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

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Abstract

Property insurance provides an important hedge against disasters, but distorted premiums can mute the pricing of disaster risks. We document that removing flood insurance subsidies precipitates a 2% average price decline, primarily concentrated in properties exposed to sea level rise. Our findings demonstrate that reducing premium distortions accelerates the incorporation of climate change risk in house prices. The house price effect is not fully explained by the cash flows from subsidy reductions, and indicates markets' increased perceptions of uninsured risks. Higher premiums reduce mortgage take-up as mandatory insurance becomes costlier, and encourage the rebuilding of homes, especially in risky locations.

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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. 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 and development activities, 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 based on two discontinuities: their location relative to flood zone boundaries and their year of construction. We find three key results. First, we document that subsidized insurance mutes risk-related price signals. Removing insurance subsidies decreases house prices, and has the largest effect on homes exposed to *future* climate risk, as measured by sea level rise exposure. This result provides novel evidence establishing a direct link between insurance prices and climate risk pricing in real estate—fairly priced insurance helps the market incorporate climate risks. Second, the observed house price effect is not fully explained by cash flows related to the subsidy reduction, but is consistent with the market's updated risk perception of uninsured damages.

Finally, higher premiums changed homeowner behavior. They decreased mortgage take-up as total mortgage costs (including mandatory insurance) increase and encourage the rebuilding of treated homes, especially those facing greater flood risks. These newly rebuilt homes are likely to be more resilient to floods as substantial changes to building codes and best practices over the last decade have made newly built homes in disaster-prone areas much more resilient.[1] To summarize, removing insurance subsidies appears to increase the sensitivity of housing markets to climate-related risks in a way that improves adaptation.

[1] See, e.g. `https://www.texastribune.org/2018/04/04/houston-city-council-approves-changes-floodplain-regulations-narrow-vo/`, `https://www.probuilder.com/construction/resilient-construction/article/55197746/the-need-for-resilient-construction-is-real-how-are-home-builders-responding`, and `https://www.floods.org/news-views/flood-mitigation/a-win-for-flood-resilience-hud-rolls-out-new-flood-standard/`.

The housing market provides an important setting to examine the effect of insurance and its role in pricing climate risks in the housing market for several reasons. Housing is directly exposed to natural disasters, with insurance serving as a critical hedge against these risks. Houses also constitute 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. Flooding is an acute issue in the U.S., with 15 million homes (10% of the total) currently exposed to substantial flooding risk.[2] This salient risk is projected to increase due to climate change. In addition, the flood insurance context also offers a unique advantage in addressing a fundamental identification challenge: insurance premiums can be confounded by changes in risk perception that drive premium adjustments. 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").[3] We refer to these High-Risk, Pre-Map homes as our treatment group. The reform aimed to gradually remove subsidies to align insurance rates with risk, without directly conveying any changes to the underlying physical risks.[4] We argue that the difference in physical risks between Pre-Map and Post-Map homes would have followed similar trends across High- and Low-Risk zones. This allows us to use

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

[3] High-Risk zones are defined as areas that would be inundated by a 100-year flood, which is a flood that has a 1% chance of being equaled or exceeded in any given year. These floods happen once every 100 years on average, thus called 100-year floods.

[4] See, e.g., https://www.fema.gov/sites/default/files/2020-07/questions-biggert-waters-flood-insurance-reform-2012.pdf.

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 the housing market's response to the insurance rate shock. To that end, we examine 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, *High-Risk* × *Pre-Map* × *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 these fixed effects and other controls, treated homes' price trajectories differ from the benchmark 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 have followed similar trends across High- and Low-Risk zones.

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

Second and more importantly, we find that premium increases have a more negative effect on the prices of houses exposed to sea-level-rise risk, compared to unexposed homes. In other words, removing insurance subsidies makes house prices more sensitive to long-term climate risks. In contrast, house prices do not become more sensitive to short-term flood risks, 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. The *Subsidy–Cash–Flow* channel operates through reduced subsidy payments, where house price declines reflect the net present value of lost subsidies. The *Risk–Updating* effect emerges when premium increases lead markets to reassess property risks. This risk reassessment could occur through various channels. For example, before the reform, market participants may have underestimated flood risks because such risks can be hedged with subsidized insurance, consistent with rational inattention (Brown and Jeon 2024). When risks are reassessed, home values are affected both by higher expected future premiums and increased expected uninsured damages, since 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. Under a pure Subsidy–Cash–Flow effect, the house price impact should not increase with rebuilding costs above the coverage limit, as coverage and thus premiums cannot rise beyond this threshold. However, we find that the price effect grows with rebuilding costs even above the coverage limit. This pattern supports the presence of a Risk–Updating channel: properties with higher uninsurable rebuilding costs experience larger price drops as perceived risks increase. Markets update their risk perceptions due to the premium increases, even though the reform did not directly convey any risk changes.

Fourth, we find that higher insurance premiums reduce mortgage take-up. Since flood insurance is mandatory for High-Risk homes, an increase in premiums effectively raises overall mortgage costs, moving the equilibrium leftward on the mortgage demand curve. At the same time, higher premiums increase borrowers' debt-to-income (DTI) ratios (as lenders incorporate monthly premium payments into their DTI calculations), shifting the mortgage supply curve to the left. As a result, both effects would decrease mortgage take-up, ultimately 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 (i.e. to qualify for subsidized Pre-Map insurance rates) diminish; (2) higher insurance costs 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 then 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 be aware of the required flood insurance and factor premium increases into their valuations. Moreover, non-primary home buyers also exhibit stronger price responses. One potential reason is that the reform mandates a larger premium increase for non-primary home buyers. Another 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 evaluate these possibilities 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* $\times$ *Post-Reform* should decline in absolute magnitude towards zero with these controls. However, our findings remain robust across all these tests, suggesting that the 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. Bakkensen and Barrage (2022) and Hino and Burke (2021b) find no impact, while Gibson and Mullins (2020) find a negative but statistically insignificant effect of insurance rates on home prices. They also use the Biggert-Waters reform, but compare High- and Low-Risk houses.[5] 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 strategy similar to ours and find a negative effect of flood insurance premiums on house values.[6] 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–Updating channel partly drives the house price effect of insurance rates. (3) We also uncover that the higher insurance rates reduce buyer financing and encourage the rebuilding of riskier homes.

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).[7] The estimates in the literature also capture differences beyond insurance premiums across flood

[5]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.

[6]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.

[7]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.

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 contribute to other flood insurance research by Wagner (2022), Sastry (2024), Mulder (2021), Weill (2023), and Hu (2022). These papers abstract away from house prices, as their focus is different. Our research complements their findings by explicitly examining the relationship between flood insurance premiums and property values, adding to a more comprehensive understanding of the economic impacts of physical risks.

Third, we contribute to the literature on climate change and real estate by demonstrating how insurance pricing serves as a channel for incorporating climate risks into home values. As climate change intensifies, disasters such as flooding pose an increasingly significant threat. Insurance is the primary financial tool households use to hedge against disaster risks. We shed light on how climate risks can be incorporated into home values through insurance pricing that better reflects the underlying risks. Bernstein et al. (2019), Baldauf et al. (2020), Keys and Mulder (2020), and Bakkensen and Barrage (2022) 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 show that insurance premiums can be an important channel through which long-term climate risks are incorporated into current asset prices.[8]

Moreover, we present novel evidence demonstrating that increases in insurance premiums encourage the rebuilding of homes in high-risk areas. Our findings contribute to the growing body of literature on adaptation to natural disasters and physical climate risks in real estate. As the rebuilding process often incorporates updated building codes and construction practices that have made homes more resilient to disasters in the recent decade, it likely enhances

[8]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.

the ability of these homes to withstand future climate-related challenges. Fried (2022) builds a model to quantify the interactions between adaptation, federal disaster policy, and climate change. Baylis and Boomhower (2022) measure the effect of California's wildfire building codes on structure survival. A few papers study the effect of the implementation of resilience infrastructure projects, such as a sea wall (Benetton et al., 2023), dunes (Dundas, 2017), and dams/levees (Gandhi et al., 2022; Kelly and Molina, 2023).

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, including homeowners' and commercial insurance, on asset values. Premiums in these markets have been increasing and will likely continue to rise in areas most affected by climate change (Keys and Mulder 2024).[9] Moreover, if climate change amplifies the systemic risk of disasters, insurance rates may increase across a wider geographic spectrum. Our findings suggest that this trend could have significant economic implications: household and business assets exposed to climate risks may experience substantial price depreciation due to escalating insurance premiums.

Despite the escalating climate-related risks, such as wildfires, state regulators have imposed limitations on premium increases for homeowners' insurance (Oh et al. 2021). However, allowing insurance premiums to accurately reflect the underlying risks in climate-vulnerable areas could serve as a powerful tool for climate adaptation. Fairly priced insurance can accelerate climate adaptation by discouraging further development in climate-vulnerable regions, and accelerate the process of adaptation to changing environmental conditions by incentivizing more resilient development practices and location choices.

[9]Stroebel and Wurgler (2021) find that 42% of survey respondents think the insurance markets do not adequately price climate risks. Other related papers in the literature include the following. Ge et al. (2024) examine the causal effect of rising home insurance premiums on mortgage outcomes, and Sastry et al. (2024) and Cookson et al. (2024) study the home insurance coverage gap. Van der Straten (2023) studies the macro-financial 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. Boomhower et al. (2024) study homeowners' insurance pricing in California. Jotikasthira et al. (2025) study insurers' strategic payment delays.

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.[10] As the dominant flood insurer with over 95% market share (Kousky et al., 2018), the NFIP fills a critical gap as standard homeowners' insurance policies typically exclude flood damage.

The NFIP provides coverage across all 50 states and Puerto Rico. From 2009 to 2018, the NFIP underwrote an average of 4.5 million flood policies annually, representing $3.5 billion in premiums 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), most of which were established between 1975 and 1990. Properties built before local FIRM implementation are classified as Pre-Map (Pre-FIRM), while those built after are classified as Post-Map (Post-FIRM). In areas where the Flood Insurance Rate Map was established before 1975, all houses built prior to 1975 qualify as Pre-Map (Georgic and Klaiber, 2022).

High-Risk Zones: The NFIP designates Special Flood Hazard Areas (SFHA) as zones with an annual flood probability of one percent or higher. We classify these as High-Risk zones and all other zones as Low-Risk zones. High-Risk and Low-Risk zones follow separate standardized insurance pricing schedules throughout our sample period.[11]

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 were commonly escrowed by

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

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

mortgage lenders. Since 2016, this has become a legal requirement.[12]

Premium Setting: NFIP flood insurance premiums are primarily determined by a property's High-Risk status (a major determinant of flood risk), construction timing, property elevation, and selected coverage.

