The Price and Distributional Impact of Flood Risk Disclosure: A Natural Experiment on the U.S. Housing Market

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Preliminary

Abstract

Although flood costs are one of the largest expenses potentially borne by homeowners, getting up-to-date information on this risk can be difficult. Traditional flood maps are often outdated while flood insurance is underutilized and thus uninformative for much of the United States. We study the impact of a novel flood risk factor that is directly shown to all potential home buyers on three major online search platforms between 2020 and 2024. After a house is disclosed to buyers as having extreme flood risk, holding all else equal, we find that its sale price drops by 3.7% or $14,165.45 on average—just under 41% of the actuarial difference in expected flooding costs. To obtain plausibly exogenous variation, we back out and utilize natural discontinuity points in the categorization of the disclosed measure. The estimated price discount is only observed for properties outside of FEMA floodplains and is up to four times stronger for properties exposed to a coastal source of flooding. The price effect is uneven across the United States: it is most pronounced in the South and Midwest, while there is no observed price change in the Northeast. Interestingly, following disclosure, those who purchase homes with extreme flood risk have 5% lower income and are 2% more likely to hold a Federal Housing Administration (FHA) loan. Together, these findings suggest that flood risk is shifted into the hands of the more financially constrained.

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1 Introduction

Flood-related natural disasters such as Hurricane Milton have been both in the news and of paramount concern for investors due to their large economic impact. A report by the Joint Economic Committee estimates that flood damages cost the United States up to 496 billion in 2023 dollars every year (Heinrich, 2024). For the average household, increasing climate risks such as floods are re-pricing their most valuable asset: their house. However, understanding a property's future flood risk is not straightforward—it not only requires an understanding of the landscape and historical flood events, but it must also model future rainfall patterns and the likelihood of natural disasters, such as a storm surge, which may vary depending on climate change scenarios. Historically, potential homebuyers relied on Federal Emergency Management Agency (FEMA) flood maps to understand if a house is in a high-risk zone—typically a 100-year floodplain that has 1% or higher probability of flooding each year. However, these FEMA maps do not reflect forward-looking projections of changing weather patterns and are often outdated—75% of FEMA maps are five years or older (Eby, 2019). While insurance could fill this gap by helping homeowners understand their risks, homeowners' insurance does not typically cover flood damage. Furthermore, flood insurance outside of designated FEMA floodplains is generally expensive and hard to obtain.

To fill in the gap in flood disclosure for homebuyers, First Street released a proprietary Flood Factor in August 2020 for all homes listed on Realtor.com, and in February 2021, for all homes listed on Redfin.com. In September 2024, Zillow.com also started disclosing First Street's flood data, making it nearly impossible for a consumer to fully view a house listing online without seeing its First Street Flood Factor. When a user views a home on one of the three search engines, they will be given a numerical flood risk score (between 1 for lowest risk and 10 for highest risk) as well as a qualitative flood risk label (minor, moderate, major, severe or extreme) based on First Street's model. By disseminating information directly to the investor through online search platforms, First Street provides homebuyers with a novel, property-level measure of flood risk. Furthermore, unlike the information previously provided by FEMA maps, this measure incorporates forward-looking forecasts of climate change from big-data models, is updated frequently, and does not rely on insurance provision.

In a 2023 survey conducted by Zillow, over 80% of prospective homebuyers report that they consider climate risks when shopping for a home. Furthermore, among all climate risks, flood risk ranks as their biggest concern (Zillow, 2023). The Flood Factor provided by First Street not only makes it easier for prospective homebuyers to understand a home's flood risk than ever before, but more importantly, it has changed the landscape of where the perceived flood risk is located. For example, a report released in 2020 finds that over 40% of at-risk properties identified by First Street were not previously identified as risky by FEMA maps. If consumers notice and believe in First Street flood models, then nearly 6

million homes were suddenly reclassified as having high flood risk, despite being largely viewed as not risky before (Humphries, 2020). In equilibrium, the pricing and distributional effects of the new flood information provided by First Street remain unclear—our paper will address this gap.

In general, it is hard to disentangle the equilibrium effects of information disclosure, because many other concurrent factors could introduce bias. On one hand, increasing natural disasters and international efforts such as the 2015 Paris Agreement have brought more attention to climate change issues in recent years. This can cause concurrent price declines for flood-prone properties, as consumers become more sensitive to flood risks, but these price declines should not be attributed to the information release of the Flood Factor by First Street. On the other hand, homes that have high flood risk may also have valuable amenities like ocean views. If these home features are becoming more valuable over time, then they could also bias our estimates of prices downward.

Importantly for our paper, First Street's Flood Factor has a unique feature. While a home's true underlying flood risk is continuous, it is not shown to homebuyers on the online search platform. Instead, as Figure 1 shows, this continuous risk (shown on x-axis) is mapped into the discrete Flood Factors (shown on y-axis) based on a set of nearly-arbitrary cutoffs (shown as dotted vertical lines) before being published on a search platform. By backing out this hidden, continuous measure, we can then compare homes with nearly identical flood risks but different disclosed scores on either side of each cutoff. Then, using a RD regression design, we can untangle the effects of disclosure from other potential omitted factors. In doing so, we can provide plausibly exogenous estimates on the pricing and distributional impacts of disclosure.

In this paper, we combine First Street, CoreLogic, and HMDA data to answer the following:

(i) What is the equilibrium price effect when property-level flood risks are disclosed directly to consumers through online search platforms?

There is an ongoing debate about whether homebuyers care about flood information, and thus, discount homes with flood risk. Prior studies have focused on a specific geography, utilized flood maps, or relied on flood insurance (Gibson et al., 2017; Murfin and Spiegel, 2020; Baldauf et al., 2020). Closest to our paper, Fairweather et al. (2024) studies the effect of First Street's flood factor utilizing a randomized experiment on the Redfin platform. In order to understand how flood disclosure influences individuals' search behavior, the authors randomly assign treatment at the user level. Our work naturally complements this analysis by utilizing a natural experiment that pseudo-randomizes the disclosed flood risk at the property level. As Figure 1 demonstrates, houses with nearly identical levels of risk but on either side of a discrete cut-off are shown to have very different risk factors. By combining this novel data design with an RD regression, we can plausibly identify the price effect of

flood disclosure when a house is revealed to be highly risky. [1]

Using the rollout of the Flood Factor across the U.S. as a natural experiment, we begin by establishing a baseline price effect using a difference-in-difference (DID) model. In this DID regression, we compare prices for homes across different flood rating categories, both before and after the rollout of the Flood Factor. Using various geographic controls, ranging from county-period fixed effects (most relaxed) to block-group and FEMA-map fixed effects (most stringent), we find a significant decline in sale price of roughly 1% for homes with "extreme" flood risk following the release of First Street's Flood factor. A pre-trend analysis shows that this decline does not exist before disclosure, and it appears immediately in the year following disclosure. Interestingly, we find that the price effect does not exist for properties *within* FEMA floodplains; it is almost entirely driven by properties *outside* FEMA floodplains. There are two possible explanations: first, flood information for homes within FEMA floodplains was already available to the public prior to First Street's disclosure, so there is less novel information added. Second, the vast majority of properties within FEMA floodplains are required to buy flood insurance if they have a mortgage. For these properties, homebuyers may reasonably expect that a significant portion of flood risk would be absorbed through insurance.

One may worry that the Flood Factor is correlated with many omitted factors, such as the proximity of the property to the sea, which is a desired amenity and may actually increase equilibrium prices. To address this, we next obtain more plausibly exogenous variation using a regression discontinuity (RD) model. Backing out the continuous but proprietary risk variable that is not disclosed to the public, we then compare nearly identical houses that were just below versus above the cut-offs used to assign the discrete flood factors. In these RD models, we restrict our sample to homes that are very similar in flood risk. Using the RD specification, we find a baseline price discount of 3.7% across all U.S. properties, and strikingly, we find up to a discount of up to 17% for properties that are not in a FEMA floodplain but are exposed to coastal flooding. This suggests that the omitted variables from our DID regressions likely included coastal amenities, which biased our estimates downwards. In a covariate balance test, we reassuringly find that most hedonic housing characteristics such as the number of bedrooms and bathrooms are otherwise similar on either side of the cutoff.

Lastly, in order to benchmark the economic magnitude of the observed price declines, we compare the dollar value of these declines to the actuarial cost estimates of future flooding provided by First Street. Since the average home sale price in our data is $382,850, the observed 3.7% drop in prices translates into a net value decline of $14,165.45. Based on First Street's cost model, the actuarial decline in value, based on a 5% discount rate and staying in the home for 10 years, should actually be about $34,752. Thus, consistent with a story of retail inattention, the observed price drop does not

[1] We sincerely thank Jeremy Porter and the research team at First Street for working closely with us to reconstruct the continuous risk variable.

seem to fully account for future flood damages; instead, it accounts for just a little under 41% of the actuarial value.

(ii) How does flood-risk disclosure change who lives in flood-prone properties?
Preliminary evidence suggests that homes with an extremely high Flood Factor (implying extreme flood risk) dropped significantly in value after First Street released its data. Since housing supply is generally inelastic, lower prices suggest lower demand for flood-prone properties. However, the change in demand may be heterogeneous and vary depending on consumer characteristics. For example, flood-prone properties may attract more climate-risk-tolerant buyers, and this risk tolerance may be correlated with observable characteristics such as age, race, and political beliefs. On the other hand, it may simply attract more first-time or lower-income buyers, because they are more financially constrained and cannot afford to buy the less flood-prone properties, which are becoming relatively more expensive. To better understand the distributive impact of disclosure, we regress various homebuyers' demographics on flood-risk disclosure.

Using the most plausibly exogenous RD regression design, we find a strong and significant decrease in average income (roughly 4.5%) for homebuyers of extremely risky properties following disclosure. Similarly, we find that homebuyers of extremely risky properties are 2.3% more likely to hold a FHA loan. Since FHA loans are intended to help first-time buyers with lower credit quality, this similarly suggests that, in equilibrium, buyers are becoming more financially constrained. On the other hand, we do not find consistently significant effects for buyer's age or race.[2]

Ultimately, both taste-related characteristics that are correlated with flood-risk tolerance (eg political views) as well as the ability to pay may factor into the redistribution that we observe after disclosure. Since it is unclear which taste-based preferences would naturally strongly correlate with income, we find that financial constraints are a likely driver behind lower equilibrium prices. In the future, we would like to test this directly by merging in data on political beliefs and education levels. In sum, evidence so far suggests that buyers are re-sorting following flood disclosure, and all else equal, buyers who can afford to hold less risky properties choose to do so—shifting flood risk otto homebuyers that are more financially constrained.

Related Literature

First, we contribute to the literature on the impact of digitization in the housing market. Despite the real estate sector's slow adoption of technology in general, online housing platforms continue to play a crucial role for households' search behavior, altering the information environment for market

[2]We do not show these results to save space, but they can be shared upon request. We are working on adding L2 Voter Data as well, which should give us homebuyer information on political affiliation as well as education levels.

participants. For example, Buchak, Matvos, Piskorski and Seru (2022) finds that algorithmic pricing deployed by iBuyers[3] provides automated intermediation by producing more accurate predictions in liquid housing markets, and Harrison et al. (2024) finds both elevated equilibrium prices as well as localized pricing spillovers after the entrance of iBuyers. In addition, Fu, Jin and Liu (2022) shows that Zillow's automated valuations ("Zestimates") influence both listing and sale prices, while Raymond (2024) finds that algorithmic valuation can have market-level effects, closing historical racial gaps in housing values. On the household side, Bailey et al. (2018) finds that networks on social media platforms significantly impact residential home-buying behavior. Finally, Fuster et al. (2022) finds that machine learning algorithms have distributional impacts on the mortgage market by being the least helpful for Black and Hispanic borrowers. Our paper builds on these works by showing that there are both pricing and redistributional impacts to providing data from large risk models directly to the buyer through home search platforms.

Next, our work naturally complements the growing literature on natural disasters and frictions in insurance pricing. Traditionally, homeowners embed the cost of natural disasters, including floods, through the price of their homeowners' insurance (Ge et al. 2022, Mulder 2024). However, as the number of natural disasters continues to increase, the property and casualty insurance market faces increasing frictions, including sharply increasing and uneven premiums due to reinsurance (Keys and Mulder 2024); riskier mortgage originations that amplify systemic and taxpayer risks (Sastry et al. 2023); insufficient coverage in the event of total loss (Cookson et al. 2025); as well as misclassified risk leading to both suboptimal insurance take-up and adaptations (Mulder 2024). In addition, widespread under-insurance (Ge et al. 2025) and increasing rates of delinquency in insurance (Sastry et al. 2024) have distributional impacts by shifting risk to the most financially constrained households. Since flood risk is generally not covered by home insurance and flood insurance is scarce outside of FEMA flood zones, our paper is among the first to show how homeowners embed flood risk when they are presented with the data directly through a search platform.

By synthesizing big data and using modeling tools to provide data on climate risks directly to the homebuyer, First Street's flood disclosure has a significant impact on how risk pricing is intermediated across the U.S. Since most homes are not in a FEMA flood zone and thus do not have access to public flood insurance, First Street's climate data on search platforms provide a novel source of flood information for most homebuyers. Across financial markets more broadly, our findings are related to papers on fintech disruptions across different financial markets—including personal credit (Di Maggio and Yao 2021), peer-to-peer lending (Balyuk 2023), forgivable loans (Erel and Liebersohn 2022), and

[3]iBuyers stands for "instant buyer," referring to real estate companies "that use algorithms and technology to buy and resell homes quickly." https://www.nerdwallet.com/article/mortgages/understanding-ibuyers, accessed August 12, 2024.

mortgages (Buchak et al. 2023).

