The Price and Distributional Impact of Flood Risk Disclosure: Evidence from US Housing Platforms

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Preliminary

Abstract

Although flood costs are one of the largest expenses potentially borne by homeowners, obtaining up-to-date information on this risk is often difficult. We study the impact of a novel flood risk factor that is displayed to all potential homebuyers on online search platforms between 2020 and 2024. To obtain plausibly exogenous variation, we back out and utilize natural discontinuity points in the categorization of the disclosed risk. We find that after a house is disclosed as having extreme flood risk, its sale price drops by 3.7% or $14,165.45. The estimated price discount is particularly pronounced for properties outside of FEMA 100-year floodplains and is up to four times stronger for properties exposed to a coastal source of flooding. We also find evidence of distributional impact: after 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, suggesting that the price effect of disclosure has shifted flood risk into the hands of the more financially constrained. Even controlling for income, we find that there is also resorting along non-financial lines: buyers of the riskiest homes after disclosure are 1.2 years older and 2% more likely to be registered as a Republican. A discrete-choice model fitted to the data reveals that resorting on income is mostly driven by prices, while resorting on age is mostly due to preference heterogeneity.

Keywords: Climate Risk; Disclosure; Online Platforms; House Prices; Distributional Impacts.
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1 Introduction

Flood-related natural disasters, such as Hurricane Katrina (2005), Sandy (2012), Harvey, Irma, and Maria (2017), Dorian (2019), Ida (2021), Ian (2022), and Milton (2024), have caused devastating losses of life, homes, and infrastructure. These events are of paramount concern for homeowners, investors, and policymakers due to their enormous 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 storm surges, which may vary depending on climate change scenarios. Historically, potential homebuyers relied on Federal Emergency Management Agency (FEMA) flood maps to understand if their house is in a 100-year floodplain, which has a 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 difficult to obtain.

To fill in the gap in flood disclosure for homebuyers, in August 2020, Realtor.com began displaying First Street Flood Factor, a property-level flood risk estimate, for all homes listed on its site. In February 2021, Redfin.com followed suit. In September 2024, Zillow.com also started disclosing First Street's flood data. Given that these are the three largest online listing platforms, accounting for over 85% of online traffic,[1] it becomes relatively easy for a prospective home buyer to obtain information about a property's flood risk when using these online listing platforms. 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 the lowest risk and 10 for the 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

[1] https://www.rubyhome.com/blog/most-visited-real-estate-websites/

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, it has also changed the location of perceived flood risk. For example, a report released in 2020 finds that over 40% of at-risk properties identified by First Street were not previously classified 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 this 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 change in beliefs could cause concurrent price declines for flood-prone properties, as consumers become more sensitive to flood risks. However, these price declines should not be attributed solely 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 changing in value over time, then they could also bias our estimates of prices.

Importantly for our paper, First Street's Flood Factor has a unique feature. While a home's true underlying flood risk is a continuous number, it is not displayed 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 numerical cutoffs (shown as dotted vertical lines) before being published on a search platform. By using the true underlying continuous measure of risk, we can compare homes with nearly identical flood risks but different disclosed Flood Factors on either side of each cutoff, where a regression-discontinuity (RD) design can untangle the effects of disclosure from other potential omitted factors (e.g., ocean views, housing quality, etc).[2] While a standard RD design in the post-disclosure period provides consistent results (shown in the Appendix), one may still be concerned that certain geographic features, such as having a waterfront location, are disproportionately more likely to be found on one side of the cutoff. Since these geographic features are fixed and do not change over time due to disclosure, we can address them by estimating our main results using a difference-in-RD design. By calculating the difference in prices on either side of the discontinuity, before versus after disclosure, we can provide plausibly exogenous estimates of the pricing and distributional impacts of disclosure.

In this paper, we combine First Street, CoreLogic, HMDA, and Voter Registration data to answer the following question: *What is the equilibrium price effect when property-level flood risks are disclosed*

[2]See Bell et al. (2024) for evidence as well as an econometric solution to the problem of omitted property attributes.

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 specific geographies, utilized flood maps, leveraged flood events, or relied on flood insurance (Gibson et al., 2017; Murfin and Spiegel, 2020; Bin and Landry, 2013; Ortega and Taşpınar, 2018; Beltrán et al., 2019; Baldauf et al., 2020). Closest to our paper, Fairweather et al. (2024) studies the effect of First Street's flood factor by 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. This analysis provides causal evidence that flood disclosure changes homebuyers' search behavior and leads to changes in home prices. Our work naturally extends this analysis to examine the overall effects of information disclosures across multiple platforms on price and the attributes of homebuyers living in properties with different flood risk by utilizing a natural experiment that pseudo-randomizes the disclosed flood risk at the property level.

Using the rollout of the Flood Factor across the U.S. as a natural experiment, we begin with a standard difference-in-differences analysis that summarizes the change in home prices 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 appears immediately in the year following disclosure. Interestingly, we also 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 will 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, our main empirical analysis employs a difference in regression discontinuity (Diff-in-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 just 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; strikingly, we find a discount of up to 17% for properties that are not in a FEMA floodplain but are exposed to coastal

flooding. In a covariate balance test, we reassuringly find that most hedonic housing characteristics, such as the number of bedrooms and bathrooms, are similar on either side of the cutoff. There could still be an imbalance around the cutoff in other unobserved attributes, such as geographic location (eg, coastal properties are disproportionately more likely to be on the right of the cutoff). However, these imbalances are fixed for each property and should not change between the pre- and post-disclosure period.

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

The remaining portion of our paper focuses on distributional impacts and answers the question: *How does flood risk disclosure change who lives in flood-prone properties?* So far, we find 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 same difference in 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, even when we control for income effects, we also find resorting along non-pecuniary lines. Following disclosure, buyers of the riskiest properties are, on average, 1.2 years older and are 2.3% more likely to be registered as Republicans.[3]

[3]We also find that buyers are more likely to be college-educated (as shown in the Appendix), although this is somewhat mechanically correlated with the age effect.

Ultimately, both taste-related characteristics that are correlated with flood-risk tolerance (eg age) as well as the ability to pay appear to factor into the redistribution that we observe after disclosure. Since it is unclear how these preferences interact with each other, we estimate a simple choice model that accounts for both dimensions of resorting observed in our data. Calibrating the model reveals that resorting on income is almost entirely driven by prices, while resorting on age is mostly due to preference heterogeneity.

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.

We also 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 participants. For example, Buchak, Matvos, Piskorski and Seru (2022) finds that algorithmic pricing deployed by iBuyers[4] 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.

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

[4]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.

choices (Agarwal et al. 2015), especially regarding 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.

Results for both prices and homebuyer attributes provide evidence that markets are capitalizing on information about flood risk, and older, more Republican, lower-income households will bear a higher risk of flooding. Our context is important, as information on flood risk (and other natural hazards) has become quite accessible to all homebuyers and, thus, should lessen the costs of unknown risks to housing investments. Ultimately, inequality in who bears the near-term cost of providing flood disclosures is important, as those living in high risk homes may require additional financial assistance given the escalating costs of insurance and the role of the public sector as the lender of last resort.

2 Data and Summary Correlations

2.1 Summary of Main Data Sources

First Street

The measure of flood risk that we focus on is the Flood Factor, a score published by the 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 the First Street Foundation was to provide property-level information on future risks of flooding for all homes in the US. Subsequently, they also expanded their database to include information on other climate risks, including wildfires, 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 that the United States will experience more occurrences of extreme rainfall in the future. As a result, inland properties that were traditionally

classified as safe based on floodplain maps are more likely to be reclassified as risky under FSF-FM.[5]

We obtained 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 (i.e., 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 in 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 logarithm of the expected depth (x-axis). We will use these cutoff points for our regression discontinuity analysis in Section 3.1.

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 fraction of home transactions per census tract that are labeled as risky by FEMA in panel a (i.e., those in a 100-year floodplain; [6]) versus First Street in panel b (i.e., those "with "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.

[5]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 has 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.

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

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 (i.e., whether it is in a 100-year floodplain) or its First Street risk (a numerical factor ranging from 2 to 10, 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 the 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 within a FEMA flood zone. As Table 2 shows, the Flood Factor and FEMA zones are positively correlated, such that larger Flood Factors have a greater fraction of homes in FEMA flood zones; however, there is still considerable disagreement. For example, even for homes in the riskiest category of 10, roughly 38% of them would **not** have been classified as risky by FEMA.

CoreLogic

Our transaction data comes from the Corelogic Multiple Listing Enterprise Solutions (MLS) Database. The MLS database comprises 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 the 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.

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 percentiles 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

For homes that are purchased with a mortgage, we obtain additional borrower characteristics through the HMDA (Home Mortgage Disclosure Act) data. We use transaction level information on census tracts, year, loan amount, and sales price to match individual mortgages for home purchases reported as part of HMDA to individual property transactions.[7] For each mortgage that we successfully match, we gather the borrower's age, ethnicity, income, and 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 better deals on their mortgages. 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 second to 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 aged 55 and above, and 39% identified themselves as non-white.

L2 Voter Registration Data

We obtain buyer's age, college attainment, as well as political party affiliation using L2 Voter Registration data. For each sales transaction in Corelogic, we match its address to the address of a household recorded in the L2 data in the next general election following the sale. Additionally, we check to make sure that at least one of the names registered to that household matches the buyer's name in Corelogic. Sometimes, registrations take a while to update, so we also use the following year of L2 data, if we cannot find an adequate match.

Table 1 summarizes the voter registration data in the last panel. We were able to match roughly 15.9 million sales to a household in the L2 data. Among these households, the average age is 44 and about 42% of them have at least one member with a college degree. In addition, the data looks very politically balanced; roughly 39% of households have at least one member registered as a Democrat, and the same fraction (39%) of households have at least one member registered as a Republican. For all analyzes in the paper, we use the dummy indicators rather than a percentage of household calculations because we do not wish to be biased by dependents who may be registered but ultimately do not make home purchase decisions. However, the results are very similar if we use a percentage instead. While we omit those from the paper for space, we can share those results upon request.

[7] This matching process has been implemented by other researchers (Bayer et al., 2016, 2025; Bernstein et al., 2022) and is fuzzy in nature. In some cases, our matching process leads to non-unique matches (¡5%), which we exclude. In general, we are able to match over 60% of mortgages to unique transactions.

2.2 Summary of Price Changes in Risky Homes Following Disclosure

As a baseline, we estimate log price changes 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 present the averages estimated from the following DID specification:

$$Ln(Price)_{ijt} = \alpha_t + \mu_{jt} + \vec{\beta_1}\vec{F_i} + \vec{\beta_2}\vec{F_i} \cdot Post_t + \vec{\beta_3}\vec{X_{ijt}} + \varepsilon_{ijt} \tag{2.1}$$

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). $\vec{X_{ijt}}$ represents 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 summarize the average *incremental* price change between homes of that category and homes in the category directly above.

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

To summarize the price changes resulting from the release of First Street's Flood Factor, we multiply the treatment $\vec{F_i}$ by $Post_t$, 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, $\vec{\beta_2}$ captures the change in prices from before to after flood disclosure.[8] If consumers cared about flood risk, this should lower prices for high-risk homes. Subsequently, we would expect the price changes in $\vec{\beta_2}$ associated with high-risk homes, such as homes with extreme flood risk, to be negative and significant.