First, the property's flood zone is a primary factor in determining the premium rate. Second, premiums depend on the amount of building and content coverage, with maximum coverage limits of $250,000 for buildings and $100,000 for contents.

Additionally, premiums are determined by construction timing relative to local map introduction. Pre-Map properties qualify for subsidized rates regardless of elevation, while Post-Map rates vary with the lowest floor's height relative to Base Flood Elevation.[13] A higher elevation corresponds to lower premiums. Table A1 presents premiums for different categories of homes under the maximum building coverage of $250,000[14]. Other factors, such as selected deductibles and community-level mitigation efforts, can also influence premium rates.

Our data do not allow us to match property data with insurance policy data, preventing us from identifying whether a house in the property data receives a Pre-Map or Post-Map rate. Therefore, we determine whether a house is Pre-Map based on its construction year relative to the introduction year of the local flood map. Owners of Pre-Map properties can sometimes secure a lower Post-Map premium rate by obtaining an elevation certificate, which can cost as much as $2,000 or more.[15] Thus, our classification of Pre-Map homes introduces noise into this variable, which could bias our results toward zero.

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

[13] 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."

[14] The premiums are calculated according to the NFIP's pricing manual

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

2.2 Flood Insurance Rate Reform

The Biggert-Waters Flood Insurance Reform Act (BW-12), enacted in July 2012, implemented major changes to NFIP rates starting in January 2013. The reform aimed to restore the program's financial stability, as it faced approximately $20 billion in debt. A key provision of the Act was the gradual elimination of subsidies for High-Risk, Pre-Map properties without directly conveying any changes in underlying flood risks.[16] 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).[17]

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 (or actuarially fair) rate.[18] The subsequent 2014 Homeowner Flood Insurance Affordability Act (HFIAA) mandated a smaller annual premium increase of 5-15% for all High-Risk, Pre-Map homes, regardless of whether they are sold.[19] The NFIP published rate tables only for the upcoming policy year, without long-term projections.

Since 2012, premium rates have increased much more rapidly for High-Risk, Pre-Map properties than other property types. Table A1 tabulates the annual premiums for different types of properties with $250,000 building coverage. From 2012 to 2018, High-Risk, Pre-Map homes experienced annual premium increases of 5.8%, corresponding to a cumulative increase of $594. In contrast, other properties experienced annual premium changes between -3.8% and +3.5% (cumulative changes between -$1,099 and +$277) depending on their High-Risk

[16] 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`.

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

[18] 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 report found on `https://www.gao.gov/assets/gao-13-607.pdf`

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

status and elevation.

3 Data

3.1 Flood Insurance Data

3.1.1 National Flood Insurance Program (NFIP) Policy Data

Our 2009–2018 NFIP administrative dataset encompasses the universe of policies written by the NFIP, totaling approximately 4.5 million policies annually. The data contain policy details (including premiums and coverage levels) and property characteristics (including year built and flood zone designation). While property addresses are redacted for privacy, the data include five-digit zip codes and latitude/longitude coordinates rounded to one decimal place. Individual properties cannot be tracked over time because unique property identifiers are not available. We supplemented this dataset with policy-level rebuilding cost estimates obtained from FEMA through a Freedom of Information Act (FOIA) request.

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, covering 95% of all U.S. properties. Areas not covered in the NFHL data usually have low population densities. We use the NFHL to identify whether a property is located in a High- or Low-Risk zone. The NFHL data we obtain are from 2021. We also obtain digital shapefiles from 1996, shared by Hino and Burke (2021a). We use the 2021 version as it is closer in time to the reform. Areas not covered by the 2021 shapefiles are excluded from our analysis. Our main result remains robust when restricted to properties whose High-Risk designations remained unchanged between 1996 and 2021.

3.1.3 NFIP Community Status Book

The NFIP Community Status Book provides the introduction dates for community flood maps, enabling Pre-Map/Post-Map property classification when merged with the 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 according to NFIP 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, number of bedrooms, and the year built. We exclude properties smaller than 600 square feet. In our final filter, we include only geographic areas that have at least one Low-Risk property sale and one High-Risk property sale. The resulting sample contains approximately 11 million transactions when an area is defined by the zip code. The sample reduces to 4.7 million when we define an area by zip code-longitude-latitude (rounded to two decimal places). For some of our analyses, we match the NFIP policy data with the Zillow data. We describe the matching procedure in the Internet Appendix, Section .

3.3 Flood Hazard Measures

The Zillow assessor files also provide the geo-coded location of each property, which we use to map to a set of location-based risks and characteristics.

Sea Level Rise: We link Zillow data to the Sea Level Rise risk measure provided by the National Oceanic and Atmospheric Administration (NOAA) based on each property's latitude and longitude(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 each home within a 5-mile radius, which we define as the distance to water. The NOAA data are only available for coastal areas, so many properties have a missing value. For our regression analyses, we standardize these distances to have a mean of zero and a standard deviation of one, with the maximum value being 2.7. We assign a standardized value of three to noncoastal properties. Whenever we use this variable, we also include a binary indicator, *Distance>5 Miles*, which equals one for noncoastal properties.

Storm Surge: We use NOAA maps 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 (storm-surge height greater than or equal to one 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 without sea level rise from First Street to proxy for medium-run flood risk. The distance between each property and the closest point in First Street data has a median of 0.01 miles and a 90th percentile of 0.03 miles.

>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, and zero otherwise.

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 $282,320. 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 matched average premium is $448 per year. We also present statistics on our flood hazard measures. For example, 9% of the homes are exposed to a six-foot 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 and 2018 for $250,000 building coverage—the largest increase across all property types.[20] Because actual premiums may vary due to factors like community mitigation discounts, we use the NFIP policy data to test whether these houses actually experienced larger relative premium increases after the reform through

[20] Table IA.1 tabulates the detailed book rates for High-Risk, Pre-Map policies.

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 (lasts for one year) 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 each policy's 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* × *Year Indicators*, *High-Risk* × *Year Indicators*, *High-Risk* × *Pre-Map*, *High-Risk*, and *Pre-Map*.

The fixed effects structure mirrors those in our main analyses on house prices, which are 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 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 to 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. Observations are at the property transaction level. The estimated coefficient on the triple interaction term, *High-Risk* $\times$ *Pre-Map* $\times$ *Post-Reform*, captures the effect of flood insurance premiums on house prices. *Lower Order Terms* include the following: *Pre-Map* $\times$ *Post-Reform*, *High-Risk* $\times$ *Post-Reform*, *High-Risk* $\times$ *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 trends of houses with the 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 controls. 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-year-by-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 after the reform.

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.[21]

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; (6) excluding New York and New Jersey, the states suffering the worst damage from Hurricane Sandy in 2012. The results are similar to those in Table 2.

Figure 3 illustrates the reform's time-varying effects using our benchmark model. We replace the *Post-Reform* indicator with a series of year indicators from 2009 to 2018. The figure plots the estimated triple interaction coefficients on *High-Risk* × *Pre-Map* × year indicators. The estimates suggest no significant pre-trends before 2012, followed by persistent negative price effects on treated homes after rate changes began in 2013. While premium in-

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

creases grew over time (Figure 2), house price effects remain stable through 2018, suggesting that markets quickly incorporated expectations of future premium increases.

6 Removing Subsidies Makes House Prices More Sensitive to Sea Level Rise Risk

6.1 Larger Price Effects for Houses Exposed to Sea Level Rise

Before the reform, subsidies kept the cost of hedging flood risks low for High-Risk, Pre-Map homes, potentially preventing these risks from being fully reflected in house prices. Moving premiums towards "full-risk" levels may help incorporate better these risks into property values. Table 3 examines whether the insurance reform makes house prices more sensitive to different flood risks.

We first analyze whether removing insurance subsidies helps the market incorporate long-term flood risks from sea level rise. Properties can be exposed to sea level rise directly through proximity to the ocean 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 risks through amplified hurricane impacts and river overflow during rainfall.[22] In Column (1), we regress the log of house prices on the interaction between our main triple interaction term and *Sea Level Rise*. We include all the lower-order interaction and standalone terms in the regression, but suppress them for presentation.

Column (2) also interacts our main triple interaction term with each of the four other flood risk measures. They include the First Street Foundation flood factor (standardized), whether the house is exposed to storm surge, distance to the highest-tide water (standardized), and whether FEMA has declared three past flooding disasters in the local area. These measures

[22] See, e.g., `https://www.washingtonpost.com/climate-environment/interactive/2024/southern-us-sea-level-rise-risk-cities/`.

capture different risk horizons: the First Street factor reflects medium-term risk (30-year outlook), while the others capture short-term exposure. We again include all the lower-order interactions and standalone terms. Columns (3) and (4) repeat (1) and (2) using house prices in thousands of dollars as the dependent variable.

The estimated coefficient on *High-Risk* × *Pre-Map* × *Post-Reform* × *Sea Level Rise* is negative and statistically significant across all specifications. Among all the quadruple interactions, it is the only one with a 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. In Column (4), the quadruple interaction term with *1st St Flood Factor* also has a negative and statistically significant coefficient, although the magnitude is only 39% of that of the interaction with *Sea Level Rise*.

These results suggest that removing insurance subsidies makes prices of treated homes more sensitive to long-term sea-level-rise risk, but not short-term risks. When hedging long-term risks becomes more expensive, markets appear to evaluate these risks more carefully and more fully incorporate them into property values. The limited response to short-term risks suggests they may have already been priced into house values, making them less sensitive to insurance rate changes.

One potential reason that house prices become more sensitive to sea-level-rise risk (but not to short-term risks) is that buyers of houses exposed to sea level rise may be more sophisticated. In Table IA.3, we use local income as a proxy for market sophistication and include its interaction with our main triple. Specifically, we use the standardized log zip-level median income from the 2012 American Community Survey (ACS). If market sophistication is the channel through which house prices become more sensitive to sea-level-rise risk, this interaction term should attenuate those effects. However, the results remain similar, suggesting market sophistication is unlikely to be the channel.

6.2 Pass-through of Premiums to House Prices

Table 4 estimates the magnitude of the pass-through from premiums to house prices, for properties exposed to sea level rise (Panel A) and those not exposed (Panel B) separately. Column (1) in both panels estimates how house prices respond to the insurance reform following the specification in Column (4) of Table 2. The estimates indicate that after the reform, High-Risk, Pre-Map home prices dropped on average by \$25,845 for exposed properties and by \$4,823 for unexposed properties.