A growing body of work investigates the pricing of climate risk in real estate. Empirical studies (Keys and Mulder 2020, Bernstein et al. 2022, Bakkensen and Barrage 2022) show that sea-level-rise (SLR) risk poses threats to the housing market. This effect is particularly pronounced in politically liberal areas where consumers are more responsive to climate warnings, highlighting how heterogeneous beliefs and risk perceptions shape market outcomes. At the same time, experimental evidence (e.g., Fairweather et al. 2024) suggests that making climate risk salient via digital channels alters buyer search behavior. We complement their work by directly estimating the equilibrium effects when disclosure is made available to all market participants, with their main results providing the key micro-foundation for how information redirects housing search.

Finally, since a house's flood risk is both intangible and often difficult to understand without disclosure, our studies also tie into a literature on the importance of information salience in finance. Studies show that effective disclosure needs to be simple and salient in order to influence household financial choices (Agarwal et al. 2015), especially when it comes to complicated issues such as global warming (Choi et al. 2020). When it comes to attention to climate-related issues, there is a divergence as institutions appear to be highly aware of their risks (Krueger et al. 2020). In contrast, regulators, academics, and practitioners generally agree that market prices underreact to climate risks—suggesting that most investors are not properly attentive (Stroebel and Wurgler 2021). Consistent with the theory of market underreaction, we find that the average price drop that we observe represents only about 41% of expected flood costs, suggesting that not all consumers are equally attentive to First Street's Flood Factor.

2 Data

First Street

The measure of flood risk that we focus on is the Flood Factor, a score published by First Street Foundation and released on popular real-estate platforms such as Zillow and Redfin (see Figure 3 for an example of how the scores are displayed for a platform user on Redfin). The initial goal of First Street Foundation was to provide property-level information on future risks of flooding. Subsequently, they also expanded their database to include information on other climate risks including wildfire, heat, wind and air. Their flood factor is produced using the First Street Flood Model (FSF-FM)—a nationwide model that calculates the potential risk of flooding based on a combination of rainfall, streamflow, rise in sea level, tidal expectations, and storm surge.

The FSF-FM model is forward-looking in nature and incorporates both historic flood risk as well as climate change-driven changes in flood risk. One notable component of their model that deviates

from standard flood models, including the FEMA floodplain maps, is the use of the First Street Precipitation Model (FS-PM). The FS-PM takes into account early 21st century rainfall records and calculates forward-looking projections, capturing the notion the United States will experience more occurrences of extreme rainfall in the future. As a result, inland properties that traditionally were classified as safe based on floodplain maps are more likely to be reclassified as risky under FSF-FM.[4]

We obtain a dataset from the First Street Foundation that provides a composite measure of future flood risk for each property, resulting in a score between 1 (lowest risk) and 10 (highest risk). As shown in Table 1, our final merged dataset consists of over 22.2 million sales transactions. 5% of all properties are at risk of coastal flooding and 13% are at risk of pluvial (ie rainfall) flooding. In general, the causes of flooding do not have to be mutually exclusive. In the rest of this paper, we define Coastal properties as all properties that are exposed to coastal flooding as a source of risk. To help visualize their general locations, Figures 6a and b plot the coastal properties as red, semi-transparent dots along with local bodies of water for Hillsborough County, Florida (panel a) and a zoomed-in subset of Hillsborough County (panel b). We see that coastal properties are those that lie within close proximity to a local body of water, whether that is a lake, river, or ocean.

Table 2 breaks down the transaction data by the property's Flood Factor (column 1) and qualitative risk category (column 2). We see that while over 84% of all sold properties have a minimal risk score of 1, there is also a substantial number of properties with either severe or extreme flood risk. For example, we observe 517,953 (370,619+147,334) homes sold that had "extreme" flood risk.

In addition to the qualitative category and quantitative risk score, we also back out the internally calculated running variable— the expected flood depth under different time horizons and the expected costs of repairs at different time horizons. Using a weighted average of the expected flood depths under various horizons (aka "return periods" under the FSF-FM), we are able to construct a continuous score called the expected flood depth. Figure 1 shows how we can cleanly infer the cutoff points by plotting the observed flood factor (y-axis) against the log expected depth (x-axis). We will use these cutoff points for our regression discontinuity analysis in Section 3.2.

First Street vs FEMA

We obtain floodplain data from FEMA, and we merge this with our First Street data to see how the two measures of flood risk compare. To illustrate the differences, Figure 4 shows the faction of home transactions per census tract that are labeled as risky by FEMA in panel a (ie are in a 100-year

[4]The First Street model improves upon existing flood map methodology by being more recently updated and forward-looking. However, a team of White House scientific advisers have warned against climate models such as First Street's, saying they are of "questionable quality" and Bloomberg has also noted that catastrophe models have large standard errors, often coming to very different conclusions (Meyer, 2024). Our paper does not take a stand on the validity of the First Street measure, but instead focuses on the impact of the information that is given to consumers.

floodplain [5]) versus First Street in panel b (ie have "extreme" flood risk) for the state of Florida. In general, we see that the two data sources seem closely related, but they are not identical. For instance, more properties sold in the upper left corner are labeled as risky by First Street, compared to FEMA.

In addition to different categorizations of risk, FEMA's flood data is often less granular than First Street's flood data. To illustrate, we zoom into a select number of census tracts in Hillsborough County, Florida in Figure 5 and we plot every transaction as an individual dot colored by either its FEMA risk (ie is in a 100-year floodplain) or its First Street risk (a numerical factor ranging from 2 to 10, ranging from least to most risky). First, by construction, we see much more variation in degrees of risk under the First Street data. Second, for example, if you look in the lower half of tract 006200 (middle right side of graph), it is totally blue in panel a or designated as not in a floodplain by FEMA. However, in panel b, we see a large variation in First Street's flood risks, ranging anywhere from 3 (moderate) to 8 (severe). If you look closely, you can see that houses right next to each other can have very different scores under both FEMA and First Street, but it is especially prominent in First Street's model due to the range of scores possible.

We formalize the comparison for all transactions in the United States in column 5 of Table 2. More specifically, we calculate the proportion of homes sold under each Flood Factor that is also classified into a FEMA flood zone. As Table 2 shows, the Flood Factor and FEMA zones are positively correlated, so that larger Flood Factors have a larger fraction of homes in FEMA flood zones, but there is still a lot of disagreement. For example, even for homes with the riskiest category of 10, roughly 38% of them would **not** have been classified as risky by FEMA.

CoreLogic

Our transactions data comes from the Corelogic Multiple Listing Enterprise Solutions (MLS) Database. The MLS database is comprised of data that real estate agents use to match buyers with sellers. In addition to the address and geolocation, we also have hedonic characteristics such as number of bedrooms, bathrooms, and lot size. In addition, we have information on the sale price and date, as well as limited agent information. Table 1 summarizes several key variables from our transactions data.

After merging the Corelogic database with First Street data, we filter the data by removing properties with sales prices below $50,000 or with more than one building. In our main estimation sample, we further restrict the sample to two time periods of interest: between January 2017 and August 2020 (aka the "pre-period") and between August 2021 and December 2024 (aka the "post-period"). As Figure 2 shows, these dates align with the period before First Street data was publicly disseminated and the period after the final version of First Street data was disseminated, respectively.

[5] FEMA's 100-year floodplain is an area that has 1% or higher probability of flooding each year.

After applying these filters, we are left with roughly 22.2 million transactions. The average sale price (see Table 1) was $382,850, although there is substantial variation. The 25th and 75th percentile of sale prices are $179,000 and $450,000, respectively. The median house sold in our sample has 3 bedrooms and 2 bathrooms, with a living area of 1,672 square feet.

HMDA

Lastly, for homes that are purchased with a mortgage, we obtain additional borrower characteristics through the HMDA (Home Mortgage Disclosure Act) data. For each mortgage that we successfully match, we gather the borrower's age, ethnicity, income, as well as a dummy variable equal to one if the loan is an FHA loan. Since the FHA insures the loan, it allows first-time and low-credit borrowers to attain a better deal on their mortgage. Thus, in general, we use the FHA loan dummy as a proxy for first-time or low-credit homebuyers.

Table 1 summarizes the HMDA data in the last panel. We were able to match roughly 8.2 million mortgage applications. For this matched sample, the average income was about $131,804 and 17% were FHA loans. In addition, about 17% of buyers were age 55 and above, and 39% identified themselves as being non-white.

3 Price Effects

To understand the impact of nationwide flood disclosure on the residential housing market, we first estimate its effect on equilibrium prices. As a baseline, in Section 3.1, we run a difference-in-difference (DID) regression to characterize the price effects across various risk cutoffs. In addition, we examine whether there is heterogeneity in price effects across different floodzones or geographic regions. Then in Section 3.2, based on our DID findings, we zoom in on only the homes with highest flood risk and estimate a regression-discontinuity (RD) regression to obtain more plausibly exogenous identification. Overall, across all analyses, we consistently find that homes with extreme flood risk face a significant decline in prices, and that this effect is primarily concentrated in non-FEMA flood zones.

3.1 Difference in Difference Estimator

To test the effect of flood disclosure, as a baseline, we examine prices across homes of different flood-risk levels, both before and after the release of First Street's Flood Factor on online platforms. More specifically, we estimate the following DID specification:

$$Ln(Price)_{ijt} = \alpha_t + \mu_{jt} + \vec{\beta_1}\vec{F_i} + \vec{\beta_2}\vec{F_i} \cdot Post_t + \vec{\beta_3}\vec{X_{ijt}} + \varepsilon_{ijt} \tag{3.1}$$

where each observation is one sales transaction and i, j, and t represent property, location, and time indices respectively. α_t and μ_{jt} represent time (year-month) and time-location fixed effects

respectively; across specifications, the unit of location varies from county (most broad) to block-group (most granular). $\vec{X_{ijt}}$ represent a vector of hedonic controls, including the building age, number of bedrooms, number of bathrooms, lot size, and living area.

Our key explanatory variables are represented by the vector $\vec{F_i}$, which is a 5x1 vector of dummy variables, each equal to one if the property's flood factor fell into one of the five respective risk categories or above (ie minimal, minor, moderate, major, or severe). The coefficients may be interpreted as the *incremental* price change between homes of that category and homes in the category directly above.

$$\vec{F_i} = \begin{pmatrix} I(> Minimal)_i \\ I(> Minor)_i \\ I(> Moderate)_i \\ I(> Major)_i \\ I(> Severe)_i \end{pmatrix}$$

$\vec{F_i}$ captures the treatment effect. A priori, we expect the treatment effect to increase with severity of flood risk, because as the likelihood and severity of flooding increases, the expected cost of fixing flood-related damages will also rise, Thus, we expect to find the strongest treatment effect for houses with extreme flood risk.

To capture the effect of releasing First Street's Flood Factor, we multiply the treatment $\vec{F_i}$ with $Post_t$, a scalar dummy equal to one if the transaction took place in the post period. As Figure 2 shows, we define the post period as the period following the official release of the final version of First Street's Flood Factor. Thus, $\vec{\beta_2}$ is our main coefficient of interest. If consumers cared about flood risk, this should lower prices for high-risk homes. Subsequently, we would expect the components of $\vec{\beta_2}$ associated with high-risk homes, such as homes with extreme flood risk, to be negative and significant.

Table 3 shows our main results, and we find that homes labeled as extreme by the Flood Factor drop significantly in price following the release of the Flood Factor. Column 1 shows baseline results with only time fixed effects and no location fixed effects or hedonic controls. As we move from column 1 to 4, we progressively add more stringent location fixed effects—ranging from county-time, which is the most lax, to block-group-time, which is the most stringent. In column 5, we add a full set of hedonic controls to the block-group-time fixed effects. Finally, in column 6, we also add fixed effects for whether a property is located in a FEMA floodplain, creating the most conservative estimates.

It is worth noting that in Table 3, if we do not include strong geographic controls, higher flood risk is not associated with higher sale prices. For example, homes in the strongest treatment group, labeled with extreme flood risk, (adding up all of the coefficients ranging from above minimal x post to above severe x post in column 1) actually sell for 2% higher than homes with minimal risk. This

is likely due to the fact that these properties tend to also have popular amenities such as proximity to the beach or having water views. Ultimately, waterfront amenities could be positively correlated with both prices and flood risk. Consistent with this conjecture, when we control for more granular measures of location, such as block-group-time fixed effects in columns 4 through 6, this premium drops and eventually becomes a discount.

Most importantly, looking at the interaction between post-disclosure and flood risk, we see that homes with extreme flood risk drop in sale value following the release of First Street data. The effect is statistically significant at the 1% level for all specifications with location controls. In our most stringent specification (column 5), we find that homes labeled with extreme flood risk dropped roughly 1% in value following the release of First Street data. Overall, while homes in the extreme category still enjoy a price premium compared to other homes, this premium appears to have diminished significantly once disclosure made the flood risk of these properties more salient. There is no significant price discount for homes that have risk below severe.

3.1.1 Heterogeneity across FEMA Zones and Geographic Regions

In Table 4, we further test whether flood risk is priced more strongly outside of FEMA floodplains. This is important for two reasons. First, FEMA floodplain maps were available for a long time prior to First Street's disclosure. As a result, homes in these floodzones were already known to be highly risky and First Street is less likely to add novel information. Second, most properties in a FEMA floodplain must purchase subsidized flood insurance if they wish to get a mortgage. Thus, prices may not react as strongly if buyers hold insurance and expect insurance to cover most flood-related damages. Outside of FEMA floodplains, however, flood insurance is only offered by private companies, and the premiums are generally so expensive that there is little demand for them.

