/sites/default/files/2020-05/NFIP_50th_Final_8.5x11_Regional_Printable.pdf for a brief history of NFIP.

[9] In 2021, NFIP introduced "Risk Rating 2.0," a methodology that incorporates house-level granular risk measures into pricing. Since this reform simultaneously altered both pricing and risk information provided to households, it does not isolate the effect of pricing changes alone.

[10] See, https://www.fdic.gov/resources/supervision-and-examinations/consumer-compliance-examination-manual/documents/5/v-6-1.pdf.

Premium Setting: First, premiums are determined by the aforementioned risk zones. Second, premiums depend on the amount of building and content coverage chosen. The maximum coverage is $250,000 for building and $100,000 for contents. Additionally, premiums are determined by construction timing relative to local map introduction. Pre-Map properties qualify for subsidized rates independent of elevation, while Post-Map rates vary with the lowest floor's height relative to Base Flood Elevation.[11] Higher elevation corresponds to lower premiums. Table A1 presents premiums for different categories of homes with the maxmium building coverage calculated using NFIP's pricing manual. Other factors, such as community-level mitigation efforts can also influence premium rates.

Owners of Pre-Map houses can choose to obtain an elevation certificate and a Post-Map premium rate. It is advantageous to do so if the Post-Map rate for the house' elevation is cheaper than the Pre-Map rate. Elevation certificates, which can cost as much as $2,000 or more.[12] Mulder and Kousky (2023) find evidence that suggests many Pre-Map houses could have benefited from lower Post-Map rates if they had obtained elevation certificates. We do not observe whether a Pre-Map house obtains a Post-Map rate in our housing data. Thus, we identify whether a house is Pre-Map using the year a house was built relative to the introduction year of the local flood map. This creates noise in our Pre-Map variable, which would bias our results toward zero.

2.2 Flood Insurance Rate Reform

The Biggert-Waters Flood Insurance Reform Act (BW-12), signed into law in July 2012, implemented major changes to NFIP rates starting January 2013. The reform aimed to improve NFIP's fiscal soundness by eliminating subsidies for High-Risk, Pre-Map properties.[13] The legislation was unexpected, as evidenced by minimal media coverage before its passage (Strother, 2018). Our analysis of Factiva news data shows virtually no reform-related coverage until the Act's signing in July 2012 (see, Figure A1).[14]

[11] Base Flood Elevation is defined by FEMA as "the elevation of surface water resulting from a flood that has a 1% chance of equaling or exceeding that level in any given year."

[12] See, https://www.massivecert.com/blog/what-does-elevation-certificate-cost.

[13] See, https://www.fema.gov/sites/default/files/2020-07/questions-biggert-waters-flood-insurance-reform-2012.pdf and https://www.ncua.gov/regulation-supervision/letters-credit-unions-other-guidance/guidance-biggert-waters-flood-insurance-reform-act-2012.

[14] Media coverage surged in late 2013 when premium increases took effect for businesses, severe repetitive loss properties, and lapsed policies.

Before the reform, Pre-Map properties in High-Risk zones received subsidized rates that were considered to be well below the actuarially fair rate. The Act mandates that, once a subsidized property is sold to a new owner, its premium must increase 25% per year until it reaches the full-risk rate.[15] Public opposition led to the 2014 Homeowner Flood Insurance Affordability Act (HFIAA), which moderated annual premium increases to 5-15% for all High-Risk, Pre-Map homes.[16]

NFIP published rate tables only for the upcoming policy year, without long-term projections. The 2021 introduction of Risk Rating 2.0 revealed the uncertainty in pricing: Mulder and Kousky (2023) found 40% of High-Risk, Pre-Map policies experienced premium decreases, revealing that even NFIP struggled to predict "full-risk" rates.

Based on Table A1, from 2012 to 2018, High-Risk, Pre-Map primary residences saw annual premium increases of 5.8% (cumulative $594 increase) for $250,000 coverage. In contrast, Low-Risk and Post-Map, High-Risk properties experienced annual changes between -3.8% and +3.5% (cumulative changes between -$1,099 and +$277).

3 Data

3.1 Flood Insurance Data

3.1.1 National Flood Insurance Program (NFIP) Policy Data

Our 2009-2018 NFIP administrative dataset covers the universe of the policies written by NFIP, approximately 4.5 million annual policies. The data contain policy details (including premiums and coverage) and property characteristics (including year built and flood zone). While property addresses are redacted for privacy, the data includes five-digit zip codes and latitude/longitude coordinates rounded to one decimal place. No identifier is available to track each property.

3.1.2 National Flood Hazard Layer (NFHL)

The NFHL is a collection of map layers that divides the US geography into flood communities and flood zones. The NFHL covers 95% of all US properties. Areas not covered in the NFHL data

[15] While the law required immediate full-risk rates for sold properties starting October 2013, buyers could effectively cap annual increases at 25% by not submitting elevation certificates. See, Pages 31-32 in the full report found on https://www.gao.gov/assets/gao-13-607.pdf.

[16] See, https://crsreports.congress.gov/product/pdf/R/R44593.

usually have low population densities. We use NFHL to identify whether a property is located in a High- or Low-Risk zone. We have access to the digital shape files from 1996 and 2021. We use the 2021 version as it is closer in time to the reform. We exclude areas not covered by the 2021 digital shape files. Our results remain robust when restricted to properties maintaining consistent High-Risk designation between 1996 and 2021.

3.1.3 NFIP Community Status Book

This dataset provides community flood map introduction dates, enabling Pre-Map/Post-Map property classification when merged with NFHL data.

3.2 Zillow Data

The Zillow Transaction and Assessment Dataset provides comprehensive property-level data across 2,750 US counties. Our 2009-2018 sample includes property characteristics (square footage, number of bedrooms, construction year, location) based on tax assessor data, as well as transaction details. The data do not provide information on the lowest-floor elevation. This prevents us from estimating "full-risk" rates for High-Risk, Pre-Map houses by assuming that Post-Map houses are charged "full-risk" rates and finding comparable Post-Map houses for Pre-Map ones.

We classify properties as Pre-Map or Post-Map based on construction dates relative to local map introduction. If the local map was established before 1975, houses built prior to 1975 are considered Pre-Map per NFIP premium rules. We exclude houses built in the same year as the map introduction year from our sample.

We filter the data as follows. First, we retain only transactions of residential properties with transaction prices between $50,000 and $5,000,000. In addition, we only include properties with sufficient non-missing property information that we control for in the regression analyses, including zip codes, square footage, the number of houses, and the year built. We exclude properties smaller than 600 square feet. Finally, we retain only areas with at least one transaction each of Low-Risk and High-Risk properties. The resulting sample contains approximately 11 million transactions when an area is defined by zip code. The sample reduces to 4.7 million when we define an area by zip-by-longitude/latitude (rounded to two decimal places).

3.3 Flood Hazard Measures

The Zillow assessor files also provide the geo-coded location of each property which we use to map to four different measures of physical risk. We utilize the location data to match with a set of location-based risks and characteristics.

Sea Level Rise: We connect latitude and longitude to the National Oceanic and Atmospheric Administration (NOAA) Sea Level Rise risk (Marcy et al. 2011). We define an indicator, *Sea Level Rise*, to be equal to one if the property would experience chronic tidal flooding after six feet of global average sea level rise, and zero otherwise.

Distance to Water: Using the same data from NOAA, we identify the distance between a property and the current highest high tide for all homes within a 5-mile radius, which we define as the distance to water. The NOAA data are only available for coastal counties, so many properties have a missing value. We standardize this variable in regressions, so that the mean is zero and the standard deviation is one. The maximum is 2.7. We assign a value of three to properties that are more than five miles away from the coast. Whenever we use this variable, we also include an indicator for when the distance is larger than five miles, *Distance>5 Miles*.

Storm Surge: We use NOAA maps to to identify the property's exposure to storm surge risk. Those maps are raster-based (see Zachry et al. 2015) so we find the house location within the raster file and extract the raster value at that point. We define the indicator, *Storm Surge*, to take a value of one if the property would experience flooding (e.g. storm-surge height greater or equal to 1 foot) after a category three hurricane.

1st Street Flood Factor: We merge each property in our data to the closest point in First Street Foundation Flood Factor data based on longitude and latitude. We use the 30-year flood risk from First Street to proxy for short- and medium-run flood risk.

>3 Past Floods: We also define a county-level indicator variable, *>3 Past Floods*, based on FEMA's disaster declarations. This variable equals one if a county has experienced more than three flood-related FEMA-declared disasters since the FEMA data began in 1953; otherwise zero.

3.3.1 Matching Flood Insurance and Zillow Data

We match the premium and insurance coverage information from NFIP to our Zillow data. The NFIP policy data do not offer detailed location information of the policies, but only provide longitude/latitude rounded to one decimal place. As a result, we cannot precisely match premium rates to the Zillow transaction data at the property level. Even if this were feasible, houses that do not have flood insurance coverage in a year will have missing premiums, while new buyers may take flood insurance into account, especially in High-Risk zones where it is required for obtaining a mortgage.

We match each house in the Zillow data to an average insurance premium rate as follows. First, we calculate the annual average premium rate (total premium divided by building plus content coverage) for houses within a group whose members have the following characteristics in common: NFIP latitude and longitude which are rounded to one decimal place, zip code, detailed flood zone (e.g., "A", "AE"), year built, and policy year. Second, we match the average premium rate to each house transaction in Zillow by the above grouping, equating the sale year in Zillow and the policy year in NFIP. For properties not matched, we adjust its year built by +1, -1, +2, -2, +3, and -3, consecutively, until a match is found. We exclude properties that do not have a matched average premium rate.

We perform a similar methodology to match average coverage in FEMA's policy data to each houses in Zillow data. To avoid any effect from policyholders changing coverage in response to premium changes, we use coverage in the policy year of 2009 (the first year of our sample) to match to the house transactions throughout our sample period. Similar to above, we calculate the average 2009 coverage amount and match to house transactions based on NFIP latitude and longitude which are rounded to one decimal place, zip code, detailed flood zone (e.g., "A", "AE"), and year built. We multiply the matched average premium rate and average 2009 coverage to obtain the premium for each house.

3.4 Summary Statistics

Table 1 summarizes the key variables for our main sample. First, we find that residential properties in our filtered sample trade on average at $282k. In our sample, 15% of the properties are in

High-Risk zones, and 38% are constructed prior to the flood map for their area. Around 7% of all homes in our sample are High-Risk, Pre-Map. The mathced average premium is $448 per year, partially reflecting the very low premiums for homes in Low-Risk areas. We also present statistics of our flood risk measures. For example, 9% of the homes are exposed to six-feet sea level rise risk and 13% are exposed to storm-surge risk in the event of a level-3 hurricane.

4 The Effect of Reform on Flood Insurance Premiums

This section analyzes how the reform affected premiums for High-Risk, Pre-Map houses, which faced mandatory subsidy reductions. According to Table A1, book rates for these properties increased by $594 between 2012-2018 for $250,000 building coverage—the largest increase across all property types. Because actual premiums may vary due to factors like community mitigation discounts, we use NFIP policy data to test whether these houses actually experienced larger relative premium increases after the reform through the following regression analysis.

$$Premium_p = \sum_{y=2009}^{2018} \beta_y \times High\text{-}Risk_p \times Pre\text{-}Map_p \times \mathbf{1}_t^y + Lower\ Order\ Terms + FE_{zip \times age} + FE_{area \times t} + \epsilon_p,$$

where *p* indexes the flood insurance policy and *t* the year. The dependent variable, *Premium*, represents policy premium rates scaled to $250,000 building coverage, expressed in thousands of dollars. We scale premiums to a fixed coverage amount to isolate premium changes from coverage adjustments in response to premium changes. Since actual premium rates are unavailable, we calculate them by dividing total premium by total coverage (building and contents) and multiplying by $250,000. The dependent variable is in thousands of dollars. Pre-Map is time-varying for each parcel *i* because the house can be rebuilt, changing its status from Pre-Map to Post-Map. $\mathbf{1}_t^y$ is an indicator for policy year *t* in year *y*, with 2012 as the benchmark year. *Lower Order Terms* include *Pre-Map* $\times$ *Year Indicators*, *High-Risk* $\times$ *Year Indicators*, *High-Risk* $\times$ *Pre-Map*, *High-Risk*, and *Pre-Map*.

The fixed effects structure mirrors those in our main analyses on house prices as described in

the next section. We control for zip-by-property age and area-by-year fixed effects. An area is defined by zip and longitude-latitude coordinates (rounded to one decimal place), which is the finest location data available in the NFIP dataset. Standard errors are two-way clustered by policy start year-quarter and zip code.

Figure 2 plots the estimated coefficients on the triple interaction terms, *High-Risk* × *Pre-Map* × *Year Indicators*. The difference in premiums between Pre-Map and Post-Map homes in High-Risk zones increased drastically relative to Low-Risk zones from 2012 to 2013. This increase continued following 2013 as mandated by the reform. Pre-reform fluctuations reflect typical annual rate adjustments that vary by risk zone and Pre-Map status.

