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

Steve Billings * Sophie Calder-Wang † Weiling Liu‡

August 29, 2025

Preliminary

Abstract

When a house is disclosed to buyers as having extreme flood risk, holding all else equal, its sale price drops by approximately 4%. To obtain plausibly exogenous variation, we reverse engineer the running variable and utilize natural discontinuity points in the categorization of a novel Flood Factor released on Redfin and Realtor.com for all homes across the United States in 2020 and 2021. The estimated price discount is not observed at lower flood risk levels. Furthermore, it is observed only for properties outside of FEMA floodplains and is up to four times stronger for properties exposed to coastal flooding. Interestingly, we find that those who purchase homes with extreme flood risk after disclosure have 5% lower income and are 2% more likely to have a Federal Housing Administration (FHA) loan. This suggests that flood disclosure has a distributional impact. Those who can afford to pay to avoid flood risk reshuffle into less risky homes—and ultimately, with better public information, more flood risk is shifted into the hands of the less financially privileged.

Keywords: Climate Risk; Financial Disclosure; House Prices; Distributional Impacts.
JEL Codes: G40, G50, G12, R31, R32

*Leeds School of Business, University of Colorado at Boulder *stephen.billings@colorado.edu*
†The Wharton School, University of Pennsylvania *sophiecw@wharton.upenn.edu*
‡D'Amore-McKim School of Business,Northeastern University *w.liu@northeastern.edu*

1 Introduction

Unprecedented natural disasters such as Hurricane Milton have been both in the news and of paramount concern for policymakers recently; their economic impact is large—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, climate risks including flood risk are now repricing their most valuable asset: their house. In the past, American homeowners could look up Federal Emergency Management Agency (FEMA) flood maps to understand if a house is in a high-risk flood zone, which is generally a 100-year floodplain that has 1% or higher probability of flooding each year. These FEMA maps are critiqued for being outdated–75% of maps are five years or older–and not reflecting forward-looking projections of changing weather patterns (Eby, 2019).

To increase the understanding of flood risk for consumers, First Street released a proprietary Flood Factor in August 2020 on Realtor.com and in February 2021 on Redfin. In September 2024, Zillow also started disclosing the First Street data, making it nearly impossible for a consumer to fully review a house listing online without seeing its First Street Flood Factor. Figures 1 and 2 show how the scores are featured on the search websites; each home is given a numerical score (between 1 for lowest risk and 10 for highest risk) and a qualitative risk label (minor, moderate, major, severe or extreme). It is now easier than ever for homebuyers to see a property-level measure of homes' flood risks, and unlike the information previously provided by FEMA maps, this measure is no longer bundled with mandatory flood insurance.[1]

In a 2023 survey conducted by Zillow, over 80% of prospective homebuyers report that they consider climate risks when shopping for a home. Furthermore, flood risk ranks as their biggest concern (Zillow, 2023). The Flood Factor provided by First Street is not only geared toward these prospective homebuyers, but it suddenly and drastically changed the landscape 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 identified by FEMA maps. If consumers take notice of and believe in First Street's flood models, then nearly 6 million homes were suddenly reclassified as having high flood risk, despite being largely perceived as not risky before (Humphries, 2020). In equilibrium, the pricing and distributional effects of the new flood information provided by First Street remain unclear. We will address this gap by studying the natural cutoff points created when mapping a proprietary, continuous measure of homes' flood risk to the discrete Flood Factor.

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

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

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

There is an ongoing debate about whether homebuyers care about flood information, and thus, discount homes with flood risk. Prior studies have focused on a specific geography or utilized flood maps that mix the cost of flooding with the cost of mandatory insurance (Gibson et al., 2017; Murfin and Spiegel, 2020; Baldauf et al., 2020b). Closest to our paper, Fairweather et al. (2024) also studies the effect of First Street's flood factor using a randomized experiment on the Redfin platform. However, their primary goal is to understand search behavior, and thus, they randomly assign treatment at the user level. This experimental design makes it difficult to identify equilibrium pricing effects across houses. Perhaps as a result, they did not find significant price effects in the overall sample.

Using the rollout of the Flood Factor across the U.S. as a natural experiment, we first establish a baseline price effect using a difference-in-difference (DID) model. Using a DID regression, we compare prices for homes across different flood rating categories, both before and after the rollout of the flood factor. However, the Flood Factor is correlated with many omitted factors, such as the proximity of the property to the sea, which is a desired amenity and may actually increase equilibrium prices. To address this, we obtain more plausibly exogenous variation using a regression discontinuity (RD) model. By reverse engineering the continuous and proprietary risk variable that is not disclosed to the public, we can compare nearly identical houses that were just below versus above the cut-offs used to assign the discrete flood factors.[2]

First, in DID regressions with geographic controls, ranging from county-period fixed effects (most relaxed) to block-group and FEMA-map fixed effects (most stringent), we find a significant decline in sale price of roughly 1% for homes with "extreme" flood risk following the release of First Street's Flood factor. A pre-trend analysis shows that this decline does not exist before disclosure, and it appears immediately in the year following disclosure. Interestingly, we find that the price effect does not exist for properties *within* FEMA floodplains; it is almost entirely driven by properties *outside* FEMA floodplains. There are two possible explanations: first, flood information for homes within FEMA floodplains was already available to the public prior to First Street's disclosure, so there may be little novel information added. Second, the vast majority of properties within FEMA floodplains are required to buy flood insurance if they have a mortgage. Thus, for these properties, a significant portion of flood risk may ultimately be absorbed through insurance.

Second, in RD models, we further restrict our sample to homes that are very similar in flood risk. We calculate the price difference when these otherwise similar homes fall on either side of a discrete

[2]We sincerely thank Jeremy Porter and the research team at First Street for helping us reconstruct the continuous risk variable.

cutoff and are thus assigned different Flood Factors. We find a baseline price discount of 4% across all U.S. properties, and strikingly, we find up to a discount of up to 17% for properties that are not in a FEMA floodplain and are located along the coast.

(ii) How does flood-risk disclosure change who lives in flood-prone properties?

Preliminary evidence suggests that homes with an extremely high Flood Factor (implying extreme flood risk) dropped significantly in value after First Street released its data. Since housing supply is generally inelastic, lower prices suggest lower demand for flood-prone properties. However, the change in demand may be heterogeneous and vary depending on consumer characteristics. For example, flood-prone properties may attract more flood-risk-tolerant buyers, and this risk tolerance may be correlated with observable characteristics such as income, age, race, and whether the house was purchased with a FHA loan. To test this theory, using HMDA data, we regress homebuyers' demographics on flood-risk disclosure.

Using a 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 less financially privileged. On the other hand, we do not find consistently significant effects for buyer's age or race.We do not show these results to save space, but they can be shared upon request.

In sum, evidence so far suggests that buyers are resorting based on flood tolerance, and all else equal, buyers who can afford to hold less risky properties choose to do so. In the future, we would like to test for the importance of of beliefs (ie political affiliation) and flood risk salience (ie prior experiences with natural disasters) as well.

Related Literature

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

In parallel, our paper also contributes 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 platform continues to play a crucial role for households' search behavior, altering the information environment for market participants. For example, Fu, Jin and Liu (2022) shows that Zillow's automated valuations ("Zestimates") influence human behavior, affecting both listing and sale. Buchak, Matvos, Piskorski and Seru (2022) finds algorithmic pricing deployed by iBuyers[3] produces more accurate predictions in liquid housing markets, allowing for automated intermediation. Raymond (2024) finds that algorithmic valuation can have market-level effects, closing historical racial gaps in housing value.

Finally, broader literature on financial disclosure underscores that while increased transparency can improve consumer decision-making, its effect could also introduce biases due to salience. Studies (e.g., Agarwal et al. (2015)) show that effective disclosure needs to be simple and salient in order to meaningfully influence household financial choices. By integrating these strands, our paper contributes to the household finance literature by examining how information from both climate risk and digital platforms jointly impacts real estate transactions and, ultimately, household wealth allocation.

Unprecedented natural disasters such as Hurricane Milton have been both in the news and of paramount concern for policymakers recently; their economic impact is large—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, climate risks including flood risk are now repricing their most valuable asset: their house. In the past, American homeowners could look up Federal Emergency Management Agency (FEMA) flood maps to understand if a house is in a high-risk flood zone, which is generally a 100-year floodplain that has 1% or higher probability of flooding each year. These FEMA maps are critiqued for being outdated–75% of maps are five years or older–and not reflecting forward-looking projections of changing weather patterns (Eby, 2019).