Consistent with our hypothesis, Table 4 shows that there is no significant price decline for extremely risky homes in FEMA floodplains (column 2), while the decline is even a little stronger for homes outside FEMA floodplains (column 3). Generally, evidence is consistent with the finding that First Street's Flood Factor introduced novel information outside of FEMA floodzones, and this novel information produced a price drop of about 1% for homes with extreme (ie above severe) risk.

More generally, in Table 5, we test whether prices are more responsive in certain geographic regions of the United States. To do this, we split our states into four main regions, as specified by the U.S. Census Bureau. They include the Northeast (CT, ME, MA, NH, RI, VT, NJ, NY, PA), the Midwest (IL, IN, MI, OH, WI, IA, KS, MN, MO, NE, ND, SD), the South (DE, FL, GA, MD, NC, SC, VA, WV, AL, KY, MS, TN, AR, LA, OK, TX, DC), and the West (AZ, CO, ID, MT, NV, NM, UT, WY, AK, CA, HI, OR, WA). Column 1 replicates the results for the full sample, and columns 2-5 show the results for the four regions, left to right. We see that there is almost no observable price decline in

the Northeast or West Coast. This is somewhat surprising since New Jersey (in the Northeast) and California (in the West) are states that are also known to have significant flood risks. Perhaps not unsurprisingly, the South (which includes three of the most flood-prone states: Florida, Louisiana, and Texas) has the strongest and largest price impact of 1.5%. Interestingly, the Midwest, which has fewer states known for flooding, has nearly identical and strong price decline of roughly 1.3%.

Overall, both of these tables illustrate that the price impact of flood disclosure is nuanced and vary greatly across the United States. We see that while there is no effect inside FEMA floodplains or in the Northeastern part of the United States; we find strong and significant effects in other regions, especially the South as well as the Midwest.

3.1.2 Is the Estimated DID Price Drop Actuarily Fair?

Given an average home sale price of $382,850 in our data (see Table 1), the observed 1% drop from severely to extremely risky homes in the First Street Model represents a $3,829 price decline. To put this magnitude into context, we utilize First Street's data on expected annual flood costs, which are estimated for each property in our dataset based on the type of expected flooding and historical cost estimates from United States Army Corps of Engineers (USACE). After factoring a building's characteristics (eg number of stories, presence of basement, etc), value of building, value of land, and expected depth of flooding, the USACE data provides an estimate of the amount of damage expected, based on historical records from past, realized insurance claims.

Using First Street's proprietary cost estimates, we find that the average annualized flood-related costs of owning a home are $2,934.00 and $7,434.50 for risk ratings of 8 and 9 in our data, respectively. A back-of-envelope calculation assuming a 5% discount rate and staying in the house for 10 years implies that these costs have net present values (NPVs) of $22,655.57 and $57,407.24, respectively. Taking a difference between these two NPVs suggests that a reasonable estimate of the difference in value (ie increased cost) between owning a home with a risk rating of 8 versus 9 is $34,752.

Overall, relative to the estimated cost difference of $34,752, the observed price decline of $3,829 is an order of magnitude smaller. Thus, while equilibrium prices reflect a change in perceived risk, they do not appear to fully account for a reasonable estimate of future costs. It is important to note that while First Street's cost estimates are not provided directly or freely to the consumer, a homebuyer can click on the risk profile of any home on Redfin, Realtor.com, or Zillow, and they can request a free 7-day trial providing access to this detailed cost data for an unlimited number of homes. The fact that the price decline does not reflect these expected costs suggests that homebuyers seldom click through to this detailed information, they have trouble discounting future values, or they simply do not internalize the expected costs. Although the presence of flood insurance could alleviate costs, this is unlikely to explain the disparity, because in Section 3.1.1, we find that the price drop is especially

strong and similar in magnitude for homes outside 100-year FEMA floodplains. For these homes, there is no subsidized, public flood insurance market, and private flood insurance is both rare and often overpriced. Yet, we continue to find that equilibrium price declines do not appear to be close to actuarial costs.

3.1.3 Robustness: Pre-trend Analysis

So far, we have found that following First Street's initial flood risk disclosure in August 2020, home prices significantly dropped about 1% for the riskiest homes. However, one may be worried that this price drop is not due to disclosure but rather time trends in climate awareness that coincide in time with the First Street disclosure. To address this concern, we conduct a robustness test by dynamically plotting the DID coefficient on the dummy for extreme flood risk properties from Eq 3.1 year-by-year in Figure 7. To do this pre-trend analysis, we also extend our time sample back several years to 2013. Looking at Figure 7, we see that the coefficient on "extreme" (ie treated) trended down a little in 2017-2018 and rose again in 2019, but in general, it was stable before the release of First Street data. However, immediately starting in the year after the first disclosure (2020) it significantly drops lower than ever before and stays there for the next three years. Overall, we do not simply observe a slow-moving time trend. Thus, it is most likely that the observed price effect is, in fact, due to novel disclosure. To further show that there are no other omitted factors that confound our results, we will next turn to an RD design in Section 3.2.

3.2 RD Estimator

While the DID regression utilizes our full sample and has the most statistical power, it suffers from large endogeneity concerns. For instance, between our pre- and post- period, several hurricanes drew national attention to flooding and increased the salience of flood risk in homes more broadly. As a result, homes with flood risk, which are naturally correlated with First Street's Flood Factor, may drop in price simply due to the increasing salience of climate risk. While the pretrend analysis and controlling for existing FEMA information ameliorate some of these concerns, they may not perfectly capture how homebuyers' perception of climate risk is changing over time. If so, then our DID estimates may still have little to do with First Street's flood disclosure, and our findings would be biased.

To address the identification concerns above, we next use a regression-discontinuity (RD) design. First, we recreate a continuous measure of homes' flood risk called "expected depth" (see Figure 1) that is monotonically mapped into the discrete First Street Flood Factor using a set of empirically observable cut-offs. Then, using a RD analysis, we compare homes just above and just below the empirical cutoff value for a given Flood Factor number. In doing so, we assume that homes right around the cutoff are otherwise very similar and only differ depending on their assigned Flood Factor. In particular, we don't believe that the potential buyers of these homes suddenly have different beliefs

about climate risk at the cutoff. Any observed price changes at the cut-off can then be reasonably assumed to be driven by the Flood Score. If we expect consumers to discount homes because they have a higher Flood Score, then we would expect to see a price jump downwards right at the cutoff.

Figure 8 illustrates the RD by plotting a binscatter graph with expected depth on the x-axis and log price on the y-axis. Based on our DiD findings in Section 3.1, we restrict our sample to just homes with scores of 8 (labeled as severe) and 9 (labeled as extreme), where we previously found the strongest treatment effects. Properties with a flood score of 8 are shown in blue while properties with a flood score of 9 are shown in red. We separately show these findings in the pre-period on the left and in the post-period on the right. We control for location, time, and basic hedonics, by residualizing log sale prices to block-group fixed effects and hedonic controls. Furthermore, each dot represents the difference in price between the post-disclosure period and the pre-disclosure period. [6]

Importantly, in our DID analyses, we saw that the price effect only existed for homes outside of FEMA floodzones. This not only allows the First Street data to provide novel flood information, but it also makes sure that observed price effects are not confounded by the expected payoffs from subsidized flood insurance. In our RD analysis, we further restrict the sample to non-FEMA only. In addition, we test whether certain types of flood risk are priced more than others. In the First Street data, the main flood types in our time sample are flooding from rain (ie pluvial) and flooding from exposure to the coast (ie fluvial). We hypothesize that since coastal flooding is both potentially more costly and more salient, it would have stronger price effects.

Figure 8 plots a binscatter of the change in sale prices (after disclosure minus before disclosure) around the cutoff point for severely (shown in blue) versus extremely (shown in red) as a function of their underlying, continuous flood risk. Panel A shows the full sample, and following First Street's Flood Factor release, there is a small jump downwards. Next, Panel B shows the coastal properties only, and we see there is a small jump down in price right after the cutoff point.

In order to calculate the magnitude of the RD jump shown in Figure 8, we estimate the following RD regression fitted (with up to a polynomial of order 3) to our restricted sample:

$$\text{Ln(Price)}_{ijt} = \mu_j + \beta_1 \text{I(extreme)} + \sum_{m=1}^{3} \rho_m \text{exp depth}_i^m + \sum_{n=1}^{3} \delta_n \text{exp depth}_i^n \cdot \text{I(extreme)}_i + + \vec{\beta_2} \vec{X_{ijt}} + \varepsilon_{ijt} \tag{3.2}$$

where each observation is a sales transaction and i, j, and t represent property, location, and time

[6] Ideally, we would not require any controls and rely solely on the RD design. While we also found effects without any controls, the estimates were quite noisy, and significant jumps right at the cutoff were harder to identify. Intuitively, even properties with similar flood risk can vary significantly in price depending on their location and characteristics such as size. By residualizing on the full sample first, we can reduce a lot of the noise and make the RD less fuzzy.

indices, respectively. μ_j represents block-group fixed effects and $\vec{X_{ijt}}$ represents a vector of hedonic controls, including the building age, number of bedrooms, number of bathrooms, lot size, and living area. exp depth$_i$ is our continuous measure of flooding risk, and I(extreme) captures the discontinuous jump. It is set equal to one if a property fell into the extreme category (ie has a flood score of 9) and is zero otherwise (ie has a flood score of 8). If we expect consumers to discount properties with higher Flood Factors, then we would expect β_1 to be significantly less than 0.

Table 6 shows the results from estimating Eq 4.1. The columns correspond to estimation using a linear auto-selected band, a polynomial of order 2, and a polynomial of order 3, respectively. Consistent with Figure 8, we find a small but significant price drop of 2.5% (column 2) to 3.7% (column 1) post disclosure.

Finally, Table 7 repeats the above analysis but estimates it over several key subsamples. For convenience, we show the main specification using the full sample in column 1. Next, column 2 repeats the analysis but for non-FEMA properties only. Confirming that our results are not driven by areas with pre-existing information and where flood insurance is prevalent, we see that the RD coefficient is similarly strong and significant for the non-FEMA subsample.

Next, within the non-FEMA subsample, we further test whether properties exposed to coastal flooding (eg fluvial flooding) have a stronger price impact. Indeed, we find that properties which are both non-FEMA and subject to coastal flooding risk experience a large price drop of roughly 17%, visually depicted in Panel A of Figure 9. This suggests that the release of First Street data has an especially strong price effect in areas where flood risk was already salient, rather than adding new pricing information to inland areas that were traditionally considered less risky. This finding largely aligns with several behavioral papers, which have found that flooding is only priced in areas where individuals believe in the flood risk (Baldauf et al., 2020) or that individuals largely respond to disaster risk only when it is salient (Dessaint and Matray, 2017; Gallagher, 2014).

3.2.1 Is the Estimated RD Price Drop Actuarily Fair?

Similar to our analyses in Section 3.1.2, we next benchmark the observed 3.7% price drop for the full sample and a 17% price drop for coastal properties in the non-FEMA zone. We again start from average home sale price of $382,850 (see Table 1). The observed 3.7% (17%) drop from severely to extremely risky homes in the First Street Model represents a net decline in value of $14,165.45 ($65,084). Based on First Street's cost model, the actuarial decline in value, for all properties, should be about $34,752—the observed price drop accounts for just a little under 41% of the actuarial value. On the other hand, the price drop for coastal properties is almost double the actuarial value. One reason why this may be the case is that the advent of coastal flooding is more likely to wipe out the entire value of a home, especially when compared to flooding caused by rainfall, and thus, the expected

costs are higher.

3.2.2 Robustness: Covariate Balance Test

In our RD analyses, the drop in log price is sharp and observed very close to the cutoff point, so it is unlikely to be driven by other factors such as an increasing salience of climate risk over our time sample. As a robustness check, however, Figure 10 tests whether other key features of houses sold are unbalanced across the cutoff point. To run this check, we only residualize our data using blockgroup fixed effects, and then we plot expected depth (x-axis) against each one of our hedonic variables (y-axis). Reassuringly, around the cutoff, we do not observe any other sudden changes in size (ie lot size or living square foot), building age, number of bedrooms, or number of bathrooms. Thus, the price difference estimated by the RD regressions are unlikely to be driven by a confounding feature of the house itself.

3.3 Discussion of Price Effect and Salience

Our DID and RD findings differ from the price findings in Fairweather et al. (2024), where they found price effects (of roughly 1.3-1.7%) for only properties that were not on the waterfront or in a FEMA flood zone. One potential explanation is that they are looking across the full spectrum of properties (ranging from minimal to extreme risk), and we are only focusing on properties that already have severe or extreme risk. As a result, our price effect is higher simply because the unconditional risk is higher; and we may be able to discern more of an effect for coastal properties because they are more prevalent in our sample. Another possibility is that, in the experiment run by Fairweather et al. (2024), the Flood Factor was being shown for the first time and only to select users. Thus, homebuyers in less flood-prone areas, who are not used to thinking about flood risk, were responding to the novelty of this information that was released for the first time. However, in our post-period, the Flood Factor has been circulating for a year. Thus, the novelty of this information should have worn off and it is possible that flood risk has become less salient to these homebuyers.

On the other hand, our price findings are very much in line with existing literature that highlights the importance of saliency when it comes to how consumers process information on flood risk. For example, existing work has shown that flood risk is only priced when individuals believe in the flood risk (Baldauf et al., 2020) or that individuals respond to disaster risk only when it is recently salient (Dessaint and Matray, 2017; Gallagher, 2014).