5 The Effect of Insurance Premium Reform on House Prices

We identify flood insurance premium effects on house prices by examining the reform's differential impact across properties. High-Risk, Pre-Map homes (built before their community's flood map release) faced the largest insurance rate increases. Using property transaction data from 2009-2018, we estimate:

We identify the effect of flood insurance premiums on house prices by exploiting the reform's differential impact across properties. High-Risk, Pre-Map homes faced the largest insurance rate increases. Using property transaction data from 2009-2018, we estimate:

$$\begin{aligned} Log(Price)_{i,t} =& \beta_1 \times High\text{-}Risk_i \times Pre\text{-}Map_{i,t} \times Post\text{-}Reform_t + Lower\ Order\ Terms \\ &+ \beta_2 \times SquareFootage + FE_{zip \times age} + FE_{area \times t \times \#bedrooms} (+FE_i) + \epsilon_{i,j,t}, \end{aligned}$$

where *i* indexes the parcel and *t* the year. The estimated coefficient on the triple interaction term, *High-Risk* × *Pre-Map* × *Post-Reform*, captures the effect of flood insurance premiums on house prices. *Lower Order Terms* include the following: *Pre-Map* × *Post-Reform*, *High-Risk* × *Post-Reform*, *High-Risk* × *Pre-Map*, *High-Risk*, and *Pre-Map*.

We control for square footage and granular fixed effects. Zip-by-property age fixed effects capture average prices of same-age houses within zip codes. Area-by-year-by-bedrooms fixed effects control for price trend of houses with same bedroom counts in the same area. Areas are defined by zip codes or zip-by-latitude/longitude (rounded to two decimal places, approximately 0.8 square

miles).

Our identifying assumption is that absent the reform, Pre-Map versus Post-Map home price differentials would have evolved similarly across High- and Low-Risk zones, conditional on our fixed effects. We present a suite of evidence against concerns about potential violations of this assumption in Section 11.

Table 2 presents our results. Column (1) uses zip-by-property age and zip-by-by-year-bedrooms fixed effects, restricted to zip codes containing both Low- and High-Risk houses. The triple interaction coefficient of -0.023 indicates High-Risk, Pre-Map homes trade at a 2.3% relative discount post-reform. More precisely, the Pre-Map minus Post-Map value differential in High-Risk zones drops by 2.3% relative to Low-Risk zones.

Column (2) adds parcel fixed effects. Within a parcel, house characteristics stay mostly the same, other than due to rebuilding or renovation. The estimate of the coefficient on the triple interaction term stays similar, at -0.017, and remains statistically significant. This result suggests that differences in houses sold before and after the reform are unlikely to drive our results.[17]

Our benchmark specification in Column (3) employs zip-by-latitude/longitude-by-year-by-bedrooms fixed effects, restricted to areas (defined by zip-by-latitude/longitude) containing both Low- and High-Risk houses. This model balances granular geographic controls with sample preservation. The coefficient on the triple interaction remains stable at -0.021. Column (4) replicates this specification using dollar values, showing an average relative decrease of $12,292 for High-Risk, Pre-Map homes.

Table IA.2 presents five robustness tests: (1) excluding 2013-2014, the period between reforms; (2) interacting the fixed effects in our benchmark specification with High-Risk; (2) interacting the fixed effects in our benchmark specification with Pre-Map; (4) controlling for other flood risk measures: exposure to sea level rise, First Street Foundation flood factor, exposure to storm surge, distance to highest-tide water, an indicator for more than three past floods, and whether the home has a basement; (5) using houses whose High-Risk status did not change between 1996 and 2021—the two versions of digital maps available to us. The results are similar to those in Table 2.

Figure 3 illustrates the reform's time-varying effects using our benchmark model. We replace

[17]Note that the variable *Pre-Map* remains identifiable when we include parcel fixed effects, because a property on the same parcel can be rebuilt, sometimes switching from Pre-Map to Post-Map.

the *Post-Reform* indicator with a series of year indicators from 2009 to 2018. Triple interaction coefficients show no significant pre-trends before 2012, followed by persistent negative effects after rate changes began in 2013. While premium increases grew over time (Figure 2), house price effects remain stable through 2018, suggesting that markets quickly incorporated expectations of future premium increases.

6 Reform Makes House Prices More Sensitive to Sea Level Rise Risk

6.1 Larger House Price Effects in the Sample Exposed to Sea Level Rise

Flood insurance subsidies lower the cost of hedging flood risks, potentially preventing these risks from being reflected in house prices. Moving premiums towards "full-risk" levels may help incorporate these risks into property values. Table 3 examines whether the insurance reform makes house prices more sensitive to different flood risks.

We first analyze long-term flood risk from sea level rise. Properties can be exposed to sea level rise directly through ocean proximity or indirectly through connected inland waterways. We define an indicator, *Sea Level Rise*, to be equal to one if the property would experience chronic tidal flooding after six feet of sea level rise. Even before a six-foot rise, these homes face increased flooding risk through amplified hurricane impacts and river overflow during rainfall.[18] In Column (1), we interact our main triple interaction term with *Sea Level Rise*.

Column (2) also interacts our main triple interaction term with each of four other flood risk measures. They include the First Street Foundation flood factor, whether the house is exposed to storm surge, distance to the highest-tide water, and whether FEMA has declared three past flooding disasters in the local area. These measures capture different risk horizons: the First Street factor reflects medium-term risk (30-year outlook), while the others capture short-term exposure. We include all the lower-order interaction and standalone terms, but suppress them for presentation. Columns (3) and (4) repeat this analysis using house prices in thousands of dollars as the dependent variable.

The estimated coefficient on *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform* $\times$ *Sea Level Rise* is negative

[18] See, e.g., https://www.washingtonpost.com/climate-environment/interactive/2024/southern-us-sea-level-rise-risk-cities/?next_url=https://www.washingtonpost.com/climate-environment/interactive/2024/southern-us-sea-level-rise-risk-cities/&tid=usw_paywall.

and statistically significant across all specifications. Among the quadruple interactions, it is the only consistently significant effect. In Column (2), its estimated coefficient of -0.029 is 2.4 times larger than the triple interaction coefficient. This suggests that the house price effect on treated homes exposed to sea level rise is 2.4 times larger than that on unexposed homes.

Another way to interpret the result is that after the reform, prices of treated homes become more sensitive to long-term sea-level-rise risk, but not short-term risks. Our findings suggest that fairly-priced insurance rates help incorporate long-run, but not short-run, flood risks into house prices. Short-term risks may already be well-understood and priced in, limiting the impact of insurance rate changes on their valuation.

6.2 Pass-through of Premiums to House Prices

A natural question is the magnitude of the pass-through from premiums to house prices. We estimate this magnitude in this section. We first describe how we match the insurance policy data with the housing transaction data and then describe our estimation results.

6.2.1 Premiums to House Prices Pass-Through Estimates

In Table 4, Panel A uses houses not exposed to sea level rise and Panel B uses houses that are exposed. Column (1) estimates how house prices respond to the insurance reform following our main specification in both panels. The estimate indicates that, among properties not exposed to six feet of sea level rise, prices of the High-Risk, Pre-Map homes drop by $4,823 more following the rate reform. The magnitude for homes exposed to sea level rise is much larger, $25,845.

To estimate the pass-through from premiums to house prices, we estimate the effect of the insurance reform on insurance premiums in Column (2). Column (2) repeats (1), replacing the dependent variable with premium rates that are matched to the house transactions in the same year multiplied by the matched 2009 building coverage. The estimate suggests that premiums increased by $85 more for the treated homes that are not exposed to sea level rise and by $116 more for these homes in the exposed sample. The larger magnitude of premium changes for the exposed homes is due to the larger average coverage amount among these homes. The effect on premium per dollar of coverage for treated homes is slightly larger for homes not exposed to sea

level rise.

Column (2) uses premium rates that are matched to the house transactions in the same year. Thus, we estimate the pass-through from the observed average premium rate changes to house values. However, the reform stipulates that subsidies will phase out gradually for High-Risk, Pre-Map homes until reaching "full-risk" rates. Although households cannot observe the future rates, they may form some expectation of the trajectory of future premiums, which is reflected in the house price effect. One useful exercise is to examine the pass-through of premium increases on house values assuming that, after the reform, the market expectation of "full-risk" premiums are the realized premiums observed in 2018. To this end, in Column (3), we repeat Column (2), replacing premium rates for home transactions between 2013 and 2018 with the matched premium rates in 2018. We again multiply the premium rates with the matched 2009 coverage. The estimates suggest that premiums increased by $128 more for the most treated homes in the sample not exposed to sea level rise and by $165 more for these homes in the exposed sample.

Based on Columns (1) and (3) in Table 4, for one dollar of premium increase in 2018, house prices fall by $38 (=4,823/128) in the sample not exposed to sea level rise.[19] Based on Columns (4) and (6), in the sample exposed to sea level rise, for one dollar of premium increase in 2018, house prices fall by $153 (=25.845/0.168). These premium-to-house price pass-throughs are overstated for two reasons. First, the market likely expects the treatment effect on premiums to increase after 2018. Indeed, in a 2013 report by the Government Accountability Office, it is estimated to take 20 years or more to reach "actuarially fair" rates for all previously subsidized homes as mandated by the reform (GAO 2013). Second, as we argue next in Section 7, the house price effect appears not purely driven by insurance cash flows, but also by the market's risk updating triggered by the premium increase. Therefore, the true pass-through of premium cash flows alone to house prices, outside of the risk updating channel, should be smaller.

The overstatement of the pass-through here is more severe for houses exposed to sea level rise. One reason is that for this sample, the market should expect a larger premium increase for the treated homes in the future due to their higher long-term flood risk. Another reason is that

[19]This result implies a discount rate of 2.7% (=128/4,823) if the treatment effect on premiums is expected to stay the same as in 2018 in perpetuity. 2.7% should be the lower bound of the implied discount rate, as this pass-through is overstated. An implied discount rate above 2.7% is reasonable given that Giglio et al. (2021) estimate the average (expected) returns of real estate to be 6% in the short/median run, and Giglio et al. (2015) estimate the very long-run discount rate to be 2.6%.

the risk-updating channel should play a larger role in this sample, as we argue below in Section 7. Regardless of the overstatement of the premium-to-house-price pass-through and the reasons behind it, results in this section suggest that fairly priced insurance premiums can accelerate the pricing of long-term climate risks into asset values today.

7 Mechanism: Subsidy-Cash-Flow and Risk-Updating

Two channels can drive the average effect of premiums on home prices documented in Table 2. We refer to the first as the "Subsidy-Cash-Flow" channel. Reducing subsidies increases premium cash flows, which can lower home prices. The corresponding price decrease should be the net present value of the expected future subsidy reductions. However, we cannot compute this subsidy cash flow effect, because NFIP did not disclose future premiums. Although it stated that premiums would eventually reach full-risk rates, it did not offer information about the full-risk rates. We also cannot use Post-Map premiums to back out the full-risk rates for Pre-Map houses because we do not know the lowest-floor elevation required to calculate the rates based on NFIP's rate tables. Mulder and Kousky (2023) examine premium changes around NFIP's 2021 reform called Risk Rating 2.0, where NFIP sets premiums according to property-level risks rather than based on High-Risk/Low-Risk classifications. They find that 40% of the High-Risk, Pre-Map policies saw decreases in premiums. This result suggests that the prior premiums were punitively high for those 40% of the High-Risk, Pre-Map policyholders. Their finding also highlights the difficulty for us to back out the expected present value of future "full-risk" premiums. We assume that the market does not update the expected full-risk premiums in this Subsidy-Cash-Flow channel.

We refer to the second channel as the "Risk-Updating" channel: Premium increases can lower home prices by increasing the market's flood risk expectations of the treated homes. There are at least three reasons for an increase in expected risks. First, before the reform, people may have underestimated risks when flood risks could be insured at a lower cost, which is consistent with the rational inattention literature (see, e.g., Brown and Jeon 2024). When the insurance costs increase, households are more likely to reassess their insurance coverage needs. To do so, they may give more consideration to the underlying risk. Second, homeowners may infer an increase in risk from insurance premiums due to the salience of the premium shock, as evidenced by the

large number of news articles summarized in Figure A1. This is related to the behavioral economics literature on salience (see, e.g., Bordalo et al. 2022). Third, as the government phases out flood insurance, the market may update its assessment of other risks related to government actions, such as reduced disaster aid after future floods. While unrelated to the flood probabilities, these policy changes can increase flood-related costs, and thus the total risk associated with flooding.

Regardless of the specific reason, if buyers' expected risk increases due to the insurance premium shock, house prices should decrease through two effects. First, when the market perceives the risk to be higher, it will update its expected "full-risk" premiums to a higher level. Second, when the perceived risks increase, it can lower home values through the expectation of uninsured damages. Flood insurance covers building replacement costs with a maximum of $250,000. Thus, the rebuilding costs beyond the (maximum) coverage and the land value are uninsured. An increase in perceived risks can increase the expected costs of the building replacement and lower the land value. Similar to our arguments earlier, we cannot estimate the first effect which is through expectations of full-risk premiums. However, we can test whether the Risk-Updating channel exists by detecting the second effect, which is through uninsured damage expectations, using data on flood insurance coverage from the NFIP.