To increase the understanding of flood risk for consumers, the nonprofit First Street released a proprietary Flood Factor in August 2020 on Realtor.com and in February 2021 on Redfin. In September 2024, Zillow also started disclosing the First Street data, making it nearly impossible for a consumer to fully review a house listing online without seeing its First Street Flood Factor. Figures 1 and 2 show how the scores are featured on the search websites; each home is given a numerical score (between 1 for lowest risk and 10 for highest risk) and a qualitative risk label (minor, moderate, major, severe or extreme). It is now easier than ever for homebuyers to see a coordinated measure of homes' flood

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

risks, and unlike FEMA maps, this measure is no longer bundled with mandatory flood insurance.[4]

In a 2023 survey conducted by Zillow, over 80% of prospective homebuyers report that they consider climate risks when shopping for a home. Furthermore, flood risk ranks as their biggest concern (Zillow, 2023). The Flood Factor provided by First Street is not only geared toward these prospective homebuyers, but it suddenly and drastically changed the landscape 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 identified by FEMA maps. If consumers take notice of and believe in First Street's flood models, then nearly 6 million homes were suddenly reclassified as having high flood risk, despite being largely perceived as not risky before (Humphries, 2020). In equilibrium, the pricing and distributional effects of the new flood information provided by First Street remain unclear. We will address this gap by studying the natural cutoff points created when mapping a continuous measure of homes' flood risk to the discrete Flood Factor.

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

2 Data

First Street

The measure of flood risk that we focus on is the Flood Factor, a score published by First Street Foundation and released on popular real-estate platforms such as Zillow and Redfin (see Figures 1 and 2 for examples of how the scores are displayed for a platform user). The initial goal of First Street Foundation was to provide property-level information on future risks of flooding. Subsequently, they also expanded their database to include information on other climate risks including wildfire, heat, wind and air. Their flood factor is produced using the First Street Flood Model (FSF-FM)—a nationwide model that calculates the potential risk of flooding based on a combination of rainfall, streamflow, rise in sea level, tidal expectations, and storm surge.

The FSF-FM model is forward-looking in nature and incorporates both historic flood risk as well as climate change-driven changes in flood risk. One notable component of their model that deviates from standard flood models, including the FEMA floodplain maps, is the use of the First Street Precipitation Model (FS-PM). The FS-PM takes into account early 21st century rainfall records and calculates forward-looking projections, capturing the notion the United States will experience more occurrences of extreme rainfall in the future. As a result, inland properties that traditionally were classified as safe based on floodplain maps are more likely to be reclassified as risky under FSF-FM.

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

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

In addition to the qualitative category and quantitative risk score, we also reverse engineer the 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 8 shows how we can cleanly infer the cutoff points by plotting the observed flood factor (y-axis) against the log expected depth (x-axis). We will use these cutoff points for our regression discontinuity analysis in Section 3.2.

First Street vs FEMA

We obtain floodplain data from FEMA, and we merge this with our First Street data to see how the two measures of flood risk compare. To illustrate the differences, Figure 4 shows the faction of home transactions per census tract that are labeled as risky by FEMA in panel a (ie are in a 100-year floodplain [5]) versus First Street in panel b (ie have "extreme" flood risk) for the state of Florida. In general, we see that the two data sources seem closely related, but they are not identical. For instance, more properties sold in the upper left corner are labeled as risky by First Street, compared to FEMA.

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

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

CoreLogic

Our transactions data comes from the Corelogic Multiple Listing Enterprise Solutions (MLS) Database. The MLS database is comprised of data that real estate agents use to match buyers with sellers. In addition to the address and geolocation, we also have hedonic characteristics such as number of

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

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 3 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 percentile of sale prices are $179,000 and $450,000, respectively. The median house sold in our sample has 3 bedrooms and 2 bathrooms, with a living area of 1,672 square feet.

HMDA

Lastly, for homes that are purchased with a mortgage, we try to obtain additional borrower characteristics through the HMDA (Home Mortgage Disclosure Act) data. For each mortgage that we successfully match, we gather the borrower's age, ethnicity, income, as well as the loan is a FHA loan. In general, we use the FHA loan dummy for proxy for first-time or low-credit homebuyers.

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

3 Price Effects

In sum, our pricing analyses fall under one of two types: a difference-in-difference (DID) regression or a regression-discontinuity (RD) regression.

3.1 Difference in Difference Estimator

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

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

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

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

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

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

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

To capture the effect of releasing First Street's Flood Factor, we multiply the treatment $\vec{F_i}$ with $Post_t$, a scalar dummy equal to one if the transaction took place in the post period. As Figure 3 shows, we define the post period as the period following the official release of the final version of First Street's Flood Factor. Thus, $\vec{\beta_2}$ is our main coefficient of interest. If consumers cared about flood risk, this should lower prices for high-risk homes. Subsequently, we would expect the components of $\vec{\beta_2}$ associated with high-risk homes, such as homes with extreme flood risk, to be negative and significant.

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

It is worth noting that in Table 3, if we do not include strong geographic controls, higher flood risk is not associated with higher sale prices. For example, homes in the strongest treatment group, labeled with extreme flood risk, (adding up all of the coefficients ranging from above minimal x post

to above severe x post in column 1) actually sell for 2% higher than homes with minimal risk. This is likely due to the fact that these properties tend to also have popular amenities such as proximity to the beach or having water views. Ultimately, waterfront amenities could be positively correlated with both prices and flood risk. Consistent with this conjecture, when we control for more granular measures of location, such as block-group-time fixed effects in columns 4 through 6, this premium drops and eventually becomes a discount.

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

Given an average sale price of $382,850, this 1% drop represents a $3,829 price decline. Using First Street's propriety cost estimates, we find that the average annualized flood-related costs of owning a home is $22,655.57 and $57,407.24 for risk ratings of 8 and 9 respectively. Thus, back-of-envelope calculation assuming 5% discount rate and staying in the house for 10 years implies a marginal decreased value (increased cost) of $34,752 using First Street's pricing model. Thus, relative to estimated costs, the price decline is quite small.

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

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

3.1.1 Robustness: Pre-trend Analysis

For robustness, we conduct a pre-trend test and plot the coefficient on the dummy for extreme flood risk properties from Eq 3.1 by year in Figure 7. In this analysis, we also extend our time sample back several years to 2013. We see that the coefficient on "extreme" (ie treated) was quite stable before the release of First Street data, and it signicantly drops in value shortly following the release.

3.2 RD Estimator

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

To address the identification concerns above, we next use a regression-discontinuity (RD) design. First, we recreate a continuous measure of homes' flood risk called "expected depth" (see Figure 8) that is monotonically mapped into the discrete First Street Flood Factor using a set of empirically observable cut-offs. Then, using a RD analysis, we compare homes just above and just below the empirical cutoff value for a given Flood Factor number. In doing so, we assume that homes right around the cutoff are otherwise very similar and only differ depending on their assigned Flood Factor. In particular, we don't believe that the potential buyers of these homes suddenly have different beliefs about climate risk at the cutoff. Any observed price changes at the cut-off can then be reasonably assumed to be driven by the Flood Score. If we expect consumers to discount homes because they have a higher Flood Score, then we would expect to see a price jump downwards right at the cutoff.

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

difference in price between the post-disclosure period and the pre-disclosure period. [6]

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

Figure 9 plots a binscatter of the change in sale prices (after disclosure minus before disclosure) around the cutoff point for severely (shown in blue) versus extremely (shown in red) as a function of their underlying, continuous flood risk. Panel A shows the full sample, and following First Street's Flood Factor release, there is a small jump downwards. Next, Panel B shows the coastal properties only, and we see there is a small jump down in price right after the cutoff point.

In order to calculate the magnitude of the RD jump shown in Figure 9, we estimate the following RD regression fitted (with up to a polynomial of order 3) to our restricted sample:

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

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

Table **??** shows the results from estimating Eq 4.1. The columns correspond to estimation using a linear auto-selected band, a polynomial of order 2, and a polynomial of order 3, respectively. Consistent with Figure 9, we find a small but significant price drop of 2.5% (column 2) to 3.7% (column 1) post disclosure.

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

Finally, 6 repeats the above analysis but estimates it over several key subsamples. For convenience, we show the main specification using the full sample in column 1. Next, column 2 repeats the analysis but for non-FEMA properties only. Confirming that our results are not driven by areas with pre-existing information and where flood insurance is prevalent, we see that the RD coefficient is similarly strong and significant for the non-FEMA subsample.

