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

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Preliminary

Abstract

This paper examines the impact on prices and distribution when property-level flood risk information is disclosed on housing platforms. On average, a property labeled as having "extreme" flood risk sells at about 1.0% lower—a discount not explained by trends in climate risk awareness or FEMA flood maps. Since the disclosed Flood Factors are derived by discretizing a continuous underlying risk measure, we compare homes just above and below the cutoff using a regression-discontinuity design. We find that a higher Flood Factor lowers property prices, particularly in coastal and high-risk counties. We also plan to analyze how the demographic profiles (income, age, race, and political affiliation) of buyers of riskier properties shift. Finally, we will calibrate a structural housing demand model that incorporates heterogeneous preferences and refined flood risk information to assess the welfare and distributional impacts of flood risk disclosure and to decompose changes in risk exposure into factors driven by flood preferences and the ability to afford safer homes.

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

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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 These FEMA maps are critiqued for being outdated–75% of maps are five years or older–and not reflecting forward-looking projections of changing weather patterns (Eby, 2019).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 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 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 it instead focuses on the impact of the information as it is given to consumers.

In this paper, we combine First Street data and CoreLogic data to answer the following key question: *What is the equilibrium price effect when property-level flood risks become available?*

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 measure the effect of flood disclosure using two strategies: (1) using a difference-in-difference (DID) model, we compare prices for homes across different flood rating categories, both before and after the rollout of the flood factor (2) using a regression discontinuity (RD) model, we compare houses that were just below versus above the cut-offs for a given flood score; to do this precisely, we first recreate homes' expected flood depth, a continuous number that is mapped by First Street into the discrete Flood Factor using a set of cut-offs.

First, in DID regressions with geographic controls, ranging from county-period fixed effects (most relaxed) to block-group fixed effects (most stringent), we find a significant decline in sale price of 1 to 2% for homes with "extreme" flood risk following the release of First Street's Flood factor. A pre-trend analysis shows that this discount only exists following disclosure, and the discount is also robust to controlling for the existing information provided by FEMA maps. Interestingly, we find that the effect is particularly strong for the sample of coastal properties—houses that had salient and historically high levels of flood risk.

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 cutoff and are thus assigned different Flood Factors. We find no effect for homes with small to medium flood risk, but find a discount of roughly 5% when a home is just above the cutoff and labeled as having "extreme" risk (versus a home that is just below the cutoff and labeled as having "severe" risk). This effect is only visible in areas with traditionally high levels of flooding, such as among coastal properties. Reassuringly, across all homes, we observe no price difference at the cutoff before the distribution of the First Street Factor.

In the near future, we plan to merge in Home Mortgage Disclosure Act (HMDA) data to answer:

(i) How does flood-risk disclosure change who lives in flood-prone properties? (ii) What is the distributional impact of flood information on households in terms of welfare and exposure to flood risks?

Preliminary evidence suggests that homes with a high Flood Factor (implying high 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 credit score, income, and age. To test this theory, using HMDA data, we will document how homebuyers' demographics are changed by new flood-risk disclosure.

Finally, we will estimate the welfare and distributional impacts of increased flood information in the U.S. housing market using a housing demand model. Our model's key feature is that households with different demographics will have heterogeneous preferences for housing characteristics such as flood risk. For instance, we hypothesize that more information allows wealthier households to selectively bid on less risky houses, while more financially constrained individuals buy flood-prone homes at lower prices. This has distributional effects for homeowners, as well as a net welfare improvement, because the market becomes more efficient at sorting homeowners based on their willingness to pay for "safer" homes.

It also remains unclear whether the market clearing prices will fully offset the anticipated cost of flood repairs (data which is also provided by First Street). This is especially relevant in areas without a substantial flood insurance market that could help defray the costs. If we could incorporate a proxy for flood insurance purchases and estimated flood repair costs, then we could also calculate the net financial consequences of flood disclosure for different homeowners.

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[2] 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.

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

[2] 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.

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 2.66 million unique properties and 14.21 million sales transactions. 25% of all properties are at risk of coastal flooding and 69% 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 Lee County, Florida (panel a) and a zoomed in subset of Lee County (panel b). We see that coastal properties are those that lie within close proximity to a local body of water.

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 80% 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 379,652 (264,401+115,251) homes sold that had"extreme" flood risk.

In addition to the qualitative category and quantitative risk score, we also obtain 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 9 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 [3]) 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 tends to be less granular than First Street's flood data. To illustrate, we zoom into a select number of census tracts in Lee 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 010601 (left hand

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

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 6 (major) to 9 (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 35% of them would **not** have been classified as risky by FEMA.

CoreLogic

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

After merging the Corelogic database with First Street data, we filter the data by removing properties with sales prices below $50,000 or with more than one building. In our main estimation sample, we further restrict the sample to two time periods of interest: between August 2018 and August 2020 (aka the "pre-period") and between August 2021 and August 2023 (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 14.21 million transactions. The average sale price (see Table 1) was $384,390, although there is substantial variation. The 25th and 75th percentile of sale prices are $185,000 and $459,000, respectively. The median house sold in our sample has 3 bedrooms and 2 bathrooms, with a living area of 1,672 square feet.

3 Price Effects

So far, 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, 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 (ie minor, moderate, major, severe, or extreme). Homes with the lowest score of 1, labeled as having minimal risk are omitted from this vector and serve as our baseline group.

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

$\vec{F_i}$ 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. Finally, in column 5, we add a full set of hedonic controls to the block-group-time fixed effects, 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 broadly associated with higher sale prices. For example, homes in the strongest treatment group, labeled with extreme flood risk, sell for up to 11% higher (column 1) 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 and 5, this premium drops significantly to only about 3%. Overall, while it never goes completely away, the positive amenity that is associated with high flood risk properties becomes significantly attenuated as we add more stringent location and hedonic controls.

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 0.9% 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.

Homes with above major and major risk also drop significantly in price following the release of the Flood Factor, but the effect is only about half or less of the extreme effect. Furthermore, we see that homes with moderate or lower levels of risk do not observe a price decline at all. These findings are consistent with the hypothesis that the expected cost of flooding is highest for homes with high flood risk, and consumers may not care about costs below a certain threshold.

Finally, in Table 4, we test whether flood risk is only priced if it is salient. To do this, we repeat the above analysis for coastal properties only, and indeed, we find that the price effect becomes both bigger and stronger. In column 5, the most stringent specification, we find that the price discount for homes with extreme flood increases from 0.9% for all properties to 1.4% for Coastal properties only. 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).

3.1.1 Robustness: Pre-trend Analysis and FEMA Controls

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 8. 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.

Furthermore, in Appendix Table 1 - DiD: Flood Risk Impact on Sale Prices [Full V3 Sample], we repeat the baseline DID but add in FEMA flood zone dummies interacted with post-disclosure. We find that our baseline price discount is smaler but still very robust, suggesting that our findings cannot be explained by pre-existing information given by the FEMA maps.

3.2 RD Estimator

While the DID regression utilizes our full sample and has the most statistical power, it suffers from 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 in Section 3.1.1 ameliorates 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 9) 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 10 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.[4] 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 our hedonic controls.[5] Then, we restrict the residualized sample to only properties with a 8 or 9 Flood Factor.

Importantly, in our DID analyses, we saw that the price effect was most pronounced in coastal properties, where flood risk is salient. We further expand upon this idea in our RD analysis by proxying for flooding salience in three ways. First, we split our sample into terciles based on the prevalence of flood risk in the county of sale. The lowest tercile contains the counties with lowest flood risk (panels e and f) while the highest tercile contains the counties with highest flood risk (panels a and b). Second, we split our sample by coastal versus non-coastal properties, same as in the DID. Lastly, we split our sample by whether propeties lie in a 100-year floodplain, which is deemed as risky by FEMA.

Figure 10 shows that, following First Street's Flood Factor release, there is a significant jump downwards at the cutoff point for properties with the highest tercile of flood risk, but there is no effect for properties in the lower terciles. In the Appendix Figure A.5, we also verify that there is no jump at the cutoff point before disclosure across all three terciles. Our findings are consistent with the hypothesis that potential homebuyers pay attention to the Flood Score, and they discount homes with higher flood risk. Based on our tercile analysis, flood risk may only be salient to homebuyers searching within counties that already have high levels of flood risk.[6]

Instead of breaking up our sample by terciles of flood risk, we could also split our sample by two other measure of flood salience: (1) coastal properties vs not (2) FEMA floodplain vs not. Figures 11 and 12 show the results, respectively, and they are very consistent with our tercile results. Again, we find that properties associated with higher levels of flood risk, either coastal or in a FEMA floodzone, show a jump downwards in price at the cutoff in the post-period. Thus, it does not matter if we use county-level flood risk, proximity to the water, or even traditional FEMA flood zones—we consistently find that the effect of the First Street data is pronounced in areas where consumers are already aware of and thinking about flood risk.

[4] In Appendix Section A3, we show the RD graphs at alternative cutoff points: 6 vs 7, 7 vs 8, and 9 vs 10. There appears to be a jump down in price for 7 vs 8 scores in the highest tercile, but we do not observe significant jumps for the other two pairings.

[5] 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.

[6] Appendix Figure A.4 shows the unconditional results when we combine all three terciles. Across all properties, we see a jump down in price for the post disclosure period but it much noisier and appears insignificant.

In order to calculate the magnitude of the RD jump shown in Figure 10, we estimate the following RD regression fitted with 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 5 shows the results from estimating Eq 3.2. The first two columns correspond to the pre- and post-period, respectively, for homes in the highest tercile of flood risk. The next two columns correspond to the middle tercile, and the last two columns correspond to the lowest tercile of flood risk. Consistent with Figure 10, we find that only homes in the highest tercile of flood risk significantly drop in value when they go from having a "severe" versus "extreme" flood risk. Interestingly, the price change is even stronger than what we found in our DiD estimates. For two homes that have similar levels of expected flood depth, the one that is labeled as having "extreme" risk has a sale value that is approximately 5% lower, all else held equal.[7]

Finally, Table 6 repeats the above analysis but uses either the FEMA 100-year floodzone (columns 1-2) or coastal properties (columns 3-4) to proxy for high salience of flood risk. Unsurprisingly, similar to the RD figures, we see that these alternative definitions yield qualitatively identical results. In fact, the price drop is even stronger for these two subsamples: about 6% for properties in a FEMA flood-plain or 7% for coastal properties. Overall, the RD results are in line with our DID findings but show an even stronger effect in areas with high flood salience.