We split our sample into two subsamples based on the average 2009 coverage amount matched to each property. We choose the 2009 coverage amount to ensure that coverage is not affected by the premium changes of the reform.[20] We choose the sample median as the cutoff. In the low-coverage subsample, the coverage amount has a mean of around $178k. In the high-coverage subsample, the mean coverage is $223k, 1.3 times as large as the high-coverage subsample.

Assume the effect on house prices is only through the Subsidy-Cash-Flow channel without risk updating. Note that premiums for High-Risk, Pre-Map homes mostly scale with coverage amount. Then the present value of the subsidy reduction should scale with coverage, because both the current and future full-risk premiums scale with coverage. Therefore, the dollar effect on house prices should scale with coverage. In other words, the house price effect for the High-Coverage subsample should be 1.3 times as large as it is for the other subsample, since the coverage ratio

[20] We match the average coverage amount by zip and longitude-latitude (rounded to one decimal place—the finest provided by FEMA) in 2009 to each property. We use the area average (rather than a finer match by detailed flood zone and year built as described in Section 3.3.1) to include more houses that may be excluded from the estimation sample due to some properties not having flood insurance in 2009.

between the two sample is 1.3.[21]

What would the Risk-Updating channel predict? A large portion of the houses in the High-Coverage sample have the maximum coverage of $250,000. Presumably, many of these houses have a rebuilding cost higher than $250,000, so the value of the structure of the High-Coverage sample relative to that of the Low-Coverage sample would be higher than 1.3. It is hard to pin down the exact predicted ratio of the house price effect under this channel.[22] However, if the house price effect for the High-Coverage subsample is more than 1.3 times as large as that for the other subsample, it can be consistent with the Risk-Expectation channel.

In Column (1) of Table 5, we repeat our main specification with dollar house prices as the dependent variable, as in Column (4) of Table 2, using the High-Coverage sample. The coefficient on the triple interaction term is -17.7. In Column (2), using the Low-Coverage sample, the coefficient is -4.7. In Column (3), we test the difference between the two estimated coefficients using the entire sample. To do so, we add an interaction between our main triple interaction term and an indicator for higher-than-median coverage. We also include interactions between this indicator and all of the lower-order terms. Our main triple interaction term has a coefficient of -5.5, and its interaction with the High Coverage dummy has a coefficient of -11.3, which is twice as large. Both coefficients are statistically significant. Thus, the effect in the High-Coverage sample is around three times (=(-11.3-5.5)/-5.5) that in the Low-Coverage sample. This ratio of three is much larger than the 1.3 predicted by the pure Subsidy-Cash-Flow channel.

These results suggest that our effects are not only driven by a pure Subsidy-Cash-Flow channel, but also by the Risk-Expectation channel through an increase in expected risks of the High-Risk, Pre-Map properties. We can use the estimates above to calculate a lower bound of the effect of the Risk-Expectation channel in the High-Coverage sample. For the Low-Coverage sample, the effect only due to cash flows should be smaller than $4.7k, the total effect for this subsample, in

[21] Table IA.1 in the Internet Appendix tabulates the detailed book rate for one dollar of coverage for High-Risk, Pre-Map houses. The rate per dollar of coverage within the basic coverage limit is actually slightly higher than that of additional coverage beyond the basic coverage limit. (The basic limit was either $50,000 or $60,000 during our sample period.) Thus, the premiums and their house price effect for the High-Coverage subsample should be less than 1.3 times as large as that for the other subsample.

[22] The Risk-Expectation effect would be somewhat proportional to the combined value of the uninsured part of the building replacement cost, part of the land value, and other costs associated with flood-related disasters (e.g., being displaced temporarily). If the Low-Coverage houses have most of the building replacement costs insured and High-Coverage houses cannot due to the replacement costs exceding the maximum coverage, the difference in the Risk-Expectation effect between the two samples can be large.

absolute magnitude. The cash flow effect for the High-Coverage subsample should be less than \$6.1k (=1.3×\$4.7k) in absolute magnitude, as the average coverage amount is 1.3 times as large as that for the Low-Coverage sample. The total effect in this sample is \$17.7k. Therefore, the risk expectation effect is at least \$17.7k-\$6.1k=\$11.6k in absolute magnitude. In other words, the risk expectation channel causes at least \$11.6k drop in the average home value of the High-Coverage subsample, which makes up 63% of the average total effect, \$17.7k.

Is the difference between the two subsamples due to different risks and thus, different full-risk premiums? To answer this question, in Column (4), we control for different measures of flood risks as in Table 3, by adding interaction terms between these risk measures and our main triple, *Pre-Map*×*High-Risk*×*Post-Reform*, as well as all the associated lower-order terms. The quadruple interaction term involving the indicator, *High-Coverage*, is estimated -9 and statistically significant. Note that the coefficient on the triple interaction term does not capture the average house price effect on treated, low-coverage houses, but the effect on the subset of these houses with all the risk measures equal to zero. The important result in Column (4) is that after controlling for risks, high-coverage homes still experience a much larger price drop. This suggests that it is unlikely that high-coverage homes have higher full-risk rates than low-coverage homes. It is most likely that the difference between the two subsamples is due to the larger uninsured component of the high-coverage homes, given similar updating of expected flood probabilities triggered by the rate reform. Our interpretation is that the uninsured component influences how house prices respond to the reform. This suggests that the "Risk-Updating" channel is likely at work, in addition to the "Subsidy-Cash-Flow" channel.

Other reasons can potentially explain this result. For example, the buyers of Low-Coverage, treated houses may be less sophisticated and do not fully take into account further increases in future premiums. Thus, the effect in the Low-Coverage sample may be an under-reaction. Although it is difficult to rule out all the other explanations, the results in Table 5 can be consistent with the Risk-Expectation channel.

8 Heterogeneous Effects of Insurance Premiums on House Prices

8.1 By State Flood-Zone Disclosure Requirements

Many anecdotes suggest that buyers often overlook whether a house is in a High-Risk zone until lending banks require them to obtain flood insurance after they pay commitment fees to sellers. Thirty-one states require sellers to disclose if the property is in a High-Risk flood zone. Figure A2 shows states' requirements for flood zone disclosure. The darker color indicates that the state requires such disclosure. We hypothesize that the effect of flood insurance premiums on house prices will be stronger if a state requires such disclosure because buyers are more likely to take flood insurance premiums into consideration in their valuation of properties.

Columns (1)-(3) of Table 6 test our hypothesis above. We repeat our main specification in Column (3) of Table 2, using the transactions in states that do not require any disclosure in Column (1) and using states that require disclosure in Column (2). The estimated coefficient on *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform* is negative and statistically significant in both columns. The magnitude in Column (2), -0.034, is 50% larger than that in Column (1), -0.021. This result is consistent with the hypothesis that the effect of flood insurance premiums is stronger in states where properties' flood-zone information is more readily available to potential buyers. In Column (3), we test whether the difference between Columns (1) and (2) is statistically significant, by using the entire sample and adding a quadruple interaction, *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform* $\times$ *Disclosure*. The estimated coefficient on this term is negative, but not statistically significant at conventional levels.

8.2 Non-primary vs Primary Owner

The effect of flood insurance premium changes on house prices can be different if the buyer is a non-primary owner, i.e., an owner who purchases a property for investment or as a second home. One reason is that such buyers can be more sophisticated and more likely to take into account flood insurance premiums in their property valuation. Robinson (2012) finds that such buyers tend to have better credit scores and higher incomes, suggesting that they are likely to be more sophisticated. The other reason is that the reform mandated larger premium increases for investors (or non-primary owners). The reform capped the increase in premiums for High-Risk, Pre-Map

homes at 18% annually for a primary owner, and 25% annually for a non-primary owner. With segmentation and illiquidity in the housing market as documented by Piazzesi et al. (2020), flood insurance premiums can have different effects on transaction prices depending on whether the buyer is an investor.

We test whether the effect of flood insurance premiums on house prices is stronger when the buyer is a non-primary owner in Columns (4)-(6) of Table 6. Our Zillow transaction data tell us whether a property is owner-occupied after the transaction, which we use as a proxy for whether the property is purchased by a primary owner.

We use the sample of transactions where buyers are primary owners in Column (4) and where the buyers are non-primary owners in Column (5). The estimated coefficient on *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform* is negative and statistically significant in both columns. The magnitude using the sample of non-primary owners, -0.035, is almost three times that using the sample of primary owners, -0.012. Column (6) tests whether the effect is statistically significantly different between the two subsamples, by using the entire sample and adding a quadruple interaction term: *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform* $\times$ *Non-Primary*. The coefficient on this interaction term is negative and statistically significant, suggesting that the house price effect is statistically significantly larger if the buyer is a non-primary owner.

9 Insurance Rate Reform and Mortgage Choice

When the flood insurance rate reform made flood insurance more costly for High-Risk, Pre-Map homes, it effectively increased the costs of mortgages for these homes because government-sponsored enterprises and lenders require borrowers to purchase flood insurance in High-Risk zones. Higher costs may make mortgages less attractive to borrowers. Lenders may also become more concerned about borrowers' default risk given the higher costs, and thus lower the approval rate for mortgages. Therefore, we hypothesize that the probability of buyers taking out mortgages decreases for High-Risk, Pre-Map homes after the reform.

In Table 7, we rerun the specifications in Table 2 replacing the dependent variable with an indicator for whether the buyer of a transaction takes out a mortgage. The mortgage information is based on assessor data provided by Zillow. In our regression sample, the percentage of home

buyers taking out a mortgage is around 50%, which is lower than recent numbers based on industry reports.[23] This indicates that our mortgage data include substantial noise. However, it is unlikely that such noise is correlated with our key independent variables to generate biased estimates.

The triple interaction term, *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform*, has a negative and statistically significant coefficient in all three columns with different fixed effects. The magnitudes suggest that the probability of buyers of High-Risk, Pre-Map homes taking out mortgages falls by between 1.0 and 1.6 percentage points after the reform, which is between 2% and 3% of the sample mean probability. This result suggests that flood insurance rate increases can have implications on households' financing decisions.

One interpretation of the mortgage effect is that households reduce take-up because mortgages, together with the required insurance, become effectively more expensive. There is a slightly different interpretation, which is the other side of the same equilibrium. As insurance rates increase for High-Risk, Pre-Map homes, mortgages for these properties can be riskier for banks for two reasons. First, a higher premium means a negative shock to households' financial strength, potentially leading to a higher default probability. Second, homeowners are more likely to decrease their flood insurance coverage when premium rates are higher (Wagner 2022), making these properties riskier for mortgage lenders. Sastry (2021) argues that lenders require greater downpayment for borrowers who under-insure. This can also make mortgages less attractive than prior to the reform.

The decrease in mortgage uptake after the exogenous change in insurance prices highlights the nuance required to set good policy in this space. To the extent that FEMA wants to better align risk and insurance prices, the reform removes subsidies and alters house prices in a way that is consistent with aligning buyers' expected risk with reality. However, if buyers respond to increased premiums by taking out fewer mortgages, then this re-concentrates the risk of flood damage in the hands of homeowners, potentially making households more vulnerable to such risk.

10 Insurance Rate Reform and Rebuilding Activity

In this section, we examine whether the larger rate increases for High-Risk, Pre-Map homes induce more rebuilding activities of such homes. There are at least three reasons to hypothesize that

[23] See, `https://www.redfin.com/news/all-cash-down-payment-april-2023/`.

higher premiums can incentivize homeowners to rebuild. First, as subsidies for High-Risk, Pre-Map houses phase out, the benefits of keeping the Pre-Map status of a house decrease. Second, as flood insurance becomes more expensive, households choose less insurance coverage, as documented by Wagner (2022). With less flood insurance coverage and thus, more exposure to flood risk, households may become increasingly likely to rebuild in a way that can better withstand flood damage. For example, homeowners can elevate the foundation of High-Risk, Pre-Map homes to lower the risk of flooding. In addition, they can qualify for a lower flood insurance rate with a higher elevation. Finally, if some of the effects on house prices are due to the market updating risk expectations, people are more likely to rebuild to increase the flood resilience of their properties.

We test our hypothesis using CoreLogic permit data and the historical tax assessor data. We match the permit data with the Zillow data by first transforming addresses in the two datasets using Safegraph into Placekeys, which is a geocode. Observations are at the parcel-year level. The dependent variable is one if the house is rebuilt in that year. We define the outcome variable, *1(Rebuilt)*, as either one of the following situations. (1) The house is matched to a permit that is of the type "Demolition" in that year, where the year is after the initial year built of the property. (2) The house in that year is matched to a permit that is of the type "New Building", where the permit year is after the initial year built of the property, or the year equals the maximum year built of a parcel that is later than its original year built based on tax assessor data. We exclude parcel-years when a property is first built in our tax assessor sample. Given the low baseline probability (326 out of one million parcel-year observations in Column 3), we mimic the specification in Column (1) of Table 2 with zip-by-year-by-beds in the fixed effects rather than zip-by-longitude/latitude-by-year-by-beds. Similar to the restriction in Column (1) of Table 2, we keep houses in zip codes (rather than zip-by-longitude/latitude areas) that have both High-Risk and Low-Risk homes.