Next, within the non-FEMA subsample, we further test whether properties exposed to coastal flooding (eg fluvial flooding) have a stronger price impact. Indeed, we find that properties which are both non-FEMA and subject to coastal flooding risk experience a large price drop of roughly 17%, visually depicted in Panel A of Figure 10. 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., 2020a) or that individuals largely respond to disaster risk only when it is salient (Dessaint and Matray, 2017; Gallagher, 2014).

3.2.1 Robustness: Covariate Balance Test

In our RD analyses, the drop in log price is sharp and observed very close to the cutoff point, so it is unlikely to be driven by other factors such as an increasing salience of climate risk over our time sample. As a robustness check, however, Figure 11 tests whether other key features of houses sold are unbalanced across the cutoff point. To run this check, we only residualize our data using blockgroup fixed effects, and then we plot expected depth (x-axis) against each one of our hedonic variables (y-axis). Reassuringly, around the cutoff, we do not observe any other sudden changes in size (ie lot size or living square foot), building age, number of bedrooms, or number of bathrooms.

3.3 Discussion of Price Effect and Salience

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

post-period, the Flood Factor has been circulating for a year. Thus, the novelty of this information should have worn off and it is possible that flood risk has become less salient to these homebuyers.

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

4 Distributional Effects

In this Section, we start to unpack the equilibrium effect of disclosure on *who* holds the riskiest properties. To do this, we use the most plausibly exogenous RD regressions from Section 3.2, but we replace the dependent variable (previously log price) with buyer characteristics:

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

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

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

First, in Table 7 we find that after disclosure, the most risky ("above severe") homes are being purchased by individuals with roughly 2.5% (column 2) to 4.6% (column 1) lower income.[7] This is notable because lower-income individuals are less likely be be able to bear the costs of a large climate event, and they are also less likely to buy insurance to help cover these tail events. This is further exacerbated by the fact that the price discount for holding a risky home does not seem to be actuarially fair, based on First Street's cost models. In equilibrium, this suggests that disclosing flood risks directly to consumers may have climate justice implications, because the heavy costs of climate change may disproportionally fall on the shoulders of individuals who can least bear it. This discontinuity is also visually shown in Panel b of Figure 9.

Furthermore, Table 8 shows the result broken down by key subsamples. Column 2 verifies that the

[7] We also test the effects of disclosure on age and race, but we find insignificant effects. We have omitted these findings in the interest of space, but they can be shared upon request.

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

Finally, in Table 9 we also examine FHA as an outcome and find that after disclosure, the most risky ("above severe") homes are purchased by individuals that are 1.5% (column 2) to 2.8% (column 3) more likely to have a FHA loan. This regression is visually depicted in Figure 9 Panel c. Since FHA loans are typically given to first-time and low-credit borrowers, this is further evidence that the expected cost of flooding and climate change may shift increasingly to the less financially stable. Table 9 further tests the finding across different subsamples. While the coefficient magnitude is similar in size for non-FEMA properties (column 2), we see that it is no longer significant. This is likely due to the reduced sample size. Again, within non-FEMA properties, we see that the magnitude of the effect is much stronger for coastal properties (2.6%, column 3) versus non-coastal properties (1.1%, column 4).

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

5 Conclusion

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

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

Going forward, more work needs to be done in order to understand whether the incorporation of flood risk depends on buyers' demographics, such as age or income level. If so, then flood disclosure would also change the demographics of homeowners in flood-prone areas and affect who ultimately holds

flood risk in equilibrium. Our findings have potential policy implications. As technology improves and new data on climate change becomes more readily available, our findings may help predict the equilibrium impact of new flood data on consumers of different types as well as consumers living in different regions of the United States.

References

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel (2015) "Regulating Consumer Financial Products: Evidence from Credit Cards *," *The Quarterly Journal of Economics*, 130 (1), 111–164, 10.1093/qje/qju037.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis (2020a) "Does climate change affect real estate prices? Only if you believe in it," *The Review of Financial Studies*, 33 (3), 1256–1295.

——— (2020b) "Does Climate Change Affect Real Estate Prices? Only If You Believe In It," *The Review of Financial Studies*, 33 (3), 1256–1295, 10.1093/rfs/hhz073.

Bernstein, Asaf, Stephen B. Billings, Matthew T. Gustafson, and Ryan Lewis (2022) "Partisan residential sorting on climate change risk," *Journal of Financial Economics*, 146 (3), 989–1015, 10.1016/j.jfineco.2022.03.004.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2022) "Why is Intermediating Houses so Difficult? Evidence from iBuyers," July, 10.2139/ssrn.3616555.

Dessaint, Olivier and Adrien Matray (2017) "Do managers overreact to salient risks? Evidence from hurricane strikes," *Journal of Financial Economics*, 126 (1), 97–121.

Eby, Matthew (2019) "Understanding FEMA Maps and Limitations,"Technical report, First Street, https://firststreet.org/research-library/understanding-fema-flood-maps-and-limitations.

Fairweather, Daryl, Matthew E. Kahn, Robert D. Metcalfe, and Sebastian Sandoval Olascoaga (2024) "Expecting Climate Change: A Nationwide Field Experiment in the Housing Market," November, 10.3386/w33119.

Fu, Runshan, Ginger Zhe Jin, and Meng Liu (2022) "Does Human-algorithm Feedback Loop Lead to Error Propagation? Evidence from Zillow's Zestimate," March, 10.3386/w29880.

Gallagher, Justin (2014) "Learning about an infrequent event: Evidence from flood insurance take-up in the United States," *American Economic Journal: Applied Economics*, 206–233.

Gibson, Matthew, Jamie Mullins, and Alison Hill (2017) "Climate change, flood risk, and property values: Evidence from New York City," *Working Paper*.

Heinrich, Martin (2024) "Flooding Costs the U.S. Between $179.8 and $496.0 Billion Each Year,"Technical report, Joint Economic Committee, https://www.jec.senate.gov/public/index.cfm/democrats/issue-briefs/?id=276AFFB8-7F15-4F16-BFE8-56C16D32BF26.

Humphries, Samuel (2020) "A Flooded Future: New Flood Model Exposes a Grim Reality,"Technical report, American Security Project, https://www.americansecurityproject.org/a-flooded-future-new-flood-model-exposes-a-grim-reality/.

Keys, Benjamin J. and Philip Mulder (2020) "Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise," October, 10.2139/ssrn.3906066.

Meyer, Robinson (2024) "Should You Trust Zillow's Climate Risk Data?"Technical report, Heatmap, https://heatmap.news/guides/zillow-climate-risk-flooding-fire.

Murfin, Justin and Matthew Spiegel (2020) "Is the Risk of Sea Level Rise Capitalized in Residential Real Estate?" *The Review of Financial Studies*, 33 (3), 1217–1255, 10.1093/rfs/hhz134.

Raymond, Lindsey (2024) "The Market Effects of Algorithms."

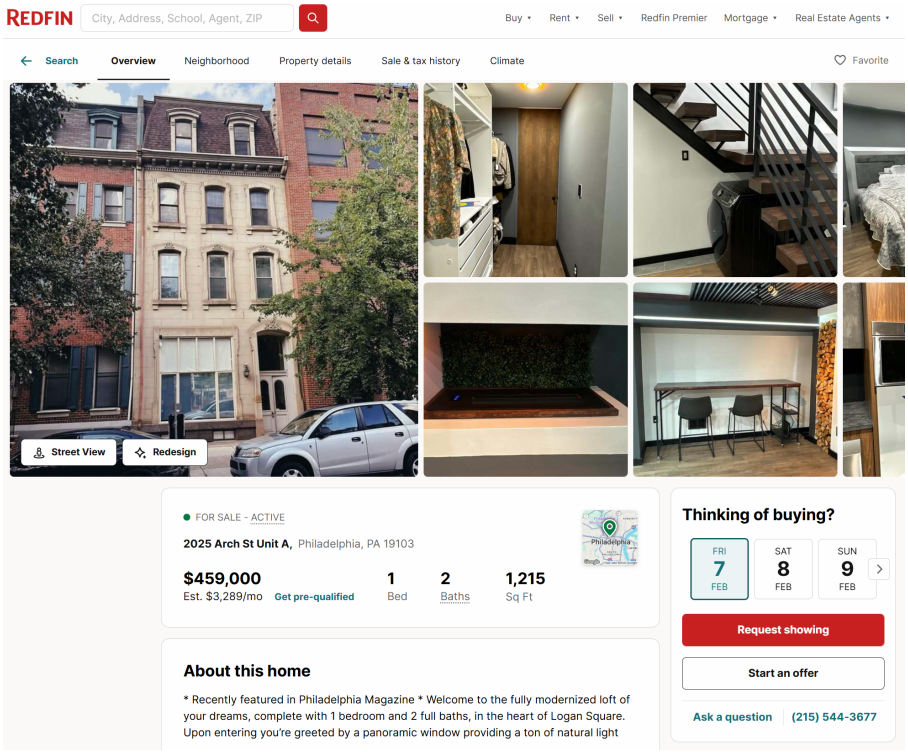
Zillow (2023) "More than 80% of home shoppers consider climate risks,"Technical report, Zillow, https://zillow.mediaroom.com/2023-09-05-More-than-80-of-home-shoppers-consider-climate-risks-when-looking-for-a-new-home.