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 to ensure the results are not affected by households' coverage response to the reform. The estimates suggest that treated homes saw premium increases of \$116 (exposed) and \$85 (unexposed).

Column (2) uses premium rates that are matched to the house transactions in the same year. 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 expectations of the trajectory of future premiums, which should be reflected in the house price effect. One useful exercise is to assume that, after the reform, the market expectation of "full-risk" premiums are the realized premiums observed in 2018. To this end, Column (3) repeats Column (2), replacing the 2013–2018 premium rates with the 2018 premium rates. Again, we multiply the premium rates with the matched 2009 coverage. The estimates suggest that premiums increased by \$129 more for the most treated homes in the sample not exposed to sea level rise and by \$170 more for these homes in the exposed sample.

Based on Columns (1) and (3), for one dollar of premium increase in 2018, house prices fall by \$152 (=25.845/0.170) among houses exposed to sea level rise, and by \$37 (=4,823/129) among houses not exposed.[23] These premium-to-house price pass-through estimates are

[23] This result implies a discount rate of 2.7% (=129/4,823) if the treatment effect on premiums is expected

overstated for two reasons. First, the market likely anticipated continued premium increases beyond 2018, with the Government Accountability Office estimating a 20-year timeline to reach actuarially fair rates(GAO 2013). Second, as we demonstrate next in Section 7, the house price response reflects not only insurance cash flow effects but also the market's risk reassessment triggered by the premium increases. Consequently, the true capitalization of premium cash flows into house prices should be more modest than our estimates suggest.

For houses exposed to sea level rise, this pass-through is even more severely overstated. One reason is that for this sample, the market should expect a larger future premium increase, given higher long-term flood risk. Another reason is that the Risk–Updating channel should play a larger role in this sample. 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 Channels: Subsidy–Cash–Flow and Risk–Updating

Two main channels can drive the effect of premiums on home prices: the "Subsidy–Cash–Flow" channel and the "Risk–Updating" channel.

On one hand, the Subsidy–Cash–Flow channel operates through direct cash-flow impact. When subsidies decrease, premium payments increase, theoretically reducing home prices by the net present value of expected future subsidy reductions. Under this channel, we assume the market does not change expectations about unsubsidized full-risk premiums around the reform, but updates expectations about future subsidies.

Quantifying the Subsidy–Cash–Flow channel is challenging because the NFIP neither disclosed future premiums nor specified full-risk rates while stating that premiums would

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, as we explain below. 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/medium run, and Giglio et al. (2015) estimate the very long-run discount rate to be 2.6%.

eventually reach these rates.[24] Mulder and Kousky (2023) study the NFIP Risk Rating 2.0 reform implemented in 2021, which aims to price flood insurance based on house-level risk profiles. They show that 40% of High-Risk, Pre-Map policies actually saw premium decreases, suggesting that previous rates were punitively high for these properties. This finding underscores the difficulty in measuring the expected future "full-risk" premiums and calculating their present value.

On the other hand, the Risk–Updating channel operates through changes in risk perception: as premiums increase, the market may elevate its assessment of flood risk for affected properties, which lowers home prices. This updating can occur through three mechanisms. First, consistent with rational inattention literature (e.g., Brown and Jeon 2024), households may have underestimated flood risks when insurance costs were low. When the insurance costs increase, it prompts households to reassess coverage needs and underlying risks. Second, as evidenced by extensive news coverage (Figure A1), the premium shock is salient, which can lead homeowners to infer heightened risk. This aligns with behavioral economics research on salience (e.g., Bordalo et al. 2022). Third, as the government cuts subsidies for flood insurance, market participants may perceive it as a signal for possible reductions in future disaster aid or other reforms. This increases expected flood-related costs even if flood probabilities remain unchanged.

Risk–Updating affects house prices through two primary mechanisms. First, when market participants perceive higher risks, they expect higher "full-risk" premiums. Second, they expect higher uninsured damages or flood-related costs. Because flood insurance caps building replacement coverage at $250,000, both excess rebuilding costs and land value remain uninsured. Consequently, as the market perceives heightened risks, it expects larger uninsured damages and lower land values. While we cannot directly estimate the premium expectation mechanism, we can test for Risk–Updating by examining the uninsured damages mechanism.

To investigate the channels, we categorize houses into quartiles based on their NFIP–

[24] 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 rate tables.

matched rebuilding costs. Panel A of Table 5 presents summary statistics for each quartile. Average rebuilding costs rise substantially across quartiles, from \$135k in the first quartile to \$527k in the fourth. The average building coverage shows a narrower spread due to the \$250,000 coverage cap, increasing from \$176k to \$233k.[25]

Under a pure Subsidy–Cash–Flow channel, the house price effects should be similar between the third and fourth quartiles. Because their building coverage amounts are nearly identical (\$230k vs. \$233k), the cash flows from the subsidy reductions will also be similar, assuming the risks and thus full-risk rates will be the same between the third and fourth quartiles. In contrast, the Risk–Updating channel suggests that the house price effects should be larger for the fourth than the third quartile. The effect under this channel should roughly correspond to the combined value of uninsured rebuilding costs, affected land value, and other flood-related costs (e.g., temporary displacement).

The first two quartiles, with rebuilding costs below \$250k, face minimal uninsurable damages. However, 83% of third-quartile homes and all fourth-quartile homes exceed the coverage limit, with average uninsurable rebuilding costs of \$29k and \$277k respectively. This pattern suggests larger price effects in the top two quartiles, with an increasing trend from the third to fourth quartile driven by uninsurable rebuilding costs. However, the presence of additional flood-related costs makes it difficult to predict the precise ratio of price effects across quartiles.

In Panel B, we examine the reform's house price effects across the quartiles. In Column (1), we augment our benchmark regression in Column (4) of Table 2 by interacting our triple interaction with indicators for each quartile, while including all the lower-order terms. The results reveal similar price effects of approximately $-$\$4k for the first two quartiles, but substantially larger effects for the third quartile, $-$\$11k, and still larger for the fourth quartile, $-$\$25k. These results are inconsistent with the predictions under a pure Subsidy–

[25]Note that building coverage can often be higher than the reported rebuilding cost. This can occur for several reasons: potential underestimation of replacement costs, households hedging against cost uncertainty, and frictions in the distribution channel (see, e.g. Collier and Ragin 2020).

Cash–Flow channel, but suggest that the Risk–Updating channel also plays a role.

We address two potential concerns about these results. First, one may be concerned that rebuilding costs can be correlated with local market sophistication. In Column (2), we include interaction terms between our main triple and standardized zip-level log median income from the 2012 ACS, using local income as a proxy for market sophistication. If market sophistication drives the large price effects observed in the fourth quartile, this interaction term should attenuate those effects.

Second, could differential flood risks and corresponding full-risk premiums explain the differential house price effects? Table IA.4 addresses this question by controlling for various flood risk measures through interactions with our main triple interaction term and all lower-order terms (as in Table 3). If the fourth quartile's large price response stems from greater physical risks in that market segment, these risk interaction terms should diminish those effects. For both analyses, we include all lower-order terms in the estimation but suppress them in the presentation.

The results persist: house price effects are small for the first two quartiles, large in the third, and much larger in the fourth quartile. These results suggest that market sophistication or differential full-risk rates cannot fully explain the cross-quartile variation. Instead, the divergent responses likely reflect the larger uninsured components of high-rebuilding-cost homes, providing evidence for the presence of the Risk–Updating channel.

8 Heterogeneous Effects of Premiums on House Prices

8.1 By State Flood Zone Disclosure Requirements

Anecdotal evidence suggests that homebuyers often remain unaware of a property's Flood Zone status until their lending bank notifies them of the flood insurance requirement, typically after they have already paid commitment fees. Thirty-one states have mandatory disclosure requirements, compelling sellers to inform potential buyers if a property lies within a High-Risk flood zone. Figure A2 illustrates these state-level disclosure requirements, with darker shading indicating states that mandate such disclosures.

We predict that flood insurance premiums will have a stronger effect on house prices in states with mandatory disclosure requirements, as buyers in these states are more likely to factor insurance costs into their property valuations. To test this hypothesis, we examine this relationship in Columns (1)–(3) of Table 6.

Following our main specification in Column (3) of Table 2, we separately analyze transactions in states without disclosure requirements (Column 1) and states with disclosure requirements (Column 2). The coefficient on *High-Risk* × *Pre-Map* × *Post-Reform* is negative and statistically significant in both columns, but the magnitude in disclosure states (-0.034) is 50% larger than in non-disclosure states (-0.021). This finding aligns with our hypothesis that flood insurance premiums have a stronger price effect when Flood Zone information is more readily available to potential buyers.

To test whether this difference between disclosure and non-disclosure states is statistically significant, we analyze the full sample with an additional quadruple interaction term, *High-Risk* × *Pre-Map* × *Post-Reform* × *Disclosure* (Column 3), including all the lower-order terms. While the estimated coefficient on this interaction term is negative, it is not statistically significant at conventional levels.

8.2 Non-primary vs. Primary Buyers

The impact of flood insurance premium changes on house prices may vary between primary buyers and non-primary buyers (those who purchase properties for investment or as second homes). This heterogeneity could stem from two reasons. First, non-primary buyers tend to be more sophisticated investors who are more likely to incorporate flood insurance premiums into their property valuations. Supporting this assumption, Robinson (2012) documents that such buyers typically have higher credit scores and incomes, characteristics associated with greater financial sophistication.

Second, the reform itself imposed differential premium increases based on owner type. For High-Risk, Pre-Map homes, the annual premium increase was capped at 18% for primary owners but 25% for non-primary owners. Given segmentation and illiquidity in housing markets (Piazzesi et al., 2020), these differential premium increases could translate into varying price effects across buyer types.

We examine this potential heterogeneity in Columns (4)–(6) of Table 6, identifying buyers as primary or not based on the assessor data. Our analysis reveals that the coefficient on *High-Risk* × *Pre-Map* × *Post-Reform* is negative and statistically significant for both buyer types, but the magnitude for non-primary buyers (-0.035) in Column (5) is double that of primary buyers (-0.017) in Column (4).

Column (6) tests whether this difference between buyer types is statistically significant. We analyze the full sample with an additional quadruple interaction term, *High-Risk* × *Pre-Map* × *Post-Reform* × *Non-Primary*, while including all the lower-order terms. The coefficient on this interaction term is negative and statistically significant, confirming that the price effect is indeed stronger for properties purchased by non-primary buyers.