Column (1) of Table **??** presents the results. The coefficient on the triple interaction term is positive and statistically significant, suggesting that High-Risk, Pre-Map homes are more likely to be rebuilt in response to flood insurance rate increases.

Next, we examine whether the rebuilding effect varies by properties' flood risk exposure. In Columns (2) and (3), we use properties whose First Street Foundation Flood Factor is larger than one and equals one, respectively. In Columns (4) and (5), we use properties that are exposed and unexposed to sea-level-rise risk. The coefficient estimates on the triple interaction term are all

positive and statistically significant. The coefficient in Column (2) is the only one that is statistically significant, with a magnitude much larger than in Column (3). In contrast, the coefficients are more close in magnitude between Columns (4) and (5).

These results suggest that the rebuilding effect is particularly pronounced among properties facing elevated short-term flood risks, as measured by the First Street Foundation Flood Factor. Notably, we find no differential rebuilding response between properties exposed and unexposed to long-term sea level rise. This pattern suggests that rebuilding efforts primarily target current flood vulnerabilities rather than long-term sea-level-rise risks, where adaptation needs may be less immediate.

11 Evidence Against Alternative Explanations

In this section, we address alternative explanations for our main result on house price effects.

11.1 Restricting to Houses Built around Map Year

One potential concern is related to the idea that Pre-Map houses are older than Post-Map ones and older houses are more vulnerable to flooding. If around 2013, the expected flood frequency and/or severity increased more for High-Risk than Low-Risk zones, then older, more vulnerable houses in High-Risk zones are likely to experience larger price drops.

We address this concern in Column (1) of Table 9. We repeat our main analysis on house prices, restricting our sample to houses that were built between three years before and after the local map year.[24] With this sample, we shrink the age difference between Pre-Map and Post-Map homes. If our main results are driven by the age difference between Pre-Map and Post-Map homes, the estimated coefficient on the triple interaction term, *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform*, should shrink toward zero. The estimated coefficient on the triple interaction term remain negative and statistically significant. The magnitude of the estimate is around 50% larger than that in our benchmark result.

[24]The sample used here is only 9% of that in our baseline regression. If we control for granular area-by-year-by-number of bedrooms fixed effects as in our benchmark model, where an area is defined by zip and rounded latitude/longitude, we lose more observations and thus, power. Hence, we replace the granular area-by-year-by-number of bedrooms fixed effects with zip-by-year-by-number of bedrooms fixed effects.

11.2 Restricting to Houses Near Flood Zone Borders

If around 2013, the expected flood frequency and/or severity increased more for High-Risk than Low-Risk zones, and Pre-Map homes are more vulnerable than Post-Map homes, we could observe a larger decline in value for Pre-Map houses in High-Risk zones. To address this concern, we repeat our main analysis using homes that are close to the boundary between High- and Low-Risk zones. Restricting to such a subsample should shrink the difference in the trend between High- and Low-Risk houses. If the alternative hypothesis explains our result, the estimated coefficient on the triple interaction should decline with this sample.

Column (2) of Table 9 presents the results. We restrict our analysis to properties within 250 feet of the border. The estimated coefficient on our main variable, the triple interaction term, remains similar to our main result, which is inconsistent with the alternative explanation.

11.3 Control for Other Risk Exposure

Another alternative explanation is that High-Risk, Pre-Map houses could be more exposed to certain flood hazard, which became more salient or priced in around 2013. As shown in Figure 3, the coefficient estimate on the triple interaction term *High-Risk* $\times$ *Pre-Map* $\times$ *Year Dummy* is not statistically significant before 2013. Exposure to other risks, even if especially high for High-Risk, Pre-Map houses, would need to be abruptly reflected in house prices in 2013 to be able to explain our findings. One may be especially concerned about the expectation of sea level rise confounding our results since an emerging literature argues that the risk of sea level rise began to be priced in for exposed properties around 2012 to 2013 (see, e.g., Bernstein et al. 2019). Similarly, one may be concerned that *High-Risk* (*Pre-Map*) may be correlated with other measures of flood risk that became more severe or priced in around 2013. If Pre-Map (High-Risk) houses are more vulnerable or exposed to these risks, it could explain our main result.

We estimate the following specification to address these concerns that our main results are

driven by flood risks being correlated with *High-Risk* × *Pre-Map*, *High-Risk*, or *Pre-Map*.

$$Log(Price)_{i,t} = \beta_1 \times High\text{-}Risk_i \times Pre\text{-}Map_{it} \times Post\text{-}Reform_t$$
$$+ \beta_2 \times Hazard_i \times Pre\text{-}Map_i \times Post\text{-}Reform_t + \beta_3 \times High\text{-}Risk_i \times Hazard_i \times Post\text{-}Reform_t$$
$$+ \beta_4 \times Hazard_i \times Post\text{-}Reform_t + \textit{Lower-Order Terms} + FE_{zip \times age} + FE_{area \times \#bedrooms \times t} + \epsilon_{i,j,t}.$$

Hazard is one of six different measures of flood risks. Under the alternative explanations, β_1 should become zero or statistically insignificant after we include the additional controls, while the newly added terms absorb the effect of the triple interaction.

Hazard is an indicator for whether or not the house is exposed to six feet of sea level rise in Column (1); the standardized value of First Street Foundation's flood factor in Column (2); an indicator for whether or not the house is exposed to storm surge in the case of a category-3 hurricane in Column (3); standardized of distance to highest-tide water in Column (4); whether the county experienced a flood declared by FEMA as a disaster in more than three years since 1950 in Column (5); and whether the house has a basement in Column (6). Although having a basement is not a natural hazard, it can make a home more vulnerable to flooding. We include all lower-order interactions between *High-Risk/Hazard*, *Pre-Map*, and *Post-Reform*, as well as standalone terms that are not absorbed by fixed effects.

Table 10 presents the results. The estimated coefficient on *High-Risk* ×*Pre-Map* ×*Post-Reform* remains negative and statistically significant, with a magnitude similar to our main result. These results argue against the alternative explanation that our main result is driven by *High-Risk*, *Pre-Map*, or their interaction being correlated with other short-/long-term flood hazards (or having a basement).

12 Conclusion

We study the effect of insurance premiums on the housing market using a 2013 flood insurance pricing reform. The reform offers an exogenous shock to insurance rates, increasing premiums the most for homes built in High-Risk areas before the establishment of the local flood map. We exploit the differential rate changes for different types of homes to identify the impact of flood insurance

prices on house prices, buyer financing, and rebuilding choices.

Our five main findings are as follows. First, houses with the largest rate increase experienced a relative price decline of around 2%. Second, phasing out flood insurance subsidies makes home prices more sensitive to *future* climate change risk, as measured by sea level rise exposure. Third, the effect of insurance premiums on house prices is driven not only by the direct cash flow effect of the subsidy reductions. The effect is likely partly driven by the market updating the expected risk of the treated homes triggered by higher premiums. Fourth, the premium increase leads to meaningful decreases in mortgage uptake, as the total cost of mortgages, including mandated flood insurance, increases. Finally, the increase in premiums also leads to more rebuilding of the affected homes, especially those exposed to higher short-term flood risks.

Our findings have important implications. First, when insurance rates are artificially low, house prices can be inflated, which can induce more development and thus, migration into riskier areas. Second, fairly priced insurance can accelerate the pricing of long-term climate risks. Third, insurance premium changes can update the housing market's expectations of risks. Fourth, insurance premium increases reduces mortgage takeup, which reduces the risk sharing between households and the financial sector.

This paper offers the implications for insurance rate regulations, including flood and homeowners' insurance. Beyond flood insurance, regulators have suppressed rate increases in risky states, such as California, where wildfire risks have been increasing with climate change. If policymakers and regulators permit insurance rates to fully reflect underlying risks, particularly in areas exposed to long-term climate change-related risks, it can effectively raise awareness of future risks and facilitate their incorporation into current asset prices. This, in turn, can support climate risk adaptation by discouraging further development and migration into risky areas.

References

Bakkensen, L. A. and L. Barrage (2021). Going underwater? flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies*.

Baldauf, M., L. Garlappi, and C. Yannelis (2020, 02). Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies 33*(3), 1256–1295.

Beltrán, A., D. Maddison, and R. J. Elliott (2018). Is flood risk capitalised into property values? *Ecological Economics 146*, 668–685.

Bernstein, A., S. B. Billings, M. T. Gustafson, and R. Lewis (2022). Partisan residential sorting on climate change risk. *Journal of Financial Economics*.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics 134*(2), 253–272.

Bordalo, P., N. Gennaioli, and A. Shleifer (2022). Salience. *Annual Review of Economics 14*(1), 521–544.

Brown, Z. Y. and J. Jeon (2024). Endogenous information and simplifying insurance choice. *Econometrica 92*(3), 881–911.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? evidence from the housing market. *Journal of political Economy 113*(2), 376–424.

Currie, J., L. Davis, M. Greenstone, and R. Walker (2015). Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. *American Economic Review 105*(2), 678–709.

Fairweather, D., M. E. Kahn, R. D. Metcalfe, and S. S. Olascoaga (2024). Expecting climate change: A nationwide field experiment in the housing market. Technical report, National Bureau of Economic Research.

GAO (2013). Flood insurance: More information needed on subsidized properties.

Ge, S., S. Johnson, and N. Tzur-Ilan (2024, October). Climate risk, insurance premiums, and the effects on mortgages. *SSRN Electronic Journal*.

Georgic, W. and H. A. Klaiber (2022). Stocks, flows, and flood insurance: A nationwide analysis of the capitalized impact of annual premium discounts on housing values. *Journal of Environmental Economics and Management 111*, 102567.

Gibson, M. and J. T. Mullins (2020). Climate risk and beliefs in new york floodplains. *Journal of the Association of Environmental and Resource Economists 7*(6), 1069–1111.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber (2021). Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies 34*(8), 3527–3571.

Giglio, S., M. Maggiori, and J. Stroebel (2015). Very long-run discount rates. *The Quarterly Journal of Economics 130*(1), 1–53.

Greenstone, M. and J. Gallagher (2008). Does hazardous waste matter? evidence from the housing market and the superfund program. *The Quarterly Journal of Economics 123*(3), 951–1003.

Hennighausen, H., Y. Liao, C. Nolte, and A. Pollack (2023). Flood insurance reforms, housing market dynamics, and adaptation to climate risks. *Journal of Housing Economics 62*, 101953.

Hino, M. and M. Burke (2021a). The effect of information about climate risk on property values. *Proceedings of the National Academy of Sciences 118*(17), e2003374118.

Hino, M. and M. Burke (2021b). Internet appendix to the effect of information about climate risk on property values. *Proceedings of the National Academy of Sciences 118*(17), e2003374118.

Hu, Z. (2022). Social interactions and households' flood insurance decisions. *Journal of Financial Economics 144*(2), 414–432.

Indaco, A., F. Ortega, and S. Taşpınar (2019). The effects of flood insurance on housing markets. *Cityscape 21*(2), 129–156.

Issler, P., R. Stanton, C. Vergara-Alert, and N. Wallace (2020). Mortgage markets with climate-change risk: Evidence from wildfires in california. *Available at SSRN 3511843*.

Jung, H., R. F. Engle, S. Ge, and X. Zeng (2023). Measuring the climate risk exposure of insurers. Technical report, Staff Report.

Keys, B. J. and P. Mulder (2020). Neglected no more: Housing markets, mortgage lending, and sea level rise. Technical report, National Bureau of Economic Research.

Keys, B. J. and P. Mulder (2024). Property insurance and disaster risk: New evidence from mortgage escrow data. Technical report, National Bureau of Economic Research.

Kousky, C., H. Kunreuther, B. Lingle, and L. Shabman (2018). The emerging private residential flood insurance market in the united states. *Wharton Risk Management and Decision Processes Center*.

Marcy, D., N. Herold, K. Waters, W. Brooks, B. Hadley, M. Pendleton, K. Schmid, M. Sutherland, K. Dragonov, J. McCombs, and S. Ryan (2011). New mapping tool and techniques for visualizing sea level rise and coastal flooding impacts. *In Proceedings of the 2011 Solutions to Coastal Disasters Conference, Anchorage, Alaska*, 474–490.

Mulder, P. (2021). Mismeasuring risk: The welfare effects of flood risk information. Technical report, Working Paper.

Mulder, P. and C. Kousky (2023). Risk rating without information provision. In *AEA Papers and Proceedings*, Volume 113, pp. 299–303. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Murfin, J. and M. Spiegel (2020). Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies 33*(3), 1217–1255.