3.2.1 Robustness

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 13 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

[7] In Appendix Table 2 - RD: Flood Risk Impact on Sale Prices by Tercile of Flood Risk, we show that the RD performs similarly if we narrow the band of estimation significantly by either (1) only keeping the middle quantile, or (2) use an auto-selected band.

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. 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 Welfare and Distributional Effects

4.1 A Stylized Model of Housing Demand

A typical housing demand model follows a discrete-choice model (Berry et al., 2004) adapted for the housing context, as in Bayer et al. (2007); Calder-Wang (2021). The key feature of the model is that we allow for heterogeneous preferences for housing characteristics by household demographics.

We start with a housing market whose total housing stock has N units of H different types, where each type is characterized by its key physical characteristics and its neighborhood. $N = \sum_{h=0}^{H} N_h$.[8]

The utility of household i derived from choosing housing unit j of type h is

$$u_{ij} = \delta_h + \lambda_{ih} + \epsilon_{ij}, \quad \epsilon_{ij} \sim i.i.d.\ EV(1). \tag{4.1}$$

[8]It is typically modeled at the housing type level as opposed to the housing unit j level for tractability. If the estimation primarily relies on cross-sectional variations, collapsing to types is required to deal with the nuisance parameter problem.

We denote the mean utility that varies at the product level to be δ_h as follows

$$\delta_h = \alpha p_h + \beta X_h + \xi_h \tag{4.2}$$

We let p_h denote the price. α denotes the mean price coefficient. X_h denotes a vector of housing characteristics of length B, including a binary indicator for being an inside option. Importantly, without loss of generality, denote $X_{h,1}$ as the flood risk. Prior to disclosure on housing platforms, flood risk is measured at the more aggregate level, such as the neighborhood-level average $X_{h,1} = X_{n(h),1}$. Post disclosure, flood risk can be measured at the house level $X_{h,1}$. Geographic-fixed effects may also be included here, with or without additional heterogeneity on them. β denotes a vector of parameters of length B, inclusive of a constant term.

We denote the utility that varies at the individual level to be $\lambda_{i,h}$ as follows

$$\lambda_{i,h} = \begin{bmatrix} \alpha_i & \beta_{i,1} & \beta_{i,2} & \cdots & \beta_{i,B} \end{bmatrix} \begin{bmatrix} p_h \\ X_{h,1} \\ X_{h,2} \\ \vdots \\ X_{h,B} \end{bmatrix}, \tag{4.3}$$

$$\begin{bmatrix} \alpha_i \\ \beta_{i,1} \\ \vdots \\ \beta_{i,B} \end{bmatrix} = \begin{bmatrix} \pi_1^{\alpha} & \pi_2^{\alpha} \cdots & \pi_K^{\alpha} \\ \pi_{1,1}^{\beta} & \pi_{1,2}^{\beta} \cdots & \pi_{1,K}^{\beta} \\ \vdots & & \vdots \\ \pi_{B,1}^{\beta} & \pi_{B,2}^{\beta} \cdots & \pi_{B,K}^{\beta} \end{bmatrix} \begin{bmatrix} z_{i,1} \\ z_{i,2} \\ \vdots \\ z_{i,K} \end{bmatrix} \tag{4.4}$$

Equivalently, we can write $\lambda_{i,h}$ as

$$\lambda_{i,h} = \left(\sum_{k=1}^{K} \pi_k^{\alpha} z_{i,k} \right) p_h + \sum_{b=1}^{B} \left(\sum_{k=1}^{K} \pi_{b,k}^{\beta} z_{i,k} \right) X_{h,b} \tag{4.5}$$

where K denotes the total number of household demographic characteristics and B still denotes the total number of housing attributes as before.

The outside option is indexed at 0. The mean utility of choosing the outside option is normalized to zero, i.e. $\delta_0 = 0$ and $u_{i0} = \epsilon_{i0}$. Hence, the probability of household i choosing housing type h then becomes

$$\Pr(y_i = h; \theta) = \frac{N_h \exp\left(\delta_h + \lambda_{ih}\right)}{\sum_{h'=0}^{H} N_{h'} \exp\left(\delta_{h'} + \lambda_{ih'}\right)} \tag{4.6}$$

where $\theta = (\boldsymbol{\delta}, \boldsymbol{\pi})$.

4.2 Data and Estimation

Data

There are several sources of data that we use to generate moments. Compared to the estimation of standard housing models, the key challenge is that the publicly-available ACS Micro Data does not have the exact address, and thus does not contain the property-level measures of flood risk, as disclosed on popular housing platforms. As a result, we use CoreLogic transaction records combined with HMDA, to obtain the requisite micro-moments that interact with the flood risk and household demographics.

1. ACS Micro Data: This includes anonymized, individual, household-level choice data at the PUMA level. We can match moments that capture the covariances between household demographics (e.g., income, household size, or age) and housing characteristics (e.g., number of bedrooms, square footage, and flood risk) to capture the sorting of households in general.

2. CoreLogic (combined with HMDA): This includes housing transactions matched with a few key borrower characteristics that are part of HMDA, namely, applicant income, age, and race. This helps us characterize if the disclosure of flood risk differentially affected different households.

Estimation

We will match the key micro-moment as provided by the data, especially when it comes to the heterogeneity in household preferences and the component that can be explained by demographics. The intuition of the estimation hinges on matching the covariance between flood risks and household demographics pre and post-disclosure.

An additional challenge in the estimation of such a model involves the endogeneity of price, which may be correlated with the observed quality ξ_h. In our setting, we consider using estimates in the literature such as Cook et al. (2024) and Calder-Wang (2021).

Distributional Implications

The disclosure of flood information can induce resorting for two reasons, which the structural model will allow us to decompose:

1. Resorting due to equilibrium price changes. This implies that higher-income households, who generally have a greater willingness to pay for everything, will sort into safer homes.

2. Resorting due to heterogeneous preferences for flood. This implies that households who have a stronger preference for safer homes (e.g., due to differences in perception, and risk preferences) will sort into safer homes.

The former could be thought of as a climate justice issue when risks are now increasingly borne by those who could not afford to avoid it, whereas the latter could be thought of more as heterogeneous risk preference or expectation.

Combining with the DiD / RD estimates on prices, the structural model allows us to speak to the re-sorting due to changes in prices. To the extent that if we find empirical moments where different types of households move into otherwise similar homes but with different flood risk post-disclosure, then we can also speak to distributional implications beyond just through the WTP channel.

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.

Preliminary findings suggest that homebuyers discount homes with flood risk by up to 5%, but this discount is largest for homes with the highest (ie "severe" or "extreme") flood risk. Furthermore, the price discount varies depending on the local geography. In particular, the price effect of flood information is most concentrated in areas where flood risk is salient—such as among coastal properties, where we find a price drop of 7%, or in 100-year FEMA floodplains, where we find a price drop of 6%.

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

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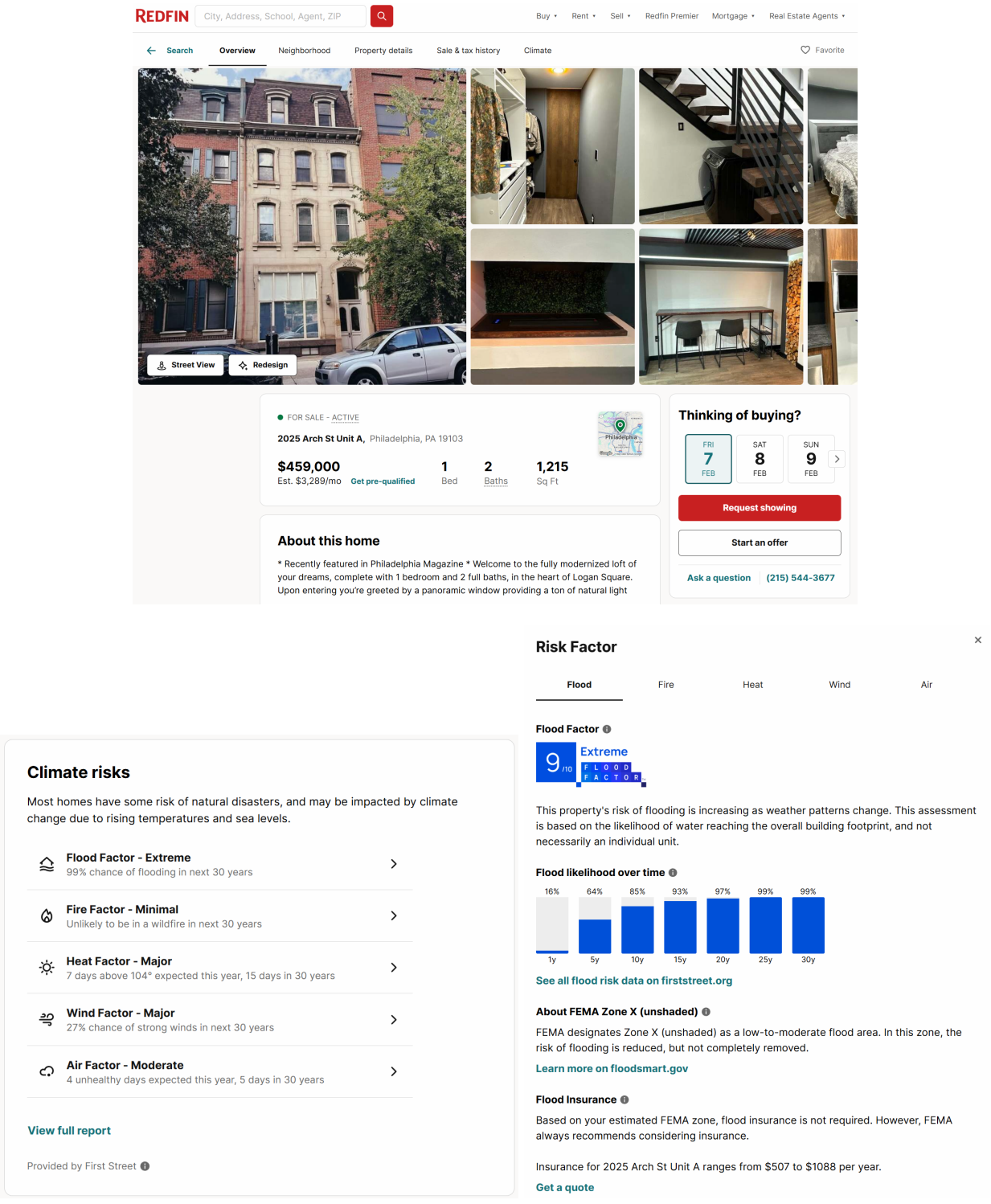
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Figures