9 Insurance Premiums and Buyer Mortgage Financing

Government-sponsored enterprises and most lenders require borrowers to purchase flood insurance for properties in High-Risk zones. When flood insurance rate reform increased premiums for High-Risk, Pre-Map homes, it effectively raised the total cost of mortgages for these properties.

These higher costs can affect both sides of the mortgage market. For borrowers, increased insurance premiums make mortgages less attractive by raising monthly payments. For lenders, higher costs may elevate concerns about default risk, potentially leading to lower mortgage approval rates. Indeed, banks include insurance payments when calculating borrowers' DTI, which increases with premiums. Using novel homeowners' insurance data matched with mortgage data, Ge et al. (2024) find that increased homeowners' insurance premiums indeed lead to higher mortgage delinquency rates. Given these reasons, we hypothesize that flood insurance reform reduced the probability of mortgage financing for High-Risk, Pre-Map homes, and increase the rate of cash purchase.

To test this hypothesis, we modify our main analysis from Table 2 by replacing the dependent variable with an indicator for mortgage financing. Table 7 presents these results using mortgage data from Zillow's assessor database. Our sample shows a mortgage utilization rate of approximately 50%, which is lower than recent industry estimates.[26] However, measurement error in the mortgage data is unlikely to correlate with our key independent variables or bias our estimates.

The triple interaction term, *High-Risk* × *Pre-Map* × *Post-Reform*, yields negative and statistically significant coefficients across all specifications with different fixed effects. The estimates indicate that flood insurance reform reduced mortgage take-up for High-Risk, Pre-Map homes by 1.1 to 1.9 percentage points, representing a 2–4% decline relative to the sample mean. This finding demonstrates how insurance rate changes can meaningfully influence household financing decisions, and at the same time, their risk sharing with lenders.

The observed decline in mortgage take-up likely reflects both demand and supply factors. On the demand side, higher total costs for mortgages, including required insurance, may deter borrowers. On the supply side, lenders may view mortgages for these properties as riskier investments for two reasons. First, higher insurance premiums strain household finances, increasing default risk, as documented by Ge et al. (2024).[27] In addition, lenders may require larger down payments from potentially underinsured borrowers (Sastry, 2024; Wagner, 2022), making mortgage financing less accessible for households.

The decline in mortgage take-up following this exogenous change in insurance prices reveals the complex policy challenges in this domain. The rate reform advances the goal of

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

[27]Blickle and Santos (2022) find that when flood map updates expand High-Risk zones within a census tract, banks reduce mortgage lending in that area. While flood map updates bundle multiple changes, including insurance requirements and risk information, our setting isolates the effect of premium changes.

aligning insurance prices with actual flood risk by removing subsidies. It also alters house prices in a way consistent with aligning the market's risk expectation with reality. However, it also comes with unintended consequences. As buyers respond to higher premiums by forgoing mortgages, risks of natural disasters and housing prices become more concentrated among individual homeowners. This financing channel could also explain some of the effects of insurance premiums on house prices.

10 Higher Premiums Encourage Rebuilding, Especially of Risky Homes

Several mechanisms suggest that higher insurance rates for High-Risk, Pre-Map homes can drive rebuilding activities. First, as subsidies phase out for these properties, maintaining Pre-Map status loses its financial advantage. Second, households tend to reduce insurance coverage when premiums rise (Wagner, 2022), which may motivate them to enhance their properties' flood resilience through rebuilding. Third, homeowners can lower their insurance rates by elevating their first floor during reconstruction. Newly rebuilt homes are likely to be more resilient to floods as substantial changes to building codes and best practices over the last decade have made newly built homes in disaster-prone areas much more resilient.[28]

To test the hypothesis on rebuilding, we combine CoreLogic permit data with historical tax assessor records. We match these datasets to our Zillow sample using Placekey geocodes generated through Safegraph's address standardization. Our analysis uses parcel-year observations, with the dependent variable *1(Rebuilt)* indicating rebuilding activity. Rebuilding is identified through: (1) a demolition permit, (2) a new building permit, or (3) the year matching the property's latest construction date in tax assessor data. To avoid including

[28] See, e.g. https://www.texastribune.org/2018/04/04/houston-city-council-approves-changes-floodplain-regulations-narrow-vo/, https://www.probuilder.com/construction/resilient-construction/article/55197746/the-need-for-resilient-construction-is-real-how-are-home-builders-responding, and https://www.floods.org/news-views/flood-mitigation/a-win-for-flood-resilience-hud-rolls-out-new-flood-standard/.

initial building activities, we exclude observations from a property's initial construction year.

Given the low baseline rebuilding probability (326 per million parcel-year observations), we follow our specification in Column (1) of Table 2 with less granular fixed effects. We use zip-by-year-by-beds fixed effects without adding longitude/latitude, while maintaining the sample restriction to zip codes containing both High-Risk and Low-Risk properties.

Column (1) of Table 8 shows a positive and statistically significant coefficient on the triple interaction term, indicating that insurance rate increases prompt more rebuilding activity among High-Risk, Pre-Map homes. The magnitude suggests that following the reform, these houses experience a 42% (=138/326) increase in rebuilding probability.

If households rebuild for stronger flood resilience, the need to do so is more imminent for houses exposed to short-term flood risks. We next investigate whether short-term flood risks affect this rebuilding response. We highlight the results using storm surge exposure as the short- and median-term risk measure in Table 8 and present the results using other risk measures in Table IA.5 in the Internet Appendix. Columns (2) and (3) of Table 8 compare properties exposed versus unexposed to storm surge risk.

The triple interaction coefficients are positive and statistically significant in both subsamples. However, the effects are much larger among properties exposed to storm surge, which is more than 2.5 times larger than those not exposed. The difference between the two subsamples is also statistically significant. Table IA.5 reveals a similar pattern using other short-term flood risk measures: the effect is consistently larger for properties facing greater short- and medium-term risks.

We then investigate whether long-term sea-level-rise risk exposure affects this rebuilding response. Columns (4) and (5) compare properties exposed versus unexposed to sea-level-rise risk. The triple interaction coefficients are both positive and statistically insignificant. The magnitudes are similar between sea-level-rise exposed and unexposed properties.

These patterns suggest that rebuilding responses are strongest among properties facing immediate flood risks. The similar responses between properties with and without sea-level-rise exposure indicate that reconstruction decisions primarily address current flood vulnerabilities rather than long-term climate risks, for which 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 might be concerned that Pre-Map houses are older than Post-Map ones and older houses are more vulnerable to flooding. If flood risk increased more in High-Risk zones relative to Low-Risk zones around 2013, older, more vulnerable houses in High-Risk zones would experience larger price declines as a result.

We address this concern in Column (1) of Table 9. We repeat our main analysis on house prices, restricting to houses built within three years before or after the establishment of the local map.[29] This approach minimizes the age difference between Pre-Map and Post-Map homes. If age differences drive our main results, we would expect the coefficient on the triple interaction term (*High-Risk* × *Pre-Map* × *Post-Reform*) to approach zero. Instead, we find that the coefficient remains negative and statistically significant, with a magnitude larger than our benchmark estimate.

11.2 Restricting to Houses Near Flood Zone Borders

Around 2013, the perceived flood risk may have increased more for High-Risk than Low-Risk zones unrelated to premium changes. If Pre-Map homes are more vulnerable, it can lead to a larger decline in value for Pre-Map houses in High-Risk zones.

[29] This restricted sample represents 9% of our baseline regression sample. To preserve statistical power, we replace our granular zip-long/lat-by-year-by-bedrooms fixed effects with zip-by-year-by-bedrooms fixed effects.

To address this concern, we repeat our main analysis using homes located within 250 feet of the boundary between High- and Low-Risk zones in Column (2) of Table 9. Restricting to such a subsample should shrink the difference in risk trends between High- and Low-Risk houses. If the alternative hypothesis explains our result, the estimated coefficient on the triple interaction should approach zero. However, we find that the coefficient remains similar to our benchmark estimate, contradicting this 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 hazards that became more salient or priced around 2013. Our event study analysis in Figure 3 shows no statistically significant effects before 2013, suggesting that any differential risk exposure would need to suddenly affect prices in 2013 to explain our findings. Sea-level-rise risk, especially, warrants attention, as research suggests it began affecting house prices around 2012–2013 (e.g., Bernstein et al. 2019 and Keys and Mulder 2020).

We estimate the following specification to address the concern that our main results are driven by flood risks being correlated with *High-Risk* × *Pre-Map*, *High-Risk*, or *Pre-Map*.

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

Hazard is one of six different measures of flood risks. It is an indicator for sea-level-rise exposure in Column (1); standardized First Street Flood Factor in (2); an indicator for storm surge exposure in (3); standardized distance to water in (4); an indicator for locating in a county with more than three flood disasters declared by FEMA since 1953 in (5). We include all lower-order interactions and standalone terms not absorbed by fixed effects. Table 10 presents the results.

Under the alternative explanation, β_1 should approach zero, with the newly added terms capturing (part of) its original effect. However, the estimated β_1 remains negative and statistically significant across all specifications, with a magnitude similar to our baseline estimate, contradicting the alternative explanation. We conduct a similar test on the property having a basement, another factor that can increase flooding vulnerability. In Table IA.6, we replace *Hazard* with an indicator for basement presence in the Zillow data. The estimated β_1 again remains similar to our main analysis. These results suggest our findings are not driven by correlations between our key variables and either other flood hazards or the property having a basement.

12 Conclusion

We examine how insurance premiums affect housing markets by analyzing a 2013 flood insurance pricing reform. The reform offers an exogenous shock to insurance rates, bringing the largest premium increases to homes built in High-Risk areas before the establishment of local flood maps. Using these differential rate changes across property types, we identify the causal impact of insurance prices on the housing market.

Our analysis yields five key findings. First, houses facing the largest premium increases experienced a relative price decline of approximately 2%. Second, phasing out flood insurance subsidies makes home prices more sensitive to long-term climate change risk, as measured by sea level rise exposure. Third, the effect of insurance premiums on house prices is driven not purely by the direct cash flow effect of reduced subsidies. Our evidence supports that higher premiums trigger markets to update the perceived underlying property risks, which drives part of the house price effects. Fourth, the premium increase leads to meaningful decreases in mortgage take-up, as the total cost of mortgages, including mandated flood insurance, increases. Fifth, premium increases stimulate more rebuilding activity, particularly among properties exposed to elevated short-term flood risks.