Nyce, C., R. E. Dumm, G. S. Sirmans, and G. Smersh (2015). The capitalization of insurance premiums in house prices. *Journal of Risk and Insurance 82*(4), 891–919.

Piazzesi, M., M. Schneider, and J. Stroebel (2020). Segmented housing search. *American Economic Review 110*(3), 720–59.

Robinson, B. L. (2012). The performance of non-owner-occupied mortgages during the housing crisis. *FRB Richmond Economic Quarterly 98*(2), 111–138.

Sastry, P. (2021). Who bears flood risk? evidence from mortgage markets in florida.

Sastry, P., I. Sen, and A.-M. Tenekedjieva (2023). When insurers exit: Climate losses, fragile insurers, and mortgage markets. *Fragile Insurers, and Mortgage Markets (December 23, 2023)*.

Sastry, P., I. Sen, A.-M. Tenekedjieva, and T. C. Scharlemann (2024). Climate risk and the u.s. insurance gap: Measurement, drivers and implications. *Available at SSRN 4909444*.

Shr, Y.-H. J. and K. Y. Zipp (2019). The aftermath of flood zone remapping: The asymmetric impact of flood maps on housing prices. *Land Economics 95*(2), 174–192.

Smith, M., O. M. Zidar, and E. Zwick (2021). Top wealth in america: New estimates and implications for taxing the rich. Technical report, National Bureau of Economic Research.

Stroebel, J. and J. Wurgler (2021). What do you think about climate finance? *Journal of Financial Economics 142*(2), 487–498.

Strother, L. (2018). The national flood insurance program: a case study in policy failure, reform, and retrenchment. *Policy Studies Journal 46*(2), 452–480.

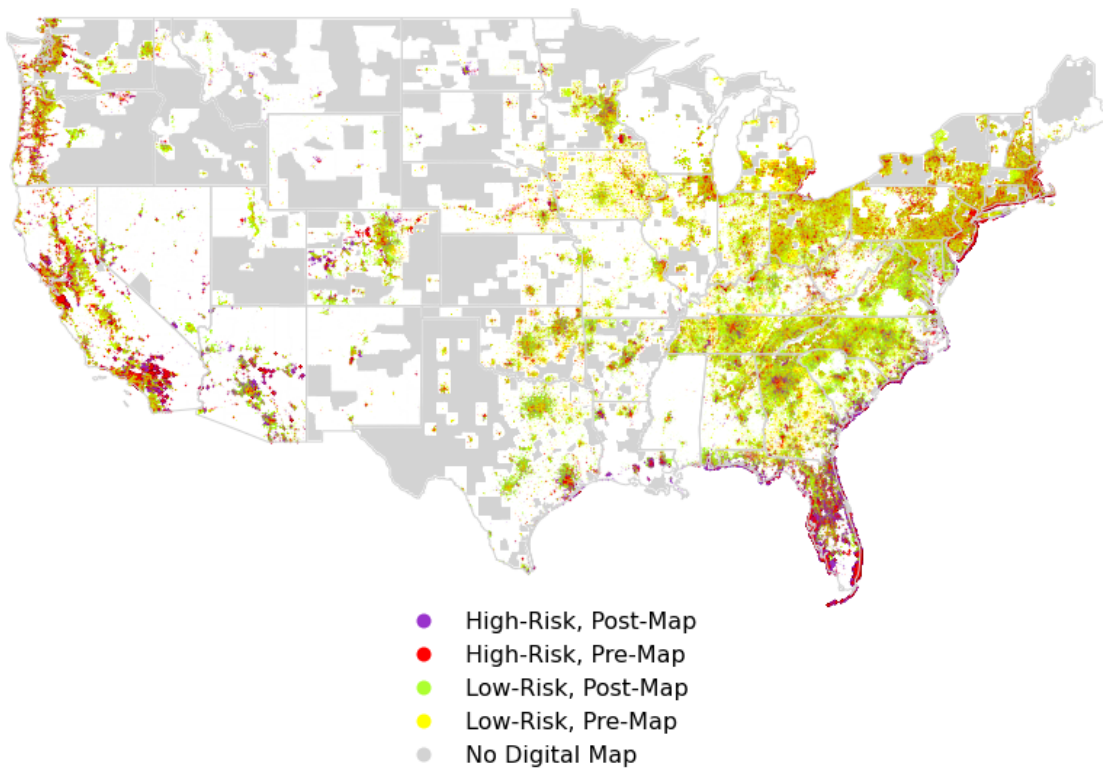
Van der Straten, Y. (2023). Flooded house or underwater mortgage? the implications of climate change and adaptation on housing, income, and wealth.

Wagner, K. R. (2022). Adaptation and adverse selection in markets for natural disaster insurance. *American Economic Journal: Economic Policy 14*(3), 380–421.

Weill, J. A. (2023). Flood risk mapping and the distributional impacts of climate information.

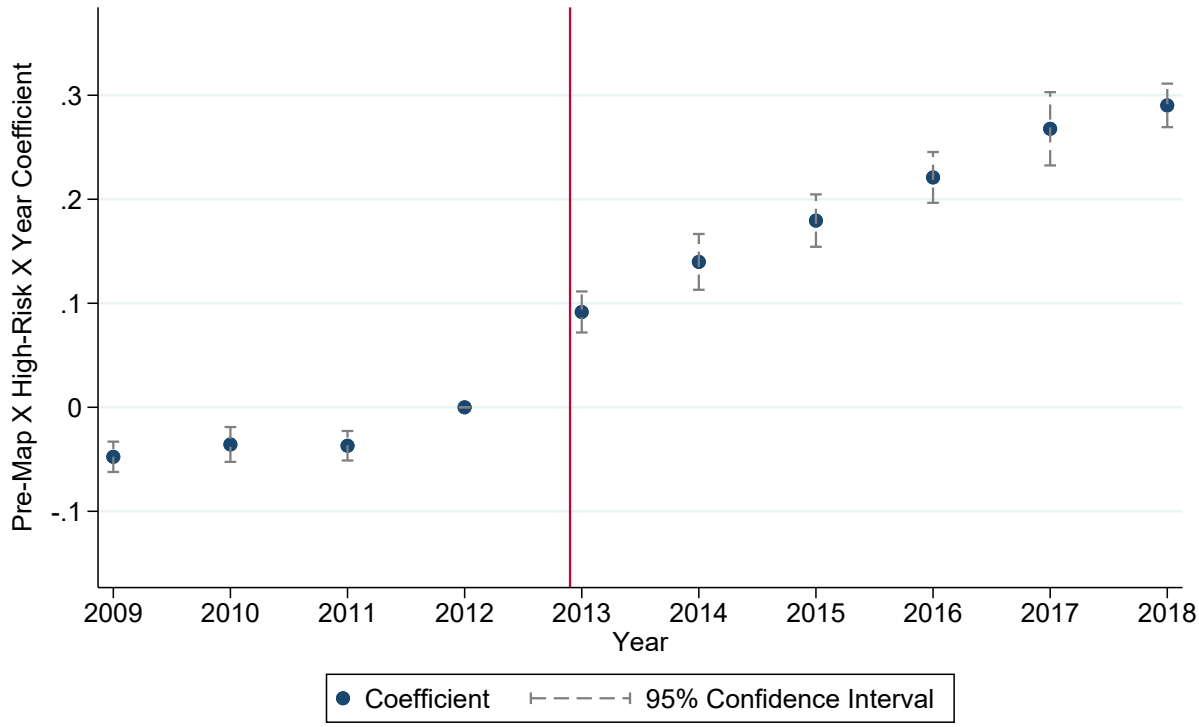
Zachry, B. C., W. J. Booth, J. R. Rhome, and T. M. Sharon (2015). A national view of storm surge risk and inundation. *Weather, Climate, and Society 7*(2), 109 – 117.

Figure 1: Distribution of Pre- vs Post-Map, High- vs Low-Risk Houses in the United States



Note: This figure plots the transacted Zillow properties in the United States overlayed with digital flood maps. Properties are colored according to their High-Risk and Pre-Map status. Purple represents High-Risk, Post-Map properties. Red represents High-Risk, Pre-Map properties. Lime green represents Low-Risk, Post-Map properties. Yellow represents Low-Risk, Pre-Map properties. Grey areas are those for which digital flood maps are not available.

Figure 2: Relative Effect of Flood Insurance Rate Reform on Premiums

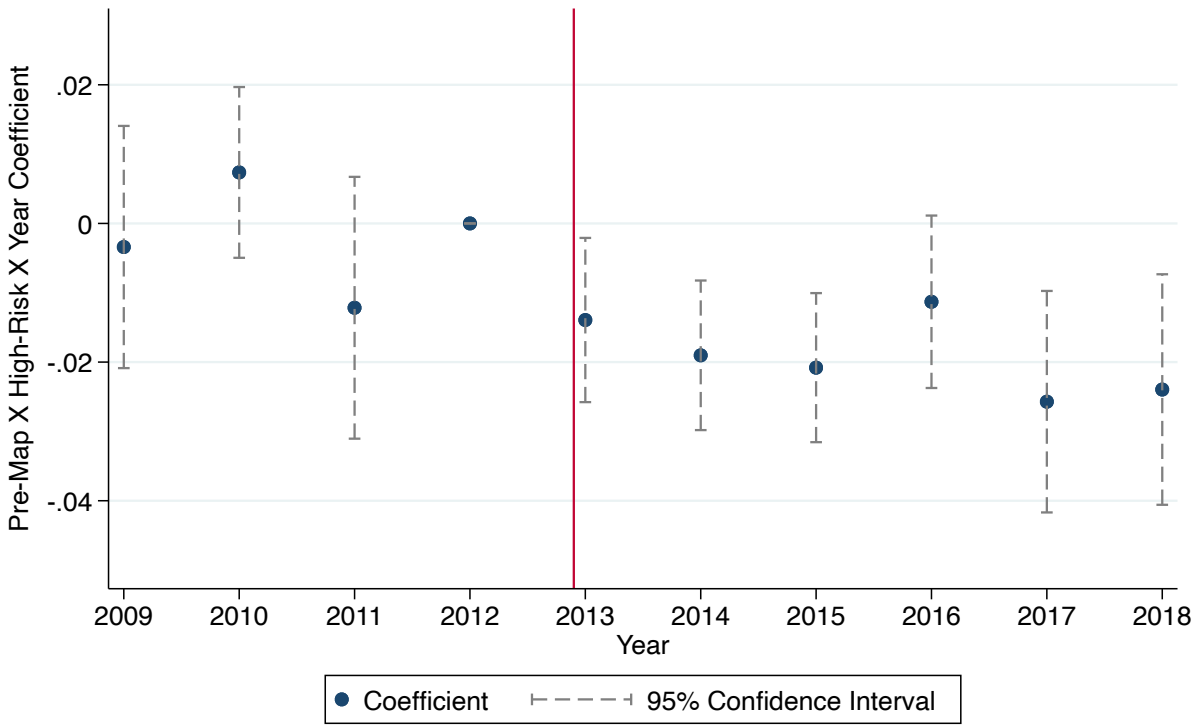


Note: Using the FEMA policies dataset, this figure plots the yearly estimates for *High-Risk*, *Pre-Map* homes (Blue Line) and the 95% confidence interval from the following regression

$$Premium_p = \sum_{y=2009}^{2018} \beta_y \times High\text{-}Risk_p \times Pre\text{-}Map_p \times \mathbf{1}_t^y + Lower\ Order\ Terms + FE_{zip \times age} + FE_{area \times t} + \epsilon_p,$$

where p indexes the flood insurance policy and t the year. *Premium* is the premium (in in \$1,000) for policy with \$250,000 building coverage, $\mathbf{1}_t^y$ is an indicator that takes a value of one if t is in year y. In fixed effects, *area* is defined by zip and longitude-latitude rounded to one decimal place. Note that this is the finest longitude and latitude that NFIP data provide. *LOT* includes all lower-order interactions between *High-Risk*, *Pre-Map*, and the year indicators, as well as standalone terms that are not absorbed by fixed effects. *Pre-Map* is an indicator that equals one if a house was built prior to flood maps being first established for the area. If the local map was established before 1975, houses built prior to 1975 are considered Pre-Map per NFIP premium rules. *Post-Reform* is an indicator that equals one if the transaction happened in 2013 and after, and zero otherwise. Standard errors are two-way clustered by policy start year-quarter and zip code. Flood insurance rate tables were updated in October in each year of 2009-2014, and in April in each year of 2015-2018. We make the following adjustment to the policy year. If an insurance policy starts in October or later in year *t*, after a new rate table becomes effective in October of year *t*, we modify the policy year as year *t+1*, since the applicable rate table is for the most part effective in year *t+1*. If a policy starts in March or earlier of year *t*, before a new rate table becomes effective in April of year *t*, then we modify the policy year to *t-1*, because the applicable rate table is previous one that was for the most part effective in year *t-1*.