Flood Risk Disclosure

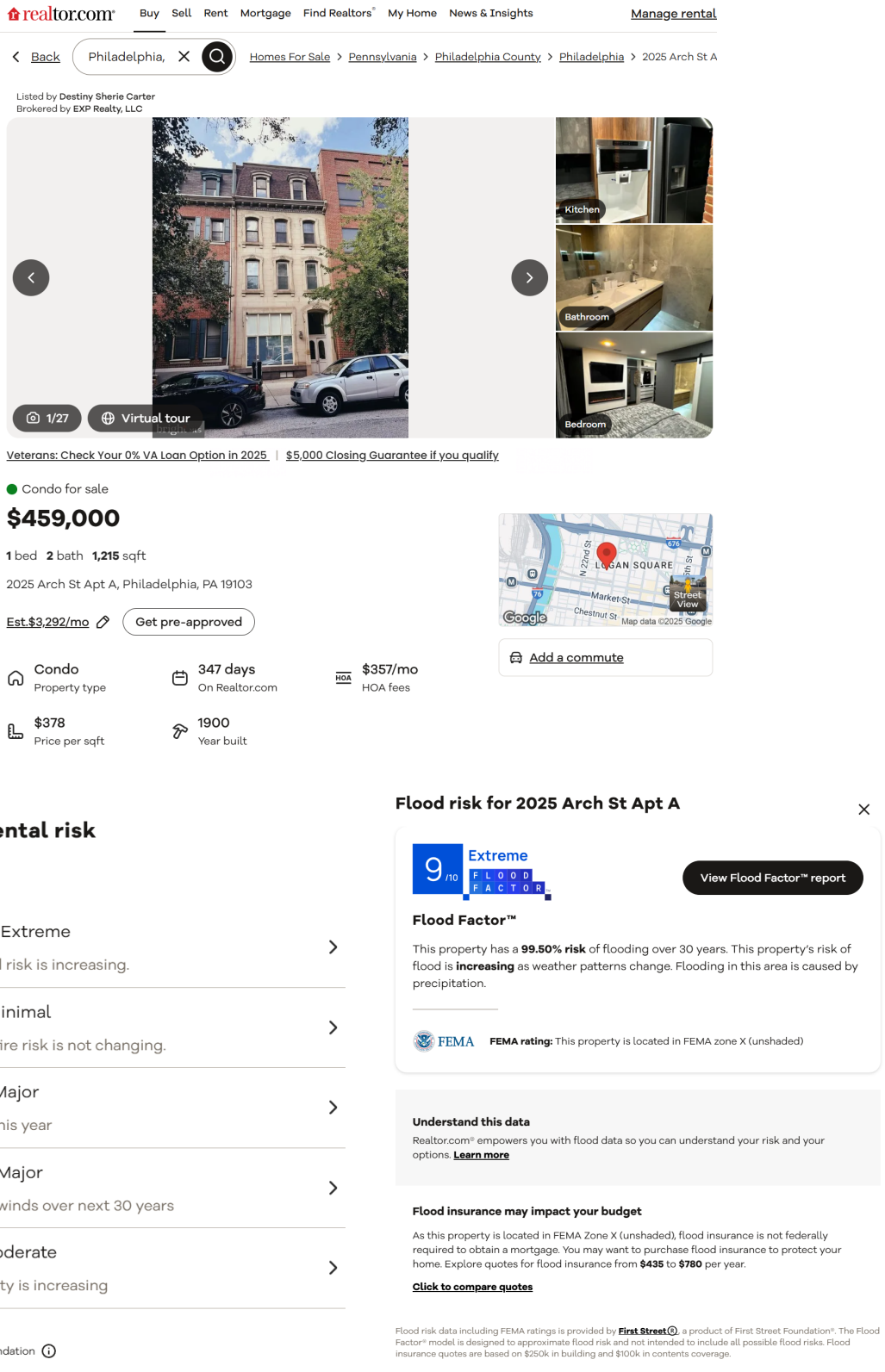
(A) Flood Risk Disclosure - RedFin

Figure 1: Screen shot of RedFin Disclosure



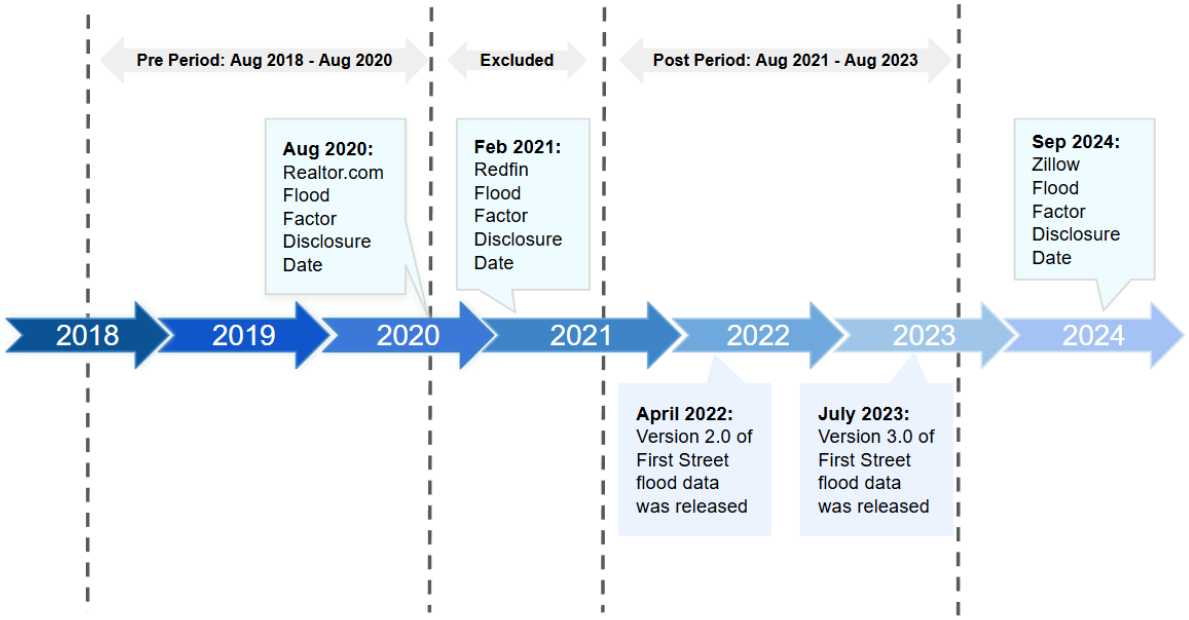
(B) Flood Risk Disclosure - Realtor.com

Figure 2: Screen shot of Realtor.com Disclosure



(C) Disclosure of First Street Flood Factor

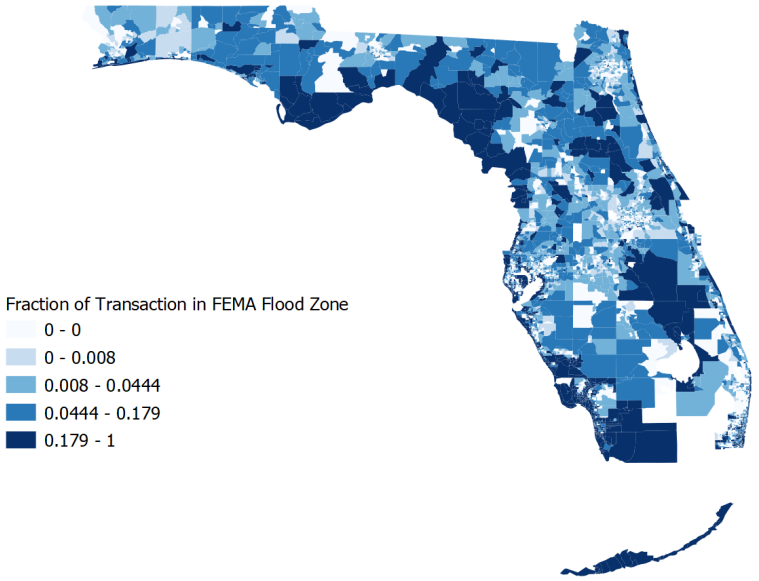
Figure 3: Disclosure of First Street Flood Factor on Housing Platforms



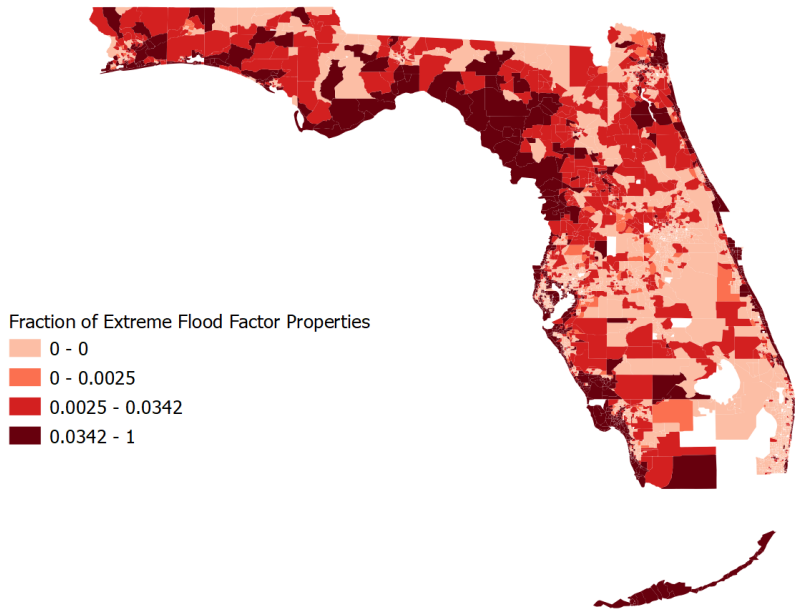
(D) Geographic Maps

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 (August 2018–August 2020) and the post-period (August 2021–August 2023).