4 Distributional Effects

In this Section, we start to unpack the equilibrium effect of disclosure on *who* holds the riskiest properties following disclosure. To do this, we use the most plausibly exogenous RD regressions from

Section 3.2, but we replace the dependent variable (previously log price) with home buyer characteristics from HMDA:

$$\text{Demographics}_{ijt} = \mu_j + \beta_1 \text{I(extreme)} + \sum_{m=1}^{3} \rho_m \text{exp depth}_i^m + \sum_{n=1}^{3} \delta_n \text{exp depth}_i^n \cdot \text{I(extreme)}_i + + \vec{\beta_2} \vec{X_{ijt}} + \varepsilon_{ijt} \tag{4.1}$$

where each observation is one sales transaction and i, j, and t represent property, location, and time indices respectively. μ_j represents block-group fixed effects and $\vec{X_{ijt}}$ represents a vector of hedonic controls, including the building age, number of bedrooms, number of bathrooms, lot size, and living area.

The buyer demographics that we consider are: income, age, race, and dummy for FHA loan. Since our demographic information comes from the HMDA dataset, for this analysis, note that we have to further restrict our sample to only home purchases that required a mortgage.

First, in Table 8 we find that after disclosure, the most risky ("above severe") homes are being purchased by individuals with roughly 2.5% (column 2) to 4.6% (column 1) lower income.[7] This is notable because lower-income individuals are less likely to be able to bear the costs of a large climate event, and they are also less likely to buy insurance to help cover these tail events. This is further exacerbated by the fact that the price discount for holding a risky home does not seem to be actuarially fair, based on First Street's cost models. In equilibrium, this suggests that disclosing flood risks directly to consumers may have climate justice implications, because the heavy costs of climate change may disproportionally fall on the shoulders of individuals who can least bear it. This discontinuity is also visually shown in Panel b of Figure 8.

Furthermore, Table 9 shows the result broken down by key subsamples. Column 2 verifies that the shift in income of buyers is still observed in non-FEMA floodzones. Within non-FEMA properties, while the coefficient of interest is insignificant in columns 3 and 4, we still see that the magnitude in column 3 (8.7%) is much larger than column 4 (3.3%). Thus, while we lose sample size and thus power in the subsample analysis, the evidence is consistent with the hypothesis that the redistribution effect is strongest in non-FEMA homes with salient (ie coastal) sources of flooding.

Finally, in Table 10 we also examine FHA as an outcome and find that after disclosure, the most risky ("above severe") homes are purchased by individuals who are 1.5% (column 2) to 2.8% (column 3) more likely to have a FHA loan. This regression is visually depicted in Figure 8 Panel c. Since FHA loans are typically given to first-time and low-credit borrowers, this is further evidence that the

[7] We also test the effects of disclosure on age and race, but while there is some evidence that average age declined, we fail to find consistent effects for these two outcomes. We have omitted these findings in the interest of space, but they can be shared upon request.

expected cost of flooding and climate change may shift increasingly to the more financially constrained. Table 10 further tests the finding across different subsamples. While the coefficient magnitude is similar in size for non-FEMA properties (column 2), we see that it is no longer significant. This is likely due to the reduced sample size. Again, within non-FEMA properties, we see that the magnitude of the effect is much stronger for coastal properties (2.6%, column 3) versus non-coastal properties (1.1%, column 4).

Overall, our RD regressions using HMDA outcomes show a consistent story—following flood disclosure, the most risky homes are increasingly held by lower-income and low-credit borrowers. This effect exists even outside of pre-existing FEMA flood zones, and it is strongest for homes exposed to coastal flooding.

5 Conclusion

Flood risk is one of the largest risks that homeowners face today, and yet, it remains unclear whether consumers are aware of and incorporate information on flood risk when they are choosing to buy a house. In this paper, we take advantage of a novel information release (ie the Flood Factor) by First Street on several major search platforms as a natural experiment to test how homebuyers respond to flood disclosure across the United States.

Following disclosure, preliminary findings suggest that homebuyers discount homes with flood risk by 4% on average and up to 17% for coastal properties outside of FEMA floodsones. Notably, this discount is largest for homes with the highest (ie "above severe" or "extreme") flood risk. Interestingly, we also find that flood information affects the demographics of homebuyers in equilibrium. Following disclosure, we find that homebuyers of the riskiest homes are lower income and more likely to hold an FHA loan. This suggests the costs of climate change may be borne disproportionately by the more financially constrained.

Going forward, more work needs to be done in order to understand whether the incorporation of flood risk depends on buyers' demographics, such as age or income level. If so, then flood disclosure would also change the demographics of homeowners in flood-prone areas and affect who ultimately holds flood risk in equilibrium. Our findings have potential policy implications. As technology improves and new data on climate change becomes more readily available, our findings may help predict the equilibrium impact of new flood data on consumers of different types as well as consumers living in different regions of the United States.

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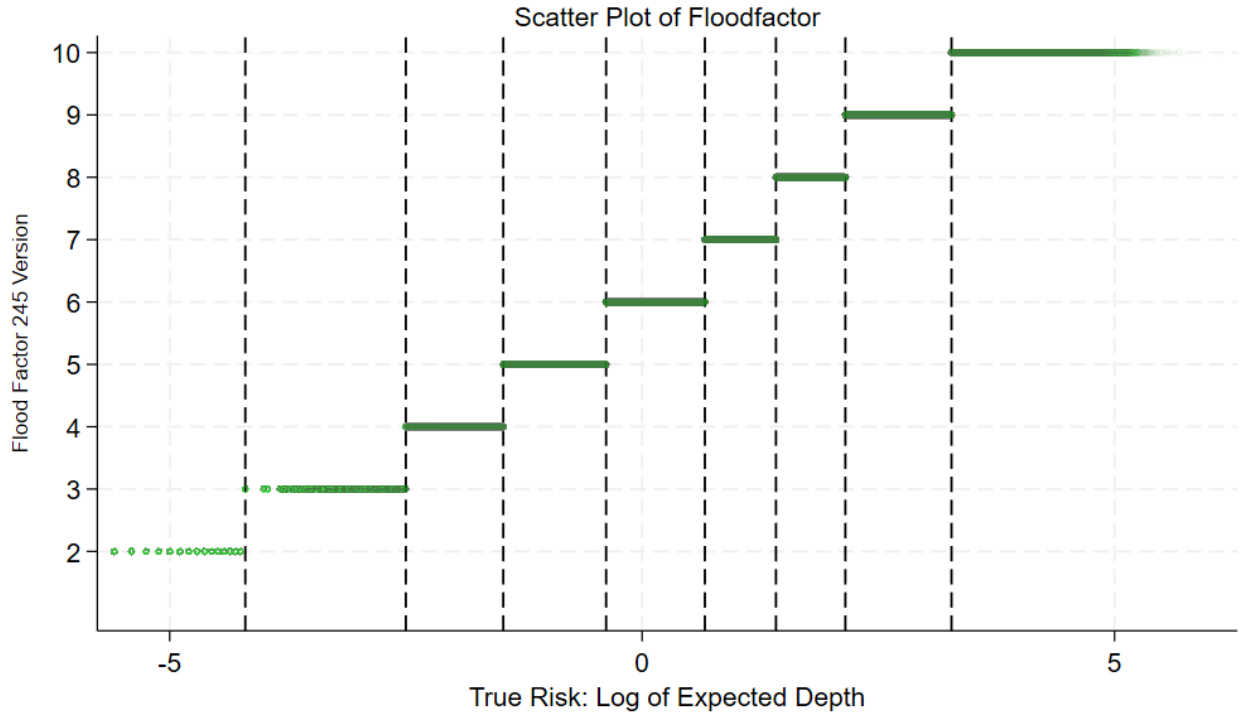
Figures

1. Background on First Street Flood Factor

(A) Mapping of Continuous Risk to Discrete Flood Scores

Figure 1: Cutoff Chart of Flood Factor

In order to estimate a regression discontinuity analysis, we back out the undisclosed running variable (shown on x-axis) that is then mapped into the discrete Flood Factor categories publicly disclosed by First Street (shown on y-axis). The running variable is a model-based proxy for continuous flood risk, estimated as the expected flood depth over the next 100 years.



(B) Disclosure of First Street Flood Factor

Figure 2: Disclosure of First Street Flood Factor on Housing Platforms

This figure shows the main timeline of when First Street flood scores were updated, as well as when they rolled out onto the Realtor.com, Redfin.com, and Zillow.com platforms. The dotted vertical lines and grey arrows further show the pre-period and post-period chosen for our empirical analyses.

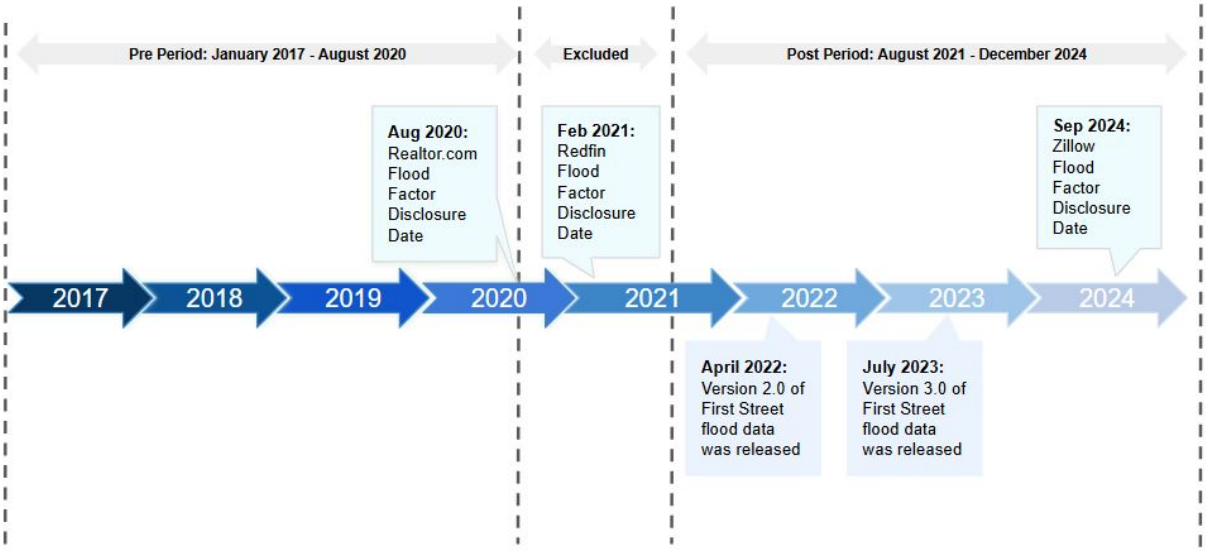
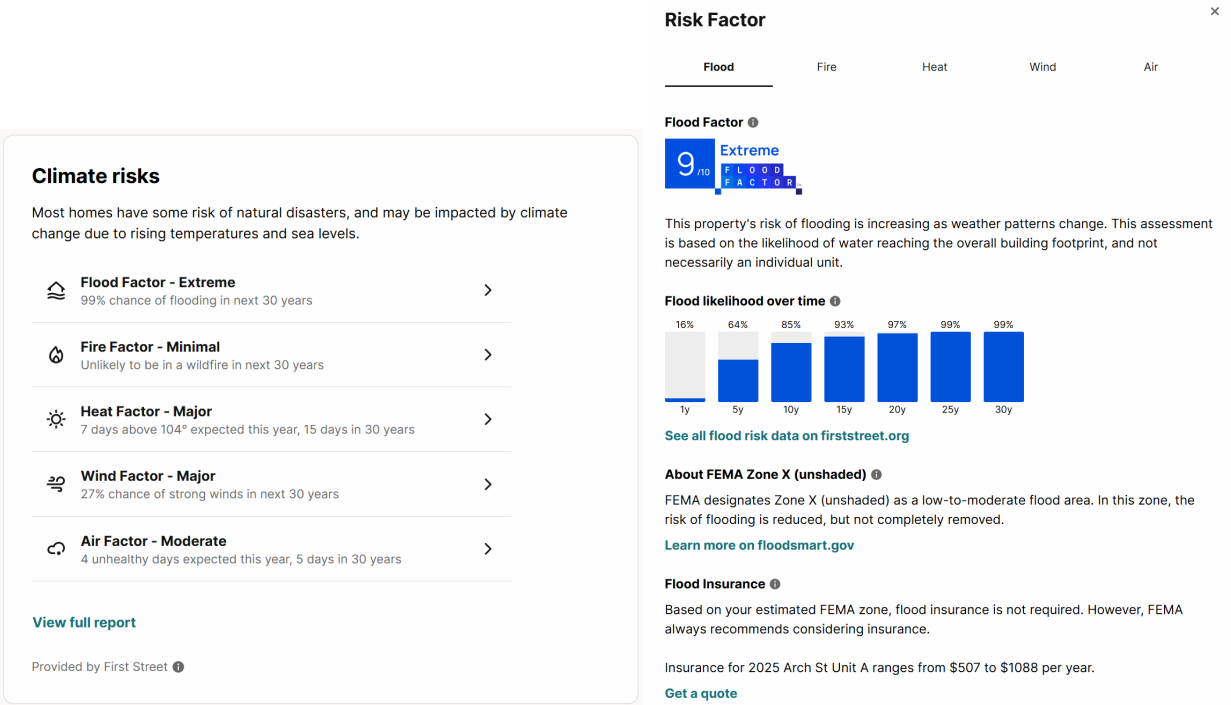