Figure 3: Relative Effect of Flood Insurance Rate Reform on House Prices



Note: This figure plots the yearly estimates for *High-Risk*, *Pre-Map* homes (blue dots) and the 95% confidence interval from the following regression

$$Log(Price)_{i,t} = \sum_{y=2009}^{2018} \beta_y \times High\text{-}Risk_i \times Pre\text{-}Map_{it} \times \mathbf{1}_t^y + LOT + \beta \times SqFt + FE_{zip \times age} + FE_{zip \times age} + FE_{zip \times Loc \times \#bed \times t} + \epsilon_{i,j,t}$$

where $\mathbf{1}_t^y$ is an indicator that takes a value of one if t is in year y. *LOT* includes all lower-order interactions between *High-Risk*, *Pre-Map*, and the year indicators, as well as standalone terms that are not absorbed by fixed effects. *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. Standard errors are two-way clustered by quarter and zip code.

Table 1: Summary statistics

	Mean	SD	25 Pctl	Median	75 Pctl
Sales Price($1,000s)	282.32	308.62	128.00	204.50	329.00
High-Risk	0.15	0.36	0.00	0.00	0.00
Pre-Map	0.38	0.48	0.00	0.00	1.00
High-Risk&Pre-Map	0.07	0.25	0.00	0.00	0.00
Sales Year	2,013.89	2.82	2,012.00	2,014.00	2,016.00
Built Year	1,984.35	22.51	1,971.00	1,988.00	2,003.00
Property Age	29.60	22.73	11.00	26.00	44.00
# Bedrooms	2.38	1.51	2.00	3.00	3.00
Building Sq. Ft.	1,939.84	1,985.52	1,312.00	1,722.00	2,299.00
Dist. to Risk Zone Border (miles)	0.14	0.23	0.03	0.09	0.19
Avg Premium ($1,000s)	447.99	288.61	332.62	353.33	403.00
Average Building Coverage	200,570.23	29,132.42	184,515.20	204,977.98	222,111.84
Sea Level Rise	0.09	0.29	0.00	0.00	0.00
1st St Flood Factor	2.69	2.67	1.00	1.00	4.00
Storm Surge	0.13	0.34	0.00	0.00	0.00
Distance to Water (miles)	1.30	1.35	0.21	0.71	2.10
Distance > 5 Miles	0.60	0.49	0.00	1.00	1.00

Note: This table presents summary statistics of variables used in the analyses. The sample used here correspond to the one use in Column (3) of Table 2. Variable definitions are in Section A.1 in the Appendix.

Table 2: The Effect of Flood Insurance Rate Reform on House Prices

Dependent Variable	Log(Price)			Price ($1,000s)
	(1)	(2)	(3)	(4)
High-Risk × Pre-Map × Post-Reform	-0.023***	-0.017**	-0.021***	-12.292***
	(-3.69)	(-2.49)	(-3.92)	(-4.52)
High-Risk × Post-Reform	-0.002	-0.005	0.004	6.674***
	(-0.36)	(-0.74)	(1.13)	(3.55)
Pre-Map × Post-Reform	-0.009*	-0.019	-0.008	-12.805***
	(-1.77)	(-1.31)	(-1.25)	(-4.11)
High-Risk × Pre-Map	-0.015	1.634***	0.002	-0.445
	(-1.29)	(13.54)	(0.31)	(-0.14)
High-Risk	0.100***		0.036***	11.880***
	(8.51)		(6.20)	(4.57)
Pre-Map	0.003	-0.027	-0.004	10.565***
	(0.37)	(-0.14)	(-0.63)	(4.13)
Sq Ft	0.044***		0.057***	24.708***
	(4.93)		(4.11)	(4.26)
Zip X Age FE	Y	Y	Y	Y
Zip X Year X Beds FE	Y	Y	N	N
Parcel FE	N	Y	N	N
Zip X Long/Lat X Year X Beds FE	N	N	Y	Y
Outcome Mean	12.320	12.242	12.256	282.320
Outcome SD	0.724	0.695	0.719	308.617
Observations	11,106,255	4,954,038	4,294,716	4,294,716

Note: This table presents OLS regressions where the dependent variable is log house prices in Columns (1)-(3) and prices in thousands of dollars in Column (4). The main variable of interest is the triple interaction term *High-Risk* × *Pre-Map* × *Post-Reform*. *High-Risk* is an indicator that takes a value of one if a house is in a high-risk flood zone. *Pre-Map* is an indicator that equals one if a house was built prior to flood maps being first established for the area. If the local map was established before 1975, houses built prior to 1975 are considered Pre-Map per NFIP premium rules. *Post-Reform* is an indicator that equals one if the transaction happened in 2013 and after, and zero otherwise. *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

Table 3: Heterogeneous Effects of Rate Reform on House Prices across Different Flood Risks

Dependent Variable	Log(Sales Price)		Sales Price ($1,000s)	
	(1)	(2)	(3)	(4)
High-Risk × Pre-Map × Post-Reform	-0.012**	-0.013	-5.768**	-2.269
	(-2.18)	(-1.53)	(-2.51)	(-0.52)
High-Risk × Pre-Map × Post-Reform × Sea Level Rise	-0.029**	-0.023*	-17.416**	-11.880**
	(-2.45)	(-1.90)	(-2.62)	(-2.03)
High-Risk × Pre-Map × Post-Reform × 1st St Flood Factor		-0.003		-4.655*
		(-0.67)		(-1.94)
High-Risk × Pre-Map × Post-Reform × Storm Surge		0.012		5.004
		(1.36)		(0.98)
High-Risk × Pre-Map × Post-Reform × Distance to Water		0.004		3.616
		(0.58)		(1.15)
High-Risk × Pre-Map × Post-Reform × Distance>5 Miles		-0.010		-11.875
		(-0.43)		(-1.06)
High-Risk × Pre-Map × Post-Reform × > 3 Past Floods		0.009		1.226
		(0.72)		(0.18)
Lower-Order Terms & Sq Ft	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y	Y
Outcome Mean	12.256	12.256	12.256	12.256
Outcome SD	0.719	0.719	0.719	0.719
Observations	4,294,716	4,294,716	4,294,716	4,294,716

Note: This table presents OLS regressions similar to Column (3) of Table 2 where the dependent variable is log house prices in Columns (1) and (2) and prices in thousands of dollars in Columns (3) and (4). *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

Table 4: The Effect of Rate Reform on House Prices and Exposure to Sea Level Rise

Panel A: Sample Not Exposed to Sea Level Rise

Dependent Variable (in $1,000s)	Price	Same-Yr Premium	2018 Premium
	(1)	(2)	(3)
High-Risk × Pre-Map × Post-Reform	-4.823**	0.085***	0.129***
	(-2.19)	(5.53)	(7.19)
Lower-Order Terms & Sq Ft	Y	Y	Y
Zip X Age FE	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y
Outcome Mean	275.208	0.447	0.433
Outcome SD	295.978	0.312	0.297
Observations	3,874,700	2,993,725	2,909,014

Panel B: Sample Exposed to Sea Level Rise

Dependent Variable (in $1,000s)	Price	Same-Yr Premium	2018 Premium
	(1)	(2)	(3)
High-Risk × Pre-Map × Post-Reform	-25.845***	0.116***	0.170***
	(-3.64)	(6.05)	(7.64)
Lower-Order Terms & Sq Ft	Y	Y	Y
Zip X Age FE	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y
Outcome Mean	336.604	0.767	0.766
Outcome SD	383.973	0.544	0.550
Observations	375,424	325,498	321,362

Note: This table repeats the structure of Columns (3) of Table 2 with two subsamples separately. In Panel A, we use the sample of homes not exposed to sea level rise. In Panel B, we use the sample of homes exposed to sea level rise. The dependent variables are all in thousands of dollars. In Column (1), it is house prices. In Column (2), the dependent variable with premium rates that are matched to the house transactions in the same year multiplied by 2009 coverage matched to each property. In Column (3), we repeat Column (2), replacing premium rates for home transactions between 2013 and 2018 with the matched premium rates in 2018. We again multiply the premium rates with the matched 2009 coverage. *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Effect of Rate Reform on House Prices by Insurance Coverage

Dependent Variable	Price ($1,000s)			
Sample	High Coverage (1)	Low Coverage (2)	All (3)	All (4)
High-Risk × Pre-Map × Post-Reform	-17.674***	-4.738**	-5.493**	0.969
	(-3.60)	(-2.27)	(-2.62)	(0.23)
High-Risk × Pre-Map × Post-Reform × High Coverage			-11.284**	-8.941*
			(-2.26)	(-2.00)
High-Risk × Pre-Map × Post-Reform × Sea Level Rise				-11.322*
				(-1.96)
High-Risk × Pre-Map × Post-Reform × 1st St Flood Factor				-4.643*
				(-1.99)
High-Risk × Pre-Map × Post-Reform × Storm Surge				5.330
				(1.05)
High-Risk × Pre-Map × Post-Reform × Distance to Water				2.718
				(0.88)
High-Risk × Pre-Map × Post-Reform × Distance>5 Miles				-3.793
				(-0.58)
High-Risk × Pre-Map × Post-Reform × > 3 Past Floods				1.446
				(0.21)
Lower-Order Terms & Sq Ft	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y	Y
Outcome Mean	368.401	193.942	282.136	282.136
Outcome SD	363.814	205.753	308.905	308.905
Coverage Mean	223k	178k	201k	201k
Coverage SD	11k	24k	29k	29k
Observations	2,156,995	2,112,166	4,275,932	4,275,932

Note: This table presents OLS regressions where the dependent variable is dollar house prices. We repeat our main specification from Column (4) of Table 2, using houses with below-median coverage amount in Column (1) and those with above-median coverage amount in Column (2). In Column (3), we include all houses. The main variable of interest is the triple interaction term *High-Risk* × *Pre-Map* × *Post-Reform*. *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

Table 6: Effect of Rate Reform on House Prices by State Disclosure Requirement and Buyer Type

Dependent Variable	Log(Price)					
Sample	No Disclosure (1)	Disclosure (2)	All (3)	Primary (4)	Non-Primary (5)	All (6)
High-Risk × Pre-Map × Post-Reform	-0.021***	-0.034***	-0.017**	-0.017***	-0.035***	-0.012**
	(-3.07)	(-4.22)	(-2.67)	(-3.54)	(-2.88)	(-2.55)
High-Risk × Pre-Map × Post-Reform × Disclosure			-0.013			
			(-1.24)			
High-Risk × Pre-Map × Post-Reform × Non-Primary						-0.014*
						(-1.85)
Sample	No Disclosure	Disclosure	All	Primary	Non-Primary	All
Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y	Y	Y	Y
Outcome Mean	12.135	12.419	12.256	12.309	12.102	12.256
Outcome SD	0.685	0.731	0.719	0.677	0.784	0.719
Observations	2,475,082	1,819,634	4,294,716	2,989,069	1,068,273	4,294,716

Note: This table presents OLS regressions where the dependent variable is log house prices. We repeat our main specification from Column (3) of Table 2, using the transactions in states that do not require any disclosure in Column (1) and using states that require disclosure in Column (2). We use the sample of houses sold to primary owners in Column (4) and those sold to non-primary owners in Column (5). *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

Table 7: The Effect of Rate Reform on Buyers' Mortgage Take-up

Dependent Variable	Buyer Take Out Mortage		
	(1)	(2)	(3)
High-Risk × Pre-Map × Post-Reform	-0.016***	-0.019**	-0.011***
	(-4.99)	(-2.52)	(-2.75)
Lower-Order Terms & Sq Ft	Y	Y	Y
Zip X Age FE	Y	Y	Y
Zip X Year X Beds FE	Y	Y	N
Property FE	N	Y	N
Zip X Long/Lat X Year X Beds FE	N	N	Y
Outcome Mean	0.523	0.457	0.498
Outcome SD	0.499	0.498	0.500
Observations	10,360,887	4,669,463	4,072,049

Note: This table repeats Columns (1)-(3) of Table 2, replacing the dependent variable with an indicator for whether the buyer uses a mortgage at the time of the property transaction. The observations are at the house-transaction level. *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

Table 8: The Effect of Rate Reform on Rebuilding Activities Across Hazard Exposure

Dependent Variable	1(Rebuilt×1M)				
Sample	All	Flood Factor		Sea Level Rise	
		>1	=1	Exposed	Not Exposed
	(1)	(2)	(3)	(4)	(5)
High-Risk × Pre-Map (Orig) × Post-Reform	138.227***	150.426**	71.193	95.745	81.610
	(2.87)	(2.11)	(0.79)	(0.70)	(1.42)
Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y	Y
Zip X Year X Beds FE	Y	Y	Y	Y	Y
Outcome Mean	326.033	336.447	331.542	346.658	331.498
Observations	240,260,750	42,517,838	189,421,009	7,145,381	225,180,765

Note: This table repeats Column (1) of Table 2, parentheses. The dependent variable is one if the house is rebuilt in that year. We define the outcome variable, *1(Rebuilt)*, as either one of the following situations. (1) The house is matched to a permit that is of the type "Demolition" in that year, where the year is after the initial year built of the property. (2) The house in that year is matched to a permit that is of the type "New Building", where the permit year is after the initial year built of the property, or the year equals the maximum year built of a parcel that is later than its original year built based on tax assessor data. We exclude parcel-years when a property is first built in our tax assessor sample. Given the low baseline probability (326 out of one million parcel-year observations in Column 3), we mimic the specification in Column (1) of Table 2 with zip-by-year-by-beds in the fixed effects rather than zip-by-longitude/latitude-by-year-by-beds. Similar to the restriction in Column (1) of Table 2, we keep houses in zip codes (rather than zip-by-longitude/latitude areas) that have both High-Risk and Low-Risk homes. Column (1) uses the full sample. In Columns (2) and (3), we use properties whose First Street Foundation Flood Factor is larger than one and equals one, respectively. In Columns (4) and (5), we use properties that are exposed and unexposed to sea-level-rise risk. The coefficient estimates on the triple interaction term are all positive and statistically significant. The coefficient in Column (2) is the only one that is statistically significant, with a magnitude much larger than in Column (3). In contrast, the coefficients are more close in magnitude between Columns (4) and (5). Standard errors are double clustered by zip code and year. ***p<0.01, **p<0.05, *p<0.1.