Table 3 summarizes price changes across the entire United States in Panel A. Furthermore, it splits the sample into houses inside a FEFMA 100-year floodplain (Panel B) or not inside a FEMA floodplain (Panel C). Looking at Panel A, we find that only homes labeled as extreme by the Flood Factor drop

[8] We can also calculate the average (incremental) price in the post-disclosure period by adding the difference to the pre-disclosure period's price.

significantly in price (by roughly 1%) following the release of the Flood Factor.[9]

Next, in Panels B and C, we further test whether flood risk is priced more strongly inside or 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 flood zones 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 obtain a mortgage. Thus, prices may not react as strongly if buyers hold insurance and expect it 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, Panel B shows that there is no significant price decline for extremely risky homes in FEMA floodplains, while Panel C indicates that the decline is even slightly stronger for homes outside FEMA floodplains. Generally, this evidence is consistent with the finding that First Street's Flood Factor introduced novel information outside of FEMA flood zones, and this novel information produced a price drop of about 1% for homes with extreme (i.e., above severe) risk.[10]

While we cannot interpret these correlations as causal, they illustrate that the price impact of flood disclosure is nuanced and varies greatly across the United States. We see that while there is no effect inside FEMA floodplains; there are strong and significant effects for homes outside the floodplains.

2.2.1 No Evidence of Pre-trend

One may be worried that the observed price drop shown in Section 2.2 is not due to disclosure but rather to time trends in climate awareness that coincide with the First Street disclosure. To address this concern, we conduct a robustness test by dynamically plotting the price difference for extreme flood risk properties from Eq 2.1 year-by-year in Figure 7. To conduct 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" (i.e., 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 demonstrate that there are no other omitted factors that confound our results, we will next turn to an RD design in Section 3.1.

[9] In general, this effect is statistically significant at the 1% level for all specifications with location controls. We find similar and significant differences with both County and Tract fixed effects as well. Furthermore, when we also add fixed effects for whether a property is located in a FEMA floodplain, the results remain largely unchanged. These results are omitted for space, but they can be shared upon request.

[10] In the Appendix, we also expand this analysis in Table A2 to test whether price changes are larger 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: the Northeast, the Midwest, the South, and the West. We find that there is almost no observable price decline in the Northeast or West Coast. Instead, we find strong and negative price declines in the South and Midwest.

3 Price Effects

To understand the impact of nationwide flood disclosure on the residential housing market, we begin by estimating its effect on equilibrium prices. To do this in a plausibly causal fashion, in Section 3.1 we estimate a difference-in-regression-discontinuity (Diff-in-RD) regression for different risk factor cutoffs. Overall, consistent with the correlative evidence shown in Table 3, we find that homes with extreme flood risk face a significant decline in prices, and this effect is primarily concentrated in non-FEMA flood zones. In Section 3.2.1, we test whether the drop in price appears to be actuarially fair.

3.1 RD Estimator

While the summaries provided in Table 3 based on DID regressions utilize our full sample and possess the most statistical power, they suffer from concerns regarding changing beliefs about flood risk, as well as unobserved time-varying changes in the value of amenities (e.g., coastal views, water access) that may be correlated with flood risk. 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 controls for existing FEMA information ameliorate some of these concerns, they may not perfectly capture how homebuyers' perceptions of climate risk are changing over time. If so, then our DID estimates may still have little to do with First Street's flood disclosure.

To address the identification concerns above, for our main empirical analyses, we use a difference in regression-discontinuity (Diff-in-RD) design. First, we recreate a continuous measure of a property's 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 Diff-in-RD analysis, we compare how prices changed for homes just above and just below the empirical cutoff values. In doing so, we assume that homes right around the cutoff are otherwise very similar and only differ depending on their assigned Flood Factor. While a standard RD-specification also works well in this setting (results are shown in Appendix Section B.1), we utilize a difference in RD approach because some unobserved house characteristics may still be discontinuous at the cutoff. To interpret our estimates as plausibly exogenous, we assume 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 disclosure. If we expect consumers to discount homes because they learn a property has a higher Flood Score, then we would expect to see a price drop right at the cutoff.

Formally, for each change in flood factor scores, we estimate the following difference-in-RD regression:

$$
\begin{aligned}
\text{Ln(Price)}_{ijt} &= \beta_1 \text{I(high-risk)} \cdot \text{I(Post)} \\
&+ \beta_2 \text{I(Post)} + \beta_3 \text{I(high-risk)} + \sum_{m=1}^{3} \rho_m \text{exp depth}_i^m \\
&+ \sum_{j=1}^{3} \gamma_j \text{exp depth}_i^j \cdot \text{I(high-risk)} + \sum_{k=1}^{3} \nu_k \text{exp depth}_i^k \cdot \text{I(Post)} \\
&+ \sum_{n=1}^{3} \delta_n \text{exp depth}_i^n \cdot \text{I(high-risk)}_i \cdot \text{I(Post)} + \vec{\beta_4} \vec{X_{ijt}} + \mu_j + \varepsilon_{ijt}
\end{aligned} \tag{3.1}
$$

where each observation is a 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. exp depth$_i$ is our continuous measure of flooding risk, and I(high-risk) captures the discontinuous jump. It is set equal to one if a property fell into the riskier 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.

In Table 4 shows the results from estimating Eq 3.1 with each panel displaying the disclosure effect estimated over the cutoff points from different pairs of flood risk factors: Panel A shows 3 vs 4, Panel B shows 4 vs 5, Panel C shows 5 vs 6, etc. In particular, Panels B, D, F may be particularly interesting because they focus on thresholds that also correspond to a change in qualitative risk (eg Panel B compares factors 4 vs 5, or moderate vs major risk homes), which is all that the user can see when they scroll through a home's listing on the online platform. To see the differences between the other risk factors, the user would have to click on the box containing the risk factor to get more information. We hypothesize that users pay more attention to the risk factors when the homes are especially risky. [11]

The columns of Table 4 correspond to estimations using a linear auto-selected band, a polynomial of order 2, and a polynomial of order 3, respectively.[12] Consistent with Section 2.2, we only find a significant price drop for the riskiest homes. Panel F shows that we find a significant price drop of 3.7% (linear specification shown in column 1), 2.5% (second order polynomial shown in column 2), or 3.1% (third order polynomial shown in column 3) post disclosure for homes in the severe versus above severe categories. Similarly, Panel E shows that there is a significant price drop of 2.8% (linear), 3.6%, (second order polynomial) or 3.5% (third order polynomial) for homes ranked as 8 versus 7. No other

[11] We omit the results for the minimal and minor categories, because they pose very little flood risk for the homeowner. In addition, the minor category holds very few homes so the estimation around this cutoff is especially noisy.

[12] The sample size varies between each estimate based on the auto-selected bandwidths for the points to the left and the right of the risk cutoff (ie the control and treatment groups, respectively). These two bands are optimized by Stata within the *rdrobust* package to minimize the Mean Squared Error (MSE) of the RD treatment effect estimators.

risk pair is consistently significant across all three specifications; risk factors 3 vs 4 and 9 vs 10 also find significant drops, but only with the second and third order polynomial specifications.

Figure 8 Panel A illustrates the Diff-in-RD for homes with scores of 8 (labeled as severe) and 9 (labeled as extreme), for which we found the strongest treatment effects. Specifically, we plot a binscatter graph with expected depth on the x-axis and log price on the y-axis. Properties with a flood score of 8 are shown in blue, while properties with a flood score of 9 are shown in red. 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 price difference between the post-disclosure period and the pre-disclosure period. [13]

Based on our findings in Table 4 and Figure 8 Panel A, we will focus on homes with 8 versus 9 risk factors (i.e., Severe versus Above Severe) for the remainder of the paper, since this is the cutoff most salient to consumers.

3.1.1 Covariate Balance & Manipulation of the Running Variable

In our RD analyzes, 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 block group fixed effects, and then we plot expected depth (x-axis) against each of our hedonic variables (y-axis). Reassuringly, around the cutoff, we do not observe any other sudden changes in size (i.e., lot size or living square footage), building age, number of bedrooms, or number of bathrooms. Thus, the price difference estimated around the cutoffs is unlikely to be driven by a confounding feature of the house itself.

The other standard concern in a RD design is bunching or manipulating one's position on either side of the discontinuity. In our case, geographical features determine the running variable, and thus a property owner is unable to change their corresponding score. We do recognize the concern that properties with flood-prone attributes (e.g., elevation, distance to coast, etc) which correlate with amenities may be over-represented on one-side of the cutoff based on how the scores are set. This is one of the main justifications for the difference-in-RD design, as it allows us to control for these pre-existing differences in our estimates.

[13] Ideally, we would not require any controls and would 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 risks can vary significantly in price depending on their location and characteristics, such as size. By residualizing on the full sample first, we can reduce much of the noise and make the RD less fuzzy.

3.1.2 Different Levels of Geographic Controls

Next, in Table 5, as a robustness test, we check whether our choice of fixed effects drives our findings. Ideally, we can rely on the RD design to produce a causal estimate without any fixed effects; however, since our sample covers all of the United States, there are many heterogeneous factors that create considerable variance in prices (e.g., location, size of house, age of house). Controlling for these factors can help us reduce noise and more precisely estimate the effect. Column 1 shows the results using no geographic fixed effects at all; column 2 adds coarse county-level fixed effects, column 3 adds census tract-level fixed effects, and column 4 adds the most granular block-group fixed effects. Across all columns, we see that the drop in price is very similar in magnitude, ranging from -2.9% with county-fixed effects to -3.7% with tract or census fixed effects. In addition, consistent with the explanation that more granular fixed effects reduce noise, the t-statistics monotonically increase from column 1 (t stat of 1.49) to column 4 (t stat of 2.86). Thus, while our findings do not hinge solely on using Block-group fixed effects, they allow us to obtain the sharpest estimates of the price effect. As a result, we focus on this specification for the remainder of the paper.

3.2 Heterogeneous Effects

In Table 6, we test whether the baseline effect for 8 vs 9 homes varies by geographic location. In Section 2.2, we presented correlative evidence that the price effect existed only for homes outside of FEMA flood zones. This not only allows the First Street data to provide novel flood information, but it also ensures that observed price effects are not confounded by the expected payoffs from subsidized flood insurance. In addition, we test whether certain types of flood risk are priced higher than others. In the First Street data, the main flood types in our time sample are flooding from rain (i.e., pluvial) and flooding from exposure to the coast (i.e., fluvial). We hypothesize that since coastal flooding is both potentially more costly and more salient, it would have stronger price effects.

For convenience, we present the main specification using the full sample in column 1. Next, column 2 repeats the analysis only for non-FEMA properties. 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 (e.g., fluvial flooding) have a stronger price impact. Indeed, we find that properties that are both non-FEMA and subject to coastal flooding risk experience a large price drop of roughly 17%. As an illustration, 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?

Given an average home sale price of $382,850 in our data (see Table 1), the observed 3.7% price drop for the full sample represents a $14,165.45 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 the United States Army Corps of Engineers (USACE). After factoring in a building's characteristics (e.g., number of stories, presence of a basement, etc), the value of the building, the value of the land, and the 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 the difference between these two NPVs suggests that a reasonable estimate of the difference in value (i.e., 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 $14,165.45 is significantly smaller—just a little under 41% of the actuarial value. 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 request a free 7-day trial that provides 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, that they have trouble discounting future values, or that 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 Table 6 shows 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.

3.3 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), while 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 shown for the first time and only to selected users. Therefore, 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. Additionally, this small set of treated homebuyers may not have had a sizable impact on the housing market, thereby limiting any larger equilibrium price effects.

Overall, 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 about 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 when 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. First, in Section 4.1, we examine the effect of disclosure on two proxies of equilibrium homebuyers' financial constraints: (1) their average income and (2) whether they took out an FHA loan, which is geared towards first-time and credit-constrained borrowers. Next, in Section 4.2, we examine how disclosure affects two other household characteristics, both on their own as well as after controlling for income: average age and a dummy for a registered Republican. Overall, we find that flood disclosure shifts the distribution of homebuyers—after disclosure, the buyers of the riskiest homes are more financially constrained, older, and more likely to be Republicans.