(a) FEMA Flood Zone



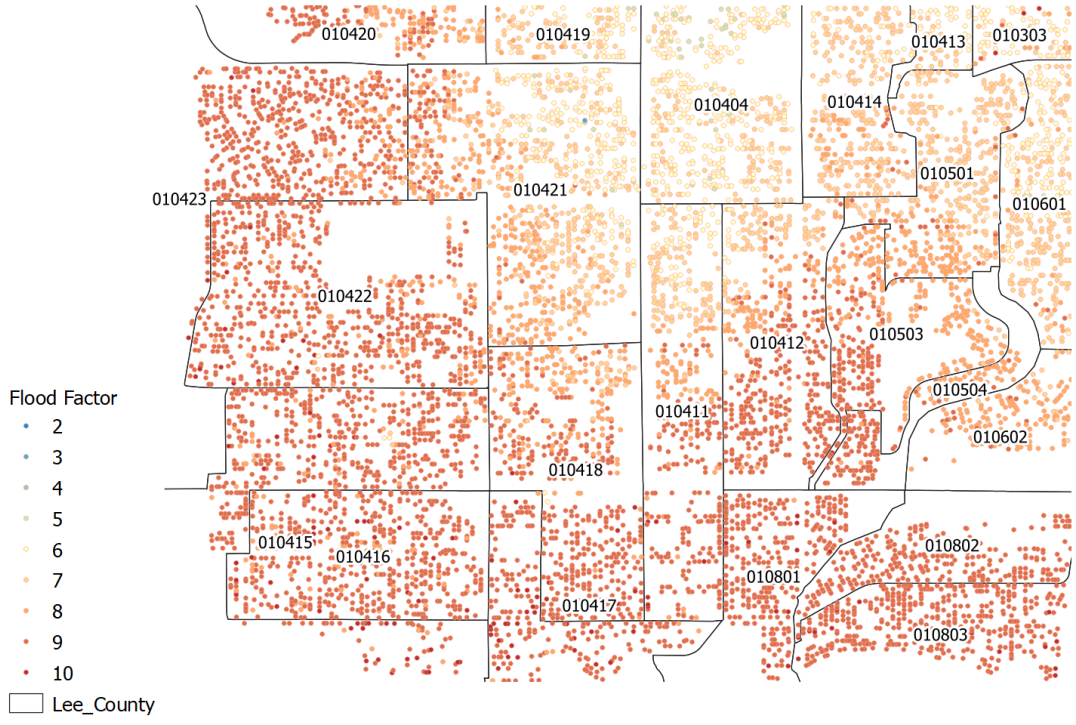
(b) Extreme Flood Risk (First Street)

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

These maps display census tract-level shapefile for a zoomed in selection from Lee 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 (August 2018–August 2020) and the post-period (August 2021–August 2023).



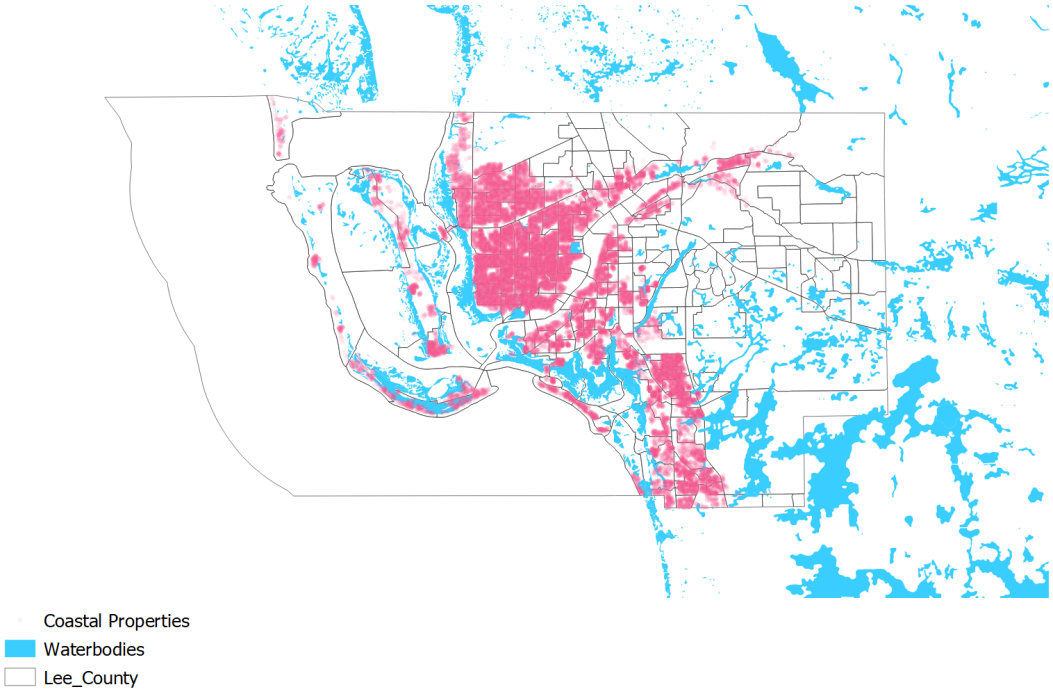
(a) FEMA Flood Zone



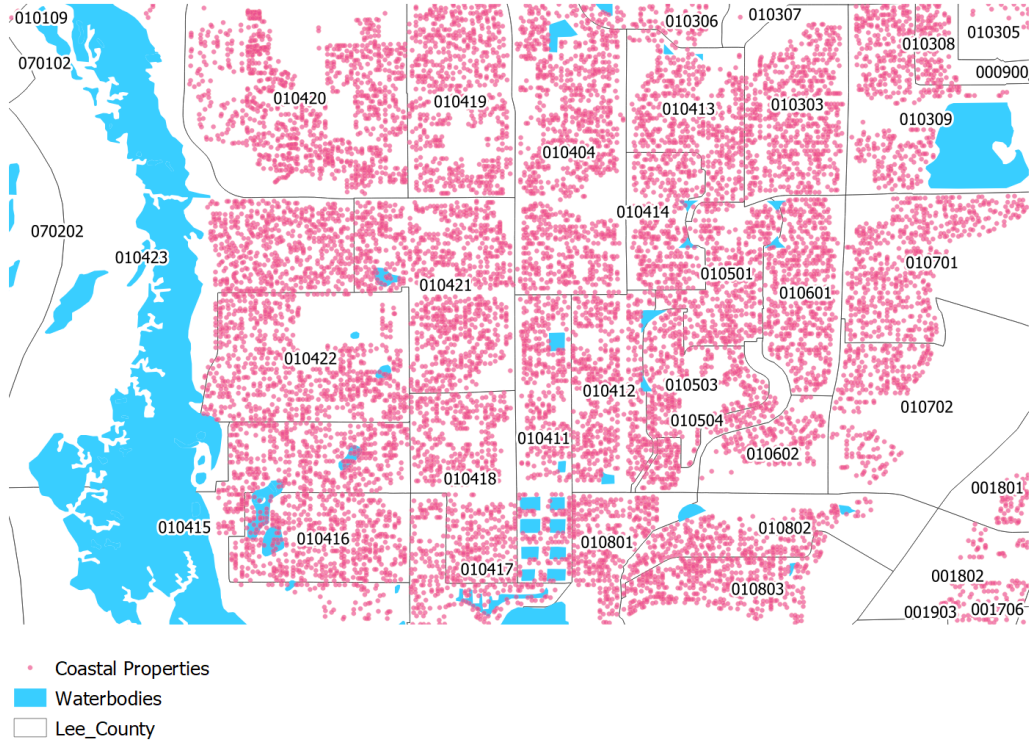
(b) Extreme Flood Risk (First Street)

Figure 6: Map of Coastal Properties and Nearby Bodies of Water, Lee County

These maps display the location of individual coastal properties in Lee County, Florida (panel a) and a select zoomed-in subsample of Lee 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 (August 2018–August 2020) and the post-period (August 2021–August 2023).