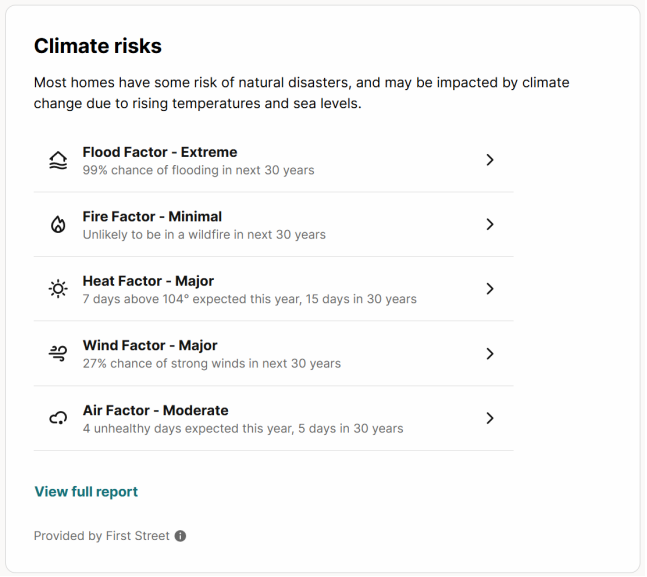
Figures

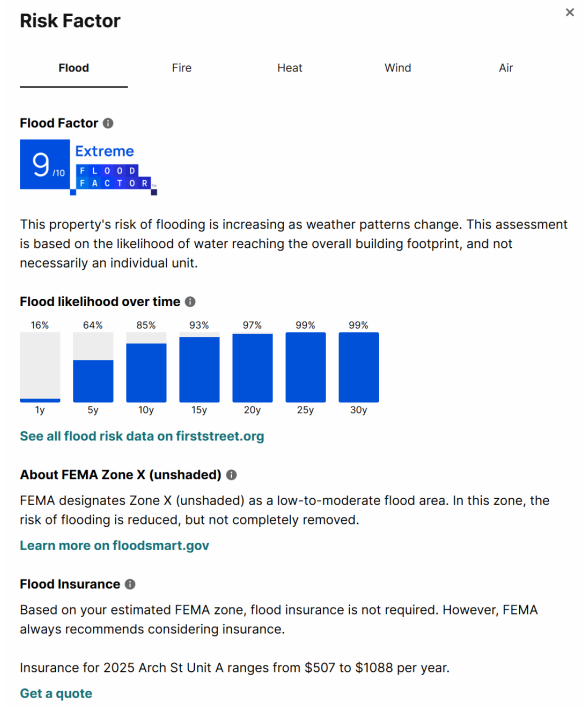
Flood Risk Disclosure

(A) Flood Risk Disclosure - RedFin

Figure 1: Screen shot of RedFin Disclosure

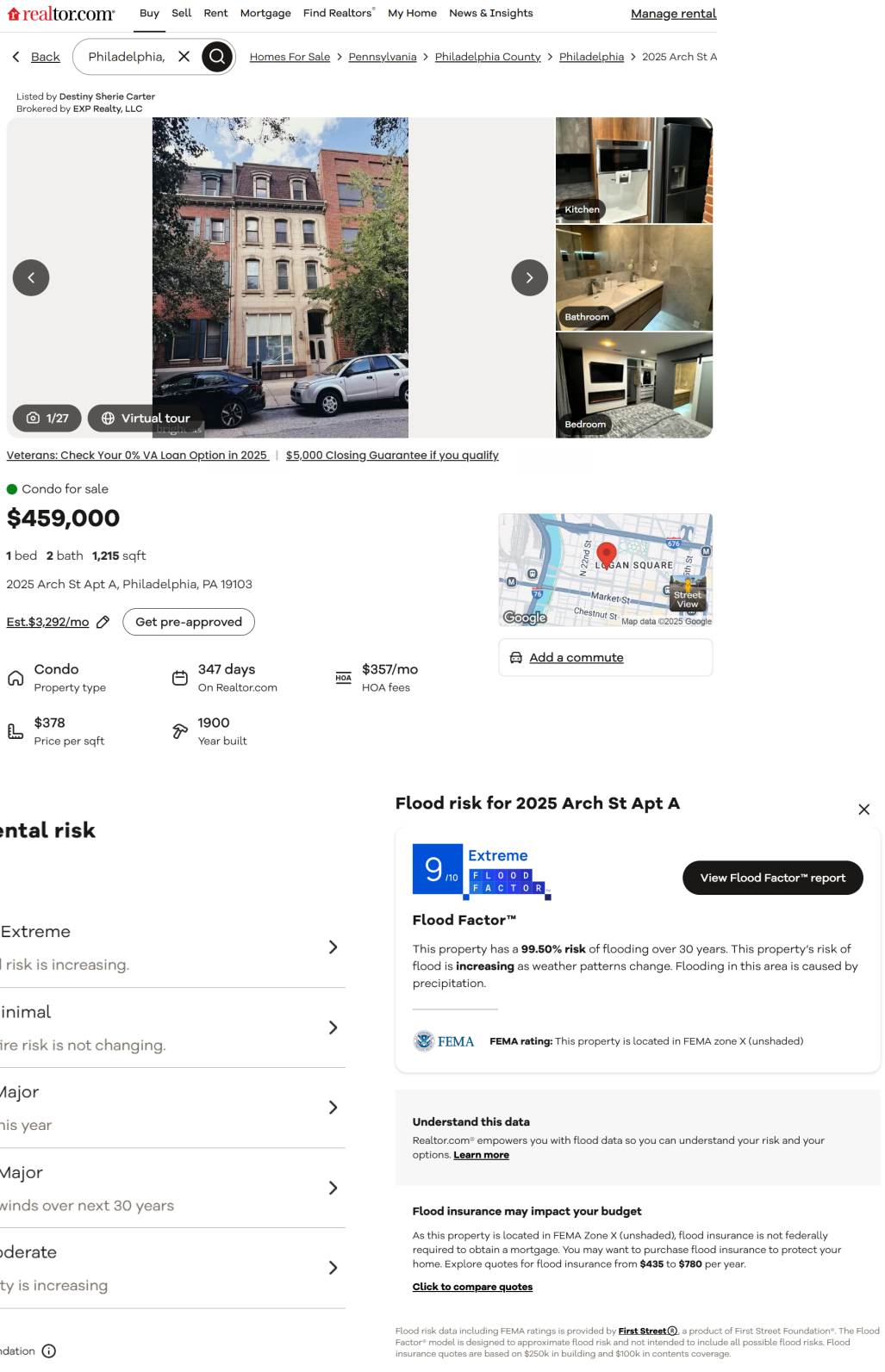






(B) Flood Risk Disclosure - Realtor.com

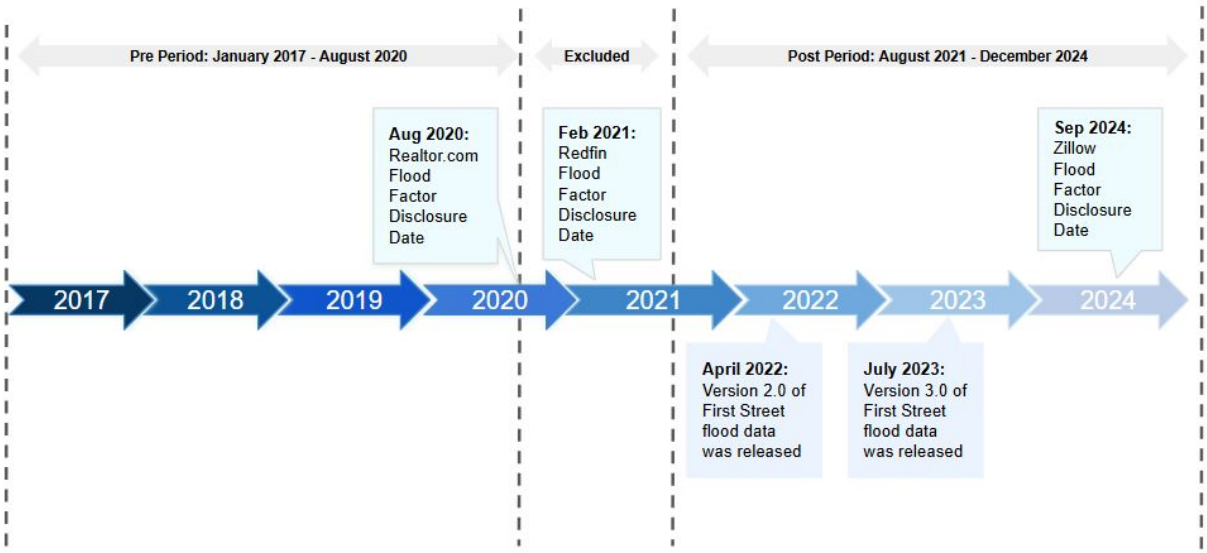
Figure 2: Screen shot of Realtor.com Disclosure



(C) Disclosure of First Street Flood Factor

Figure 3: Disclosure of First Street Flood Factor on Housing Platforms

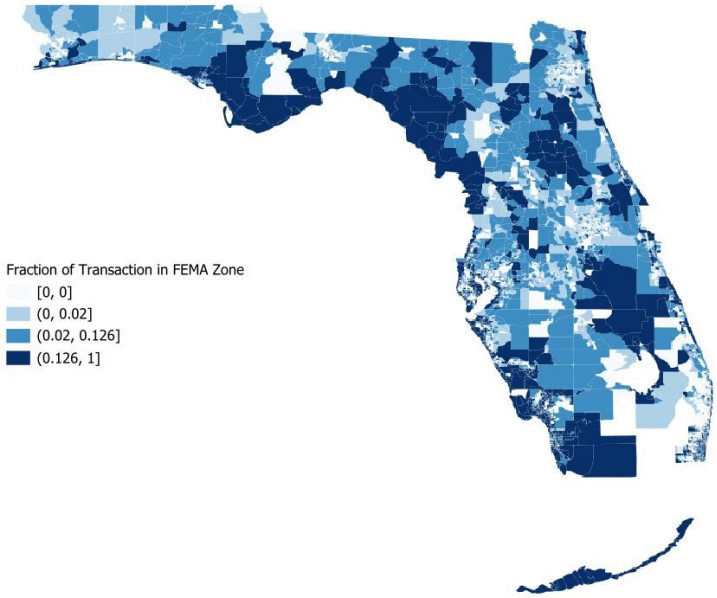