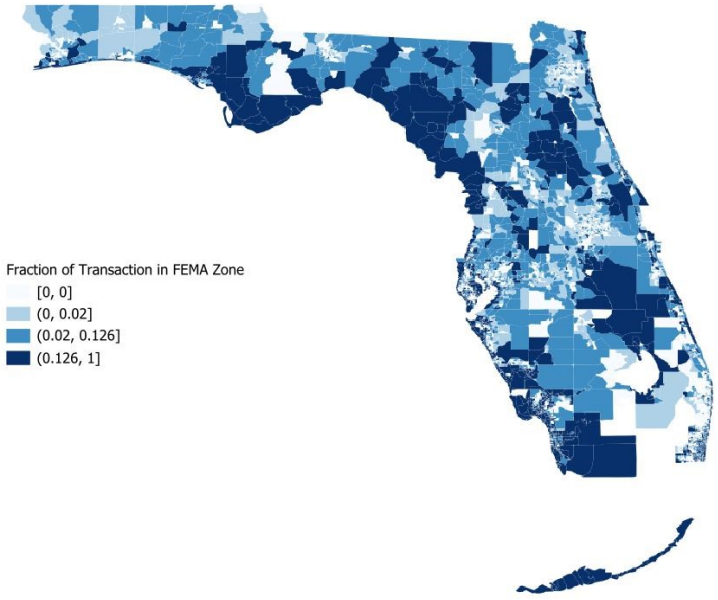
Figure 3: Example of Flood Score as Shown on Redfin



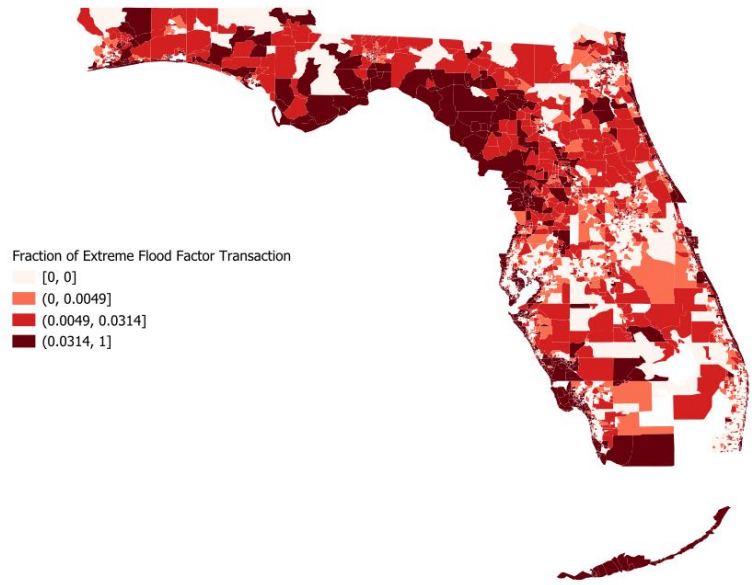
(C) Geographic Maps

Figure 4: Census Tract level Map of Flood-prone Properties in Florida

These maps display a census tract-level shapefile for Florida, where each polygon represents a tract. Panel a shows the fraction of transactions that are in a designated FEMA Flood Zone for each tract, while Panel b shows the fraction of transactions that are rated as having"extreme" flood risk by First Street. The shading reflects these fractions, with a darker shade representing a larger fraction. We limit the sample of house transactions to the pre-period (January 2017–August 2020) and the post-period (August 2021–December 2024). Our data comes from First Street and Corelogic, and our data sample covers the years 2017 to 2024.



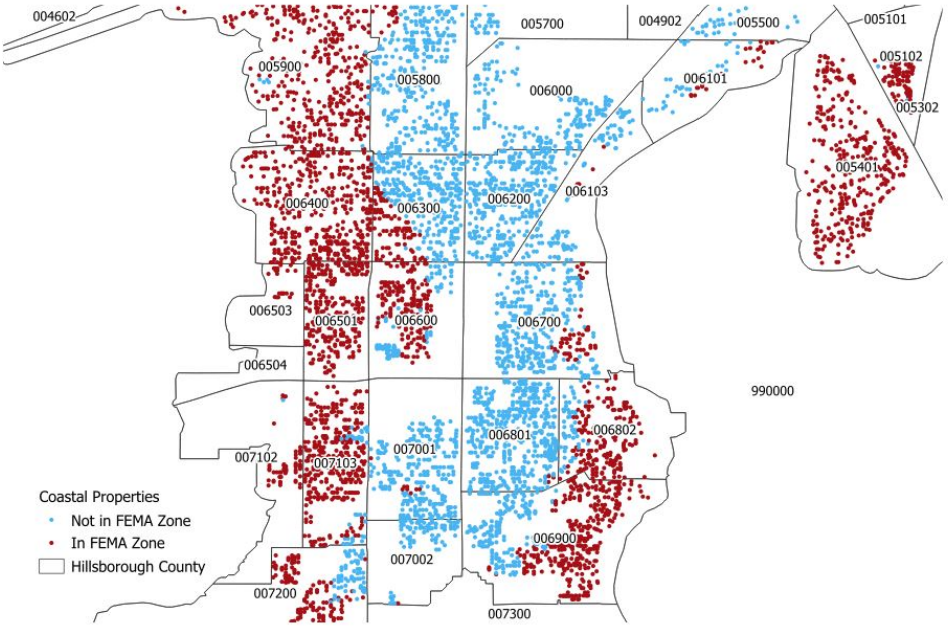
(a) FEMA Flood Zone



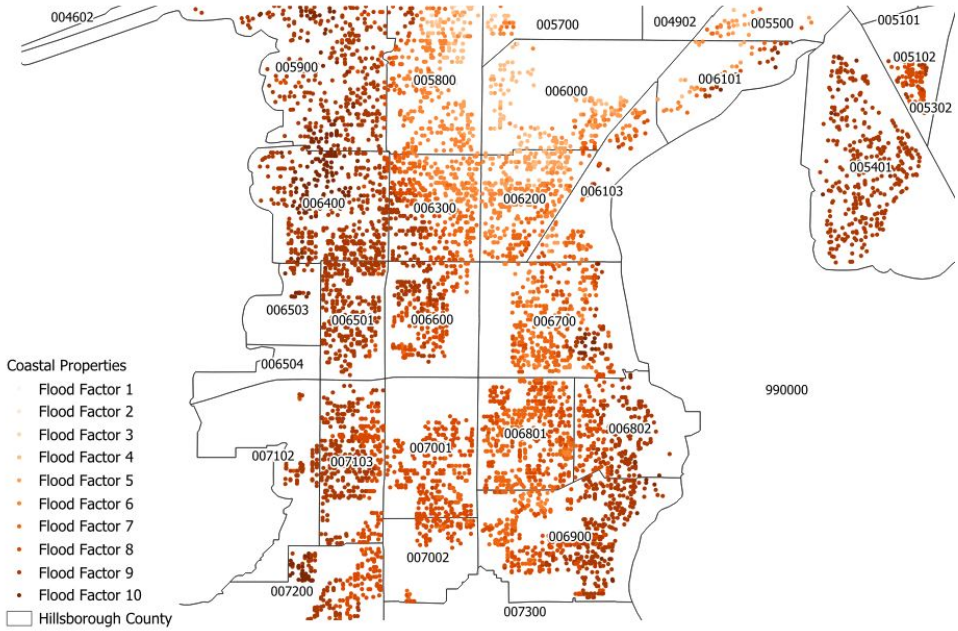
(b) Extreme Flood Risk (First Street)

Figure 5: Map of Properties Based on Flood Risk in Hillsborough County

These maps display census tract-level shapefile for a zoomed in selection from Hillsborough County, Florida. Panel a shows all properties that are (not) in a designated FEMA Flood Zone as a red (blue) dot, while Panel b shows the properties as dots colored based on the severity of their First Street Flood Factor. We limit the sample of house transactions to the pre-period (January 2017–August 2020) and the post-period (August 2021–December 2024). Our data comes from First Street and Corelogic, and our data sample covers the years 2017 to 2024.



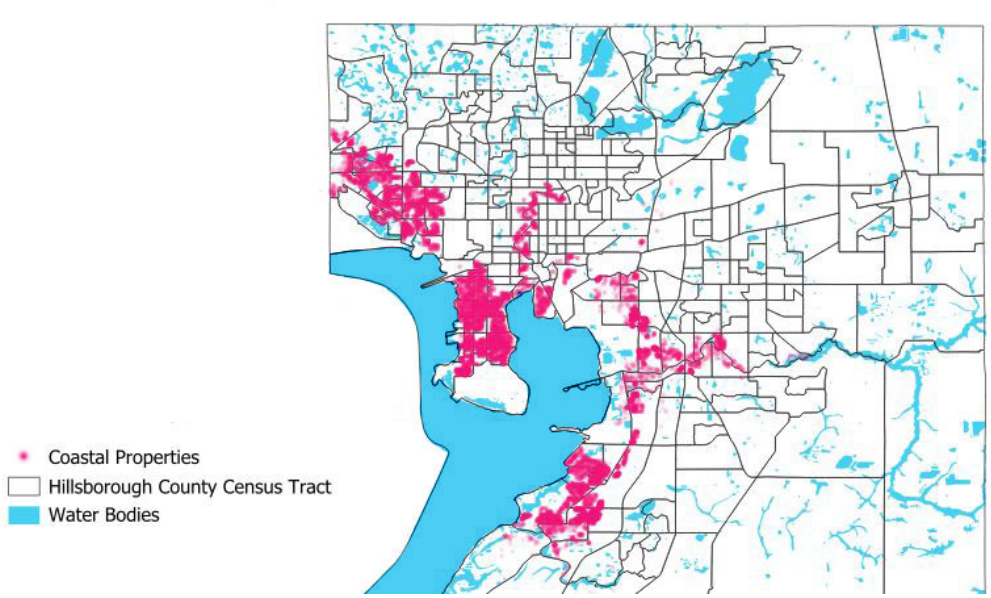
(a) FEMA Flood Zone



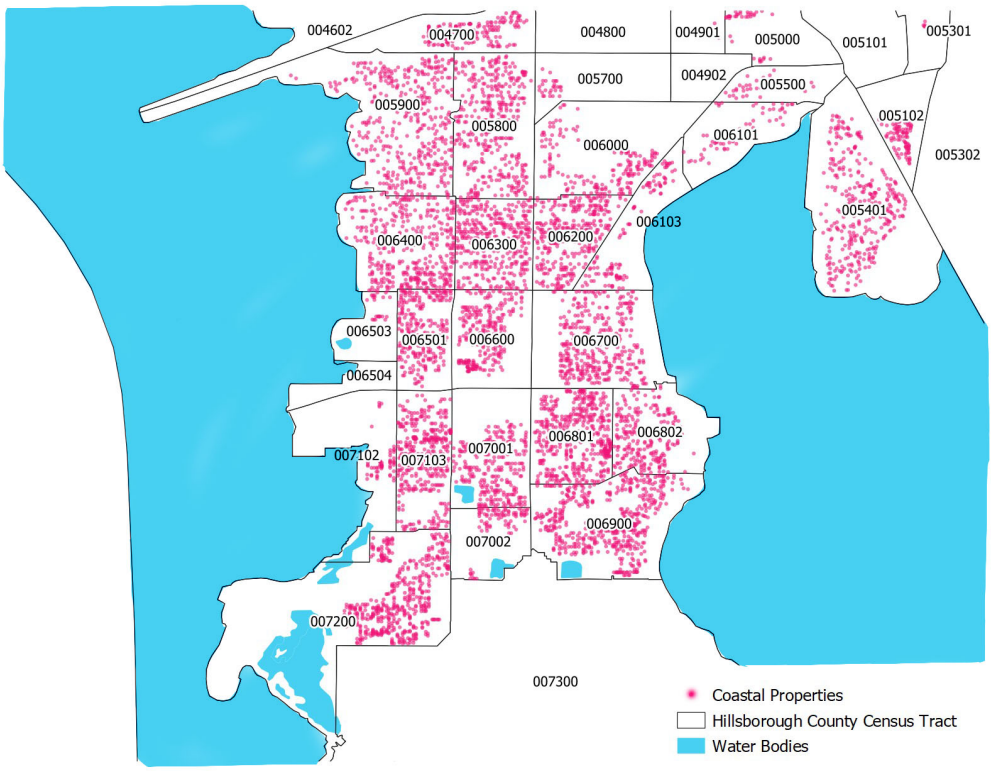
(b) Extreme Flood Risk (First Street)

Figure 6: Map of Coastal Properties and Bodies of Water for Hillsborough County

These maps display the location of individual coastal properties in Lee County, Florida (panel a) and a select zoomed-in subsample of Hillsborough County, Florida (panel b). Each dot represents a property that is designated as "Coastal" by First Street, and we also overlay local bodies of water in blue. We limit the sample of house transactions to the pre-period (January 2017–August 2020) and the post-period (August 2021–December 2024). Our data comes from First Street and Corelogic, and our data sample covers the years 2017 to 2024.