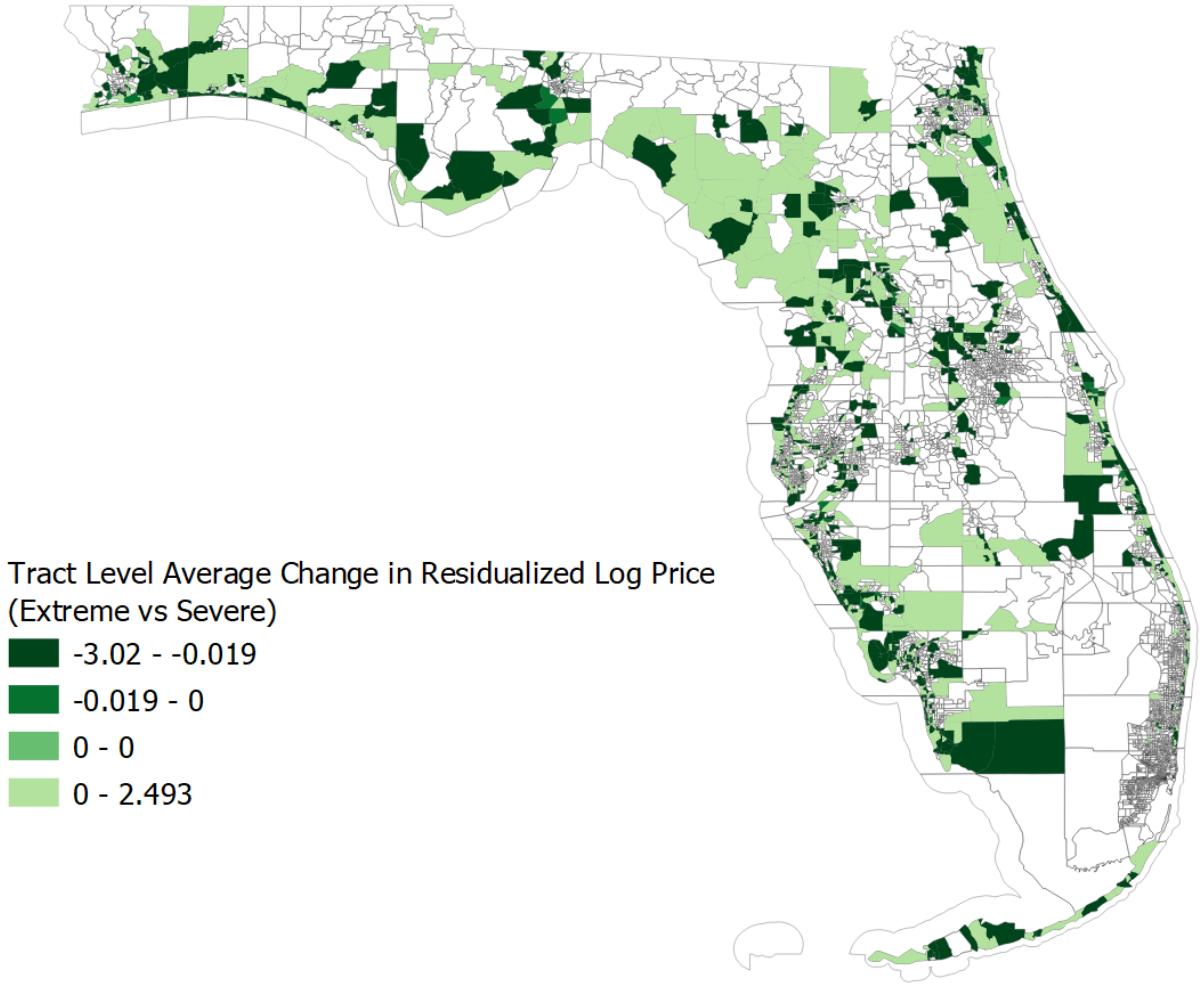
(a) Lee County, Florida



(b) Select Subsample of Lee County

Figure 7: Map of Price Changes for Flood-Prone Properties in Florida

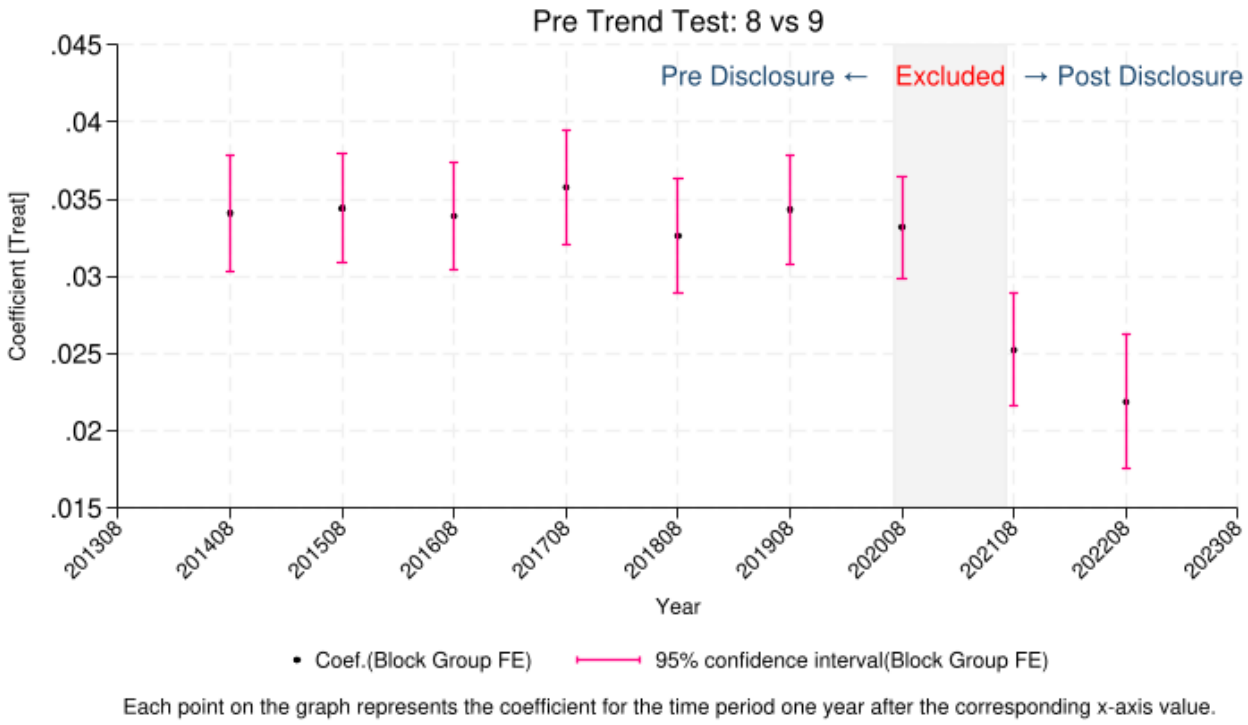
This map displays a census tract-level shapefile for Florida, where each polygon represents a census tract. To help visualize our baseline difference-in-difference regression, we show the average change in log price for each census tract from the pre-period to the post-period, controlling for county-level fixed effects. The shading reflects the size of these differences, with a darker shade representing a steeper price decline. We compare prices from house transactions in the pre-period (August 2018–August 2020) versus the post-period (August 2021–August 2023).



1. Difference in Difference

(A) DiD Pre-trend Test

Figure 8: Pre Trend Analysis

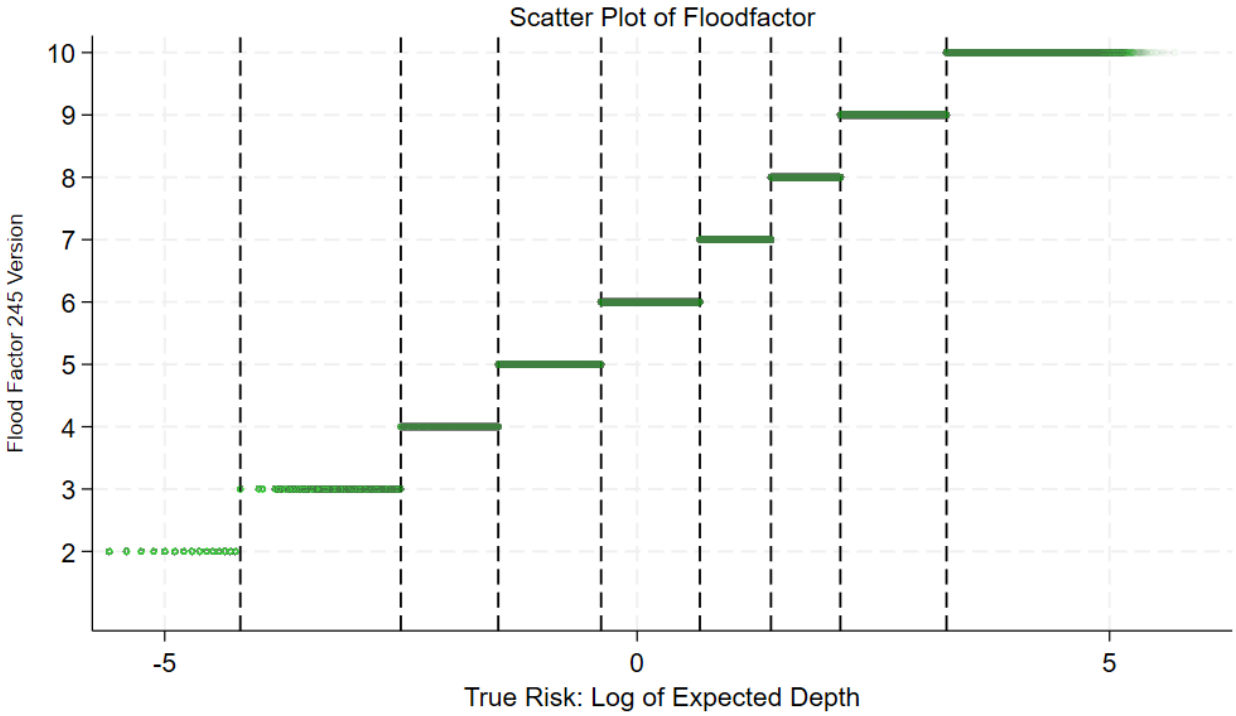


(a)