This figure shows the main timeline of when First Street flood scores were updated, as well as when they rolled out onto the Realtor.com, Redfin.com, and Zillow.com platforms. The dotted vertical lines and grey arrows further show the pre-period and post-period chosen for our empirical analyses.



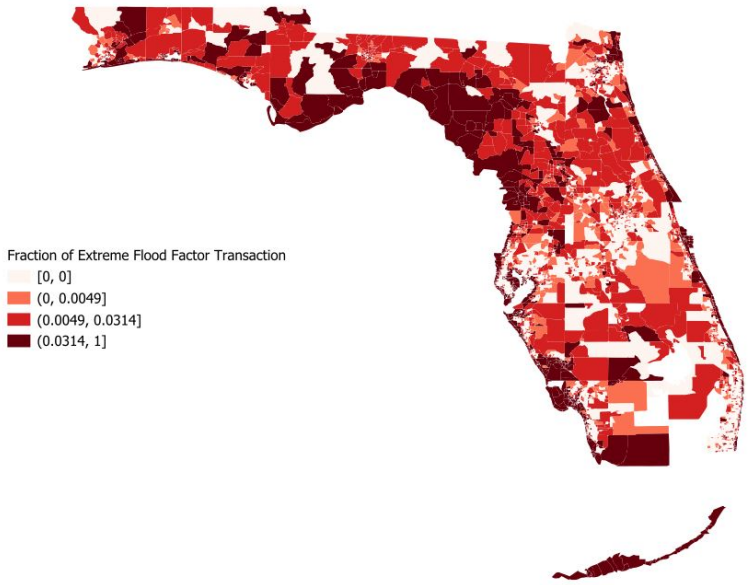
(D) Geographic Maps

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).



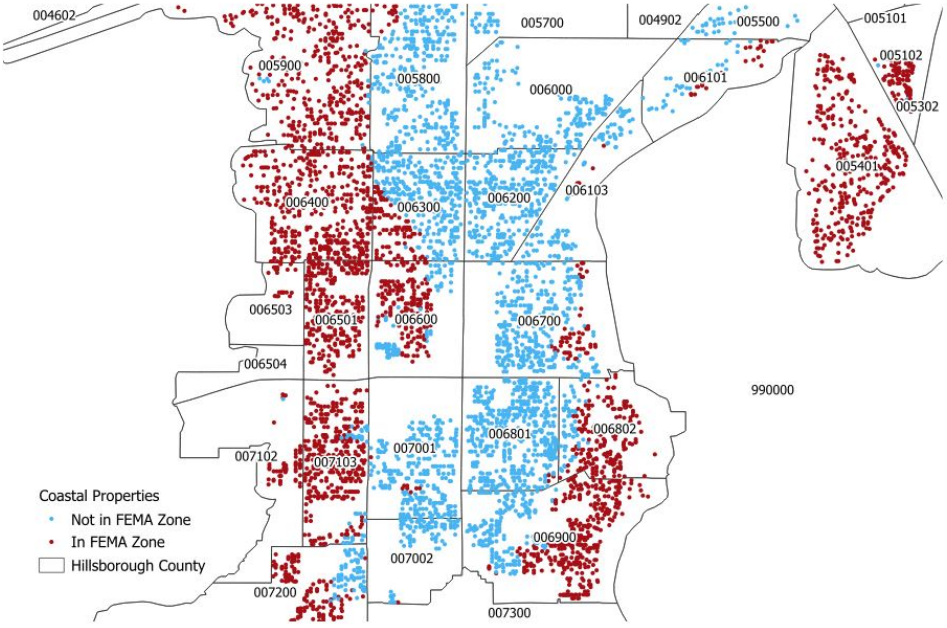
(a) FEMA Flood Zone



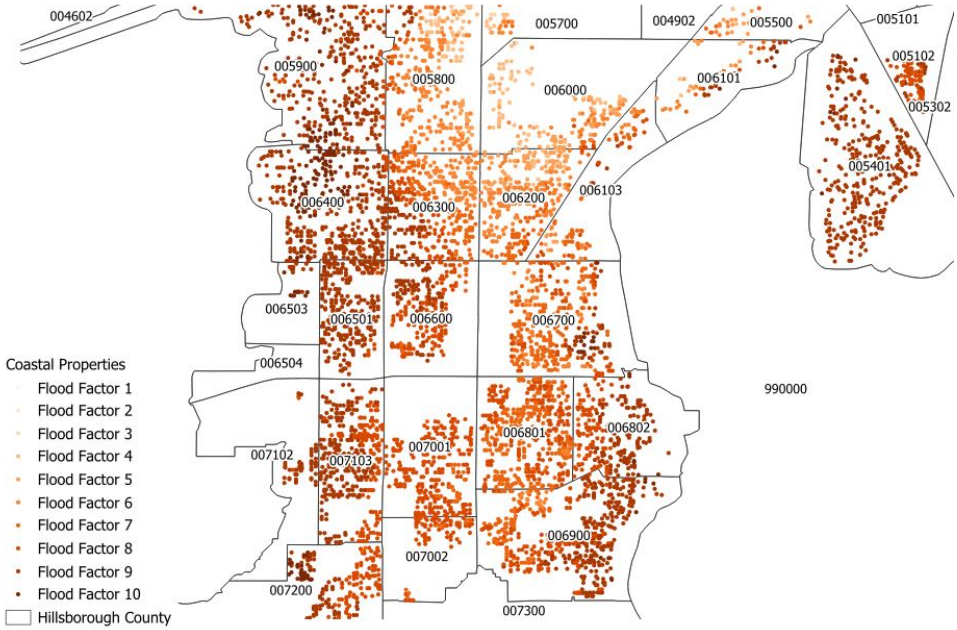
(b) Extreme Flood Risk (First Street)

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).