(a) Hillsborough County, Florida

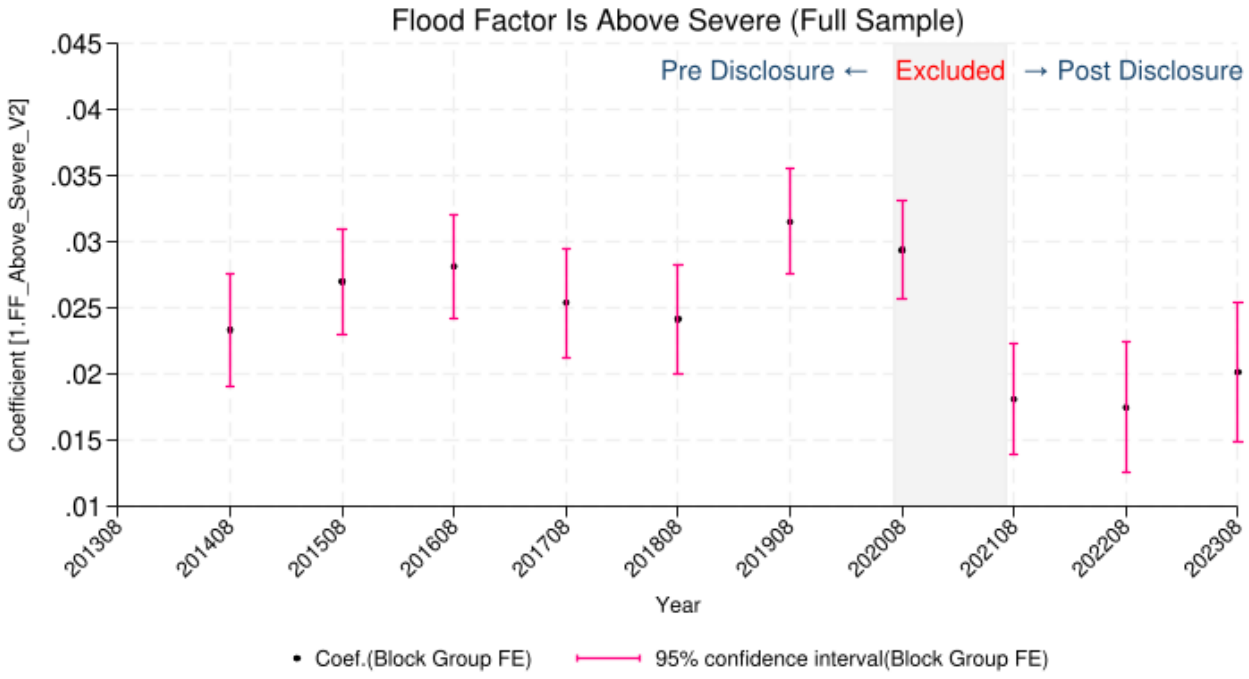


(b) Select Subsample of Hillsborough County

2. Difference in Difference Regression

Figure 7: DiD: Pretend Test

Each point on the graph represents the coefficient β_1 and associated standard errors from the following difference-in-difference regression:
$\ln(\mathbf{SalePrice}_i) = \alpha + \beta_1 \mathbf{FloodCategory}_i + \beta_2 \mathbf{Treat}_i + \beta_3 \mathbf{HedonicControls}_i + \epsilon_i$. Each point corresponds to a sample that starts at the date shown on the x-axis and ends one year later. Note that January 2014-July 2014 and August 2024-December 2024 are included in our full sample but omitted from this pretend analysis, since they do not consist of a full year. Our data comes from First Street and Corelogic, and our data sample for this analysis covers the years 2013 to 2024.

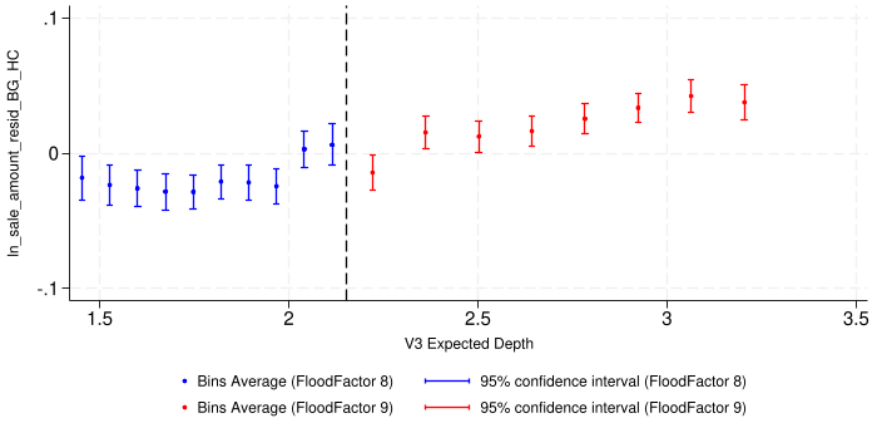


3. Regression Discontinuity

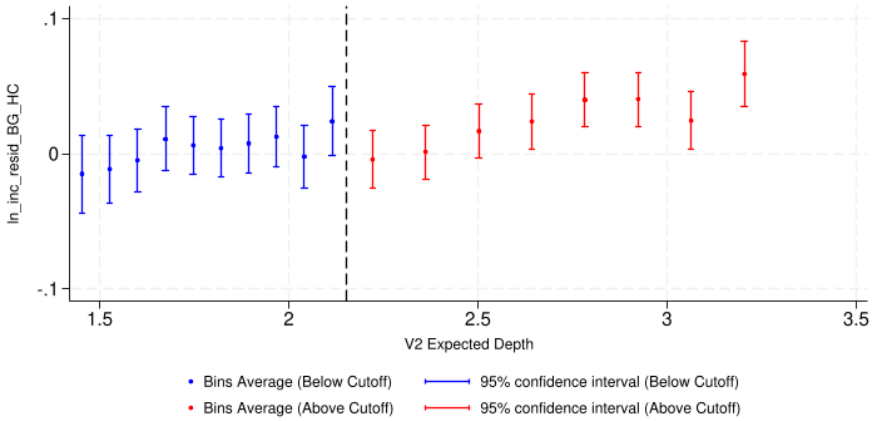
(A) Visualizing RD Regressions

Figure 8: RD Regressions for Full Sample

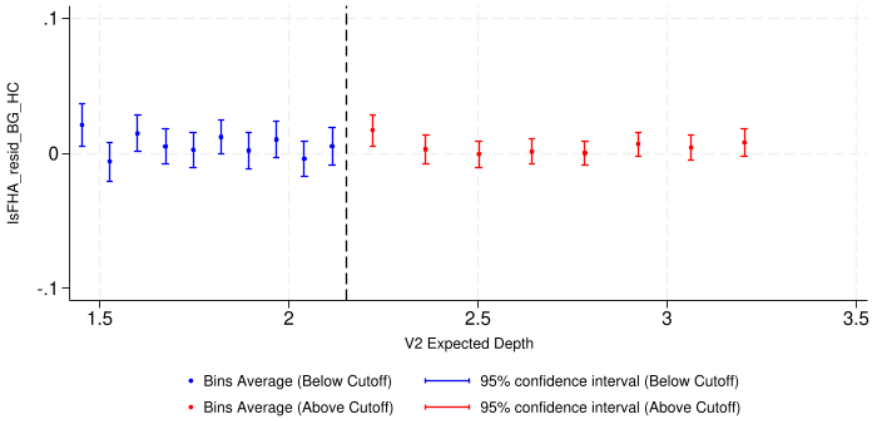
The figures below visually show RD Analysis using the full data sample, explaining: log price (Panel a), log applicant income (Panel b), and a dummy for whether the applicant is FHA (Panel c). To control for omitted variable bias, the LHS variable is residualized with block-group fixed effects and basic hedonics. Each dot represents the difference between the average log home prices in the post-period minus the average log home prices in the pre-period. The point on the x-axis represents the midpoint of each equal-width bin, and the bars represent the standard errors. Our data comes from First Street, Corelogic, and HMDA, and our data sample covers the years 2017 to 2024.



(a) RD for Log Home Price



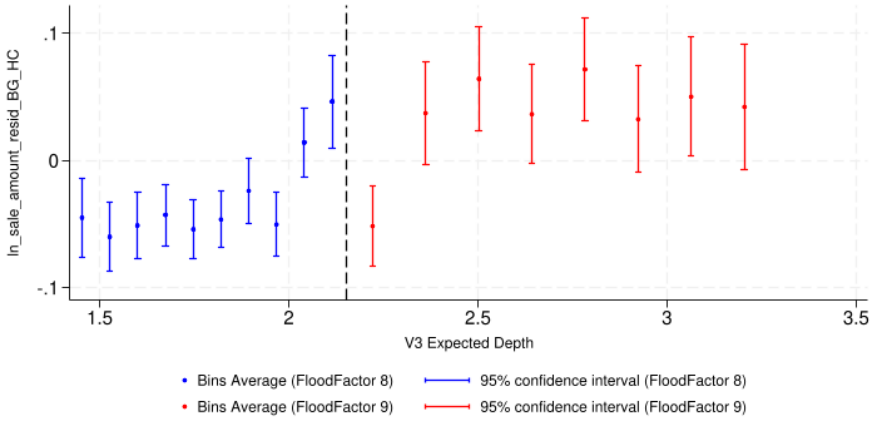
(b) RD for Log Applicant Income



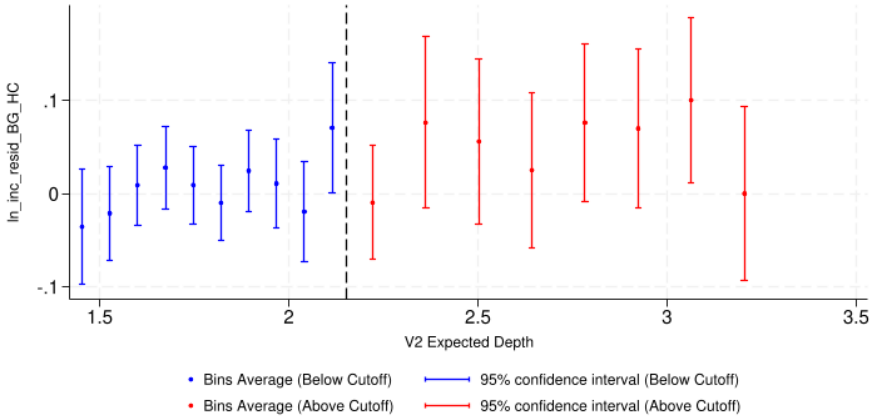
(c) RD for Is FHA Dummy

Figure 9: RD Regressions for *Non-FEMA and Coastal Properties Only*

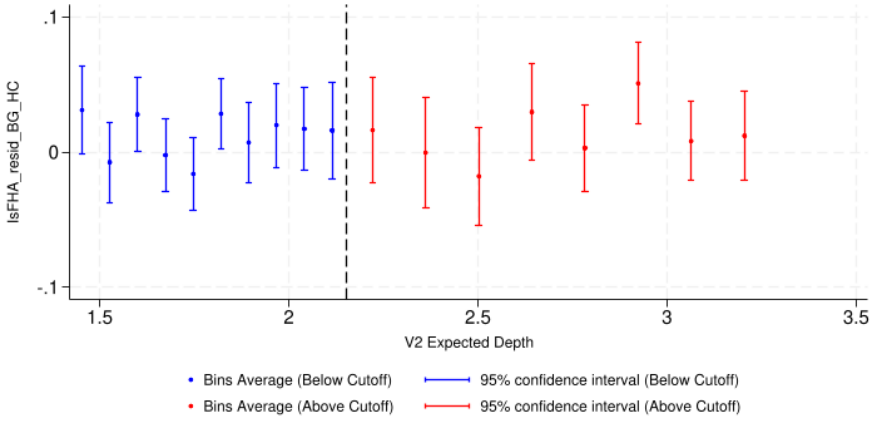
The figures below visually show RD Analysis using a subsample of properties that are *not already in a FEMA floodplain and are also exposed to coastal flooding risk based on First Street's flood model.* Otherwise similar to Figure 8, Panels a through c show RD plots explaining: log price (Panel a), log applicant income (Panel b), and a dummy for whether the applicant is FHA (Panel c). To control for omitted variable bias, the LHS variable is residualized with block-group fixed effects and basic hedonics. Each dot represents the difference between the average log home prices in the post-period minus the average log home prices in the pre-period. The point on the x-axis represents the midpoint of each equal-width bin, and the bars represent the standard errors. Our data comes from First Street, Corelogic, and HMDA, and our data sample covers the years 2017 to 2024.