2. Regression Discontinuity

(A) Cutoff Chart

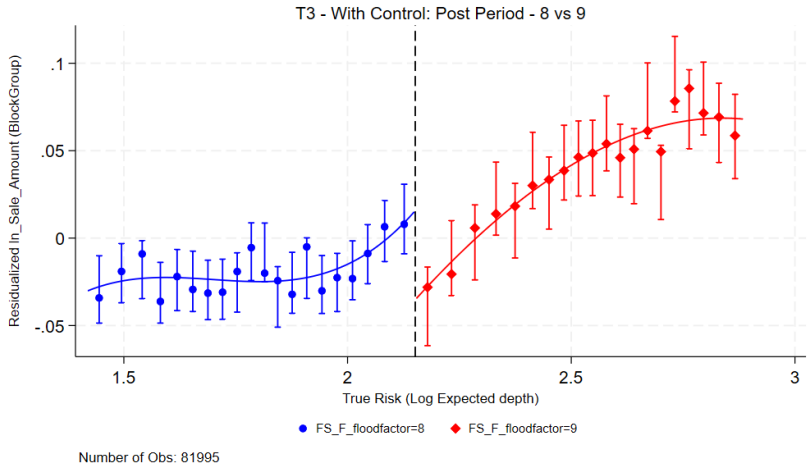
Figure 9: Cutoff Chart of Flood Factor



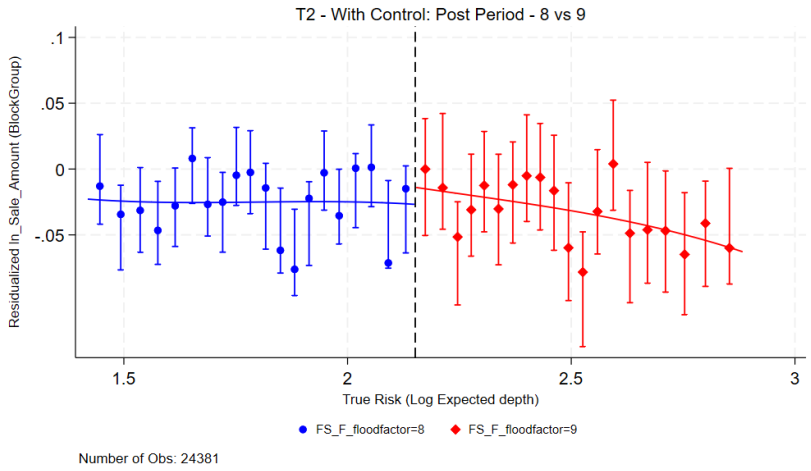
(a) 245 Version 3

(B) Main RD Figure

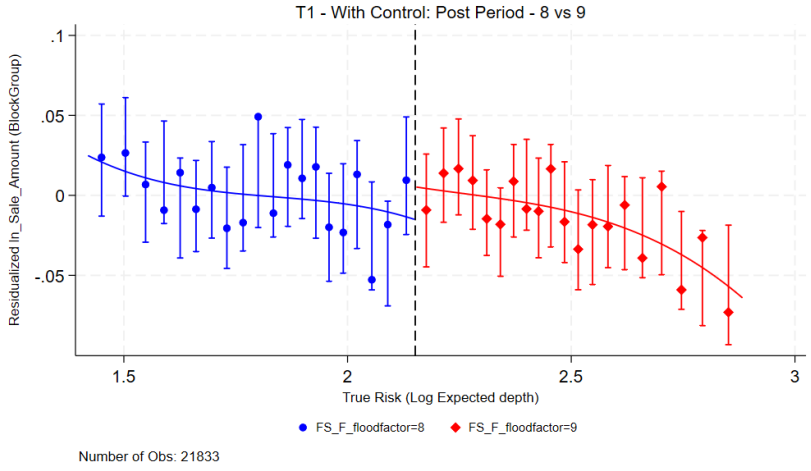
Figure 10: Tercile by county-level Risk Exposure(8 vs 9)]