Table 9: The Effect of Rate Reform on House Prices — Built Around Map Year or Boundary

Dependent Variable	Log(Sales Price)	
	(1)	(2)
High-Risk × Pre-Map × Post-Reform	-0.037**	-0.016***
	(-2.47)	(-2.76)
Sample	MapYr+-3	250ft
Lower-Order Terms & Sq Ft	Y	N
Zip X Age FE	Y	Y
Zip X Year X Beds FE	Y	Y
Zip X Long/Lat X Year X Beds FE	N	Y
Outcome Mean	12.039	12.231
Outcome SD	0.688	0.717
Observations	397,835	1,202,817

Note: This table presents OLS regressions similar to Columns (1) and (3) of Table 2. We restrict our sample to houses that were built within three years of the local map establishment in Column (1). We restrict our analysis to properties within 250 feet of the border in Column (2). The main variable of interest is the triple interaction term *High-Risk* × *Pre-Map* × *Post-Reform*. *High-Risk* is an indicator that takes a value of one if a house is in a high-risk flood zone. *Pre-Map* is an indicator that takes a value of one if a house was built prior to flood maps being released for the area. *Post-Reform* is an indicator that equals one if the transaction happened in 2013 and after. *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

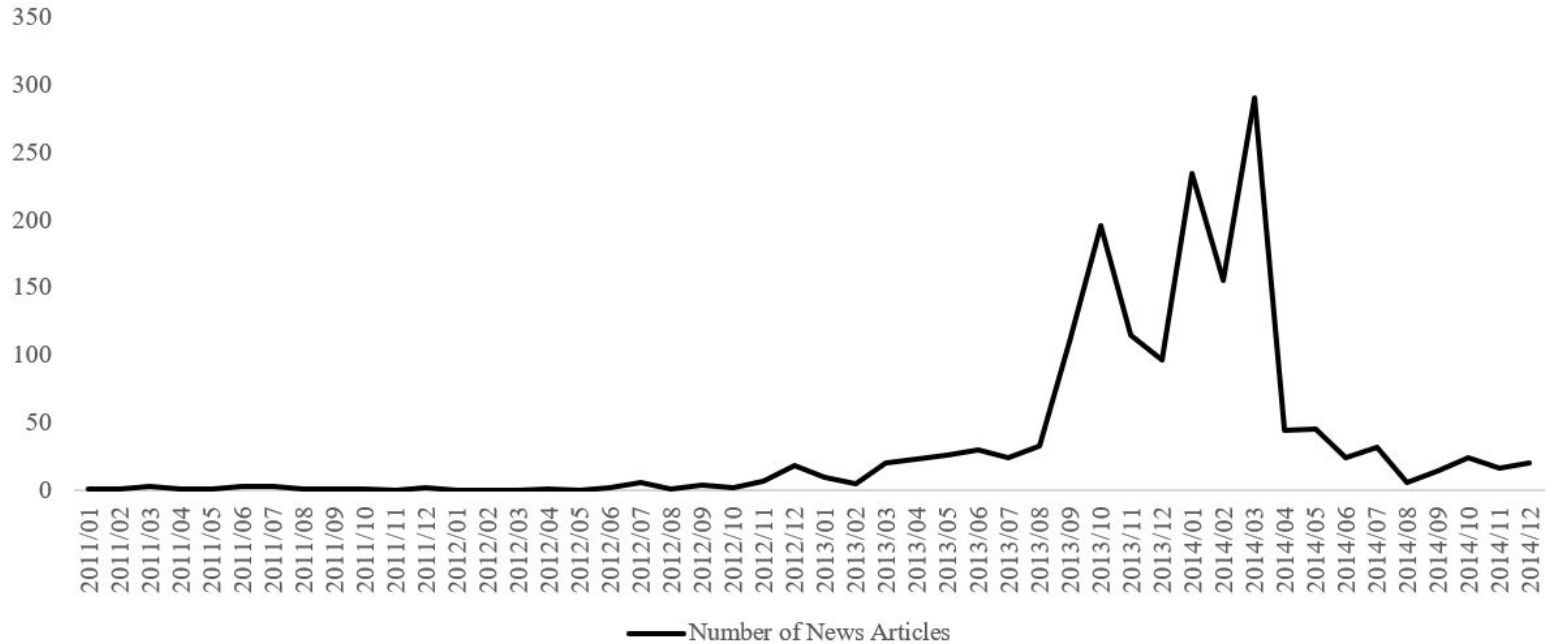
Table 10: The Effect of Rate Reform on House Prices — Additional Flood Risk Controls

Dependent Variable	Log(Sales Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
High-Risk × Pre-Map × Post-Reform	-0.018***	-0.013**	-0.017***	-0.018***	-0.018***	-0.016***
	(-3.40)	(-2.55)	(-3.63)	(-3.63)	(-3.60)	(-3.30)
Hazard Measure × High-Risk × Post-Reform	0.008	-0.001	0.011**	0.005	-0.001	-0.017*
	(1.16)	(-0.59)	(2.51)	(1.43)	(-0.08)	(-1.96)
Hazard Measure × Pre-Map × Post-Reform	-0.003	-0.003	-0.002	-0.002	-0.004	-0.007
	(-0.37)	(-1.43)	(-0.45)	(-0.28)	(-0.39)	(-1.15)
Hazard Measure × Post-Reform	-0.012*	0.001	0.004	0.007	0.014	0.014**
	(-1.73)	(0.65)	(1.25)	(1.34)	(1.20)	(2.61)
Distance>5 miles × High-Risk × Post-Reform				-0.010*		
				(-1.76)		
Distance>5 miles × Pre-Map × Post-Reform				0.010		
				(1.12)		
Distance>5 miles × Post-Reform				0.022**		
				(2.45)		
Hazard Measure	Sea Level Rise	1st St Flood Factor	Storm Surge	Dist to Water	>3 Floods	Basement
Other Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y	Y	Y	Y
Outcome Mean	12.256	12.256	12.256	12.256	12.256	12.256
Outcome SD	0.719	0.719	0.719	0.719	0.719	0.719
Observations	4,294,716	4,294,716	4,294,716	4,294,716	4,294,716	4,294,716

Note: This table presents OLS regressions similar to Column (3) of Table 2. *Hazard* is an indicator for whether or not the house is exposed to six feet of sea level rise in Column (1); the standardized value of First Street Foundation's flood factor in Column (2); an indicator for whether or not the house is exposed to storm surge in the case of a category-3 hurricane in Column (3); standardized distance to highest-tide water in Column (4); whether or not the county experienced a flood declared by FEMA as a disaster in more than three years since the beginning of FEMA's disaster data in 1953 in Column (5); whether the property has a basement in Column (6). In Column (4), when the property is more than five miles away from water, we set the standardized distance to three. We also include an indicator for when distance is more than five miles and its interaction with *High-Risk*, *Pre-Map*, and *Post-Reform*. The main variable of interest is the triple interaction term *High-Risk* × *Pre-Map* × *Post-Reform*. *Loc* in fixed effects stands for location defined by longitude and latitude rounded to two decimal places. We include all lower-order terms, including those involving Hazard measures and standalone terms that are not absorbed. We also control for square footage. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

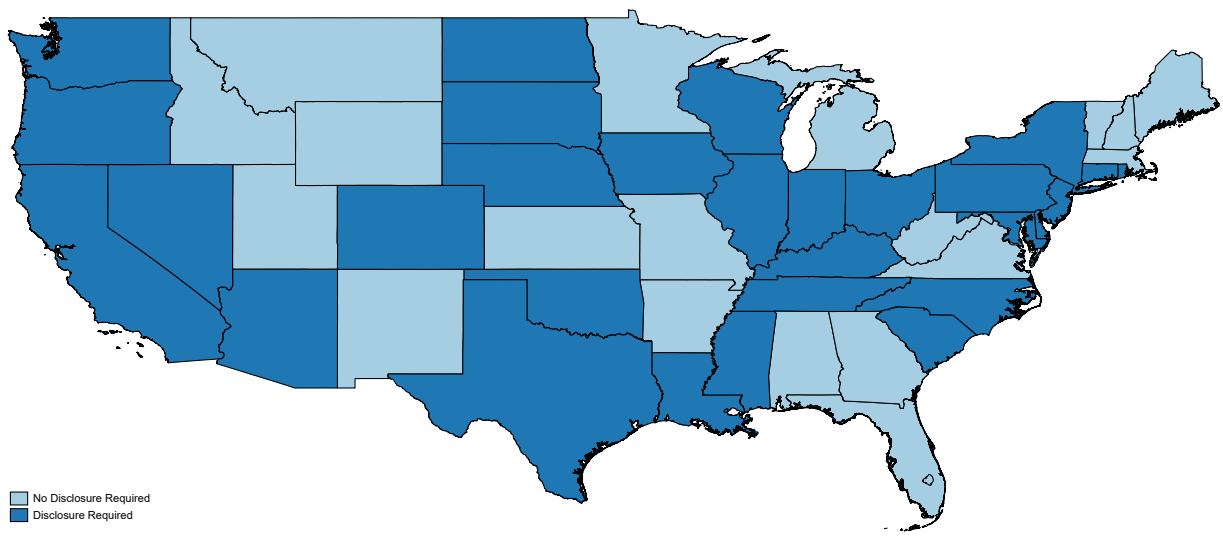
A Appendix

Figure A1: Number of News Articles Related to the Reform



Note: This figure plots the number of unique news articles in Factivia with the following keywords: "Biggert-Waters", "Grimm-Waters", "Homeowner Flood Insurance Affordability", or "HFIAA".

Figure A2: Requirements on Flood Zone Disclosure Across States



Note: This figure plots the state-level requirements on flood zone disclosure by propoerty sellers, based on a FEMA 2022 Report.[a] The lighter shade indicates no disclosure. The darker shade indicates that the seller is required to disclose whether the house is located in a High-Risk zone.

[a] See, `https://www.fema.gov/sites/default/files/documents/fema_state-flood-risk-disclosure-best-practices_07142022.pdf`. Tennessee requires sellers to disclose whether flood insurance is required to property buyers (but not renters). We classify Tennessee as requiring disclosure.

Table A1: Example Premium for Primary Residence, Single Family Home without Basement, $250,000 Coverage Policy

	High-Risk, Pre-Map	High-Risk, Post-Map			Low-Risk, Pre-/Post-Map
		Elev. Relative to Flood			
		+1	0	-1	
Effective Year	Premium for $250k coverage				
2008	1300	495	855	4075	735
2009	1460	530	940	4680	810
2010	1539	585	1067	4921	867
2011	1596	628	1188	4955	953
2012	1710	640	1315	4730	1002
2013	1919	616	1315	4483	1051
2014	2009	616	1315	4255	1088
2015	1992	616	1315	4255	1088
2016	2073	646	1414	3471	1113
2017	2179	756	1598	3643	1181
2018	2304	769	1592	3631	1187
2012-2018 Δ	594	129	277	-1099	185
Avg Annual Δ	5.8%	3.4%	3.5%	-3.9%	3.1%

Note: This table shows the insurance premium for a primary residence, single family home without a basement from 2008-2018. The premium is calculated assuming the policy includes $250,000 building coverage and $0 content coverage, and include no other adjustments that lead to rate discount. The premium rates for each year are taken from NFIP Flood Insurance Manuals. "Elev. Relative to Flood" refers to the elevation of the lowest floor of the house above base flood elevation. From 2014 to 2015, the premium for High-Risk, Pre-Map policies did not increase, contrary to the mandate of the law. NFIP's then chief actuary, Andy Neal, explained in an email that "it is a combination of implementing the reserve fund and HFIAA as well as the timing of the law compared to what changes we had made."