(a) RD for Log Income, Non-FEMA and Coastal Only



(b) RD for Log Income, Non-FEMA and Coastal Only

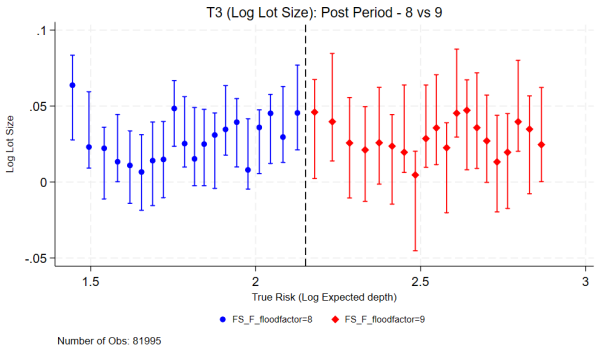


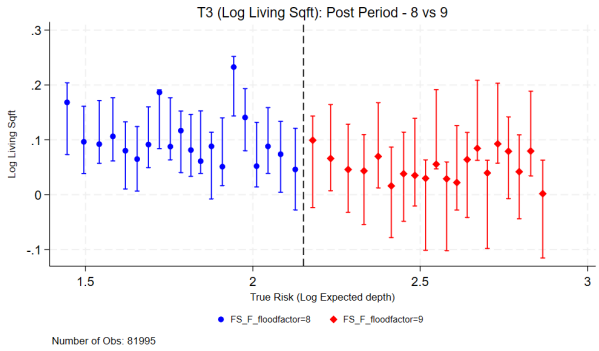
(c) RD for Non-FHA, Non-FEMA and Coastal Only

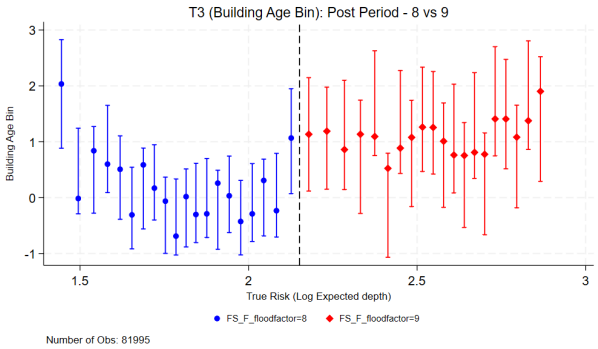
(B) RD Balance Check: Hedonic Characteristics

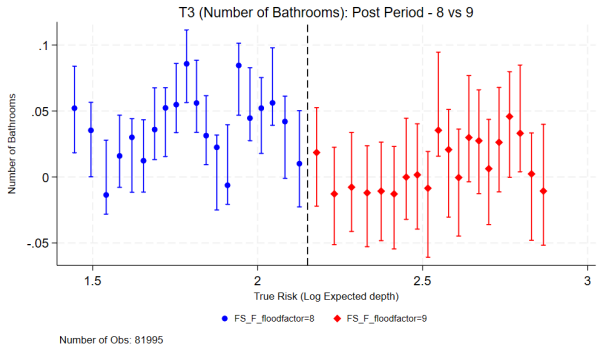
Figure 10: Covariate-balance Test: 8 vs 9

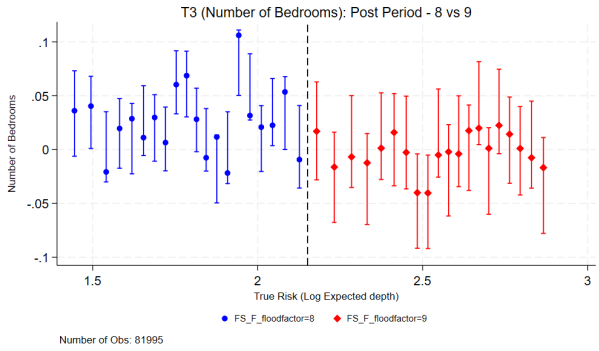
The figures show that basic housing hedonics are balanced across the regression discontinuity. From left to right, top to bottom, they are: total lot size, living square foot, age of building, total number of bathrooms, and total number of bedrooms. Our data comes from First Street and Corelogic, and our data sample covers the years 2017 to 2024.











Tables

Part 1. Summary Statistics

Table 1: Summary Statistics

This table summarizes the key variables used in our DID and RD Regressions. Flood risk data is sourced from First Street, while housing price and property characteristics data come from CoreLogic. Our demographic variables come from HMDA. Our data sample covers the years 2017 to 2024.

	Count	Mean	SD	p25	p50	p75
CoreLogic:						
Sale Price ($k)	22,223,965	382.85	356.86	179.00	289.00	450.00
Living Area (Sqft)	22,223,965	1,771.05	995.46	1,220.00	1,672.00	2,279.00
Lot Size (Sqft)	22,223,965	20,112.04	37,533.46	6,300.00	9,375.00	16,117.00
Number of Bathrooms	22,223,965	1.95	1.23	1.00	2.00	3.00
Number of Bedrooms	22,223,965	2.25	1.67	0.00	3.00	3.00
Building Age	22,223,965	32.90	30.85	5.00	26.00	53.00
Sale Year	22,223,965	2,020.19	2.29	2,018.00	2,020.00	2,022.00
First Street:						
V3 Expected Depth (cm)	4,183,011	4.73	11.36	0.12	0.76	3.87
Flood Source include Coastal	22,223,965	0.05	0.21	0.00	0.00	0.00
Flood Source include Pluvial	22,223,965	0.13	0.34	0.00	0.00	0.00
HMDA Variables:						
Age Above 55	8,242,127	0.17	0.37	0.00	0.00	0.00
Applicant Race: NonWhite	8,242,127	0.39	0.49	0.00	0.00	1.00
Applicant income ($)	8,170,346	131,804.34	29,846.83	65,000.00	98,000.00	149,000.00
Loan Type: Is FHA	8,215,296	0.17	0.38	0.00	0.00	0.00

Table 2: Summary Statistics - Flood Factor

This table tabulates homes' First Street risk factor against whether they are classified as being in a 100-year floodplain by FEMA. Flood risk data is sourced from First Street, while FEMA and home sale data comes from CoreLogic. Our data sample covers the years 2017 to 2024.

First Street Flood Factor	First Street Risk Category	Count	Fraction	Fraction in FEMA Flood Zone
1	Minimal	17,723,700	84.02%	0.84%
2	Minor	201,321	0.95%	7.09%
3	Moderate	449,088	2.13%	6.80%
4	Moderate	346,910	1.64%	7.94%
5	Major	394,005	1.87%	8.88%
6	Major	679,577	3.22%	11.42%
7	Severe	381,554	1.81%	16.50%
8	Severe	400,459	1.90%	24.64%
9	Extreme	370,619	1.76%	44.97%
10	Extreme	147,334	0.70%	62.19%
Total		21,094,567	100 %	3.57%

Observations are at transaction level.

Part 2. Difference-in-Difference Analyses

Table 3: Full DiD Analysis of the Impact of Flood Risk on Sale Prices

This table presents cross-sectional regressions of the log of sale amount on FloodFactor, constructed from flood factor(1–10), across the pre-period (August 2018 to August 2020) and post-period (August 2021 to December 2024). FloodFactor groups properties into six categories: Minimal (1), Minor (2), Moderate (3-4), Major (5-6), Severe (7-8), and Extreme (9-10). Observations with sale prices below $50,000 and properties with more than one building are excluded, and sale prices are winsorized at the 99th percentile. All hedonic controls are winsorized at the 1st and 99th percentile. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Flood risk data is sourced from First Street, while housing price and property characteristics data come from CoreLogic, covering transactions from 2007 onward. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

	Dep. Variable: Log Sale Price					
	(1)	(2)	(3)	(4)	(5)	(6)
Risk is Above Severe × Post Disclosure	-0.00388	-0.0133***	-0.0122***	-0.0117***	-0.0111***	-0.00970***
	(-1.48)	(-6.43)	(-6.49)	(-6.28)	(-6.29)	(-5.48)
Risk is Above Major × Post Disclosure	0.00640***	-0.00176	-0.00107	-0.000728	-0.000582	-0.000103
	(2.93)	(-1.02)	(-0.71)	(-0.49)	(-0.42)	(-0.07)
Risk is Above Moderate × Post Disclosure	-0.00405*	-0.00265	0.000990	0.00121	0.00113	0.00133
	(-1.86)	(-1.56)	(0.69)	(0.86)	(0.85)	(1.00)
Risk is Above Minor × Post Disclosure	-0.0210***	-0.00373	-0.000284	-0.000798	-0.00140	-0.00130
	(-5.71)	(-1.30)	(-0.12)	(-0.35)	(-0.65)	(-0.60)
Risk is Above Minimal × Post Disclosure	0.0415***	0.00205	-0.00246	-0.00224	-0.00128	-0.00112
	(12.57)	(0.79)	(-1.12)	(-1.05)	(-0.64)	(-0.56)
Risk is Above Severe	0.0836***	0.115***	0.0325***	0.0247***	0.0280***	0.0260***
	(47.87)	(83.29)	(25.96)	(19.89)	(23.98)	(22.10)
Risk is Above Major	-0.00186	0.0599***	0.0110***	0.00483***	-0.000130	-0.000861
	(-1.30)	(52.72)	(11.20)	(5.00)	(-0.14)	(-0.95)
Risk is Above Moderate	0.0178***	0.0136***	-0.000421	0.000279	-0.00103	-0.00134
	(12.54)	(12.23)	(-0.45)	(0.30)	(-1.18)	(-1.55)
Risk is Above Minor	-0.00294	0.00104	-0.00572***	-0.00399***	-0.00400***	-0.00416***
	(-1.23)	(0.56)	(-3.69)	(-2.66)	(-2.84)	(-2.95)
Risk is Above Minimal	0.0361***	-0.0392***	-0.00619***	-0.00223	0.00196	0.00171
	(16.81)	(-23.20)	(-4.35)	(-1.61)	(1.51)	(1.31)
Obs	21,094,567	21,094,454	21,090,230	21,073,732	21,073,732	21,073,732
R2	0.0411	0.4185	0.6154	0.6539	0.6937	0.6938
R2-Adj	0.0411	0.4183	0.6127	0.6472	0.6878	0.6878
County-Period FE		✓				
Tract-Period FE			✓			
Block Group-Period FE				✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Flood Zone FE						✓
Hedonic Controls					✓	✓

Table 4: Subsample DiD Analysis of Sale Prices for FEMA vs non-FEMA Properties

This table presents cross-sectional regressions of the log of sale amount on FloodFactor, broken down by two main subsamples: properties that are in a FEMA-designated 100-year floodplain versus properties that are not in a FEMA-designated 100-year floodplain. Regression data is constructed from flood factor(1–10), across the pre-period (August 2018 to August 2020) and post-period (August 2021 to December 2024). FloodFactor groups properties into six categories: Minimal (1), Minor (2), Moderate (3-4), Major (5-6), Severe (7-8), and Extreme (9-10). Observations with sale prices below $50,000 and properties with more than one building are excluded, and sale prices are winsorized at the 99th percentile. All hedonic controls are winsorized at the 1st and 99th percentile. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Flood risk data is sourced from First Street, while housing price and property characteristics data come from CoreLogic, covering transactions from 2007 onward. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

	Dep. Variable: Log Sale Price		
Subsample:	All Properties	FEMA Only	Non-FEMA Only
	(1)	(2)	(3)
Risk is Above Severe × Post Disclosure	-0.0111***	-0.000359	-0.0148***
	(-6.29)	(-0.08)	(-6.97)
Risk is Above Major × Post Disclosure	-0.000582	0.00528	0.000101
	(-0.42)	(1.07)	(0.07)
Risk is Above Moderate × Post Disclosure	0.00113	0.00132	0.00141
	(0.85)	(0.23)	(1.02)
Risk is Above Minor × Post Disclosure	-0.00140	-0.00190	-0.000763
	(-0.65)	(-0.20)	(-0.34)
Risk is Above Minimal × Post Disclosure	-0.00128	-0.000943	-0.00148
	(-0.64)	(-0.10)	(-0.72)
Risk is Above Severe	0.0280***	0.0363***	0.0117***
	(23.98)	(12.58)	(8.37)
Risk is Above Major	-0.000130	-0.0256***	0.000422
	(-0.14)	(-7.82)	(0.43)
Risk is Above Moderate	-0.00103	-0.0134***	0.00000990
	(-1.18)	(-3.54)	(0.01)
Risk is Above Minor	-0.00400***	0.00494	-0.00435***
	(-2.84)	(0.77)	(-3.00)
Risk is Above Minimal	0.00196	-0.0108*	0.00384***
	(1.51)	(-1.74)	(2.86)
Obs	21,073,732	726,786	20,320,514
R2	0.6937	0.7240	0.6954
R2-Adj	0.6878	0.7030	0.6893
Block Group-Period FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Table 5: Geographic Variation across Different U.S. Regions

This table presents cross-sectional regressions of the log of sale amount on FloodFactor, broken down by four main regions of the United States as defined by the U.S. Census Bureau: the Northeast, Midwest, South, and West. Regression data is constructed from flood factor(1–10), across the pre-period (August 2018 to August 2020) and post-period (August 2021 to December 2024). FloodFactor groups properties into six categories: Minimal (1), Minor (2), Moderate (3-4), Major (5-6), Severe (7-8), and Extreme (9-10). Observations with sale prices below $50,000 and properties with more than one building are excluded, and sale prices are winsorized at the 99th percentile. All hedonic controls are winsorized at the 1st and 99th percentile. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Flood risk data is sourced from First Street, while housing price and property characteristics data come from CoreLogic, covering transactions from 2007 onward. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

	Log Sale Price				
	All Properties	Northeast Only	Midwest Only	South Only	West Only
	(1)	(2)	(3)	(4)	(5)
Risk is Above Severe × Post Disclosure	-0.0111***	-0.000924	-0.0131**	-0.0150***	-0.00436
	(-6.29)	(-0.22)	(-2.10)	(-5.93)	(-1.26)
Risk is Above Major × Post Disclosure	-0.000582	-0.00205	0.00157	-0.00136	-0.00136
	(-0.42)	(-0.54)	(0.36)	(-0.66)	(-0.56)
Risk is Above Moderate × Post Disclosure	0.00113	0.00230	-0.00305	0.00230	-0.000760
	(0.85)	(0.60)	(-0.79)	(1.12)	(-0.37)
Risk is Above Minor × Post Disclosure	-0.00140	0.00189	0.00594	-0.00333	0.00234
	(-0.65)	(0.27)	(0.76)	(-1.05)	(0.71)
Risk is Above Minimal × Post Disclosure	-0.00128	-0.00215	-0.00849	-0.0000399	-0.00450
	(-0.64)	(-0.33)	(-1.15)	(-0.01)	(-1.45)
Risk is Above Severe	0.0280***	-0.00452	0.00565	0.0514***	0.0175***
	(23.98)	(-1.56)	(1.33)	(30.36)	(8.01)
Risk is Above Major	-0.000130	-0.0120***	0.00665**	0.00447***	-0.00182
	(-0.14)	(-4.66)	(2.28)	(3.32)	(-1.21)
Risk is Above Moderate	-0.00103	-0.00779***	0.00317	-0.000883	-0.000202
	(-1.18)	(-3.00)	(1.21)	(-0.65)	(-0.16)
Risk is Above Minor	-0.00400***	-0.0117**	-0.0115**	-0.00425**	-0.000789
	(-2.84)	(-2.46)	(-2.17)	(-2.04)	(-0.38)
Risk is Above Minimal	0.00196	0.00751*	0.00735	0.00770***	-0.00636***
	(1.51)	(1.70)	(1.47)	(4.06)	(-3.28)
Obs	21,073,732	2,789,230	3,605,356	9,398,481	4,604,773
R2	0.6937	0.7427	0.5997	0.6053	0.7669
R2-Adj	0.6878	0.7356	0.5894	0.5993	0.7623
Block Group-Period FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓	✓