4.1 Financial Constraints

In this section, we estimate the model given by Equation 3.1, but we replace the dependent variable (previously log price) with two proxies for homebuyers' financial constraints from HMDA: income and a dummy for FHA loans.[14] Since our demographic information comes from the HMDA dataset, we note that we must further restrict our sample to only home purchases that required a mortgage.

First, in Panel A of Table 7, we find that after disclosure, the most risky ("above severe") homes

[14]We also consider race from the HMDA data; however, since it is insignificant, we present the results in the appendix instead.

are being purchased by individuals with roughly 2.5% (column 2) to 4.6% (column 1) lower income.[15] 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 disproportionately fall on the shoulders of individuals who can least bear them. This discontinuity is also visually shown in Panel b of Figure 8.

In the Appendix, Table A4 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 Panel B of Table 7, 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 expected costs of flooding and climate change may increasingly shift to the more financially constrained. In the Appendix, Table A5 further tests the findings 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 financial 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.

4.2 Taste-based Preferences Unrelated to Financial Constraints

To test whether homebuyers may also sort on other demographic factors unrelated to financial constraints, we re-estimate Equation 3.1 but replace the left-hand side variable with buyer demographics. The buyer demographics that we consider are the average age of the household and a dummy variable

[15] We also test the effects of disclosure on race, but while there is some evidence that average age declined, we fail to find consistent effects. The results are instead presented in Appendix Table A6.

for whether anyone in the household registered as a Republican.[16]

In some specifications, we additionally control for the correlation between these outcomes and income (e.g., older individuals tend to work in higher-level positions and, thus, on average, have higher incomes) by adding both a control variable for income as well as interacting this income variable with the post-disclosure dummy (e.g., over time, higher-level positions may disproportionately pay more, and thus, on average, older individuals have a larger income gap over time).

Table 8 Panels A and B show our results for average age and the dummy variable for Republican, respectively. Column 1 shows the estimation without income controls, while column 2 repeats the analysis using income controls. Columns 3 and 4 show the results with income controls but using alternative specifications; instead of a linear fit within an auto-estimated band, they use a polynomial of order 2 or 3, respectively. From Panel A of Table 8, we see that the average homebuyer for above-severely risky homes becomes older following disclosure. When we add income controls (columns 2-3), the effect becomes even stronger and is generally significant. We find that the average homebuyer becomes 0.98 to 1.86 years older, depending on the exact specification. This suggests that older generations of homebuyers are less concerned about climate risks and, as a result, potential future flood risks in their homes.

Next, Panel B of Table 8 shows that the average homebuyer for above-severely risky homes is more likely to identify as Republican following disclosure. While this result is just below the level required to be statistically significant at the 10% level (column 4), it is consistent in direction and general magnitude across all specifications, even when controlling for income. We find a roughly 1% to 3% increase in the likelihood of identifying as Republican. Since the continued use of fossil fuels is a key component of the Republican party's agenda, this is consistent with the narrative that Republicans are less concerned about climate change (compared to Democrats) and, all else being equal, are more likely to bid on a flood-prone property. Figure 9 visually depicts both regressions using a linear auto-band. We can see a small jump at the threshold for average age and, to a lesser extent, for the Republican dummy.

Overall, the results in this section show that there are other demographic characteristics that may be correlated with a taste for climate-related risks, which drive resorting after information disclosure. These preferences are partially correlated with income, but even after controlling for income effects, we find that they continue to significantly change the landscape of who holds climate risk.

[16]Results are reversed but similar if we regress on a dummy variable for Democrat. This is shown in Panel A of Appendix Table A12. We also test the results for education, as proxied using a dummy variable for college attainment; however, this is insignificant and likely to be correlated with age. The results are shown in Panel B of Appendix Table A12.

5 Discrete-Choice Model and Estimation

In order to characterize the extent of resorting based on flood-disclosure, in this section, we set up and calibrate a discrete-choice model of housing. After fitting the model, we will use a Shapley decomposition to measure how much of the documented resorting is due to prices versus preference heterogeneity.

5.1 Model and Score Moments

In our model, we assume that household i chooses among homes j with utility

$$u_{ij}(\theta) \;=\; -(\alpha_0 + \pi_{p,y} \ln y_i)\, \ln p_j \;+\; (\beta_r + \pi_{r,\text{age}} \cdot \text{age}_i + \beta_{r,\text{rep}} \cdot \text{is_rep}_i)\, \text{is-risky}_j \;+\; \beta_{\text{run}} \cdot \text{running}_j \;+\; \varepsilon_{ij},$$

The variable *running* is the underlying predicted risk, which is a continuous measure. The variable *is-risky* is a binary variable where the property is disclosed to be of high risk (i.e., Flood Factor 9). The error ε_{ij} i.i.d. Type-I extreme value, implying standard logit choice probabilities $P_{ij}(\theta)$.

In terms of the sample, we focus on the set of homes within the bandwidth of homes near the 8 vs. 9 cutoff with price, income, age all residualized to block-group fixed effects.

For simplicity, all homes in this sample are in the choice set. All household demographics are centered or scaled (e.g., $\ln$ income and $\ln$ price are mean-centered; running standardized).

We estimate the parameters via GMM. Let c_{ij} be the indicator for the observed choice and define the per-alternative derivative vector

$$z_{ij} \equiv \frac{\partial u_{ij}}{\partial \theta} \;=\; \begin{bmatrix} -\ln p_j \\ -\ln y_i \;\ln p_j \\ \text{is-risky}_j \\ \text{age}_i \;\times \text{is-risky}_j \\ \text{is_rep}_i \;\times \text{is-risky}_j \\ \text{running}_j \end{bmatrix}.$$

The household score contribution is $g_i(\theta) = \sum_j z_{ij}\,(c_{ij} - P_{ij}(\theta))$ and the sample moments are $G(\theta) = \frac{1}{N}\sum_i g_i(\theta)$. The GMM objective is

$$Q(\theta) \;=\; G(\theta)'\, W\, G(\theta).$$

5.2 Estimation Results

Since we have detailed, micro-data on household choices, the coefficients in terms of preference heterogeneity is well-identified with our current model. With $N = 12{,}284$ households, the parameter estimates are shown in Table 9.

Both heterogeneity parameters $\pi_{p,y}$ and $\pi_{r,\text{age}}$ are well-estimated, suggesting that price sensitivity decreases as income increases, and tolerance for homes disclosed to be risky increase with age. Given that the RD results shows very weak results on the Republican dummy, we focus on just age based heterogeneity. The other mean parameters are estimated not to be significantly different from zero; that said, since the original stats are all de-meaned, this is to be expected.

5.3 Shapley Decomposition of Resorting

Even though we cannot use the model to estimate equilibrium without specifying the supply side, we can still use the model to assess how much observable resorting is due to prices versus preference heterogeneity using a two-switch Shapley decomposition. We compare four scenarios where we "undo" the estimated price wedge due to disclosure and toggle the taste heterogeneity:

M00: (price=PRE, hetero=OFF),

M01: (price=PRE, hetero=ON),

M10: (price=POST, hetero=OFF),

M11: (price=POST, hetero=ON).

For any metric M (here we use covariances), the Shapley split is

$$\Delta M = M_{11} - M_{00} = \underbrace{\tfrac{1}{2}\left[(M_{10} - M_{00}) + (M_{11} - M_{01})\right]}_{\text{price}} + \underbrace{\tfrac{1}{2}\left[(M_{01} - M_{00}) + (M_{11} - M_{10})\right]}_{\text{heterogeneity}}.$$

Table 10 summarizes two key sorting metrics involving the neighborhood attribute `running`; results are percentages of the total change attributable to each channel.

The first row indicates that the resorting of exposure to flood risk by income is almost entirely price-driven, while the second shows that the resorting of exposure to risk by age is almost entirely due to preference heterogeneity (via $\beta_{r,\text{age}}$).

6 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, and no price discount is observed for homes with lower and less salient levels of 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. Even controlling for income, we find some evidence that resorting occurs based age and political affiliation as well. Finally, using a discrete-choice housing model, we find that prices are the first-order driver of income-based resorting and preference heterogeneity is the first-order driver of age-based resorting.

Going forward, more work needs to be done in order to disentangle the various factors that drive resorting after flood disclosure. One potential path forward is to create a structural model that incorporates both an income effect as well as orthogonal taste-based preferences, as proxied by age and political affiliation. This will also allow us to simulate counterfactual future scenarios, such as an aging homebuyer population or further polarization of political beliefs. 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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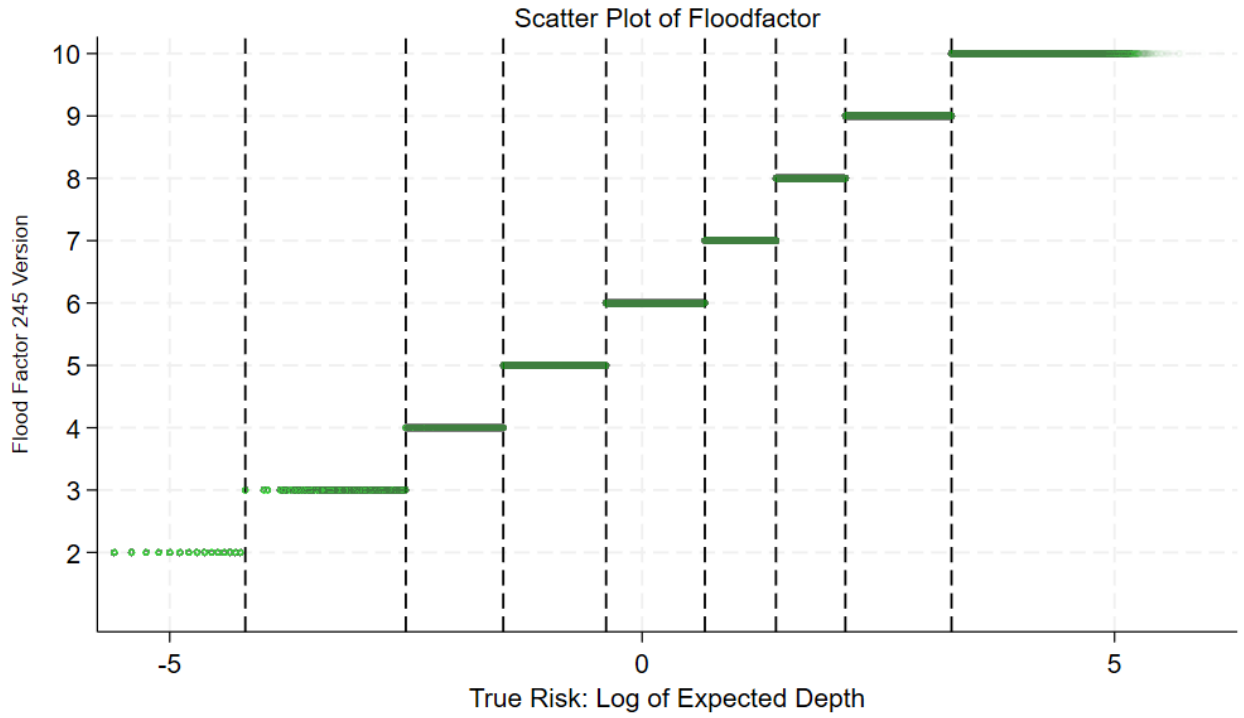
Figures

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.