A.1 Variable Definition

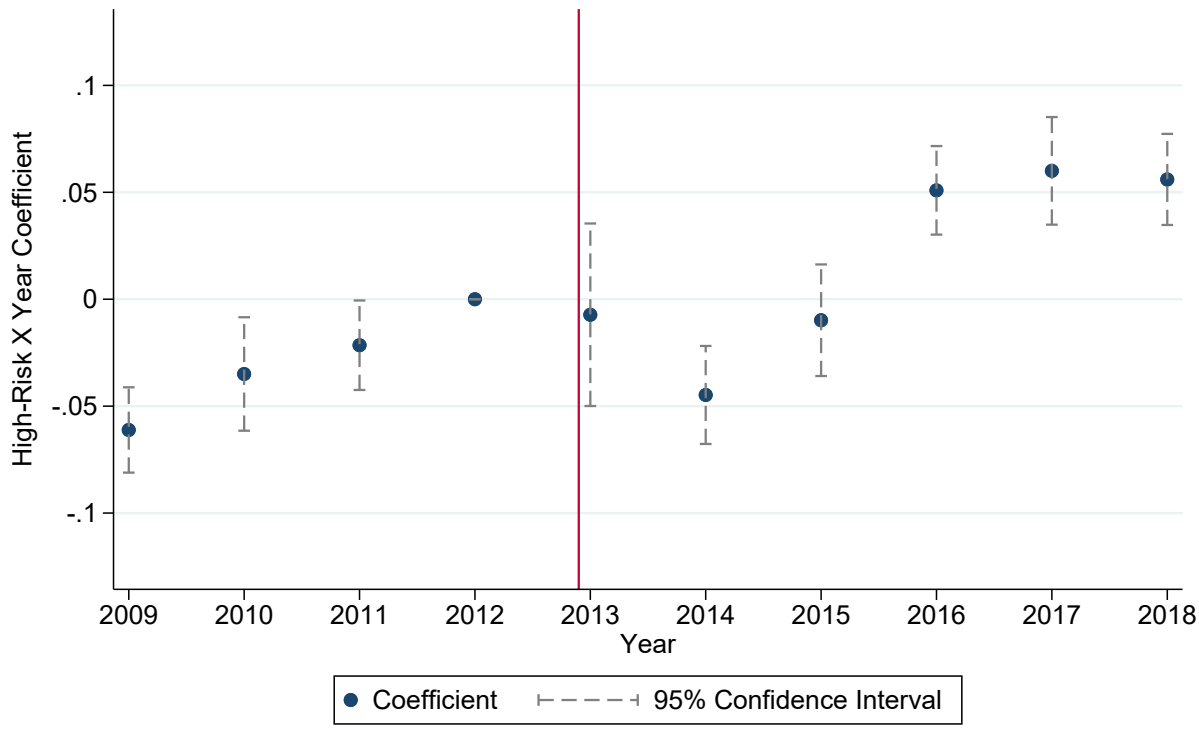
- *Price*: house transaction price
- *High-Risk*: an indicator that takes a value of one if a house is in a high-risk flood zone
- *Pre-Map*: an indicator that equals one if a house was built prior to flood maps being first established for the area. If the local map was established before 1975, houses built prior to 1975 are considered Pre-Map per NFIP premium rules
- *Post-Reform*: an indicator that equals one if the transaction happened in 2013 and after, and zero otherwise
- *Post-Reform*: an indicator that equals one if the house transaction happened in 2013 and after, and zero otherwise
- *Sq Ft*: the square footage of the house
- *Loc*: area defined by longitude and latitude (rounded to two decimal places)
- *Sea Level Rise*: an indicator that equals to one if the property would experience chronic tidal flooding after six feet of global average sea level rise according to National Oceanic and Atmospheric Administration (NOAA) Sea Level Rise risk layer which covers coastal areas
- *1st Street Flood Factor*: 30-year flood risk from First Street Flood Factor data at the closest point to each property in our data
- *Distance to Water*: the distance between a property and the current highest high tide for all homes within five miles radius using the NOAA Sea Level Rise risk layer, so the raw value is only available for coastal areas covered by the layer; this variable is standardized in regressions with a mean of zero and standard deviation of one; if a house is more than 5 miles away from the water, we assign a value of one to it for the standardized variable
- *Distance>5 Miles*: an indicator that equals one if the property is more than five miles from the coast, and zero otherwise
- *Storm Surge*: an indicator that equals one if the property would experience flooding (e.g. Storm-Surge height greater or equal to 1 foot) after a category three hurricane according to NOAA storm surge risk
- *>3 Past Floods*: an indicator that equals one if a county has experienced more than 3 flood-related FEMA-declared disasters since the FEMA data began in 1953, and zero otherwise
- *Disclosure*: an indicator that equals one if a state requires the seller to disclose whether the house is in a high-risk flood zone, and zero otherwise
- *Non-Primary*: an indicator that equals one if the buyer of a house is a non-primary owner, and zero otherwise
- *Demolish*: an indicator that equals one if the house in that year is matched to a permit that is of the type "Demolition", where the permit year is after the initial year built of the property, and zero otherwise

- *Rebuilt*: an indicator that equals one if the house in that year is matched to a permit that is of the type "New Building", where the permit year is after the initial year built of the property, or if the year equals the maximum year built of a parcel that is later than its original year built based on tax assessor data
- *Pre-Map (Orig)*: an indicator that equals one if a house was *originally* built prior to flood maps being first released for the area, and zero otherwise

Internet Appendices

IA Additional Figures and Tables

Figure IA.1: Relative Effect of Flood Insurance Rate Reform on Premiums, High-Risk vs Low-Risk



Note: Using the FEMA policies dataset, this figure plots the yearly estimates for β_y (blue dots) and the 95% confidence interval from the following regression

$$Premium_{i,t} = \sum_{y=2009}^{2018} \beta_y \times High\text{-}Risk_i \times \mathbf{1}_t^y + \lambda \times High\text{-}Risk_i + FE_{zip \times age} + FE_{area \times t} + \epsilon_{i,j,t}$$

where *Premium* is the premium from a $250,000 coverage policy in $1,000, $\mathbf{1}_t^y$ is an indicator that takes a value of one if *t* is in year *y*. Variable definitions are in Section A.1 in the Appendix. In the fixed effects, *area* is defined by zip code as well as longitude and latitude rounded to one decimal place. Note that this is the finest longitude and latitude that NFIP data provide. Standard errors are two-way clustered by quarter and zip code.

Table IA.1: Book Rate for High-Risk, Pre-Map Properties

Manual Publish Year	Basic Limit ($)	Basic Rate, $ (per $ of Basic Coverage)	Additional Rate, $ (per $ of Additional Coverage)
2008	50,000	0.76	0.54
2009	60,000	0.76	0.57
2010	60,000	0.76	0.6
2011	60,000	0.76	0.66
2012	60,000	0.76	0.77
2013	60,000	0.91	0.77
2014	60,000	0.85	0.78
2015	60,000	0.89	0.81
2016	60,000	0.94	0.95
2017	60,000	0.99	0.9

Note: This table tabulates the book rate of flood insurance premiums for High-Risk, Pre-Map properties, according to FEMA's rate manuals. The second column tabulates the basic coverage limit, for which the basic rate for each dollar of coverage (third column) applies. The last column tabulates the addition rate, which is the per dollar cost of insurance for each dollar of additional coverage.

Table IA.2: Additional Robustness Tests for Flood Insurance Rate Reform and House Prices

Dependent Variable	Log(Sales Price)				
	Excluding 2013-2014 (1)	FE×High-Risk (2)	FE×Pre-Map (3)	Additional Controls (4)	High-Risk: 1996=2021 (5)
High-Risk × Pre-Map × Post-Reform	-0.019***	-0.027**	-0.019***	-0.022***	-0.019**
	(-3.13)	(-2.47)	(-3.48)	(-4.14)	(-2.50)
Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y
Additional Risk Controls	N	N	N	Y	N
Zip X Age FE	Y	N	N	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	N	N	Y	Y
Zip X Age X High-Risk FE	N	Y	N	N	N
Zip X Long/Lat X Year X Beds X High-Risk FE	N	Y	N	N	N
Zip X Age X Pre-Map FE	N	N	Y	N	N
Zip X Long/Lat X Year X Beds X Pre-Map FE	N	N	Y	N	N
Outcome Mean	12.267	12.252	12.252	12.256	12.246
Outcome SD	0.719	0.716	0.714	0.719	0.710
Observations	3,389,537	4,172,729	4,190,125	4,294,716	3,063,827

Note: This table presents OLS regressions similar to Column (3) of Table 2 where the dependent variable is log house prices. In Column (1), we exclude the years 2013 and 2014, the period between the two reforms. In Column (2), we interact fixed effects with the *High-Risk*. In Column (3), we interact fixed effects with the *Pre-Map*. In Column (4), we include additional controls: exposure to sea level rise, First Street Foundation flood factor, exposure to storm surge, distance to highest-tide water, frequent past floods, and whether the home has a basement. In Column (5), we only include houses, for which the High-Risk dummy did not change between 1996 and 2021. The main variable of interest is the triple interaction term *High-Risk* × *Pre-Map* × *Post-Reform*. Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

Table IA.3: Effect of Rate Reform on House Prices and Sea Level Rise by Insurance Coverage

Dependent Variable	Price ($1,000s)	
Sample	High Coverage	Low Coverage
High-Risk × Pre-Map × Post-Reform	-8.223*	-3.992*
	(-1.91)	(-1.84)
High-Risk × Pre-Map × Post-Reform × Sea Level Rise	-19.467*	-10.575
	(-1.71)	(-1.53)
Lower-Order Terms & Sq Ft	Y	Y
Zip X Age FE	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y
Outcome Mean	368.023	193.896
Outcome SD	363.583	205.762
Observations	2,162,319	2,107,008

Note: This table presents OLS regressions where the dependent variable is dollar house prices. We repeat our main specification from Column (4) of Table 2, using houses with below-median coverage amount in Column (1) and those with above-median coverage amount in Column (2). Variable definitions are in Section A.1 in the Appendix. *t*-statistics are reported in parentheses. Standard errors are double clustered by zip code and quarter. ***p<0.01, **p<0.05, *p<0.1.

IA Data Appendix

IA.1 Construction of the NFIP policies dataset

We start with The NFIP policies dataset for the years 2009-2018. We limit our sample to only single-family housing, which is 85% of all written policies. Furthermore, we limit our policy sample to primary residences only, which composes 80% of all policies. We drop the 1% of the policies with the property's original date of construction missing, since the original construction date is necessary for classifying whether a house is Pre- or Post-Map, which in turn decides whether a house is in the treatment or control group. We exclude the 4% of policies for which the coverage is less than or equal to 0. We exclude policies with premia that are smaller than the first or greater than the ninety-ninth percentile. We drop the policies with missing zip code (less than 0.01%).

Flood zones: The NFIP policies dataset provides a granular classification for the flood zones. The A, numbered A (e.g. A1-30, except for A99), V, numbered V, and D zones are classified under the Special Flood Hazard Area (SFHA) (i.e. High-Risk flood zones), whereas A99, B, C, and X zones are classified as non-SFHA (i.e. Low-Risk flood zone).[25] We exclude High-Risk Zone VE, which makes up than 0.08% of our sample, because the reform had a different treatment effect on VE zones compared to other High-Risk zones.

Premium rate: Premium rate is calculated by taking the total insurance premium of the policy, divided by the sum of building coverage and content coverage of the policy. While several other factors that could impact the premium rate (such as Community Rating System (CRS) discount), the premium rate is primarily impacted by the basic limit rates and the additional limit rates specified in the rate schedule. Holding other variables fixed, an increase in the basic limit rates and the additional limit rates would directly reflect in an increase in the overall premium rate.

IA.2 Construction of the Zillow dataset

We filter the data as follows. First, we retain only transactions of residential properties for which the price of the transaction is between \$50,000 and \$5,000,000. In addition, we only include transactions where both low- and high-risk properties exist within a particular geographic area as

[25] Technically, A99 (areas with a 1% annual chance of flooding protected by a Federal flood control system) are also SFHA in FEMA's terminology. But for the purpose of setting insurance premium rate, A99 rate follows the same rate schedule as Low-Risk zones B, C and X.

defined by our fixed effect structure. Third, we only include properties with sufficient non- missing property information.

IA.3 Merging flood insurance policies to Zillow properties

The policies dataset has been anonymized to protect the privacy of individuals; therefore, we only have latitude and longitude coordinates up to one decimal place. In order to match the policy rate data to the Zillow home transaction data, we utilized a few additional characteristics of the house. An insurance policy in the NFIP policies dataset is matched to a Zillow transacted property if (i) the latitude and longitude (rounded to one decimal place) are the same; (ii) the zip code is the same; (iii) the policy year is the same as the sale year; and (iv) the year built on the NIFP record and the Zillow record are within a three- year difference. We first aggregate the policy dataset to obtain an average premium rate, average coverage, and average claim amount for such grouping, then we merge them to properties in the Zillow dataset.