Our findings carry broad implications. First, artificially suppressed insurance rates inflate housing prices, potentially encouraging excessive development in high-risk areas. Second, actuarially fair insurance pricing accelerates the incorporation of long-term climate risks into current asset values, improving market efficiency. Third, fairly–priced insurance encourages the market to update risk perceptions and adapt to risks through rebuilding activities. Fourth, higher premiums may reduce risk–sharing between households and the financial sector through reduced mortgage take-up.

These implications extend beyond flood insurance to broader insurance rate regulation, especially in disaster-prone states like California. Premiums in these markets have been increasing and will likely continue to rise in areas most affected by climate change. Climate change is likely to exacerbate the systemic risk of disasters, potentially leading to widespread increases in insurance rates across diverse geographical areas. Our findings suggest that this trend could have significant economic implications: household and business assets exposed to climate risks may experience substantial price depreciation due to escalating insurance premiums.

State regulators have restricted premium increases in homeowners' insurance despite escalating climate-related risks such as wildfires (Oh et al. 2021). If policymakers allow premiums to fully reflect the underlying risks in climate-vulnerable areas, insurance can discourage further development in climate-vulnerable regions, thereby accelerating the process of adaptation to changing environmental conditions.

References

Bakkensen, L. A. and L. Barrage (2022). Going underwater? flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies 35*(8), 3666–3709.

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.

Baylis, P. W. and J. Boomhower (2022). Mandated vs. voluntary adaptation to natural disasters: the case of us wildfires. Technical report, National Bureau of Economic Research.

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

Benetton, M., S. Emiliozzi, E. Guglielminetti, M. Loberto, and A. Mistretta (2023). *Does Climate Change Adaptation Matter? Evidence from the City on the Water*. SSRN.

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.

Blickle, K. and J. A. Santos (2022). Unintended consequences of "mandatory" flood insurance. Technical report, Federal Reserve Staff Report.

Boomhower, J., M. Fowlie, J. Gellman, and A. Plantinga (2024). How are insurance markets adapting to climate change? risk selection and regulation in the market for homeowners insurance. Technical report, National Bureau of Economic Research.

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.

Collier, B. L. and M. A. Ragin (2020). The influence of sellers on contract choice: Evidence from flood insurance. *Journal of Risk and Insurance 87*(2), 523–557.

Cookson, J. A., E. Gallagher, and P. Mulder (2024). Coverage neglect in homeowners insurance. *Available at SSRN 5057551*.

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.

Dundas, S. J. (2017). Benefits and ancillary costs of natural infrastructure: Evidence from the new jersey coast. *Journal of Environmental Economics and Management 85*, 62–80.

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.

Fried, S. (2022). Seawalls and stilts: A quantitative macro study of climate adaptation. *The Review of Economic Studies 89*(6), 3303–3344.

Gandhi, S., M. E. Kahn, R. Kochhar, S. Lall, and V. Tandel (2022). Adapting to flood risk: Evidence from a panel of global cities. 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*.

Jotikasthira, C., A. Kartasheva, C. T. Lundblad, and T. Ramadorai (2025). Strategic claim payment delays: Evidence from property and casualty insurance.

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

Kelly, D. L. and R. Molina (2023). Adaptation infrastructure and its effects on property values in the face of climate risk. *Journal of the Association of Environmental and Resource Economists 10*(6), 1405–1438.

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.

Oh, S., I. Sen, and A.-M. Tenekedjieva (2021). Pricing of climate risk insurance: Regulatory frictions and cross-subsidies. *Available at SSRN 3762235*.

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. (2024). Who bears flood risk? evidence from mortgage markets in florida. *Review of Financial Studies, forthcoming*.

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.

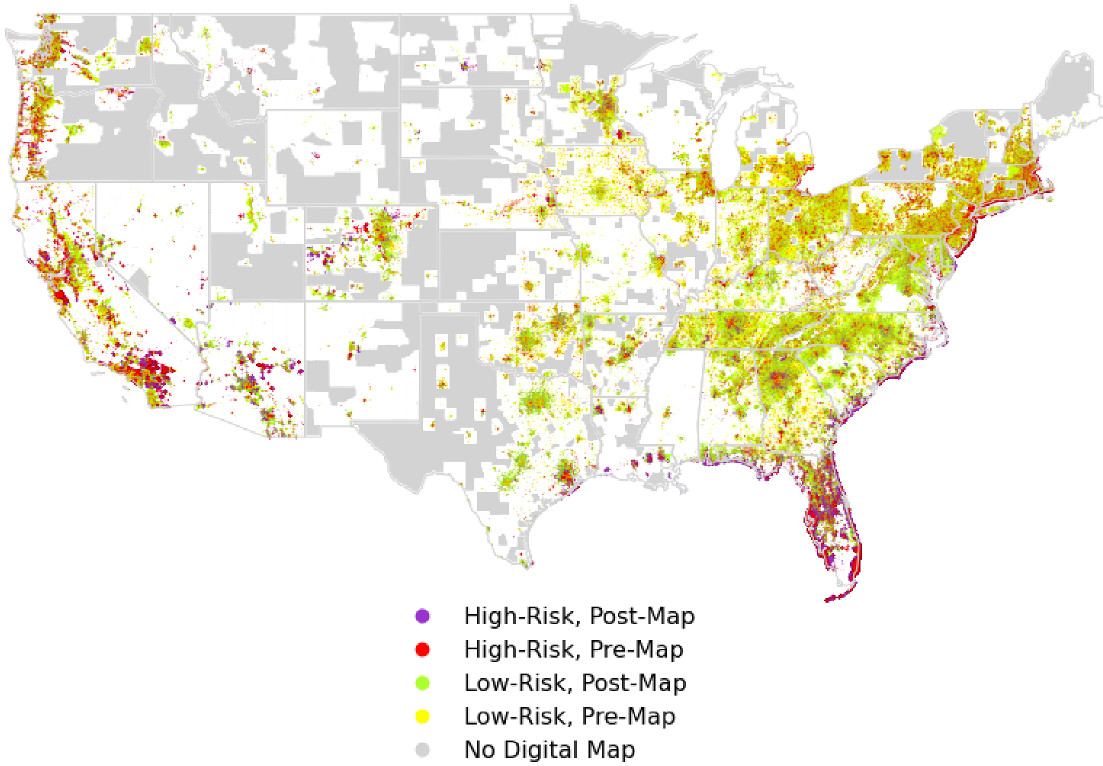
Van der Straten, Y. (2023). Flooded house or underwater mortgage? the implications of climate change and adaptation on housing, income, and wealth.

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.

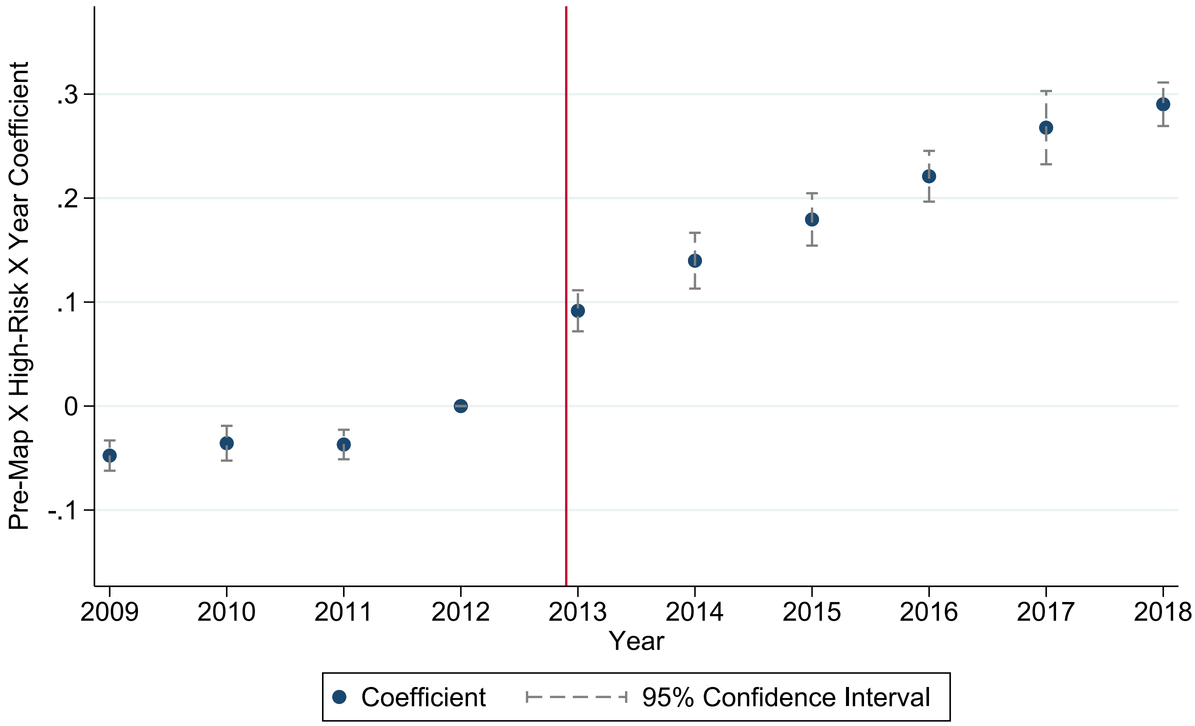
Zachry, B. C., W. J. Booth, J. R. Rhome, and T. M. Sharon (2015). A national view of storm surge risk and inundation. *Weather, Climate, and Society 7*(2), 109 – 117.