(a) Highest Tercile



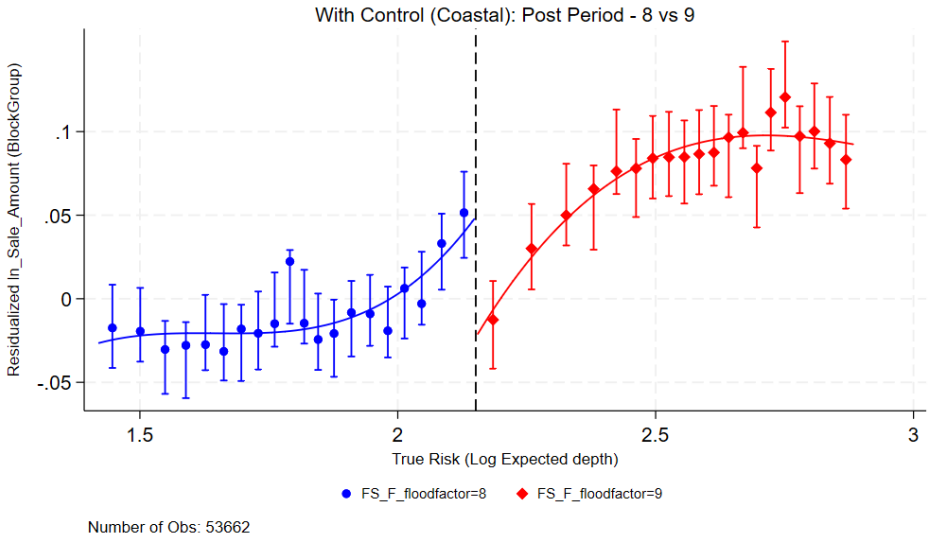
(b) Middle Tercile



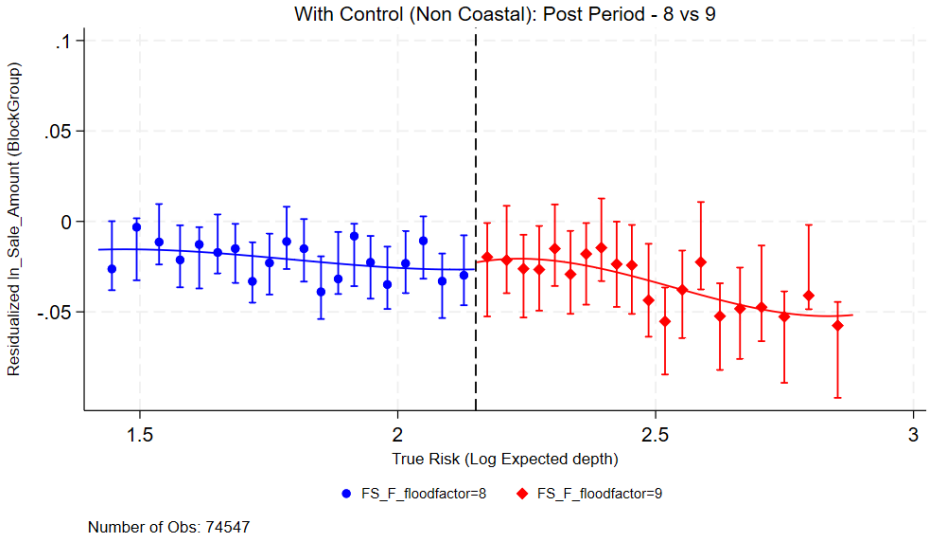
(c) Lowest Tercile

(C) Alternative Subsamples

Figure 11: RD Analysis by Coastal vs Non-coastal Properties

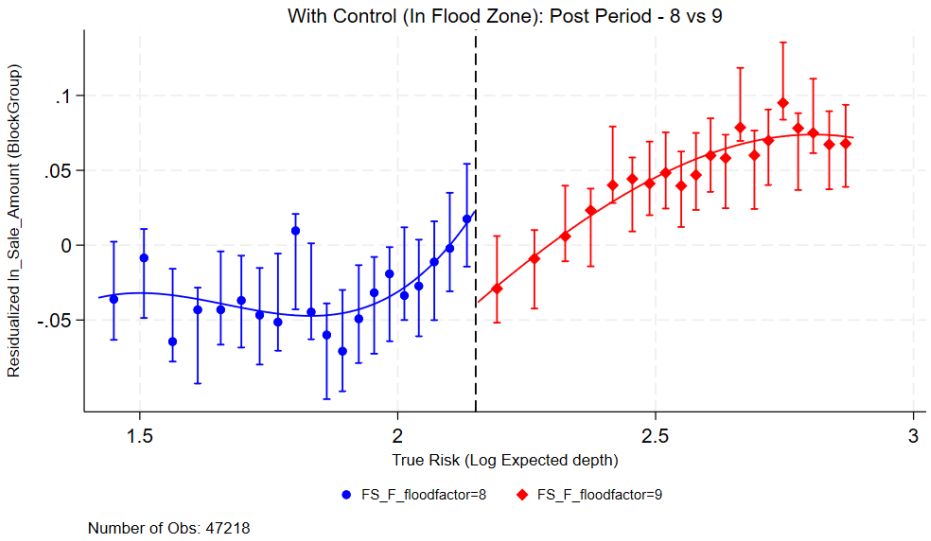


(a) Post Period: Coastal

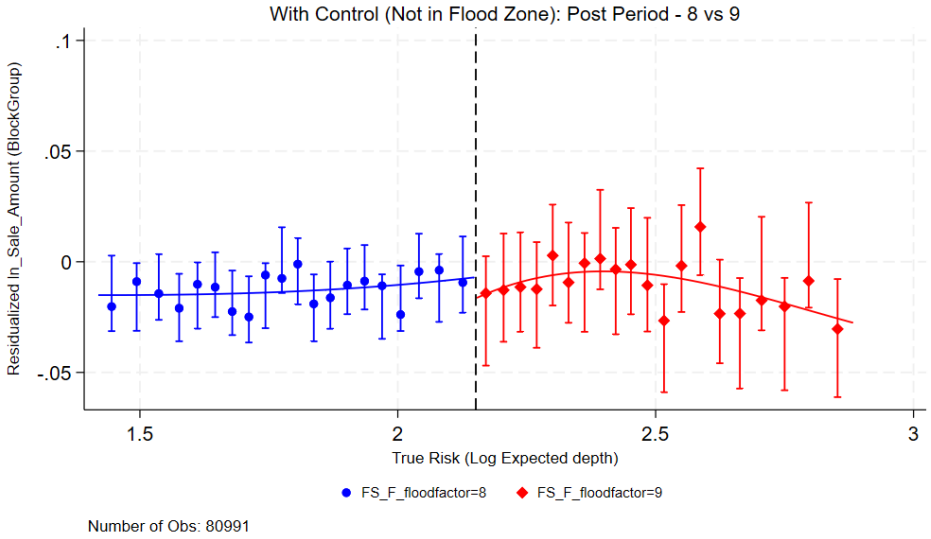


(b) Post Period: Non Coastal

Figure 12: RD Analysis by FEMA Flood Zone vs non-FEMA Flood Zone



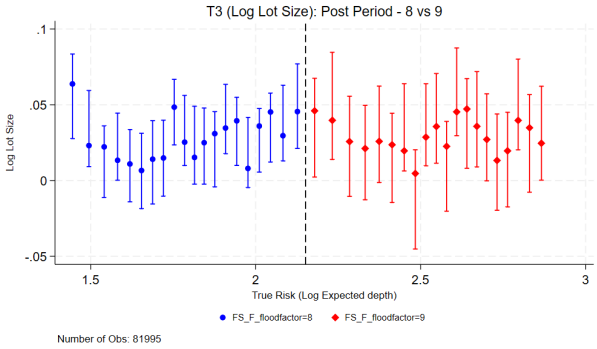
(a) Post Period: In FEMA Flood Zone

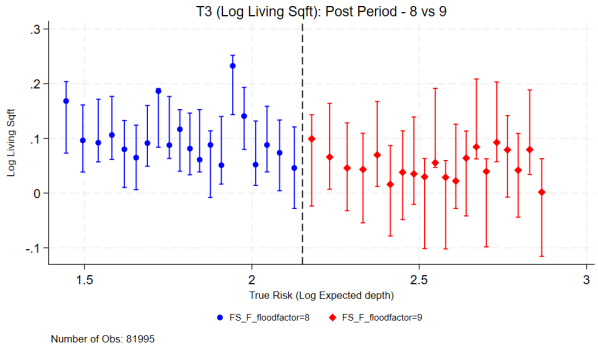


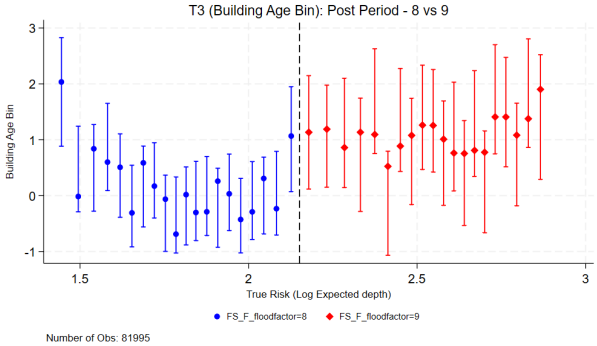
(b) Post Period: Not In FEMA Flood Zone

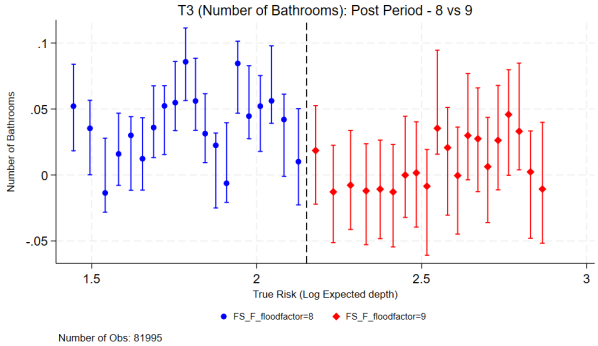
(D) RD Balance Check: Hedonic Characteristics

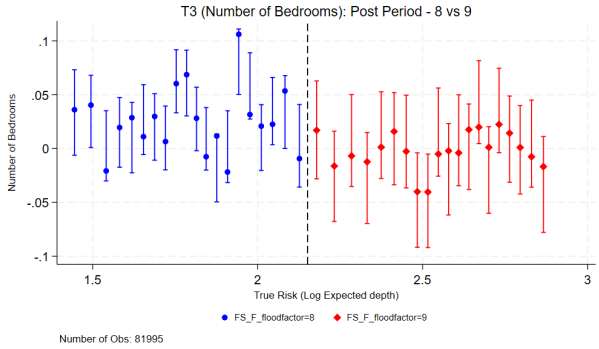
Figure 13: Covariate-balance Test: 8 vs 9











Tables

Summary Statistics

Table 1: Summary Statistics - Key Variables

	Count	Mean	SD	p25	p50	p75
CoreLogic:						
Sale Price ($k)	14,206,950	384.39	332.14	185.00	298.40	459.00
Living Area (Sqft)	14,206,950	1,765.28	997.82	1,216.00	1,672.00	2,277.00
Lot Size (Sqft)	14,206,950	21,400.34	46,920.33	6,276.00	9,350.00	16,117.00
Number of Bathrooms	14,206,950	1.97	1.29	1.00	2.00	3.00
Number of Bedrooms	14,206,950	2.24	1.67	0.00	3.00	3.00
Building Age	14,206,950	32.54	30.93	4.00	25.00	53.00
Sale Year	14,206,950	2,020.54	1.60	2,019	2,020	2,022
First Street:						
Expected Depth (cm)	2,663,340	4.75	11.40	0.12	0.76	3.90
Flood Source include Coastal	2,663,340	0.25	0.43	0.00	0.00	0.00
Flood Source include Pluvial	2,663,340	0.69	0.46	0.00	1.00	1.00

Observations are at transaction level.

We exclude properties with sale prices below $50,000 and winsorized at the 99th percentile.

Living area and lot size are winsorized between the 1st and 99th percentiles.

Number of bedrooms and bathrooms are are capped at 6 and 5.

First Street risk variable are only estimated among properties that have greater than minimal flood risks.

Table 2: Summary Statistics - Flood Factor

First Street Flood Factor	First Street Risk Category	Count	Fraction	Fraction in FEMA Flood Zone
1	Minimal	11,543,610	81.25%	0.75%
2	Minor	43,451	0.31%	5.01%
3	Moderate	341,799	2.41%	4.49%
4	Moderate	541,939	3.81%	6.71%
5	Major	337,604	2.38%	8.12%
6	Major	504,722	3.55%	10.09%
7	Severe	247,774	1.74%	14.41%
8	Severe	266,399	1.88%	21.66%
9	Extreme	264,401	1.86%	45.36%
10	Extreme	115,251	0.81%	65.11%
Total		14,206,950	100 %	3.57%

Observations are at transaction level.

Part 1. Difference in Difference

Table 3: DiD: Flood Risk Impact 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 August 2023). FloodFactor groups properties into six categories: Minimal (1), Minor (2), Moderate (3-4), Major (5-6), Severe (7-8), and Extreme (9-10). Properties in the extreme flood risk category (9–10) are treated as the "treated group". 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.

	Log Sale Price				
	(1)	(2)	(3)	(4)	(5)
Risk is Extreme(Treated) × Post Disclosure	0.00794***	-0.0200***	-0.0104***	-0.0115***	-0.00933***
	(2.59)	(-8.19)	(-4.67)	(-5.20)	(-4.70)
Risk is Extreme(Treated)	0.114***	0.116***	0.0368***	0.0308***	0.0326***
	(53.09)	(67.13)	(23.40)	(19.65)	(23.27)
Risk is Minor	0.0801***	-0.0430***	-0.000344	0.00388	0.00764***
	(16.57)	(-11.33)	(-0.11)	(1.22)	(2.69)
Risk is Moderate	0.00951***	-0.0355***	-0.0100***	-0.00459***	0.000808
	(8.58)	(-39.65)	(-12.78)	(-5.92)	(1.16)
Risk is Major	0.0274***	-0.00566***	-0.00513***	-0.00216***	0.000304
	(24.22)	(-6.16)	(-6.18)	(-2.61)	(0.41)
Risk is Above Major	0.00114	0.0306***	0.00258**	0.00288***	0.000756
	(0.79)	(26.07)	(2.48)	(2.79)	(0.82)
Risk is Minor × Post Disclosure	0.0415***	0.00384	-0.00472	-0.00366	-0.000505
	(6.04)	(0.71)	(-1.02)	(-0.81)	(-0.12)
Risk is Moderate × Post Disclosure	0.0107***	-0.000442	-0.00219*	-0.00171	-0.00109
	(6.79)	(-0.35)	(-1.96)	(-1.54)	(-1.10)
Risk is Major × Post Disclosure	-0.00428***	-0.0106***	-0.00600***	-0.00495***	-0.00344***
	(-2.65)	(-8.06)	(-5.07)	(-4.21)	(-3.27)
Risk is Above Major × Post Disclosure	0.00120	-0.00651***	-0.00388***	-0.00300**	-0.00121
	(0.59)	(-3.91)	(-2.62)	(-2.04)	(-0.92)
Obs	14206950	14206898	14202532	14183514	14183514
R2	0.0346	0.4125	0.6058	0.6474	0.7184
R2-Adj	0.0346	0.4123	0.6016	0.6372	0.7103
County-Period FE		✓			
Tract-Period FE			✓		
Block Group-Period FE				✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Hedonic Controls					✓

Table 4: DiD: Flood Risk Impact on Sale Prices, **Coastal Properties Only**

This table presents the same regression as Table 3 but restricted to coastal properties only. FloodFactor groups properties into six categories: Minimal (1), Minor (2), Moderate (3-4), Major (5-6), Severe (7-8), and Extreme (9-10). Properties in the extreme flood risk category (9–10) are treated as the "treated group". 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.

	Log Sale Price				
Coastal Subsample	(1)	(2)	(3)	(4)	(5)
Risk is Extreme(Treated) × Post Disclosure	0.0276***	-0.0193***	-0.0190***	-0.0184***	-0.0141***
	(5.35)	(-4.14)	(-4.29)	(-4.07)	(-3.61)
Risk is Extreme(Treated)	0.263***	0.178***	0.100***	0.0957***	0.0728***
	(72.82)	(54.45)	(32.23)	(30.21)	(26.62)
Risk is Moderate	-0.0289**	0.0336***	0.0262***	0.0217**	0.0164**
	(-2.25)	(3.10)	(2.95)	(2.50)	(2.20)
Risk is Major	0.0213*	0.125***	0.0618***	0.0500***	0.0279***
	(1.67)	(11.56)	(6.86)	(5.65)	(3.66)
Risk is Above Major	-0.00465	0.173***	0.101***	0.0875***	0.0466***
	(-0.36)	(15.92)	(11.08)	(9.69)	(5.98)
Risk is Moderate × Post Disclosure	0.0189	-0.00360	-0.0107	-0.0102	-0.00989
	(1.04)	(-0.23)	(-0.85)	(-0.83)	(-0.93)
Risk is Major × Post Disclosure	0.00806	-0.0134	-0.0178	-0.0136	-0.0118
	(0.45)	(-0.87)	(-1.40)	(-1.08)	(-1.09)
Risk is Above Major × Post Disclosure	0.000266	-0.00937	-0.0140	-0.00842	-0.00510
	(0.01)	(-0.61)	(-1.08)	(-0.66)	(-0.46)
Obs	658464	658446	657382	655565	655565
R2	0.0678	0.3393	0.5846	0.6317	0.7256
R2-Adj	0.0678	0.3387	0.5780	0.6193	0.7164
County-Period FE		✓			
Tract-Period FE			✓		
Block Group-Period FE				✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Hedonic Controls					✓

Part 2. Regression Discontinuity

Table 5: RD: Flood Risk Impact on Sale Prices by Flood Risk Tercile

This table presents the regression discontinuity results examining the relationship between the log of sale prices and expected flood depth for both the pre-period (August 2018 to August 2020) and the post-period (August 2021 to August 2023). The regression discontinuity specification incorporates a polynomial fit of order 3. The log sale price is residualized using hedonic controls, block group fixed effects, and sale year-month fixed effects across three time frames: the pre-pre period (April 2014 to August 2016), the pre-period (August 2016 to August 2018), and the combined pre- and post-periods. 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.