Part 2. Regression Discontinuity

Table 6: RD: Flood Risk Impact on Sale Prices

This table presents the regression discontinuity results examining the relationship between log sale price and expected flood depth after First Street. The regression discontinuity specifications include: a linear fit within a auto-selected bandwidth around the cutoff, a polynomial fit of order 2, and a polynomial fit of order 3. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Housing data comes from Corelogic while flood risk data comes from First Street. Our time sample spans 2017 to 2024. Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Dep. Var: Log Sale Price	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)
FloodFactor = 9 × Post Disclosure	-0.0373***	-0.0250**	-0.0310**
	(-2.86)	(-2.55)	(-2.32)
Expected Depth(1st order)	-0.0907	-0.0472	-0.0724
	(-1.24)	(-1.57)	(-0.96)
FloodFactor = 9	0.000511	-0.00239	0.000633
	(0.06)	(-0.37)	(0.07)
FloodFactor = 9 × Expected Depth(1st order)	0.102	0.0548	0.0660
	(1.34)	(1.58)	(0.76)
Post Disclosure	0.0231**	0.0124*	0.0180*
	(2.18)	(1.71)	(1.82)
Post Disclosure × Expected Depth(1st order)	0.294***	0.180***	0.267**
	(2.64)	(3.95)	(2.35)
FloodFactor = 9 × Post Disclosure × Expected Depth(1st order)	-0.205*	-0.0946*	-0.178
	(-1.77)	(-1.81)	(-1.35)
Expected Depth(2nd order)		-0.0496	-0.136
		(-1.23)	(-0.57)
FloodFactor = 9 × Expected Depth(2nd order)		0.0510	0.168
		(1.19)	(0.66)
Post Disclosure × Expected Depth(2nd order)		0.197***	0.494
		(3.24)	(1.37)
FloodFactor = 9 × Post Disclosure × Expected Depth(2nd order)		-0.230***	-0.536
		(-3.55)	(-1.39)
Expected Depth(3rd order)			-0.0790
			(-0.37)
FloodFactor = 9 × Expected Depth(3rd order)			0.0609
			(0.27)
Post Disclosure × Expected Depth(3rd order)			0.273
			(0.84)
FloodFactor = 9 × Post Disclosure × Expected Depth(3rd order)			-0.268
			(-0.80)
Constant	-0.0149**	-0.0117**	-0.0134**
	(-2.13)	(-2.45)	(-2.05)
Obs	109,544	420,074	420,074
Blockgroup FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Table 7: RD: Subsample Analysis of Flood Risk Impact on Sale Prices

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between log sale price and expected flood depth after First Street. The key subsamples shown are: Full sample (column 1), Non-FEMA properties only (column 2), Non-FEMA properties that are exposed to coastal flood risk (column 3), Non-FEMA properties that are *not* exposed to coastal flood risk (column 4). The regression discontinuity specification shown represents a linear fit within a auto-selected bandwidth around the cutoff between Flood Scores 8 and 9. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Housing data comes from Corelogic while flood risk data comes from First Street. Our time sample spans 2017 to 2024. Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

			Sub-Samples	
Dep. Var: Log Sale Price	All	NonFEMA Only	NonFEMA &Coastal Only	NonFEMA &NonCoastal Only
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	-0.0373***	-0.0349**	-0.170***	0.00109
	(-2.86)	(-2.33)	(-5.53)	(0.06)
Expected Depth	-0.0907	-0.0101	-0.302**	0.103
	(-1.24)	(-0.12)	(-2.02)	(1.06)
FloodFactor = 9	0.000511	0.000858	0.0625***	-0.0161
	(0.06)	(0.09)	(3.10)	(-1.43)
FloodFactor = 9 × Expected Depth	0.102	0.0153	0.270*	-0.0776
	(1.34)	(0.18)	(1.66)	(-0.76)
Post Disclosure	0.0231**	0.0142	0.0950***	-0.0110
	(2.18)	(1.18)	(4.06)	(-0.79)
Post Disclosure × Expected Depth	0.294***	0.177	0.924***	-0.0745
	(2.64)	(1.41)	(4.00)	(-0.50)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.205*	-0.111	-0.470*	0.0804
	(-1.77)	(-0.84)	(-1.87)	(0.52)
Constant	-0.0149**	-0.00307	-0.0259*	0.00481
	(-2.13)	(-0.39)	(-1.68)	(0.52)
Obs	109,544	76,882	13,563	63,319
County FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table 8: RD: Flood Risk Impact on Income

This table presents the regression discontinuity results examining the relationship between log applicant income and expected flood depth. The regression discontinuity specifications include: a linear fit within a auto-selected bandwidth around the cutoff, a polynomial fit of order 2, and a polynomial fit of order 3. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Housing data comes from Corelogic, and demographic information comes from HMDA. Flood risk data comes from First Street. Our time sample spans 2017 to 2024. Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Dep. Var: Log Income	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)
FloodFactor = 9 × Post Disclosure	-0.0455**	-0.0250	-0.0421*
	(-2.05)	(-1.47)	(-1.83)
Expected Depth(1st order)	-0.362**	0.00346	-0.218
	(-2.49)	(0.06)	(-1.48)
FloodFactor = 9	0.0382**	0.0213*	0.0284
	(2.27)	(1.66)	(1.63)
FloodFactor = 9 × Expected Depth(1st order)	0.364**	-0.0866	0.206
	(2.40)	(-1.26)	(1.20)
Post Disclosure	0.0359**	0.0114	0.0243
	(1.99)	(0.92)	(1.44)
Post Disclosure × Expected Depth(1st order)	0.329*	-0.0102	0.194
	(1.73)	(-0.13)	(0.99)
FloodFactor = 9 × Post Disclosure × Expected Depth(1st order)	-0.268	0.111	-0.0498
	(-1.35)	(1.23)	(-0.22)
Expected Depth(2nd order)		0.0276	-0.727
		(0.35)	(-1.55)
FloodFactor = 9 × Expected Depth(2nd order)		0.0484	0.645
		(0.57)	(1.28)
Post Disclosure × Expected Depth(2nd order)		-0.0668	0.629
		(-0.64)	(1.02)
FloodFactor = 9 × Post Disclosure × Expected Depth(2nd order)		0.0232	-0.768
		(0.21)	(-1.16)
Expected Depth(3rd order)			-0.694
			(-1.63)
FloodFactor = 9 × Expected Depth(3rd order)			0.788*
			(1.80)
Post Disclosure × Expected Depth(3rd order)			0.640
			(1.15)
FloodFactor = 9 × Post Disclosure × Expected Depth(3rd order)			-0.582
			(-1.01)
Constant	-0.0393***	-0.0119	-0.0260**
	(-2.89)	(-1.26)	(-2.03)
Obs	34886	131183	131183
Blockgroup FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Table 9: RD: Subsample Analysis of Flood Risk Impact on Log Income

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between the applicant's log income and expected flood depth after First Street. The key subsamples shown are: Full sample (column 1), Non-FEMA properties only (column 2), Non-FEMA properties that are exposed to coastal flood risk (column 3), Non-FEMA properties that are *not* exposed to coastal flood risk (column 4). The regression discontinuity specification shown represents a linear fit within a auto-selected bandwidth around the cutoff between Flood Scores 8 and 9. Housing data comes from Corelogic, and demographic information comes from HMDA. Flood risk data comes from First Street. Our time sample spans 2017 to 2024. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively..

		Sub-Samples		
Dep. Var: Log Applicant Income	All	NonFEMA Only	NonFEMA &Coastal Only	NonFEMA &NonCoastal Only
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	-0.0455**	-0.0415*	-0.0870	-0.0327
	(-2.05)	(-1.66)	(-1.39)	(-1.19)
Expected Depth	-0.362**	-0.414**	-0.198	-0.481***
	(-2.49)	(-2.55)	(-0.54)	(-2.63)
FloodFactor = 9	0.0382**	0.0369*	0.0366	0.0383*
	(2.27)	(1.95)	(0.77)	(1.85)
FloodFactor = 9 × Expected Depth	0.364**	0.428**	0.182	0.503***
	(2.40)	(2.51)	(0.46)	(2.64)
Post Disclosure	0.0359**	0.0372*	0.0640	0.0307
	(1.99)	(1.85)	(1.35)	(1.38)
Post Disclosure × Expected Depth	0.329*	0.410*	0.542	0.386
	(1.73)	(1.93)	(1.13)	(1.62)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.268	-0.392*	-0.222	-0.398
	(-1.35)	(-1.76)	(-0.43)	(-1.60)
Constant	-0.0393***	-0.0412***	-0.0250	-0.0458***
	(-2.89)	(-2.71)	(-0.70)	(-2.72)
Obs	34,886	26,066	3,971	22,095
County FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table 10: RD: Flood Risk Impact on FHA

This table presents the regression discontinuity results examining the relationship between a dummy for an FHA applicant and expected flood depth. The regression discontinuity specifications include: a linear fit within a auto-selected bandwidth around the cutoff, a polynomial fit of order 2, and a polynomial fit of order 3. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Housing data comes from Corelogic, and demographic information comes from HMDA. Flood risk data comes from First Street. Our time sample spans 2017 to 2024. Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Dep. Var: Is FHA	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)
FloodFactor = 9 × Post Disclosure	0.0229*	0.0151*	0.0282**
	(1.90)	(1.71)	(2.35)
Expected Depth(1st order)	0.0773	-0.00882	0.0423
	(1.07)	(-0.31)	(0.59)
FloodFactor = 9	-0.0143*	-0.00313	-0.0125
	(-1.68)	(-0.50)	(-1.48)
FloodFactor = 9 × Expected Depth(1st order)	-0.0417	0.0213	0.0318
	(-0.55)	(0.64)	(0.38)
Post Disclosure	0.00256	0.00285	0.00138
	(0.26)	(0.44)	(0.16)
Post Disclosure × Expected Depth(1st order)	0.00921	-0.00530	-0.0285
	(0.09)	(-0.13)	(-0.28)
FloodFactor = 9 × Post Disclosure × Expected Depth(1st order)	-0.107	-0.0564	-0.151
	(-0.99)	(-1.20)	(-1.28)
Expected Depth(2nd order)		-0.0282	0.146
		(-0.74)	(0.64)
FloodFactor = 9 × Expected Depth(2nd order)		0.00853	-0.301
		(0.21)	(-1.24)
Post Disclosure × Expected Depth(2nd order)		0.00786	-0.0715
		(0.14)	(-0.22)
FloodFactor = 9 × Post Disclosure × Expected Depth(2nd order)		0.0441	0.382
		(0.76)	(1.11)
Expected Depth(3rd order)			0.160
			(0.78)
FloodFactor = 9 × Expected Depth(3rd order)			-0.0797
			(-0.38)
Post Disclosure × Expected Depth(3rd order)			-0.0728
			(-0.25)
FloodFactor = 9 × Post Disclosure × Expected Depth(3rd order)			-0.0808
			(-0.27)
Constant	0.00737	0.000484	0.00375
	(1.08)	(0.11)	(0.61)
Obs	62,396	234,542	234,542
County FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Table 11: RD: Subsample Analysis of Flood Risk Impact on FHA Dummy

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between a dummy for whether an applicant is FHA and expected flood depth after First Street. The key subsamples shown are: Full sample (column 1), Non-FEMA properties only (column 2), Non-FEMA properties that are exposed to coastal flood risk (column 3), Non-FEMA properties that are *not* exposed to coastal flood risk (column 4). The regression discontinuity specification shown represents a linear fit within a auto-selected bandwidth around the cutoff between Flood Scores 8 and 9. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Housing data comes from Corelogic, and demographic information comes from HMDA. Flood risk data comes from First Street. Our time sample spans 2017 to 2024. Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

			Sub-Samples	
Dep. Var: Dummy for FHA Applicant	All	NonFEMA Only	NonFEMA &Coastal Only	NonFEMA &NonCoastal Only
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	0.0229*	0.0145	0.0264	0.0114
	(1.90)	(1.01)	(0.78)	(0.72)
Expected Depth	0.0773	0.134	0.223	0.0961
	(1.07)	(1.60)	(1.27)	(1.00)
FloodFactor = 9	-0.0143*	-0.0148	-0.0288	-0.0114
	(-1.68)	(-1.48)	(-1.22)	(-1.02)
FloodFactor = 9 × Expected Depth	-0.0417	-0.119	-0.134	-0.0922
	(-0.55)	(-1.35)	(-0.70)	(-0.91)
Post Disclosure	0.00256	0.00747	0.00597	0.00888
	(0.26)	(0.65)	(0.23)	(0.69)
Post Disclosure × Expected Depth	0.00921	0.0383	-0.109	0.100
	(0.09)	(0.32)	(-0.43)	(0.73)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.107	-0.111	-0.0704	-0.160
	(-0.99)	(-0.88)	(-0.26)	(-1.11)
Constant	0.00737	0.0123	0.0142	0.0111
	(1.08)	(1.54)	(0.80)	(1.24)
Obs	62,396	45,002	7,341	37,661
County FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