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

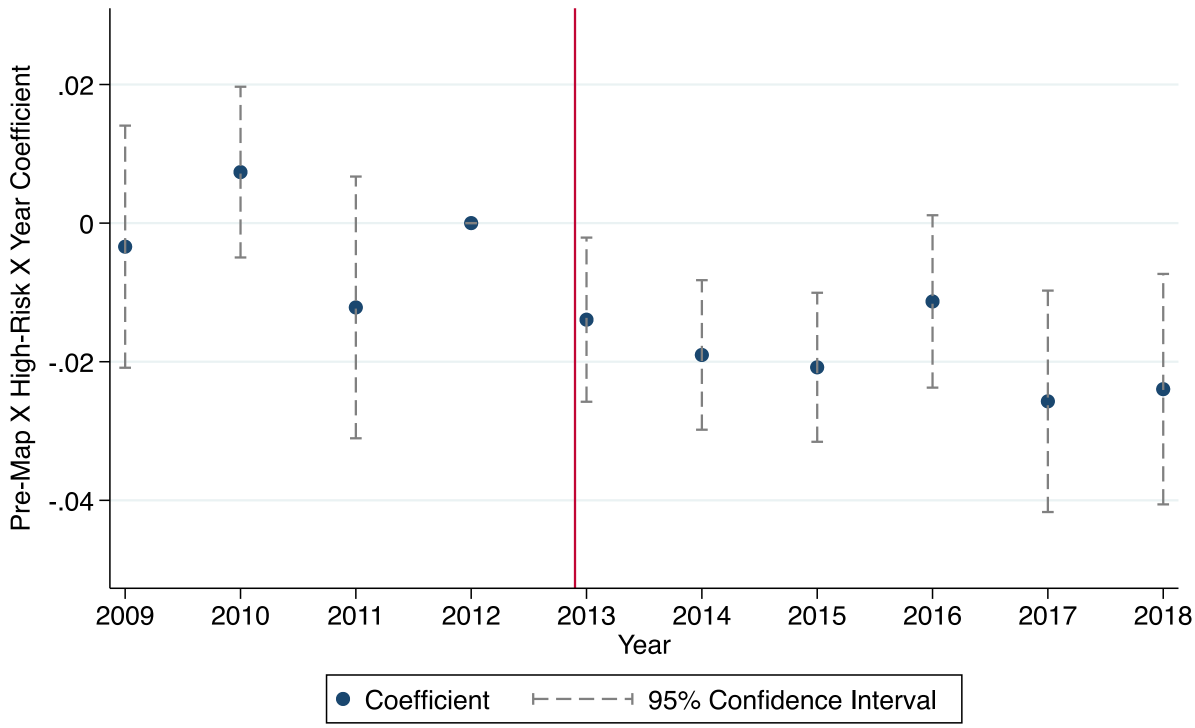


Note: Using the FEMA flood insurance policies dataset, this figure plots the yearly estimate, β_y (blue dots) and the 95% confidence interval from the following regression.

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

where p indexes the flood insurance policy and t the year. *Premium* is the premium (in \$1,000) for policies 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, the most granular level available in the NFIP data. 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 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.

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



Note: this figure plots the yearly estimate, β_y (blue dots) and the 95% confidence interval from the following regression. $Log(Price)_{i,t} = \sum_{y=2009}^{2018} \beta_y \times \textit{High-Risk}_i \times \textit{Pre-Map}_{it} \times \mathbf{1}_t^y + Lower\ Order\ Terms$ $+ \beta \times SqFt + FE_{zip \times age} + FE_{area \times \#bed \times t} + \epsilon_{i,j,t}$, where $\mathbf{1}_t^y$ is an indicator that takes a value of one if t is in year y. *Lower Order Terms* include 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. *Area* in fixed effects stands for location defined by zip and longitude/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. See Table A2 for variable definitions. 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 used in Column (3) of Table 2. See Table A2 for variable definitions.

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

Dependent Variable	Log(Sales Price)			Sales 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)
Square Footage	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 rules. *Post-Reform* is an indicator that equals one if the transaction happened in 2013 and after, and zero otherwise. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. We include only geographic areas that have at least one Low-Risk property sale and one High-Risk property sale. We define an area by zip in Columns (1) and (2), and by zip-longitude/latitude (rounded to two decimal places) in (3) and (4). See Table A2 for variable definitions. 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 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 following Column (3) of Table 2, while adding interaction terms between different flood risk measures and *High-Risk* × *Pre-Map* × *Post-Reform*. The dependent variable is log house prices in Columns (1) and (2) and prices in thousands of dollars in Columns (3) and (4). *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. *1st St Flood Factor* and *Distance to Water* are standardized to have a mean of zero and standard deviation of one. The standardized *Distance to Water* has a maximum value of 2.7. We assign a standardized value of three to properties that have this measure missing as they are noncoastal. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. *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 Reform on House Prices and Premiums by Sea-Level-Rise Exposure

Panel A: Houses Exposed to Sea Level Rise

Dependent Variable (in $1,000s)	House Sales 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

Panel B: Houses Not Exposed to Sea Level Rise

Dependent Variable (in $1,000s)	House Sales 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

Note: This table uses the structure of Columns (3) of Table 2 to study the effect of the flood insurance reform on house prices and insurance premiums with two subsamples separately. Observations are at the transaction level. In Panel A, we use the sample of homes exposed to sea level rise. In Panel B, we use the sample of homes not 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 is matched insurance premiums, calculated as 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. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. *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 Rebuilding Cost

Panel A: Summary Statistics by Rebuilding Cost

Rebuild Cost Quartile	Max Rebuild Cost	Mean Rebuild Cost	Mean Coverage	Mean Coverage Gap	Mean Coverage Gap@250K	Share Fully Covered	Share Fully Covered @250K
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	184,000	135,270	175,576	3,779	0	0.85	1.00
2	250,000	215,808	215,620	11,592	0	0.58	1.00
3	329,333	278,873	230,335	48,538	28,873	0.15	0.17
4	1,369,386	527,028	233,065	293,963	277,028	0.00	0.00

Panel B: Effect of Rate Reform on House Prices by Rebuilding Cost

Dependent Variable	Sales Price($1,000) (1)	Sales Price($1,000) (2)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 1	-4.424*	-8.293**
	(-1.82)	(-2.64)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 2	-4.731	-7.288*
	(-1.13)	(-1.70)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 3	-11.018**	-11.951**
	(-2.20)	(-2.41)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 4	-25.397**	-24.715**
	(-2.58)	(-2.51)
High-Risk × Pre-Map × Post-Reform × Log Median Income		-2.729
		(-0.97)
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	281.840	281.674
Outcome SD	307.639	307.901
Observations	4,205,235	4,188,925

Note: We sort houses into four quartiles based on the NFIP rebuilding costs matched to the Zillow data. Panel A presents summary statistics for each rebuilding cost quartile. Column (1) reports the maximum rebuilding costs of each quartile. Column (2) shows the average rebuild cost in each quartile. Column (3) tabulates the average coverage. Column (4) presents the average coverage gap, which is the average of the greater between zero and coverage minus rebuild cost. Column (5) presents the average coverage gap at the coverage limit ($250k), which is the average of the greater between zero and $250k minus rebuild cost. Column (6) reports the ratio of homes that are fully covered, i.e., whose coverage amount is no less than the rebuild cost. Column (6) essentially reports the ratio of homes that are fully covered at the coverage limit, i.e., whose rebuild cost is less than $250k. Rebuilding costs are winsorized at the 1st and 99th percentiles. Panel B presents OLS regressions where the dependent variable is house prices in thousands of dollars. *Log Median Income* is local zip-level median income from 2012 ACS, standardized with the mean being zero and the standard deviation being one. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. 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(Sales Price)					
Sample	No Disclosure	Disclosure	All	Primary	Non-Primary	All
	(1)	(2)	(3)	(4)	(5)	(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). We use the full sample in Columns (3) and (6). We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. 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: Effect of Rate Reform on Buyers' Mortgage Take-up

Dependent Variable	1(Buyer Takes 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. Observations are at the transation level. The observations are at the house-transaction level. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. 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: Effect of Rate Reform on Rebuilding Activities Across Hazard Exposure

Dependent Variable	1(Rebuilt×1M)				
Sample	All	Storm Surge		Sea Level Rise	
		Exposed	Not Exposed	Exposed	Not Exposed
	(1)	(2)	(3)	(4)	(5)
High-Risk × Pre-Map (Orig) × Post-Reform	138.222***	356.573***	104.249*	95.999	81.605
	(2.87)	(2.73)	(1.83)	(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	409.134	328.500	346.657	331.502
Observations	240,260,736	9,982,048	222,347,050	7,145,390	225,180,961
Difference: Exposed vs Not Exposed		252.324*		14.394	
		(1.87)		(0.10)	

Note: This table repeats Column (1) of Table 2, replacing the dependent variable with an indicator for if the house is rebuilt in that year. We define the outcome variable, *1(Rebuilt)*, as one of the following situations: (1) a demolition permit, (2) a new building permit, or (3) the year matching the property's latest construction date in tax assessor data. We exclude observations from a property's initial construction year. Given the low baseline probability (326 out of one million parcel-year observations), 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 that are exposed and unexposed to storm surge, respectively. In Columns (4) and (5), we use properties that are exposed and unexposed to sea-level-rise risk, respectively. The last two rows tabulate the differences and the associated t-statistics between the two samples. Standard errors are double clustered by zip code. ***p<0.01, **p<0.05, *p<0.1.

Table 9: Effect of Reform on House Prices, Built Around Map Year or Flood Zone Boundaries

Dependent Variable	Log(Sales Price)	
	(1)	(2)
High-Risk × Pre-Map × Post-Reform	-0.037**	-0.016***
	(-2.47)	(-2.76)
Sample	Built within 3 Yrs of Map Yr	Within 250 ft of Flood Zone Border
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 between High- and Low-Risk zones in Column (2). The dependent variable is log of house transaction prices. 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. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. 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.