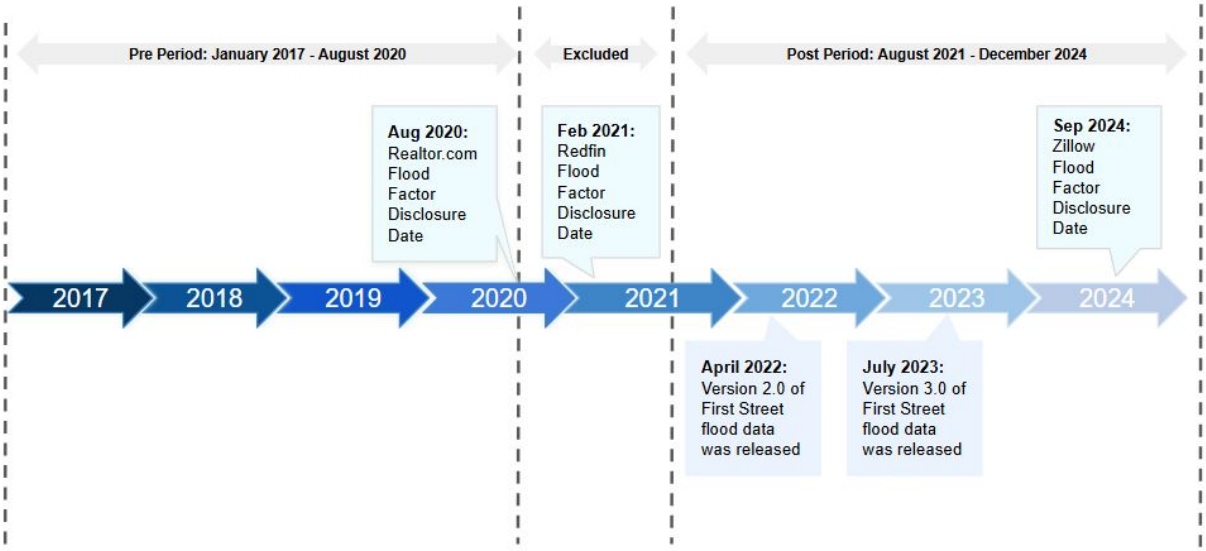
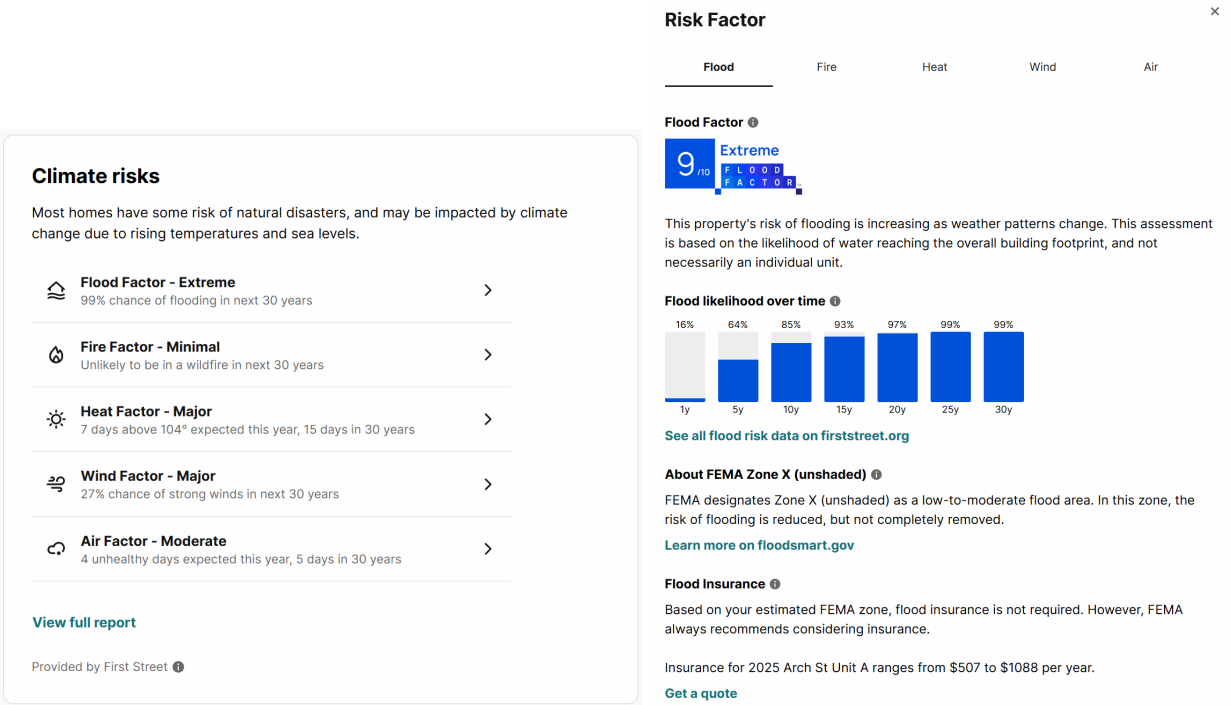


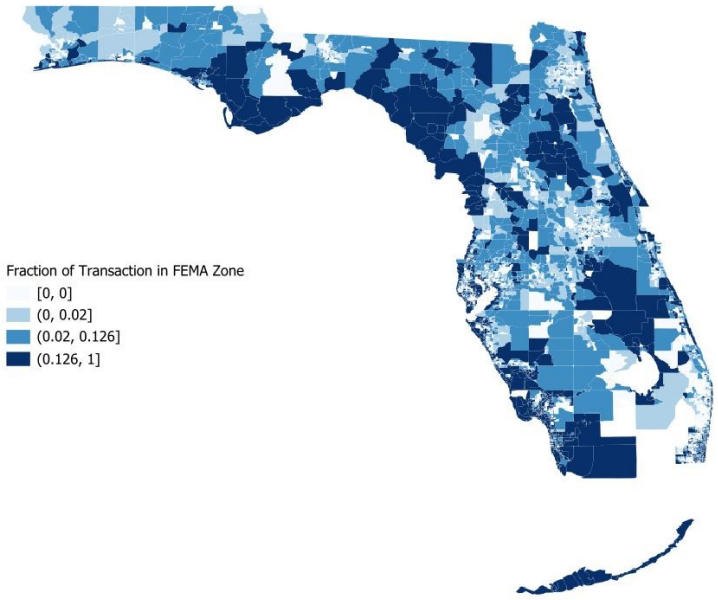
Figure 3: Example of Flood Score as Shown on Redfin



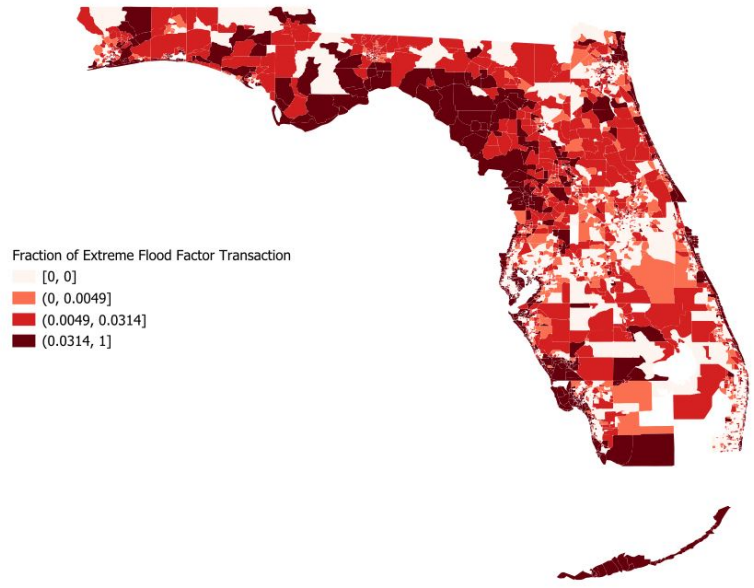
(C) Geographic Maps

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.



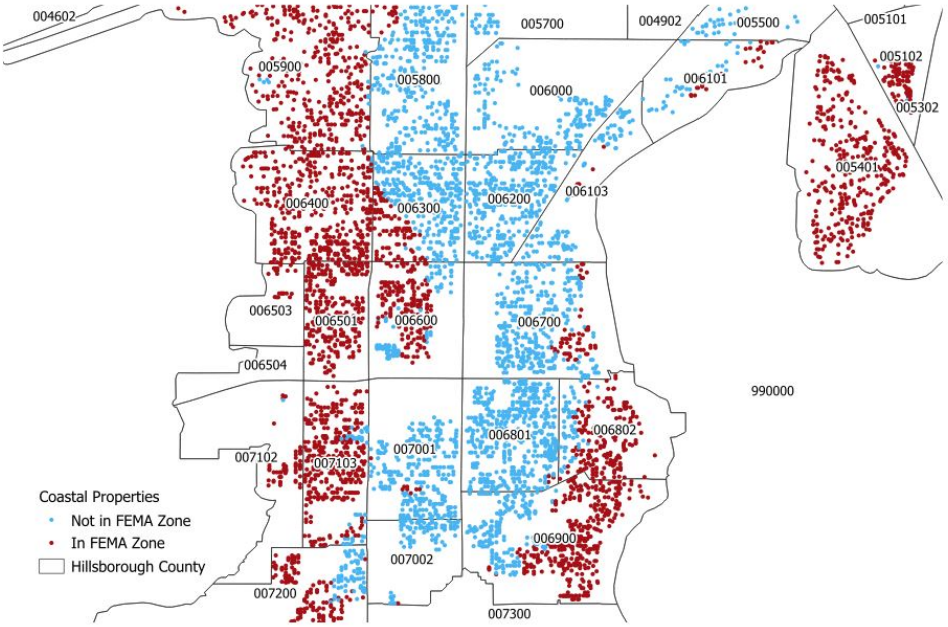
(a) FEMA Flood Zone



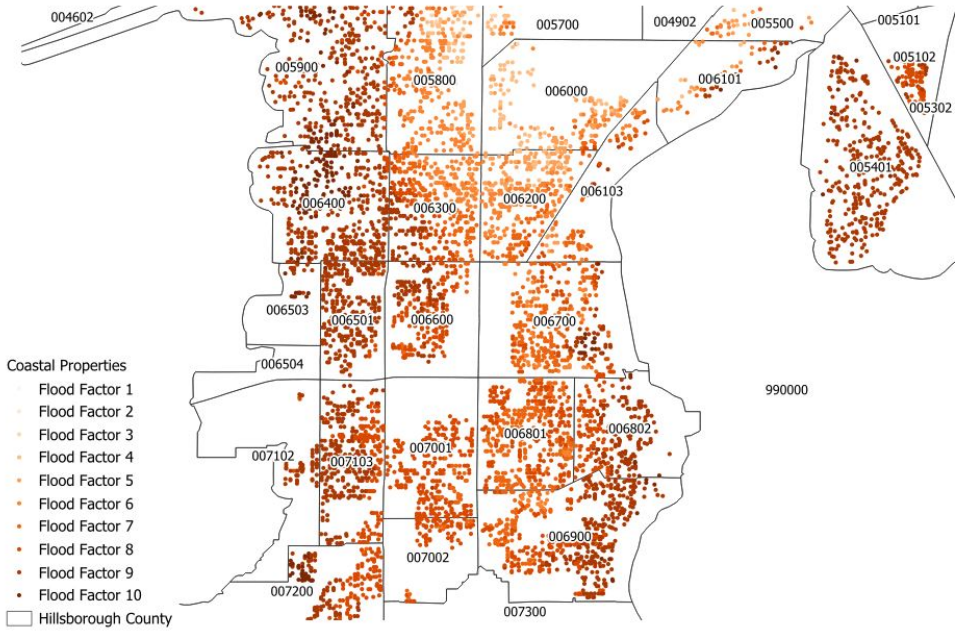
(b) Extreme Flood Risk (First Street)

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.