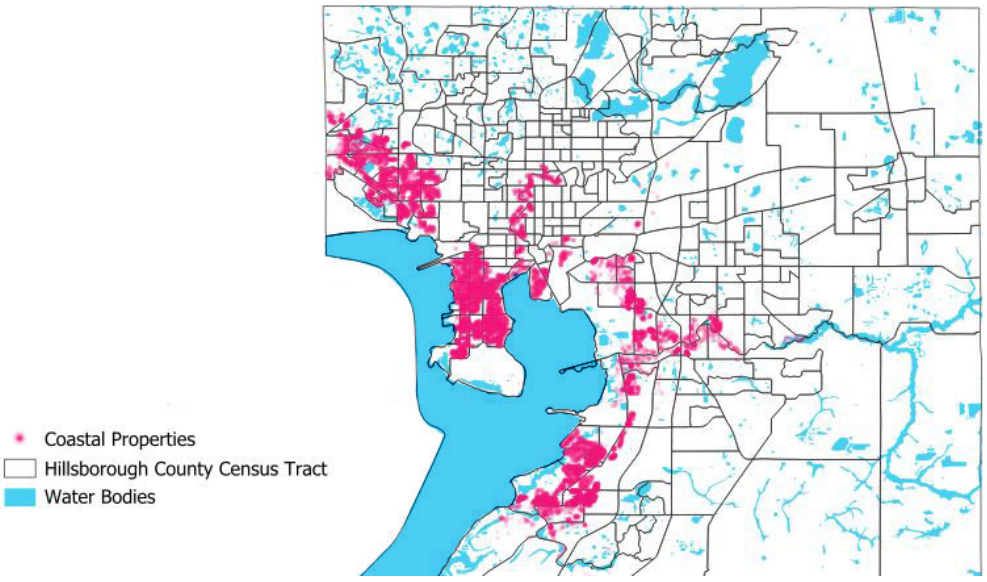
(a) FEMA Flood Zone



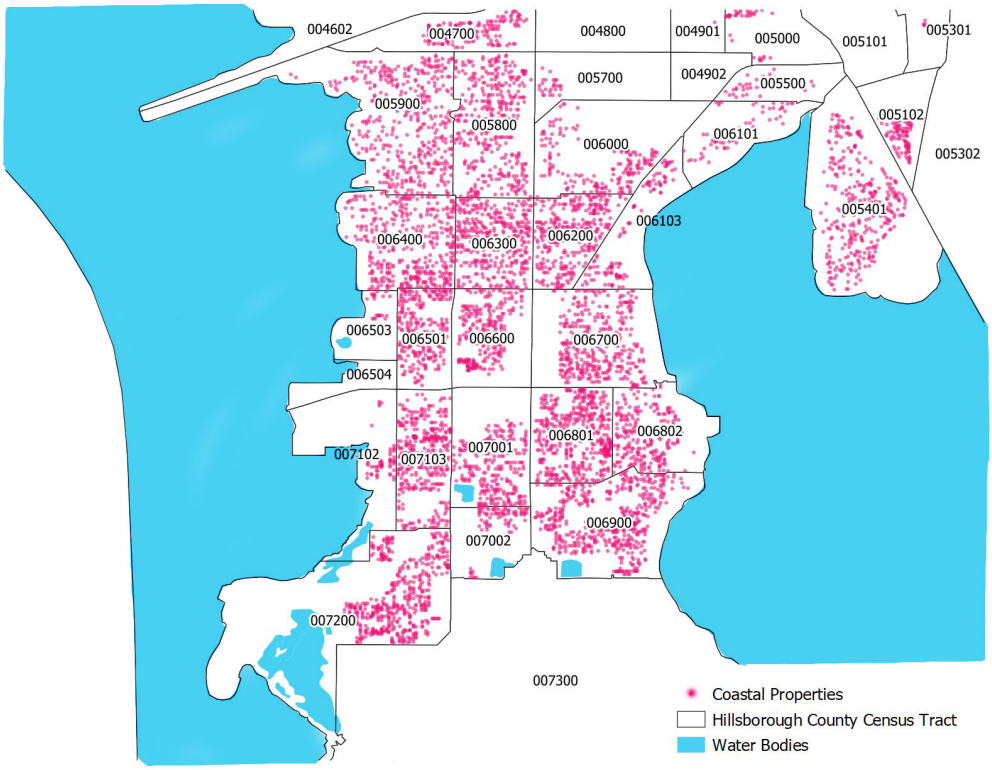
(b) Extreme Flood Risk (First Street)