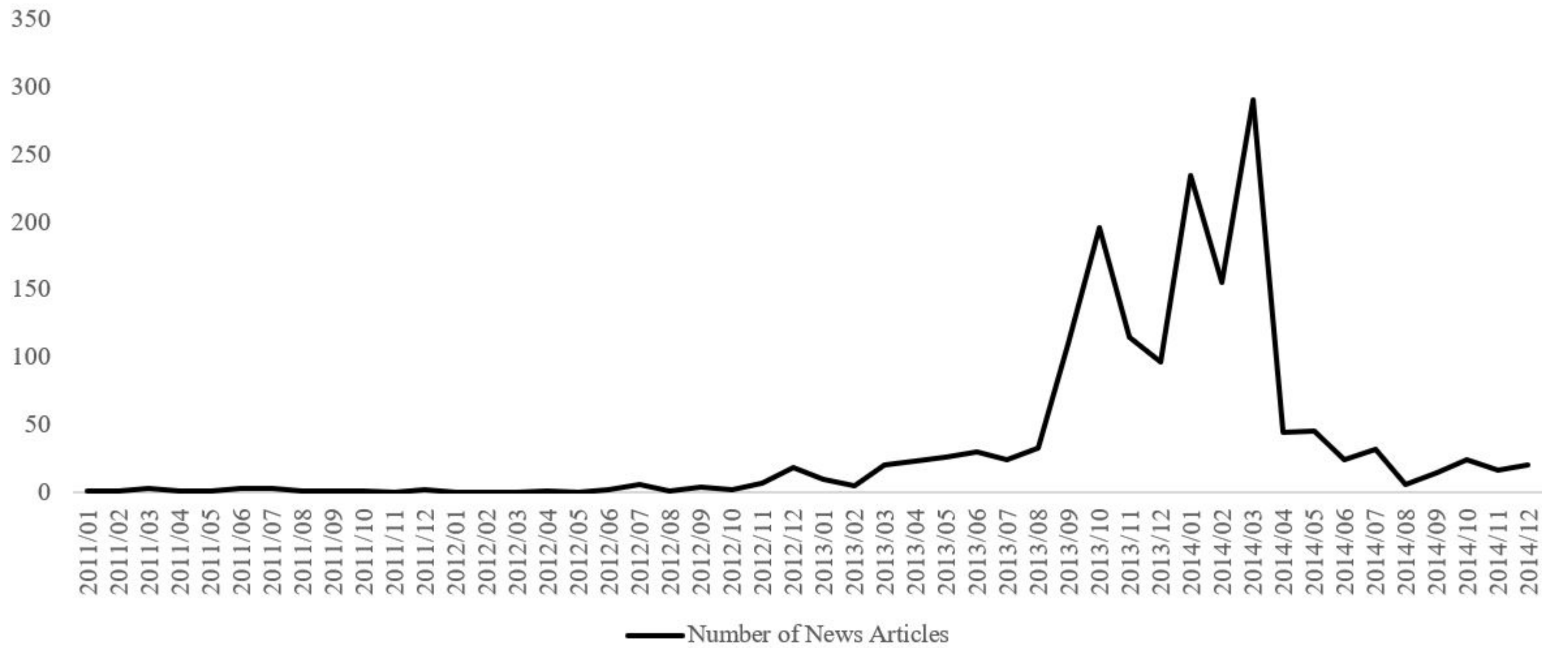
Table 10: Effect of Rate Reform on House Prices, Additional Flood Risk Controls

Dependent Variable	Log(Sales Price)				
	(1)	(2)	(3)	(4)	(5)
High-Risk × Pre-Map × Post-Reform	-0.018***	-0.013**	-0.017***	-0.018***	-0.018***
	(-3.40)	(-2.55)	(-3.63)	(-3.63)	(-3.60)
Hazard Measure × High-Risk × Post-Reform	0.008	-0.001	0.011**	0.005	-0.001
	(1.16)	(-0.59)	(2.51)	(1.43)	(-0.08)
Hazard Measure × Pre-Map × Post-Reform	-0.003	-0.003	-0.002	-0.002	-0.004
	(-0.37)	(-1.43)	(-0.45)	(-0.28)	(-0.39)
Hazard Measure × Post-Reform	-0.012*	0.001	0.004	0.007	0.014
	(-1.73)	(0.65)	(1.25)	(1.34)	(1.20)
Distance>5 miles × High-Risk × Post-Reform				-0.020*	
				(-1.85)	
Distance>5 miles × Pre-Map × Post-Reform				0.013	
				(0.73)	
Distance>5 miles × Post-Reform				0.008	
				(0.59)	
Hazard Measure	Sea Level Rise	1st St Flood Factor	Storm Surge	Dist to Water	>3 Floods
Other Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y	Y	Y
Outcome Mean	12.256	12.256	12.256	12.256	12.256
Outcome SD	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

Note: This table presents OLS regressions similar to Column (3) of Table 2, adding additional terms interacting with different hazard measures. *Hazard Measure* 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). In Column (4), when the property is more than five miles away from water, for which the distance measure is missing, we set the standardized distance to three. In Column (4), 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*. We include all lower-order terms, including those involving Hazard measures and standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. 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.

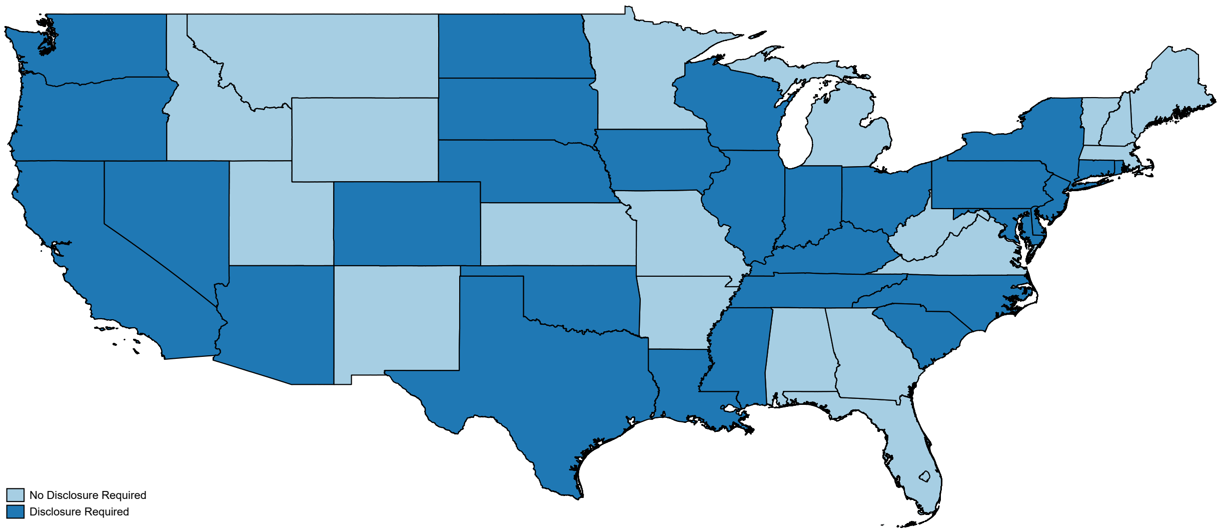
A Appendix

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 property sellers. The lighter shade indicates no disclosure is required. The darker shade indicates that the seller is required to disclose whether the house is located in a High-Risk zone. Tennessee requires sellers to disclose whether flood insurance is required to property buyers (but not renters). We classify Tennessee as requiring disclosure. The information is based on a FEMA 2022 Report. See, `https://www.fema.gov/sites/default/files/documents/fema_state-flood-risk-disclosure-best-practices_07142022.pdf`.

Table A1: Example Premiums with $250,000 Building Coverage

Effective Year	High-Risk, Pre-Map	High-Risk, Post-Map, Elev. Relative to Flood: +1	0	-1	Low-Risk, Pre-/Post-Map
	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%

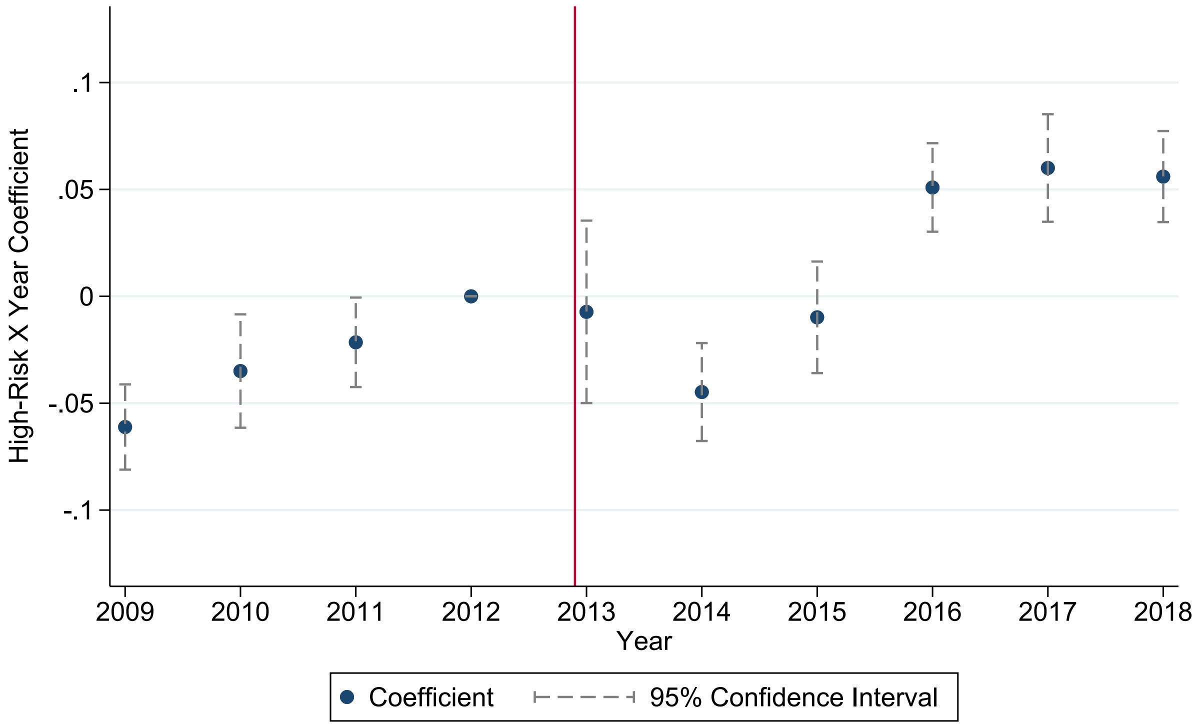
Note: This table shows the insurance premium for a primary residence, single family home without a basement from 2008 to 2018. The premium is calculated assuming the policy includes $250,000 building coverage and $0 content coverage, and include no other adjustments that lead to rate discount. The premium 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. The 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."