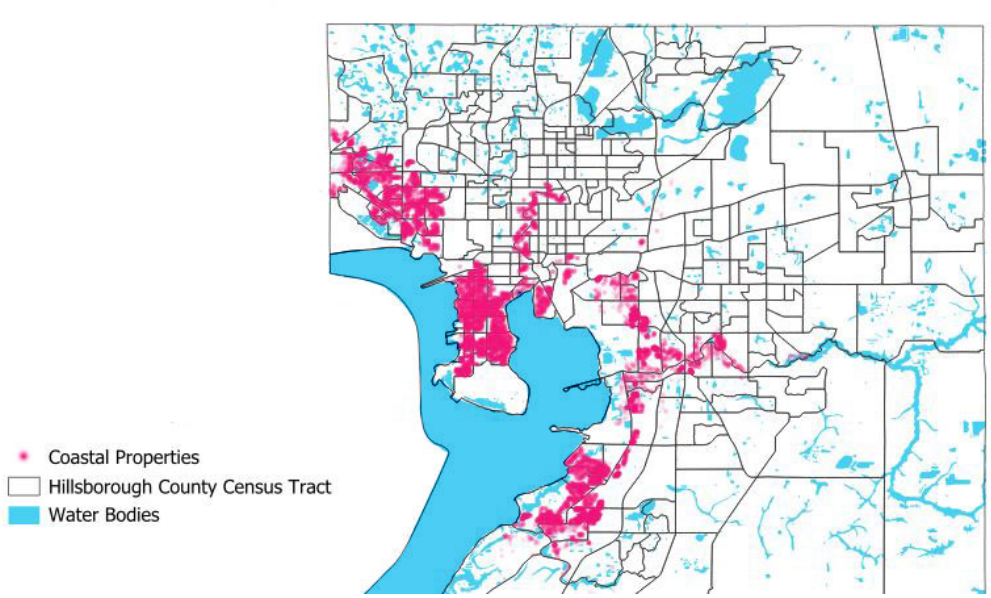
(a) FEMA Flood Zone



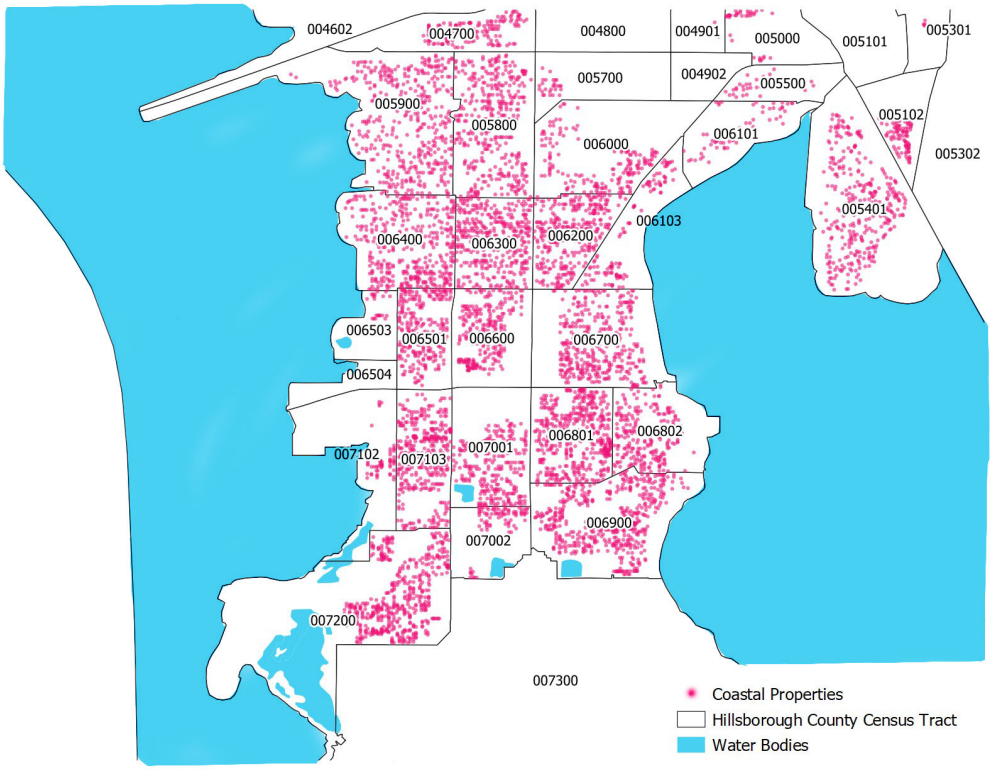
(b) Extreme Flood Risk (First Street)

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

These maps display the location of individual coastal properties in Hillsborough 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.



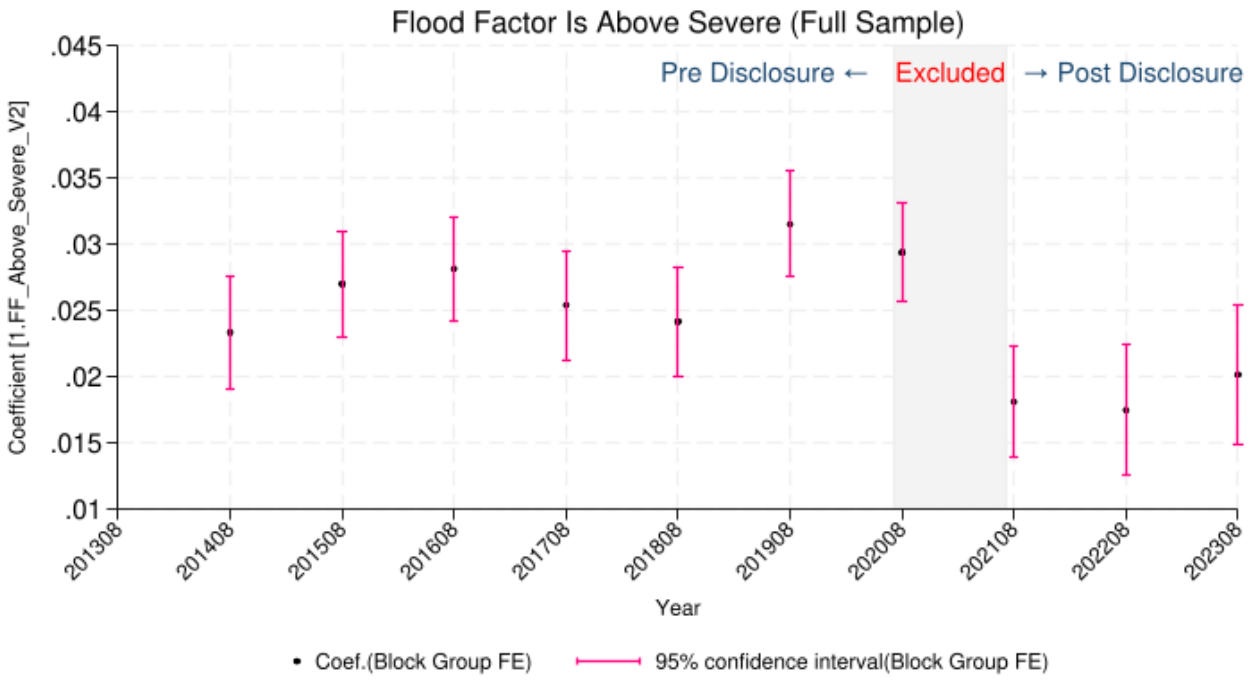
(a) Hillsborough County, Florida



(b) Select Subsample of Hillsborough County

Figure 7: Pretend Test for Log Home Prices

To test whether there are notable pre-trends in the prices of flood-prone properties prior to disclosure, each point on the graph represents the coefficient β_1 and associated standard errors from the following difference-in-difference regression: $\ln(\mathbf{SalePrice}_i) = \alpha + \beta_1 \mathbf{FloodCategory}_i + \beta_2 \mathbf{Treat}_i + \beta_3 \mathbf{HedonicControls}_i + \mathbf{BlockGroup\ FE} + \epsilon_i$. 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.

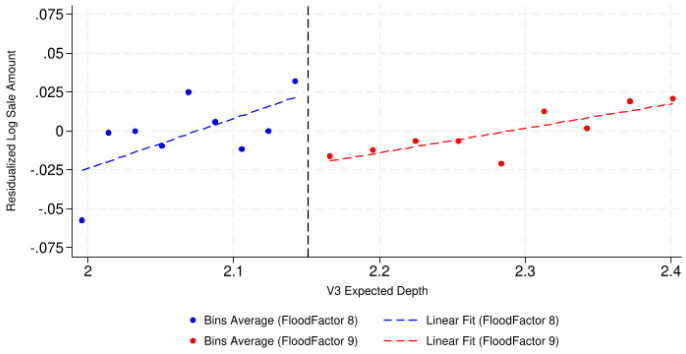


2. Regression Discontinuity

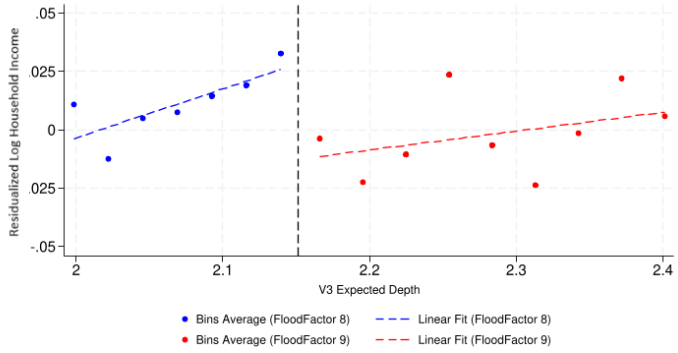
(A) Visualizing RD Regressions

Figure 8: Full Sample RD Plots for Price, Income, and FHA Status

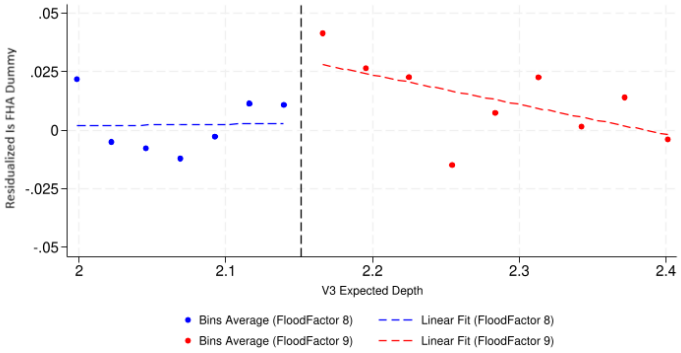
The figures below visually show a linear RD Analysis with auto-selected bandwidths using the full data sample, explaining: log price (Panel a) log income (Panel b), and a dummy for whether the applicant is FHA (Panel c). To control for omitted variable bias, the LHS variable is residualized with block-group 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 Price