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

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



(a) Hillsborough County, Florida

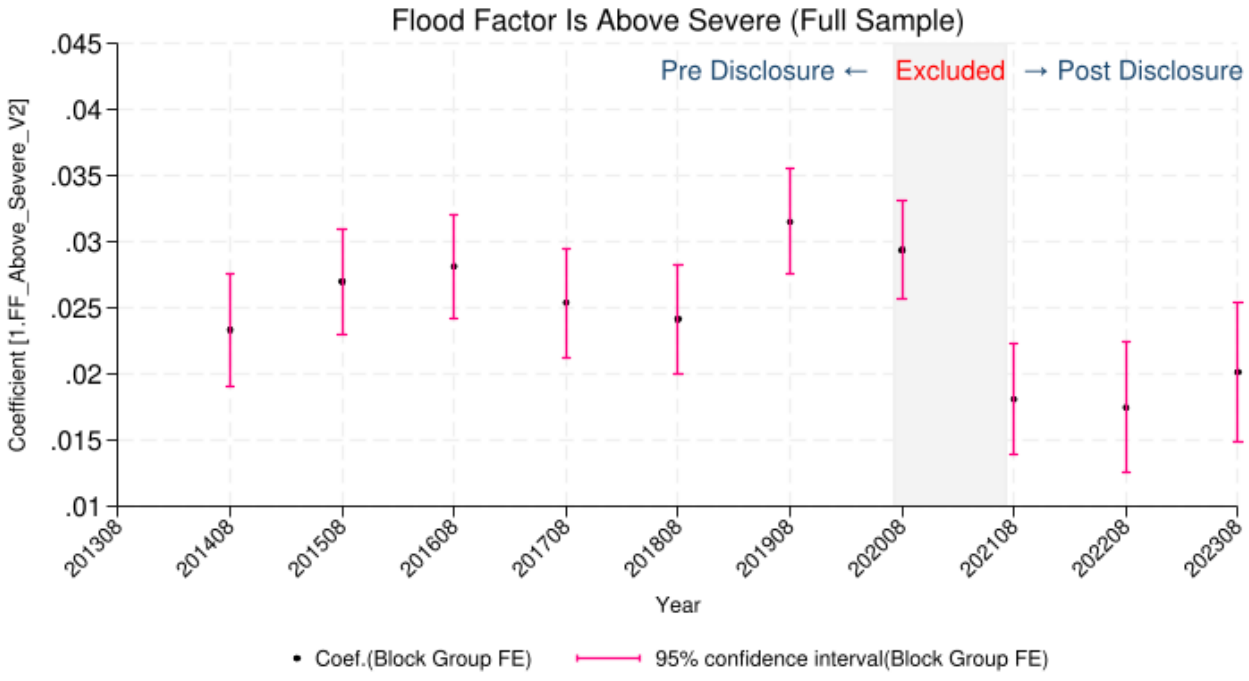


(b) Select Subsample of Hillsborough County

1. Difference in Difference Regression

Figure 7: DiD: Pretend Test

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

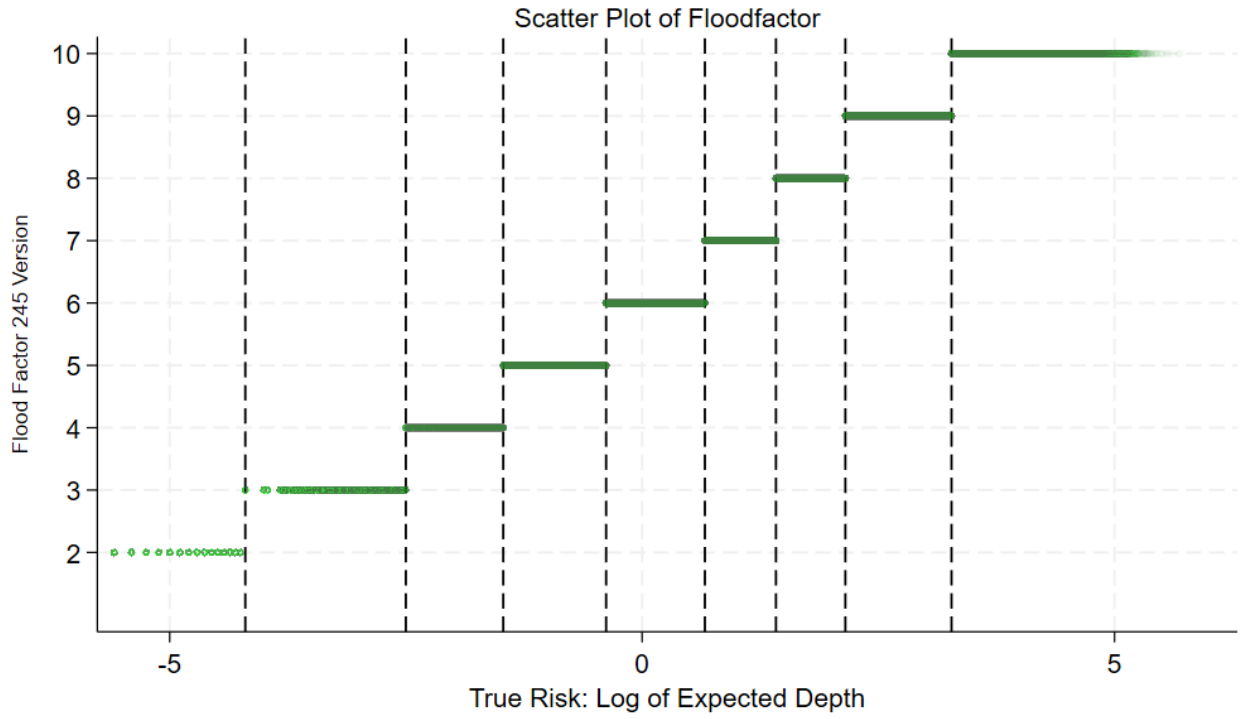


2. Regression Discontinuity

(A) Cutoff Chart

Figure 8: Cutoff Chart of Flood Factor

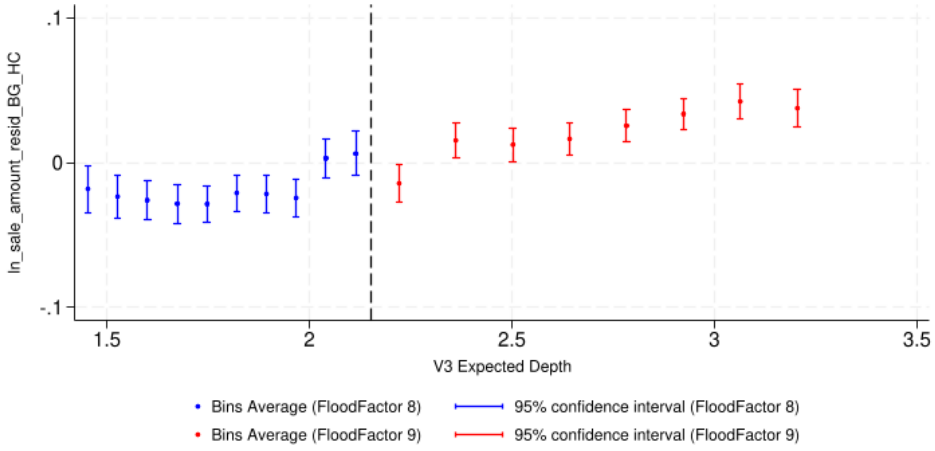
In order to estimate a regression discontinuity analysis, we must reverse engineer the running risk variable that is broken into the discrete Flood Factor categories by First Street. This figure validates our process by plotting the recreated (hidden) running variable, expected flood depth over the next 100 years, on the x-axis and the final (shown) First Street Flood Factor on the y-axis.



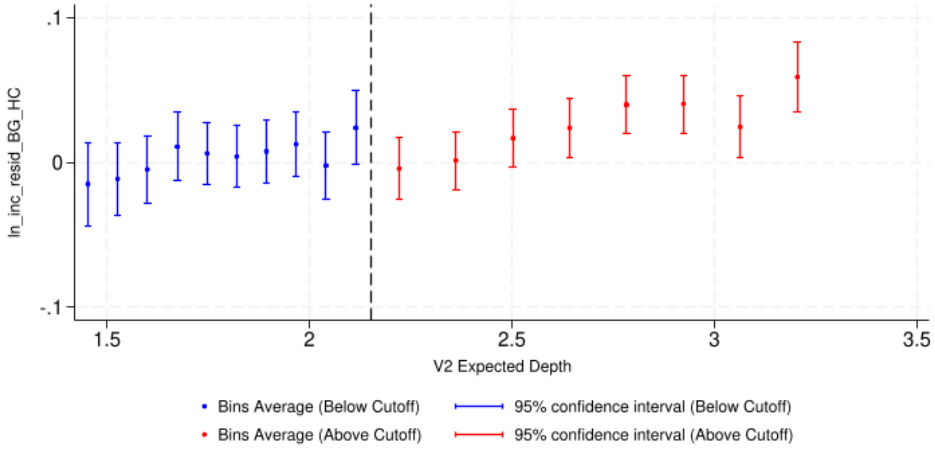
(B) Visualizing RD Regressions

Figure 9: RD Regressions for Full Sample

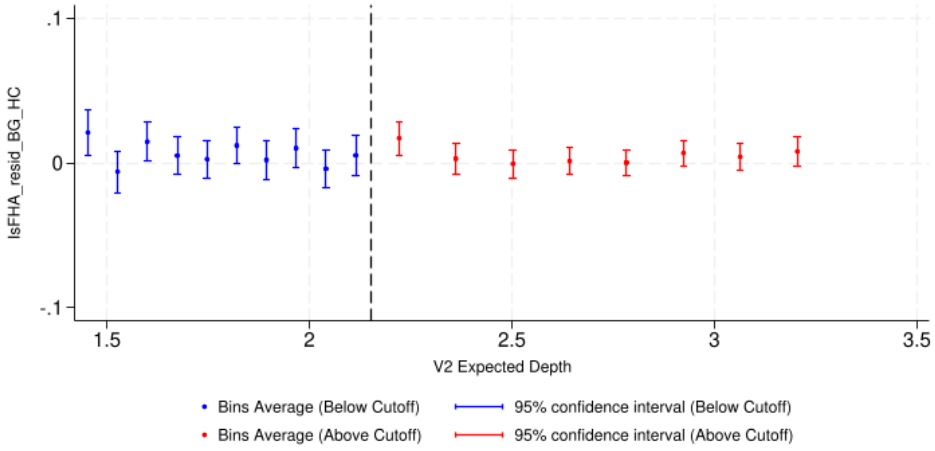
The figures below visually show RD Analysis using the full data sample, explaining: log price (Panel a), log applicant income (Panel b), and a dummy for whether the applicant is FHA (Panel c). To control for omitted variable bias, the LHS variable is residualized with block-group fixed effects and basic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