Table A2: Vairable Definition

Variable	**Description**
Price	House transaction prices from Zillow.
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 rules.
Post-Reform	An indicator that equals one if the transaction happened in 2013 and after, and zero otherwise.
Sq Ft	The square footage of the house.
Sea Level Rise	An indicator that equals one if the property would experience chronic tidal flooding after six feet of global average sea level rise according to the NOAA Sea Level Rise risk layer.
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. If a house is more than 5 miles away from the water, we assign a value of three 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 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 three 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.
Rebuild Cost Quartile n	An indicator if the rebuilding cost matched to NFIP data falls into the nth quartile.
Log Median Income	ACS 2012 zip-level median income, standardized with the mean being zero and the standard deviation being one.
Non-Primary	An indicator that equals one if the buyer of a house is a non-primary owner, and zero otherwise, based on assessor data.
1(Buyer Takes Out Mortage)	An indicator for the buyer using mortgage according to assessor data.
Rebuilt	*1(Rebuilt)* indicating rebuilding activity identified through: (1) a demolition permit, (2) a new building permit, or (3) the year matching the property's latest construction date in tax assessor data. We exclude observations from a property's initial construction year.
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

Figure IA.1: Effect of 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

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

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. Observations are at the policy level. See Table A2 for variable definitions. In the fixed effects, *area* is defined by zip code as well as longitude and latitude rounded to one decimal place, the most granular level available in NFIP data. Note that this is the finest longitude and latitude that NFIP data provide. Standard errors are two-way clustered by policy start 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	0.90
2018	60,000	1.04	0.95

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)					
	Exclude 2013-2014	Fixed Effects ×High-Risk	Fixed Effects ×Pre-Map	Additional Controls	High-Risk Status 1996=2021	Exclude Sandy
	(1)	(2)	(3)	(4)	(5)	(6)
High-Risk × Pre-Map × Post-Reform	-0.019***	-0.027**	-0.019***	-0.022***	-0.019**	-0.017***
	(-3.13)	(-2.47)	(-3.48)	(-4.14)	(-2.50)	(-3.24)
Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y	Y
Additional Risk Controls	N	N	N	Y	N	N
Zip X Age FE	Y	N	N	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	N	N	Y	Y	Y
Zip X Age X High-Risk FE	N	Y	N	N	N	N
Zip X Long/Lat X Year X Beds X High-Risk FE	N	Y	N	N	N	N
Zip X Age X Pre-Map FE	N	N	Y	N	N	N
Zip X Long/Lat X Year X Beds X Pre-Map FE	N	N	Y	N	N	N
Outcome Mean	12.267	12.252	12.252	12.256	12.246	12.234
Outcome SD	0.719	0.716	0.714	0.719	0.710	0.712
Observations	3,389,537	4,172,729	4,190,125	4,294,716	3,063,827	4,069,780

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. In Column (6), we exclude New York and New Jersey, the states that sustained the most damage from Hurricane Sandy. The main variable of interest is the triple interaction term *High-Risk* × *Pre-Map* × *Post-Reform*. See Table A2 for variable definitions. 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: Heterogeneous Effects of Reform on House Prices across Different Flood Risks, Controlling for Local Income

Dependent Variable	Log(Sales Price)		Sales Price ($1,000s)	
	(1)	(2)	(3)	(4)
High-Risk × Pre-Map × Post-Reform	-0.012**	-0.015	-7.454***	-4.991
	(-2.07)	(-1.62)	(-3.02)	(-1.08)
High-Risk × Pre-Map × Post-Reform × Sea Level Rise	-0.028**	-0.022*	-17.246**	-10.990*
	(-2.33)	(-1.72)	(-2.52)	(-1.81)
High-Risk × Pre-Map × Post-Reform × 1st St Flood Factor		-0.003		-5.110**
		(-0.65)		(-2.11)
High-Risk × Pre-Map × Post-Reform × Storm-Surge		0.012		5.018
		(1.33)		(1.00)
High-Risk × Pre-Map × Post-Reform × Distance to Water		0.005		3.309
		(0.68)		(1.07)
High-Risk × Pre-Map × Post-Reform × Distance>5 Miles		-0.011		-9.523
		(-0.49)		(-0.88)
High-Risk × Pre-Map × Post-Reform × > 3 Past Floods		0.011		4.401
		(0.88)		(0.65)
High-Risk × Pre-Map × Post-Reform × Log Median Income	0.001	0.001	-5.077**	-5.816**
	(0.21)	(0.20)	(-2.13)	(-2.38)
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	12.254	12.254	12.254	12.254
Outcome SD	0.718	0.718	0.718	0.718
Observations	4,188,925	4,188,925	4,188,925	4,188,925

Note: This table repeats Table 3, while adding interactions between standardized log zip-level median income based on ACS 2012 and *High-Risk × Pre-Map × Post-Reform*. The dependent variable is log house prices in Columns (1) and (2) and prices in thousands of dollars in Columns (3) and (4). *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. We include all lower-order terms, including standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. *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.4: Effect of Rate Reform on House Prices by Rebuilding Cost

Dependent Variable	Sales Price($1,000)				
	(1)	(2)	(3)	(4)	(5)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 1	-4.542	-2.812	-7.573**	-9.532**	-9.071***
	(-1.39)	(-0.75)	(-2.32)	(-2.14)	(-2.92)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 2	-2.352	-0.383	-6.356	-6.863	-8.286*
	(-0.56)	(-0.09)	(-1.42)	(-1.34)	(-1.82)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 3	-6.500	-4.207	-10.959**	-11.325**	-12.537**
	(-1.33)	(-0.86)	(-2.20)	(-2.08)	(-2.43)
High-Risk × Pre-Map × Post-Reform × Rebuild Cost Quartile 4	-18.662*	-16.170*	-23.399**	-23.335**	-25.269**
	(-1.96)	(-1.75)	(-2.42)	(-2.39)	(-2.48)
High-Risk × Pre-Map × Post-Reform × Log Median Income	-3.186	-3.723	-2.945	-3.637	-2.921
	(-1.14)	(-1.36)	(-1.06)	(-1.27)	(-1.07)
High-Risk × Pre-Map × Post-Reform × Hazard Measure	-15.630**	-6.658***	-2.224	4.903	3.014
	(-2.41)	(-2.85)	(-0.49)	(1.62)	(0.47)
Hazard Measure	Sea Level Rise	1st St Flood Factor	Storm Surge	Distance to Water	>3 Floods
Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y	Y
Zip X Long/Lat X Year X Beds FE	Y	Y	Y	Y	Y
Outcome Mean	12.256	12.256	12.256	12.256	12.256
Outcome SD	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

Note: This table presents OLS regressions similar to Column (1) of Table 5. *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). 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*. We include all lower-order terms, including those involving Hazard measures and standalone terms that are not absorbed. See Table A2 for variable definitions. 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.5: Effect of Rate Reform on Rebuilding Activities Across Hazard Exposure

Dependent Variable	1(Rebuilt×1M)					
Sample	Flood Factor		Coastal		>3 Past Floods	
	>1	=1	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
High-Risk × Pre-Map (Orig) × Post-Reform	150.026**	71.353	134.211***	6.924	178.105	112.309**
	(2.11)	(0.80)	(2.73)	(1.62)	(2.06)	
Lower-Order Terms & Sq Ft	Y	Y	Y	Y	Y	Y
Zip X Age FE	Y	Y	Y	Y	Y	Y
Zip X Year X Beds FE	Y	Y	Y	Y	Y	Y
Outcome Mean	336.426	331.552	331.934	155.159	201.733	404.567
Observations	42,517,583	189,421,139	232,368,615	7,482,654	83,174,380	149,171,687
Difference: Exposed vs Not Exposed	78.672		127.286		65.796	
	(0.75)		(1.10)		(0.54)	

Note: This table repeats Column (1) of Table 2, replacing the dependent variable with an indicator for if the house is rebuilt in that year. We define the outcome variable, *1(Rebuilt)*, as one of the following situations: (1) a demolition permit, (2) a new building permit, or (3) the year matching the property's latest construction date in tax assessor data. We exclude observations from a property's initial construction year. Given the low baseline probability (326 out of one million parcel-year observations), 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 sample of homes with the 1st Street Flood Factor above one, and (2) those with the Flood Factor equal to one. In Columns (4) and (5), we use properties that are within five miles of the coast and the rest, respectively. In Columns (4) and (5), we use properties in counties that experience more than three flood related FEMA-declared disasters and the rest, respectively. The last two rows tabulate the differences and the associated t-statistics between the two samples. Standard errors are double clustered by zip code. ***p<0.01, **p<0.05, *p<0.1.

Table IA.6: Effect of Rate Reform on House Prices, Controlling for Having a Basement

Dependent Variable	Log(Sales Price)
High-Risk × Pre-Map × Post-Reform	-0.016***
	(-3.30)
Basement × High-Risk × Post-Reform	-0.017*
	(-1.96)
Basement × Pre-Map × Post-Reform	-0.007
	(-1.15)
Basement × Post-Reform	0.014**
	(2.61)
Lower-Order Terms & Sq Ft	Y
Zip X Age FE	Y
Zip X Long/Lat X Year X Beds FE	Y
Outcome Mean	12.256
Outcome SD	0.719
Observations	4,294,716

Note: This table presents OLS regressions similar to Column (3) of Table 2. *Basement* is an indicator for whether or not the house has a basement according to the Zillow data. The main variable of interest is the triple interaction term *High-Risk* × *Pre-Map* × *Post-Reform*. We include all lower-order terms, including those involving Hazard measures and standalone terms that are not absorbed. We also control for square footage. See Table A2 for variable definitions. 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

The construction of the NFIP policies dataset involves several steps, including filtering properties by type, identifying their flood zones and Pre-Map status, calculating premium rates, and determining the effective policy year. 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 premium 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 of 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 zones).[30] We exclude High-Risk Zone VE, which makes up than 0.08% of our sample, because the reform affected insurance premiums for VE zone properties differently than for other High-Risk zones.

Premium rate: The premium rate is calculated by dividing the total insurance premium of the policy by the sum of the building coverage and content coverage of the policy. After identifying a property's flood zone and Pre-Map status, although several factors can impact the premium rate [31], it is primarily determined by the basic limit rates and additional limit

[30]Technically, A99 (areas with a 1% annual chance of flooding protected by a Federal flood control system) are also SFHA in FEMA's terminology. However, since A99 flood zone properties follows the same rate schedule as Low-Risk zones B, C and X, we classify A99 as a Low-Risk type for the purpose of studying insurance premiums.

[31]Such as the Community Rating System (CRS) discount

rates specified in the rate schedule. Holding other variables fixed, an increase in the basic limit rates and the additional limit rates would directly result in a higher overall premium rate.

Determining the effective year of a policy: Flood insurance rate tables were updated in October in each year from 2009 to 2014, and in April of each year from 2015 to 2018. We make the following adjustment to obtain the effective 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 set the effective 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 set the effective policy year to $t-1$, because the applicable rate table is the previous one that was for the most part effective in year $t-1$.

IA.2 Matching Flood Insurance and Zillow Data

We match the premium, rebuilding cost, and insurance coverage information from NFIP to our Zillow data. NFIP policy data do not include detailed location information for policies, providing only longitude and latitude rounded to one decimal place. As a result, we cannot precisely match premium rates to 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. We exclude properties that do not have a matched average premium rate. We perform the same procedure to match average rebuilding costs to properties in Zillow.

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, unless stated otherwise.