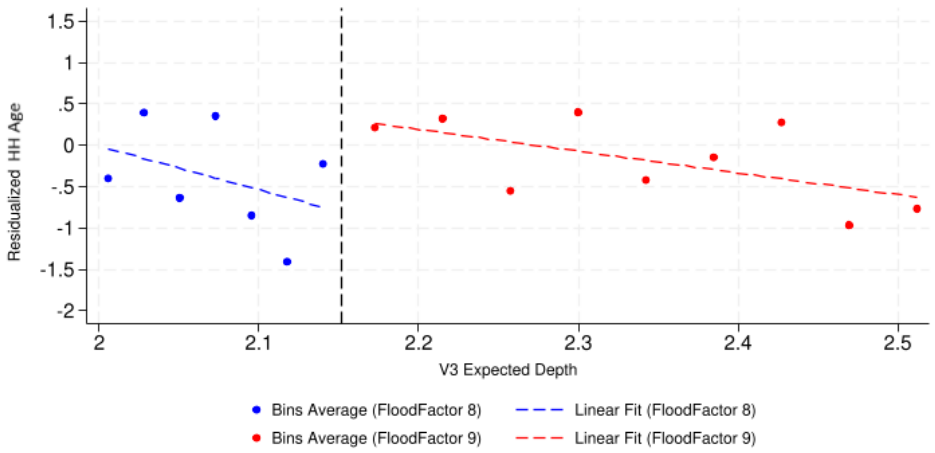
(b) RD for Log Income



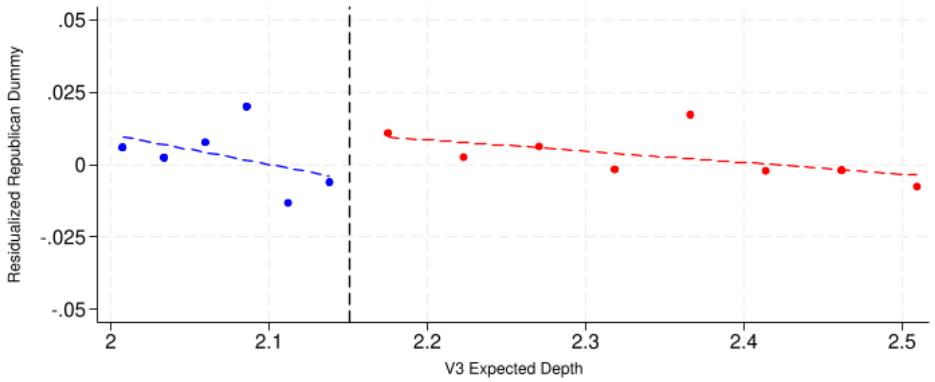
(c) RD for Is FHA Dummy

Figure 9: Full Sample RD Plots for Average Household Age and Republican Dummy

The figures below visually show a linear RD Analysis with auto-selected bandwidths using the full data sample, explaining: average household age (Panel a) and a dummy for whether there is a registered Republican in household (Panel b). 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 Average Household Age

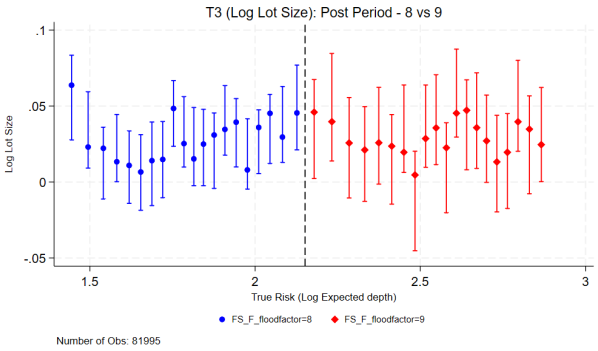


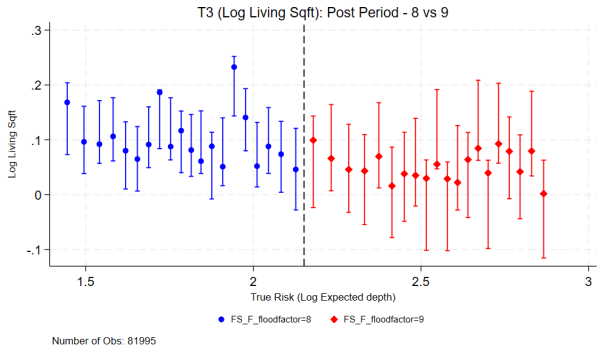
(b) RD for Republican Dummy

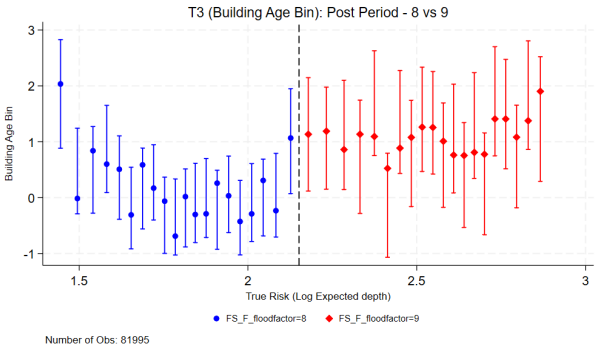
(B) RD Balance Check: Hedonic Characteristics

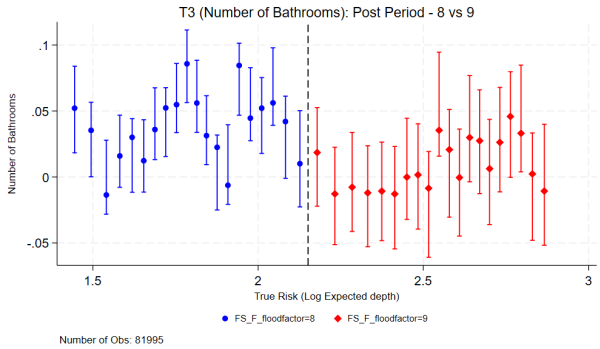
Figure 10: Covariate-balance Test: 8 vs 9

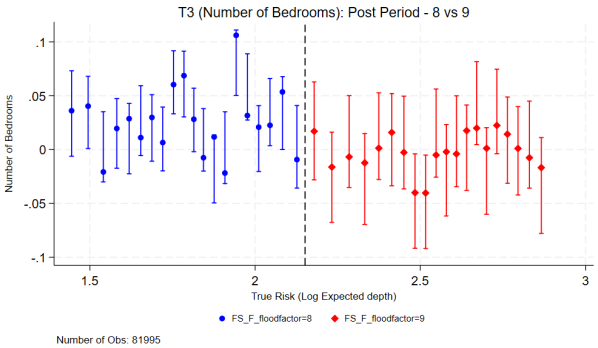
The figures show that basic housing hedonics are balanced across the regression discontinuity. From left to right, top to bottom, they are: total lot size, living square foot, age of building, total number of bathrooms, and total number of bedrooms. Our data comes from First Street and Corelogic, and 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. We observe fewer observations for the expected-depth variable because properties classified as minimal flood risk have no expected-depth values.

	Count	Mean	SD	p25	p50	p75
CoreLogic:						
Sale Price ($k)	22,223,965	382.85	356.86	179.00	289.00	450.00
Living Area (Sqft)	22,223,965	1,771.05	995.46	1,220.00	1,672.00	2,279.00
Lot Size (Sqft)	22,223,965	20,112.04	37,533.46	6,300.00	9,375.00	16,117.00
Number of Bathrooms	22,223,965	1.95	1.23	1.00	2.00	3.00
Number of Bedrooms	22,223,965	2.25	1.67	0.00	3.00	3.00
Building Age	22,223,965	32.90	30.85	5.00	26.00	53.00
Sale Year	22,223,965	2,020.19	2.29	2,018.00	2,020.00	2,022.00
First Street:						
V3 Expected Depth (cm)	4,183,011	4.73	11.36	0.12	0.76	3.87
Flood Source includes Coastal	22,223,965	0.05	0.21	0.00	0.00	0.00
Flood Source includes Pluvial	22,223,965	0.13	0.34	0.00	0.00	0.00
HMDA Variables:						
Age Above 55	8,242,127	0.17	0.37	0.00	0.00	0.00
Applicant Race: NonWhite	8,242,127	0.39	0.49	0.00	0.00	1.00
Applicant Nncome ($)	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
Voter Registration (per household):						
Average Age	15,861,104	43.56	13.79	33.00	45.00	52.00
Dummy for a Registered Democrat	15,861,104	0.39	0.49	0.00	0.00	1.00
Dummy for a Registered Republican	15,861,104	0.39	0.49	0.00	0.00	1.00
Dummy for a College Graduate	15,861,104	0.42	0.49	0.00	0.00	1.00

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.

Table 3: Summary of Price Changes in Risky Homes Following Disclosure

This table presents average log sale prices for homes before and after flood disclosure from 3 different samples: all of United States (Panel A), properties in FEMA 100-year floodplains only (Panel B), or properties not in FEMA 100-year floodplains only. 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. To control for unrelated variation in sale prices, the log price averages are estimated from cross-sectional regressions of the log of sale amount on FloodFactors, controlling for Block-group fixed effects, month-year fixed effects, and a set of hedonic controls. The pre-period runs from August 2017 to August 2020 and post-period runs from August 2021 to December 2024. 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. For the test of differences (column 3), significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

Panel A: Full Sample			
	Before Disclosure	After Disclosure	Difference
Risk Above Severe	0.028	0.017	-0.011***
Risk Above Major	0.000	-0.001	-0.001
Risk Above Moderate	0.018	0.019	0.001
Risk Above Minor	-0.001	-0.002	-0.001
Obs	21,073,732	21,073,732	21,073,732
Panel B: FEMA Only			
	Before Disclosure	After Disclosure	Difference
Risk Above Severe	0.0363	0.0253	-0.000
Risk Above Major	-0.026	-0.021	0.005
Risk Above Moderate	-0.013	-0.012	0.001
Risk Above Minor	-0.005	-0.006	-0.001
Obs	726,786	726,786	726,786
Panel C: Non-FEMA Only			
	Before Disclosure	After Disclosure	Difference
Risk Above Severe	0.012	0.001	-0.015***
Risk Above Major	0.000	0.001	0.001
Risk Above Moderate	0.000	0.001	0.001
Risk Above Minor	-0.004	-0.005	-0.001
Obs	20,320,514	20,320,514	20,320,514

Part 2. Regression Discontinuity

Table 4: 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. Each panel represents a different pair of flood risks, and for each pair, we show the RD estimate from three specifications: a linear fit within a auto-selected bandwidth around the cutoff (column 1), a polynomial fit of order 2 (column 2), and a polynomial fit of order 3 (column 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.

	Full Sample		
Dep. Var: Residualized Log Sale Price	Linear(Auto Bandwidth) (1)	2nd Order (2)	3rd Order (3)
	Panel A: Risk Factor 3 vs 4		
FloodFactor = 4 × Post Disclosure	-0.00815	-0.0184**	-0.0245**
	(-0.72)	(-2.05)	(-2.08)
Obs	87531	212570	212570
	Panel B: Risk Factor 4 vs 5		
FloodFactor = 5 × Post Disclosure	-0.0205	-0.00821	-0.0115
	(-1.35)	(-0.76)	(-0.78)
Obs	52,589	253,165	253,165
	Panel C: Risk Factor 5 vs 6		
FloodFactor = 6 × Post Disclosure	0.00272	-0.00495	-0.00771
	(0.24)	(-0.63)	(-0.74)
Obs	117331	421814	421814
	Panel D: Risk Factor 6 vs 7		
FloodFactor = 7 × Post Disclosure	0.0207	0.0178*	0.0215
	(1.55)	(1.85)	(1.64)
Obs	97,609	417,825	417,825
	Panel E: Risk Factor 7 vs 8		
FloodFactor = 8 × Post Disclosure	-0.0284**	-0.0361***	-0.0350**
	(-1.97)	(-3.40)	(-2.43)
Obs	71497	311928	311928
	Panel F: Risk Factor 8 vs 9		
FloodFactor = 9 × Post Disclosure	-0.0373***	-0.0250**	-0.0310**
	(-2.86)	(-2.55)	(-2.32)
Obs	109,544	420,074	420,074
	Panel G: Risk Factor 9 vs 10		
FloodFactor = 10 × Post Disclosure	-0.0281	-0.0302***	-0.0438***
	(-1.64)	(-2.77)	(-3.01)
Obs	79,543	359,548	359,548
Block-Group FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Table 5: Robustness Check: Different Levels of Fixed Effects for 8 vs 9 Homes

For homes that are rated 8 or 9, this table presents the difference in regression discontinuity results examining the relationship between log sale price and expected flood depth using an auto-selected bandwidth around the cutoff. In columns 1, 2, 3 and 4, we residualize the outcome variable with no geographic fixed effects, county fixed effects, tract fixed effects and block group fixed effects, respectively. 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.