(a) RD for Log Home Price



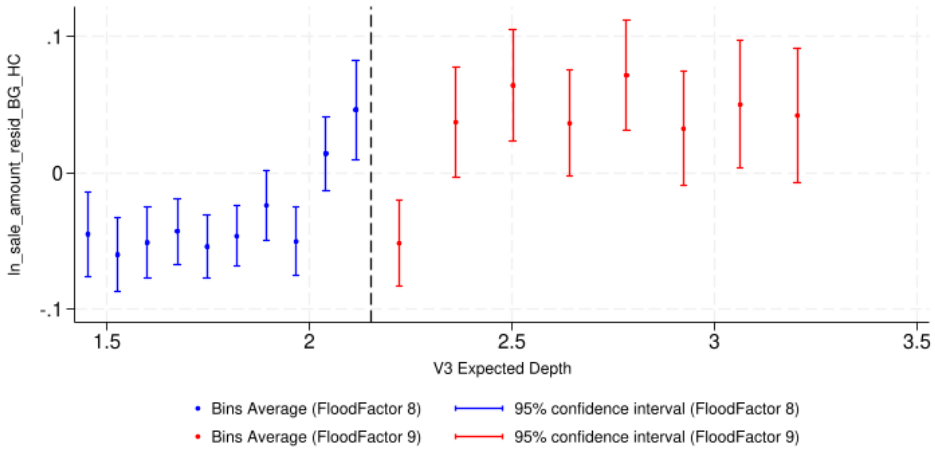
(b) RD for Log Applicant Income



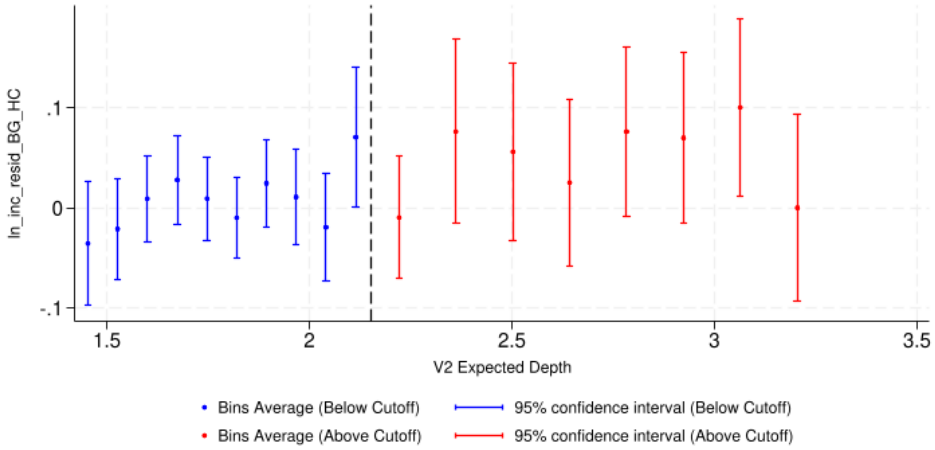
(c) RD for Is FHA Dummy

Figure 10: RD Regressions for Non-FEMA and Coastal Properties Only

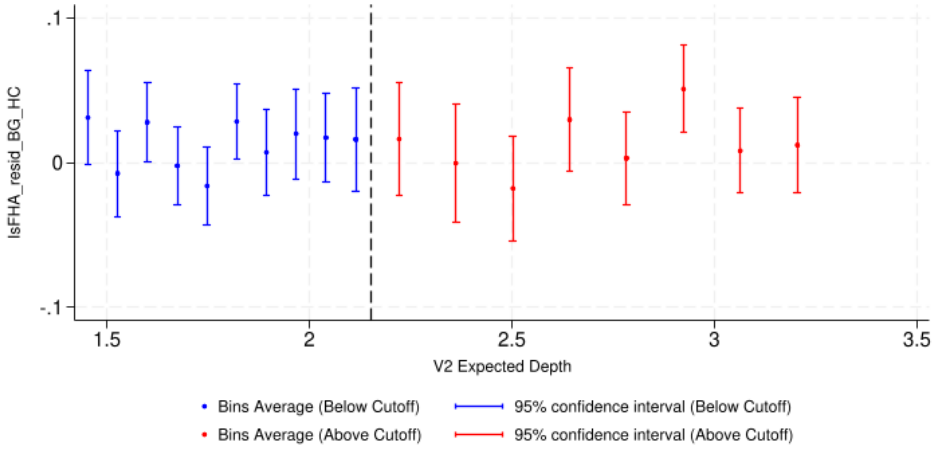
The figures below visually show RD Analysis using a subsample of properties that are not in a FEMA floodplain and are exposed to coastal flooding risk based on First Street's flood model. Panels a through c show RD plots explaining: log price (Panel a), log applicant income (Panel b), and a dummy for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



(a) All Properties



(b) Non-FEMA Properties Only

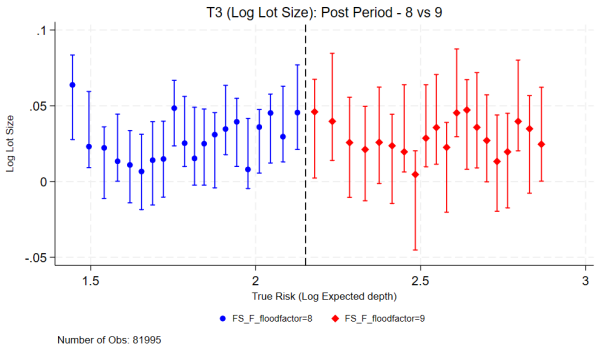


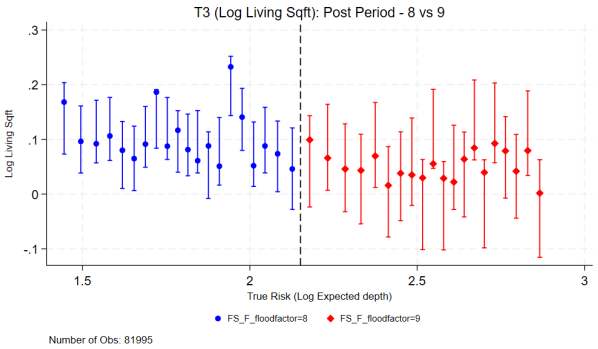
(c) Coastal & Non-FEMA Properties Only

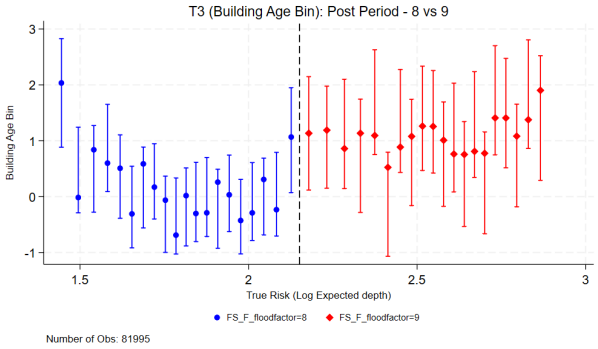
(E) RD Balance Check: Hedonic Characteristics

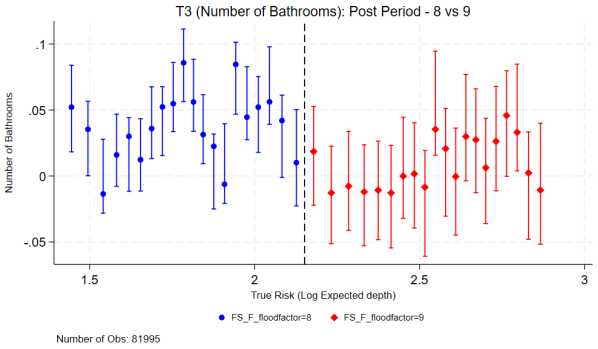
Figure 11: Covariate-balance Test: 8 vs 9

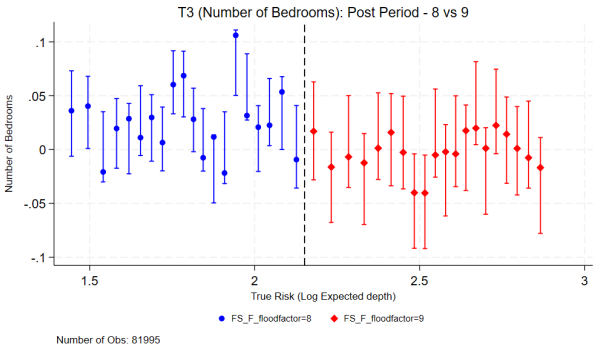
The figures show that basic housing hedonics are balanced across the regression discontinuity. From left to right, top to bottom, they are: total lot size, living square foot, age of building, total number of bathrooms, and total number of bedrooms.











Tables

Part 1. Summary Statistics

Table 1: Summary Statistics

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

Table 2: Summary Statistics - Flood Factor(Version 2)

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.

FEMA Zone is defined using Version 3 data.

Part 2. Difference-in-Difference Analyses

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

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

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

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

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

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

Part 2. Regression Discontinuity

Table 5: RD: Flood Risk Impact on Sale Prices

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

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

Table 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). Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

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

Table 7: RD: Flood Risk Impact on Income

This table presents the regression discontinuity results examining the relationship between log applicant income and expected flood depth. The regression discontinuity specifications include: a linear fit within a auto-selected bandwidth around the cutoff, a polynomial fit of order 2, and a polynomial fit of order 3. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

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

Table 8: 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. 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 9: RD: Flood Risk Impact on FHA

This table presents the regression discontinuity results examining the relationship between a dummy for an FHA applicant and expected flood depth. The regression discontinuity specifications include: a linear fit within a auto-selected bandwidth around the cutoff, a polynomial fit of order 2, and a polynomial fit of order 3. Hedonic controls include building age bin, bedroom (1–6), bathroom (1–5), lot size (sqft), and living area (sqft). Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

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

Table 10: RD: Subsample Analysis of Flood Risk Impact on FHA Dummy

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