	Full Sample			
Dep. Var: Residualized Log Sale Price	Linear(Auto Bandwidth)			
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	-0.0318	-0.0294*	-0.0373***	-0.0373***
	(-1.49)	(-1.81)	(-2.75)	(-2.86)
Expected Depth	0.694***	0.460***	-0.0879	-0.0907
	(5.78)	(5.01)	(-1.15)	(-1.24)
FloodFactor = 9	-0.0893***	-0.0852***	0.000458	0.000511
	(-6.32)	(-7.90)	(0.05)	(0.06)
FloodFactor = 9 × Expected Depth	-0.362***	-0.192**	0.112	0.102
	(-2.89)	(-2.00)	(1.40)	(1.34)
Post Disclosure	0.298***	0.00560	0.0203*	0.0231**
	(17.25)	(0.42)	(1.84)	(2.18)
Post Disclosure × Expected Depth	0.114	0.244*	0.304***	0.294***
	(0.62)	(1.75)	(2.62)	(2.64)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.00895	-0.143	-0.216*	-0.205*
	(-0.05)	(-0.99)	(-1.79)	(-1.77)
Constant	12.44***	0.0520***	-0.0136*	-0.0149**
	(3.91)	(5.95)	(-1.87)	(-2.13)
Obs	109,593	109,593	109,582	109,544
Level of FE's	**None**	**County**	**Tract**	**Block Group**
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table 6: 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	NonFEMA &Coastal	NonFEMA &NonCoastal
	(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
Block Group FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table 7: Financial Constraints: Flood Risk Impact on Log Income and FHA Status

The tables below present regression discontinuity models examining the relationship between the buyer's log income (panel A) or FHA status (panel B) 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.

Panel A. Log Income

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)
Post Disclosure	0.0359**	0.0114	0.0243
	(1.99)	(0.92)	(1.44)
Expected Depth	-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)
Obs	34,886	131,183	131,183
Control for Higher Order Polynomials		✓	✓
Blockgroup FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Panel B. FHA Status

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)
Post Disclosure	0.00256	0.00285	0.00138
	(0.26)	(0.44)	(0.16)
Expected Depth	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)
Obs	62,396	234,542	234,542
Controls for Higher Order Polynomials		✓	✓
Block Group FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Table 8: Taste-based Preferences: Flood Risk Impact on Age and Dummy for Republican

The tables below present regression discontinuity results examining the relationship between the average household age (panel A) or dummy for Republican in household (panel B) and expected flood depth for both the pre-period (January 2017 to August 2020) and the post-period (August 2021 to December 2024). Column 1 does not include any income controls, while columns 2 through 4 control for income and income interacted with a post-disclosure dummy. The alternate regression discontinuity specifications (columns 3 and 4) 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. The outcome variable is residualized using hedonic controls, block group fixed effects, and sale year-month fixed effects. 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.

Panel A. Average Household Age

Dep. Var: Residualized LHS Variable	Linear(Auto Bandwidth)	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	0.660	1.200	0.978*	1.856**
	(1.13)	(1.61)	(1.84)	(2.57)
Post Disclosure	-0.741*	-1.625***	-1.345***	-1.817***
	(-1.71)	(-2.92)	(-3.46)	(-3.45)
Expected Depth	2.435	1.621	0.171	3.376
	(0.84)	(0.40)	(0.10)	(0.76)
FloodFactor = 9	-0.322	-0.0738	-0.0402	-0.191
	(-0.82)	(-0.14)	(-0.10)	(-0.36)
Obs	35,925	19,019	84,941	84,941
Control for Income		✓	✓	✓
Controls for Higher Order Polynomials			✓	✓
Block-Group FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Panel B. Dummy for a Registered Republican in Household

Dep. Var: Residualized LHS Variable	Linear(Auto Bandwidth)	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	0.00757	0.0234	0.00696	0.0304
	(0.57)	(1.14)	(0.45)	(1.45)
Post Disclosure	-0.00195	-0.00818	0.0125	-0.00722
	(-0.22)	(-0.58)	(1.11)	(-0.47)
Expected Depth	0.0359	0.153*	0.00892	0.179
	(0.70)	(1.78)	(0.17)	(1.34)
FloodFactor = 9	-0.0114	-0.0334**	-0.0200*	-0.0325**
	(-1.21)	(-2.14)	(-1.71)	(-2.05)
Obs	66,033	29,301	126,532	126,532
Control for Income		✓	✓	✓
Controls for Higher Order Polynomials			✓	✓
Block Group FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table 9: Model Output: Parameter Estimates

The table below shows the key estimation results of our discrete-choice housing model. For our estimation sample, based on empirical findings, we focus the set of homes within the bandwidth of homes near the 8 vs. 9 cutoff with price, income, age all residualized to block-group fixed effects.

Parameter	Estimate	S.E.
α_0	-0.015783	0.018578
$\pi_{p,y}$	-2.515008	0.043714
β_r	-0.012081	0.034186
$\pi_{r,\text{age}}$	0.024859	0.015329
β_{run}	-0.001580	0.016283

Table 10: Model Output: Shapely Decomposition

This table summarizes two key sorting metrics involving the neighborhood attribute `running`; results are percentages of the total change attributable to each channel. The first row indicates that the resorting of exposure to flood risk by income is almost entirely price-driven, while the second shows that the resorting of exposure to risk by age is almost entirely due to preference heterogeneity.

Metric	M_{00}	M_{01}	M_{10}	M_{11}	Price %	Heterog. %
Cov(ln income, $\mathbb{E}$[running])	0.013037	0.012988	0.004445	0.004405	99.48	0.52
Cov(age, $\mathbb{E}$[running])	0.000341	0.015467	0.000537	0.015638	1.19	98.81

Internet Appendix

A Part 1: Difference-in-Difference Analyses

Table A1: DID Regression: Full Specification

This table presents progressive difference-in-difference regressions of the log of sale amount on FloodFactor. Regression data is constructed from flood factor(1–10), across the pre-period (January 2017 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 - Full V2				
	(1)	(2)	(3)	(4)	(5)
Risk is Above Severe × Post Disclosure	0.00149	-0.0111***	-0.00991***	-0.0106***	-0.0102***
	(0.46)	(-4.31)	(-4.20)	(-4.53)	(-4.61)
Risk is Above Major × Post Disclosure	0.00254	-0.00178	-0.00186	-0.00286	-0.00236
	(0.94)	(-0.83)	(-0.99)	(-1.55)	(-1.35)
Risk is Above Moderate × Post Disclosure	-0.00337	-0.00107	0.0000884	0.000929	0.000718
	(-1.24)	(-0.51)	(0.05)	(0.52)	(0.43)
Risk is Above Minor × Post Disclosure	-0.0154***	0.000663	0.00418	0.00281	0.000654
	(-3.36)	(0.19)	(1.40)	(0.97)	(0.24)
Risk is Above Minimal × Post Disclosure	0.0367***	-0.00287	-0.00605**	-0.00495*	-0.00308
	(8.90)	(-0.89)	(-2.20)	(-1.84)	(-1.22)
Risk is Above Severe	0.0789***	0.111***	0.0302***	0.0235***	0.0270***
	(34.55)	(61.65)	(18.31)	(14.28)	(17.46)
Risk is Above Major	-0.00152	0.0589***	0.0115***	0.00621***	0.00110
	(-0.81)	(39.52)	(8.84)	(4.85)	(0.92)
Risk is Above Moderate	0.0148***	0.0116***	0.0000425	0.000664	-0.000628
	(7.92)	(7.92)	(0.03)	(0.54)	(-0.54)
Risk is Above Minor	-0.0101***	-0.00380	-0.0105***	-0.00831***	-0.00763***
	(-3.21)	(-1.54)	(-5.11)	(-4.15)	(-4.05)
Risk is Above Minimal	0.0439***	-0.0330***	-0.00205	0.00127	0.00494***
	(15.47)	(-14.80)	(-1.09)	(0.69)	(2.84)
Obs	13274860	13274760	13270055	13251378	13251378
R2	0.0300	0.4133	0.6092	0.6509	0.6908
R2-Adj	0.0300	0.4131	0.6048	0.6403	0.6814
County-Period FE		✓			
Tract-Period FE			✓		
Block Group-Period FE				✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Hedonic Controls					✓

Table A2: DID Regression: Geographic Variation across 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 (January 2017 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 FE	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓	✓

B Part 2: Regression Discontinuity

B.1 Standard RD Analyses using the Post-Disclosure Period Only

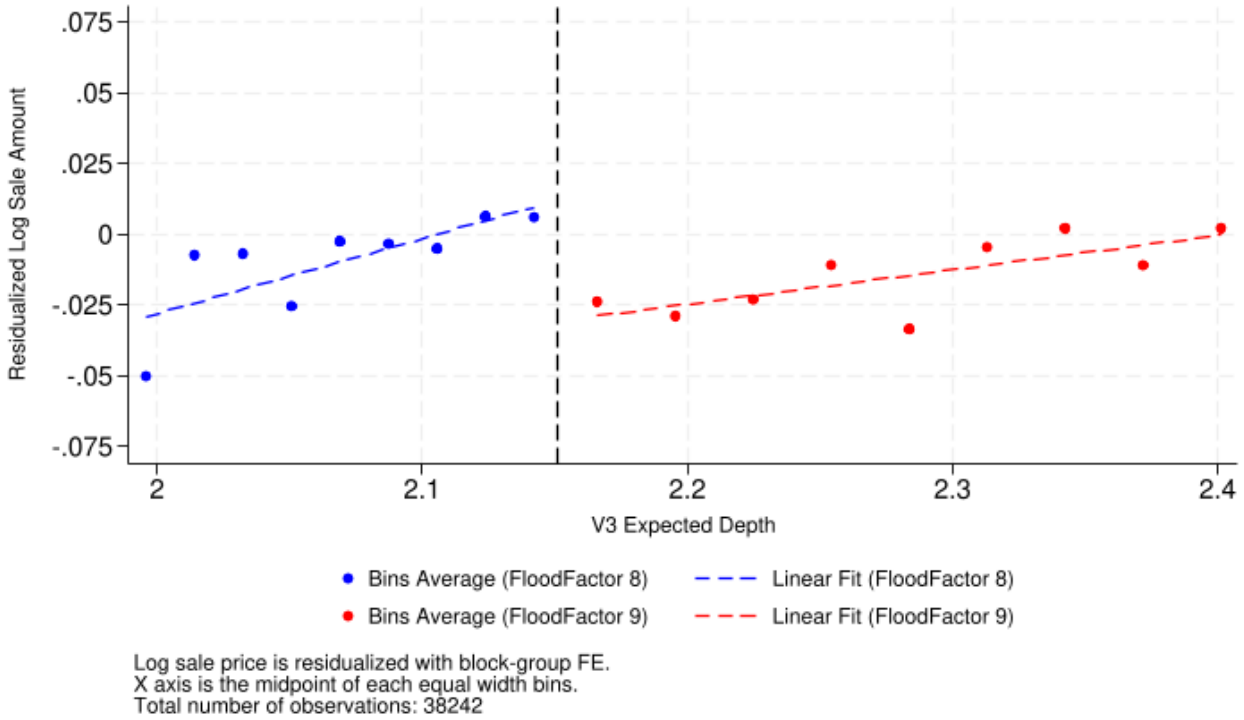
Table A3: Impact of Flood Risk Impact on Log Prices: Post-Period Only

This table presents the regression discontinuity results when we only examine around the cutoff in the post-disclosure period. The regression discontinuity specifications shown include a linear fit within a auto-selected bandwidth around the cutoff (column 1), fitted polynomials of order 2 (column 2) and fitted polynomials of order 3 (column 3). 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..

	Full Sample		
Dep. Var: Residualized Log Sale Price	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)
FloodFactor = 9	-0.0368***	-0.0274***	-0.0304***
	(-3.61)	(-3.57)	(-2.91)
Expected Depth	0.203**	0.132***	0.194**
	(2.33)	(3.73)	(2.19)
FloodFactor = 9 × Expected Depth	-0.103	-0.0398	-0.112
	(-1.13)	(-0.97)	(-1.09)
Obs	48,410	186,738	186,738
Control for Higher-order Polynomials		✓	✓
County FE	✓	✓	✓
Year-Month FE	✓	✓	✓
Hedonic Controls	✓	✓	✓

Figure 11: Plot of Log Price: Post-Period Only

The figure below visually show a standard linear RD Analysis with auto-selected bandwidths using the full data sample for log price in the post-disclosure period only. To control for omitted variable bias, the LHS variable is residualized with block-group fixed effects and basic hedonics. Each dot represents the post-period average log home prices. 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.



B.2 Analyses Across Different Subsamples

Table A4: 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 A5: RD: Subsample Analysis of Flood Risk Impact on FHA Dummy

This table presents the regression discontinuity results 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	✓	✓	✓	✓

Table A6: RD: Subsample Analysis of Flood Risk Impact on Dummy for Nonwhite

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between a dummy for whether an applicant identifies as non-white and expected flood depth after First Street. The different subsamples include: all homes (column 1), homes outside of an 100 year FEMA floodplain only (column 2), homes outside of a floodplain that is exposed to a coastal source of flooding (column 3), or homes outside a foodplain that is **not** exposed to a coastal source of flooding (column 4). The regression discontinuity specifications shown use 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: Log Applicant Income	All	NonFEMA Only	NonFEMA &Coastal Only	NonFEMA &NonCoastal Only
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	0.00348	0.0000200	-0.0133	0.00371
	(0.34)	(0.00)	(-0.55)	(0.26)
Expected Depth	-0.00914	0.00518	-0.140	0.0346
	(-0.18)	(0.09)	(-1.34)	(0.49)
FloodFactor = 9	-0.00338	-0.00397	0.0143	-0.00949
	(-0.50)	(-0.49)	(0.90)	(-1.02)
FloodFactor = 9 × Expected Depth	0.0336	0.00842	0.261*	-0.0373
	(0.57)	(0.12)	(1.96)	(-0.46)
Post Disclosure	0.00753	0.00473	0.0244	-0.000167
	(0.99)	(0.52)	(1.43)	(-0.02)
Post Disclosure × Expected Depth	0.0931	0.0960	0.170	0.0901
	(1.21)	(1.06)	(1.06)	(0.84)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.116	-0.0774	-0.230	-0.0596
	(-1.32)	(-0.74)	(-1.12)	(-0.49)
Constant	0.00163	0.00170	-0.0257**	0.00898
	(0.32)	(0.29)	(-2.29)	(1.30)
Obs	86975	62861	12382	50479
BlockGroup FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table A7: RD: Subsample Analysis of Flood Risk Impact on Average Age

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between average household age and expected flood depth after First Street. The different subsamples include: all homes (column 1), homes outside of an 100 year FEMA floodplain only (column 2), homes outside of a floodplain that is exposed to a coastal source of flooding (column 3), or homes outside a foodplain that is **not** exposed to a coastal source of flooding (column 4). The regression discontinuity specifications shown use 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.

Dep. Var: Residualized LHS Variable	All	NonFEMA Only	NonFEMA Coastal	NonFEMA nonCoasta
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	1.201	1.387	0.955	1.532
	(1.61)	(1.61)	(0.44)	(1.62)
Post Disclosure	-1.623***	-1.563**	-0.711	-1.797**
	(-2.92)	(-2.46)	(-0.49)	(-2.54)
Expected Depth	1.864	2.831	-7.111	5.755
	(0.46)	(0.62)	(-0.71)	(1.11)
FloodFactor = 9	-0.0936	-0.283	0.322	-0.464
	(-0.17)	(-0.45)	(0.20)	(-0.67)
Obs	18955	14536	2245	12291
Income Controls	✓	✓	✓	✓
BlockGroup FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table A8: RD: Subsample Analysis of Flood Risk Impact on Dummy for Dummy Republican

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between a dummy for whether a member of the household registered as republican and expected flood depth after First Street. The different subsamples include: all homes (column 1), homes outside of an 100 year FEMA floodplain only (column 2), homes outside of a floodplain that is exposed to a coastal source of flooding (column 3), or homes outside a foodplain that is **not** exposed to a coastal source of flooding (column 4). The regression discontinuity specifications shown use 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.

Dep. Var: Residualized LHS Variable	All	NonFEMA Only	NonFEMA Coastal	NonFEMA NonCoastal
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	0.0215	0.00720	-0.0658	0.0226
	(1.05)	(0.30)	(-1.26)	(0.85)
Post Disclosure	-0.00691	0.00266	0.0337	-0.00604
	(-0.49)	(0.17)	(1.02)	(-0.33)
Expected Depth	0.152*	0.0519	-0.187	0.140
	(1.78)	(0.54)	(-0.99)	(1.25)
FloodFactor = 9	-0.0325**	-0.0227	0.00583	-0.0309
	(-2.08)	(-1.27)	(0.15)	(-1.54)
Obs	29256	22464	4260	18204
Control for Income	✓	✓	✓	✓
BlockGroup FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

B.3 Alternative Estimation using County FE's

Table A9: RD: Subsample Analysis of Flood Risk Impact on Sale Prices- County Fixed Effects

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. Instead of residualizing the data using block-group fixed effects, we use county fixed effects. 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	-0.0294*	-0.0267	-0.223***	0.0176
	(-1.81)	(-1.45)	(-5.15)	(0.87)
Expected Depth	0.460***	0.452***	1.287***	0.196*
	(5.01)	(4.49)	(6.10)	(1.70)
FloodFactor = 9	-0.0852***	-0.0847***	-0.377***	-0.0145
	(-7.90)	(-7.03)	(-13.28)	(-1.09)
FloodFactor = 9 × Expected Depth	-0.192**	-0.233**	-0.0253	-0.166
	(-2.00)	(-2.21)	(-0.11)	(-1.38)
Post Disclosure	0.00560	-0.00750	0.0523	-0.0277*
	(0.42)	(-0.51)	(1.58)	(-1.68)
Post Disclosure × Expected Depth	0.244*	0.0587	0.773**	-0.194
	(1.75)	(0.38)	(2.37)	(-1.10)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.143	0.0554	0.0992	0.195
	(-0.99)	(0.34)	(0.28)	(1.07)
Constant	0.0520***	0.0379***	0.142***	0.00749
	(5.95)	(3.92)	(6.52)	(0.69)
Obs	109593	76917	13568	63349
County FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table A10: RD: Subsample Analysis of Flood Risk Impact on Log Income- County Fixed Effects

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between log income and expected flood depth after First Street. Instead of residualizing the data using block-group fixed effects, we use county fixed effects. 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 Applicant Income	All	NonFEMA Only	NonFEMA &Coastal Only	NonFEMA &NonCoastal Only
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	-0.0273	-0.0173	-0.0210	-0.0187
	(-1.02)	(-0.58)	(-0.26)	(-0.59)
Expected Depth	0.244	0.107	1.557***	-0.326
	(1.39)	(0.55)	(3.26)	(-1.54)
FloodFactor = 9	-0.0595***	-0.0595***	-0.487***	0.0298
	(-2.94)	(-2.65)	(-7.89)	(1.24)
FloodFactor = 9 × Expected Depth	0.00835	0.139	0.0479	0.350
	(0.05)	(0.69)	(0.09)	(1.59)
Post Disclosure	0.0207	0.0150	0.0301	0.0126
	(0.96)	(0.63)	(0.49)	(0.49)
Post Disclosure × Expected Depth	0.221	0.228	0.111	0.290
	(0.96)	(0.90)	(0.18)	(1.05)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.166	-0.206	0.212	-0.286
	(-0.69)	(-0.78)	(0.31)	(-1.00)
Constant	0.0297*	0.00379	0.129***	-0.0309
	(1.81)	(0.21)	(2.76)	(-1.59)
Obs	34953	26113	3979	22134
BlockGroup FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Table A11: RD: Subsample Analysis of Flood Risk Impact on FHA Status- County Fixed Effects

This table presents the regression discontinuity results, broken down by key subsamples, examining the relationship between a dummy variable equal to one if the buyer took out a FHA loan and expected flood depth after First Street. Instead of residualizing the data using block-group fixed effects, we use county fixed effects. 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: Dummy for FHA Applicant	All	NonFEMA Only	NonFEMA &Coastal Only	NonFEMA &NonCoastal Only
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	0.0238*	0.0141	0.0311	0.0104
	(1.89)	(0.95)	(0.87)	(0.64)
Expected Depth	-0.0944	-0.0427	-0.250	0.0107
	(-1.25)	(-0.49)	(-1.34)	(0.11)
FloodFactor = 9	0.00331	0.00518	0.0935***	-0.0138
	(0.37)	(0.50)	(3.72)	(-1.20)
FloodFactor = 9 × Expected Depth	0.0656	0.00920	-0.0501	0.00270
	(0.83)	(0.10)	(-0.25)	(0.03)
Post Disclosure	0.00372	0.0105	0.00932	0.0119
	(0.36)	(0.88)	(0.34)	(0.89)
Post Disclosure × Expected Depth	0.00520	0.0593	-0.0894	0.119
	(0.05)	(0.48)	(-0.33)	(0.84)
FloodFactor = 9 × Post Disclosure × Expected Depth	-0.107	-0.147	-0.162	-0.190
	(-0.96)	(-1.12)	(-0.55)	(-1.28)
Constant	-0.00905	0.000367	-0.0293	0.00815
	(-1.27)	(0.04)	(-1.55)	(0.88)
Obs	62452	45043	7344	37699
BlockGroup FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

B.4 Alternative Taste-based Outcomes

Table A12: RD: Flood Risk Impact on Dummy Democrat and College Attainment

The tables below present the regression discontinuity results examining the relationship between whether the buyer is a democrat (Panel A) and whether they went to college (Panel B) versus expected flood depth for both the pre-period (January 2017 to August 2020) and the post-period (August 2021 to December 2024). The outcome variable is residualized using hedonic controls, block group fixed effects, and sale year-month fixed effects. 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.

Panel A. Dummy for Registered Democrat

	Full Sample			
Dep. Var: Residualized LHS Variable	Linear(Auto Bandwidth)	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	-0.00796	-0.00649	-0.00132	-0.0141
	(-0.64)	(-0.32)	(-0.09)	(-0.69)
Post Disclosure	-0.00364	-0.00639	0.00350	0.00252
	(-0.43)	(-0.46)	(0.32)	(0.17)
Expected Depth	0.0445	0.0557	-0.0301	-0.0415
	(0.93)	(0.66)	(-0.58)	(-0.32)
FloodFactor = 9	-0.00267	0.000465	0.00107	0.00912
	(-0.30)	(0.03)	(0.09)	(0.59)
Obs	67290	29851	126532	126532
Control for Income		✓	✓	✓
Controls for Higher Order Polynomials			✓	✓
Block Group FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

Panel B. College Attainment

	Full Sample			
Dep. Var: Residualized LHS Variable	Linear(Auto Bandwidth)	Linear(Auto Bandwidth)	2nd Order	3rd Order
	(1)	(2)	(3)	(4)
FloodFactor = 9 × Post Disclosure	0.00695	0.0186	0.00317	0.00819
	(0.52)	(0.86)	(0.20)	(0.39)
Post Disclosure	-0.00157	-0.000920	0.00694	0.00931
	(-0.15)	(-0.05)	(0.61)	(0.60)
Expected Depth	0.0278	0.0773	0.0267	-0.0974
	(0.36)	(0.57)	(0.49)	(-0.72)
FloodFactor = 9	-0.00439	-0.0175	-0.0180	-0.0117
	(-0.46)	(-1.07)	(-1.52)	(-0.73)
Obs	65139	28707	126532	126532
Control for Income		✓	✓	✓
Controls for Higher Order Polynomials			✓	✓
Block Group FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