	By County-Level Risk Exposure					
	Highest Tercile		**Middle Tercile**		**Lowest Tercile**	
Dep. Var: Log Sale Price	Pre	Post	Pre	Post	Pre	Post
	(1)	(2)	(3)	(4)	(5)	(6)
RD_Estimate	-0.00895	-0.0509***	-0.0120	0.0129	-0.0331	0.0205
	(-0.70)	(-3.50)	(-0.53)	(0.50)	(-1.43)	(0.77)
Obs	85206	81995	25544	24381	23500	21833
Block Group FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓	✓	✓

Table 6: RD: Flood Risk Impact on Sale Prices by Alternate Flood Measures

This table presents the regression discontinuity results examining the relationship between the log of sale prices and expected flood depth for both the pre-period (August 2018 to August 2020) and the post-period (August 2021 to August 2023). The regression discontinuity specification incorporates a polynomial fit of order 3. The log sale price is residualized using hedonic controls, block group fixed effects, and sale year-month fixed effects across three time frames: the pre-pre period (April 2014 to August 2016), the pre-period (August 2016 to August 2018), and the combined pre- and post-periods. 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.

	By SubSamples			
	In Flood Zone		**Coastal Properties**	
Dep. Var: Log Sale Price	Pre	Post	Pre	Post
	(1)	(2)	(3)	(4)
RD_Estimate	0.00219	-0.0629***	0.000618	-0.0721***
	(0.11)	(-2.85)	(0.04)	(-3.85)
Obs	47621	47218	56674	53662
Block Group FE	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓

A Internet Appendix

A.1 DiD Tables with Flood Zone Control:

Table 1 - DiD: Flood Risk Impact on Sale Prices [Full V3 Sample]

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 August 2023). FloodFactor groups properties into six categories: Minimal (1), Minor (2), Moderate (3-4), Major (5-6), Severe (7-8), and Extreme (9-10). Properties in the extreme flood risk category (9–10) are treated as the "treated group". 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.

	Log Sale Price				
	(1)	(2)	(3)	(4)	(5)
Risk is Extreme(Treated) × Post Disclosure	0.00435	-0.0149***	-0.00802***	-0.00910***	-0.00697***
	(1.38)	(-5.92)	(-3.55)	(-4.05)	(-3.48)
Risk is Extreme(Treated)	0.110***	0.110***	0.0364***	0.0298***	0.0298***
	(49.54)	(62.04)	(22.85)	(18.85)	(21.06)
Risk is Minor	0.0795***	-0.0435***	-0.000374	0.00382	0.00745***
	(16.46)	(-11.44)	(-0.12)	(1.20)	(2.62)
Risk is Moderate	0.00889***	-0.0360***	-0.0101***	-0.00471***	0.000472
	(8.00)	(-40.21)	(-12.83)	(-6.06)	(0.68)
Risk is Major	0.0264***	-0.00681***	-0.00523***	-0.00238***	-0.000368
	(23.11)	(-7.38)	(-6.28)	(-2.88)	(-0.50)
Risk is Above Major	-0.00104	0.0280***	0.00237**	0.00238**	-0.000733
	(-0.72)	(23.55)	(2.25)	(2.29)	(-0.79)
Risk is Minor × Post Disclosure	0.0410***	0.00420	-0.00449	-0.00345	-0.000347
	(5.96)	(0.78)	(-0.97)	(-0.76)	(-0.09)
Risk is Moderate × Post Disclosure	0.0101***	0.0000247	-0.00187*	-0.00139	-0.000811
	(6.36)	(0.02)	(-1.67)	(-1.25)	(-0.82)
Risk is Major × Post Disclosure	-0.00530***	-0.00953***	-0.00538***	-0.00433***	-0.00288***
	(-3.25)	(-7.25)	(-4.54)	(-3.67)	(-2.73)
Risk is Above Major × Post Disclosure	-0.000806	-0.00419**	-0.00254*	-0.00164	0.0000372
	(-0.39)	(-2.48)	(-1.70)	(-1.11)	(0.03)
In FEMA Flood Zone	0.0127***	0.0188***	0.00205	0.00542***	0.0162***
	(7.71)	(13.94)	(1.58)	(4.03)	(13.46)
In FEMA Flood Zone × Post Disclosure	0.0110***	-0.0168***	-0.0121***	-0.0140***	-0.0138***
	(4.72)	(-8.88)	(-6.62)	(-7.44)	(-8.18)
Obs	14206950	14206898	14202532	14183514	14183514
R2	0.0346	0.4125	0.6058	0.6474	0.7184
R2-Adj	0.0346	0.4123	0.6016	0.6372	0.7103
County-Period FE		✓			
Tract-Period FE			✓		
Block Group-Period FE				✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Hedonic Controls					✓

A.2 Regression Discontinuity by Tercile

Table 2 - RD: Flood Risk Impact on Sale Prices by Tercile of Flood Risk

This table presents the regression discontinuity results examining the relationship between the log of sale prices and expected flood depth for both the pre-period (August 2018 to August 2020) and the post-period (August 2021 to August 2023). The log sale price is residualized using hedonic controls, block group fixed effects, and sale year-month fixed effects across three time frames: the pre-pre period (April 2014 to August 2016), the pre-period (August 2016 to August 2018), and the combined pre- and post-periods. Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Panel A. Tercile 3 (highest flood risk)

	By County-Level Risk Exposure					
	Full Sample - 3rd Order		**Middle Quantile - Linear**		**Auto Selected - Linear**	
Dep. Var: Log Sale Price	Pre	Post	Pre	Post	Pre	Post
	(1)	(2)	(3)	(4)	(5)	(6)
RD_Estimate	-0.00895	-0.0509***	-0.00948	-0.0543***	-0.0107	-0.0484***
	(-0.70)	(-3.50)	(-0.77)	(-3.84)	(-0.90)	(-2.98)
Obs	85206	81995	85206	81995	85206	81995
Block Group FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓	✓	✓

Panel B. Tercile 2 (medium flood risk)

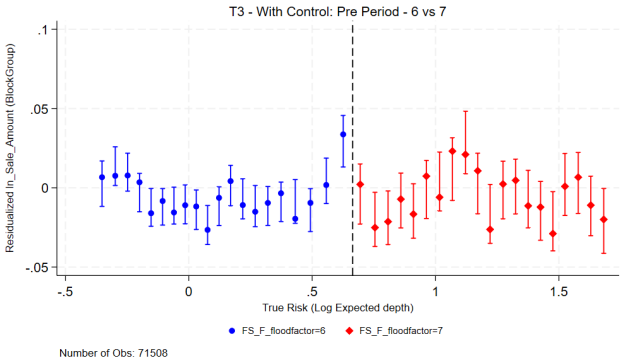
	By County-Level Risk Exposure					
	Full Sample - 3rd Order		**Middle Quantile - Linear**		**Auto Selected - Linear**	
Dep. Var: Log Sale Price	Pre	Post	Pre	Post	Pre	Post
	(1)	(2)	(3)	(4)	(5)	(6)
RD_Estimate	-0.0120	0.0129	-0.000583	0.0169	-0.0157	0.0466
	(-0.53)	(0.50)	(-0.03)	(0.70)	(-0.72)	(1.61)
Obs	25544	24381	25544	24381	25544	24381
Block Group FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓	✓	✓

Panel C. Tercile 1 (lowest flood risk)

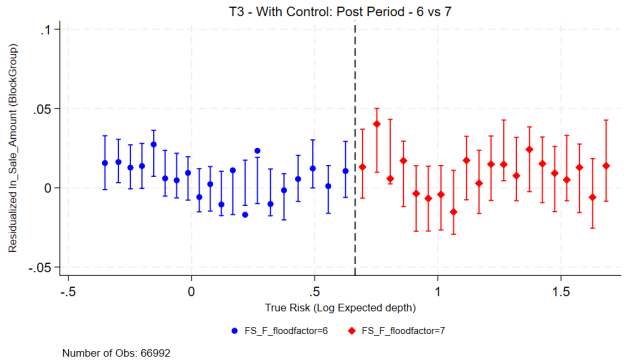
	By County-Level Risk Exposure					
	Full Sample - 3rd Order		**Middle Quantile - Linear**		**Auto Selected - Linear**	
Dep. Var: Log Sale Price	Pre	Post	Pre	Post	Pre	Post
	(1)	(2)	(3)	(4)	(5)	(6)
RD_Estimate	-0.0331	0.0205	-0.0303	0.0153	-0.0359	-0.00498
	(-1.43)	(0.77)	(-1.39)	(0.61)	(-1.49)	(-0.17)
Obs	23500	21833	23500	21833	23500	21833
Block Group FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Hedonic Controls	✓	✓	✓	✓	✓	✓

A.3 Other Score Pair Tercile RD Plots:

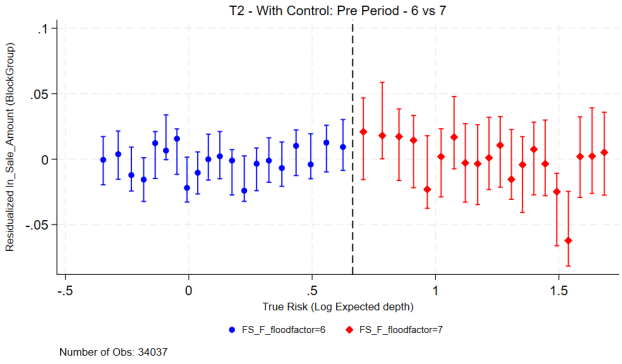
Figure A.1: RD Plot - 6vs7 (Same Score)



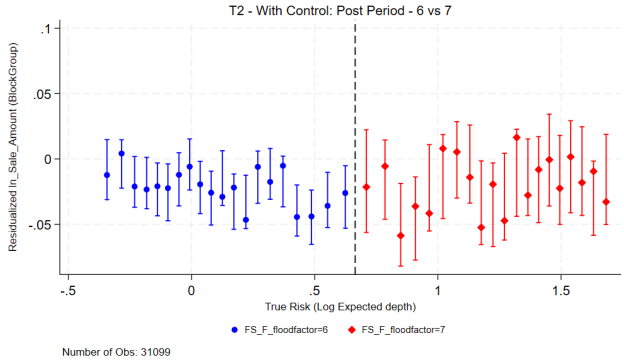
(a) Highest Tercile - Pre Period



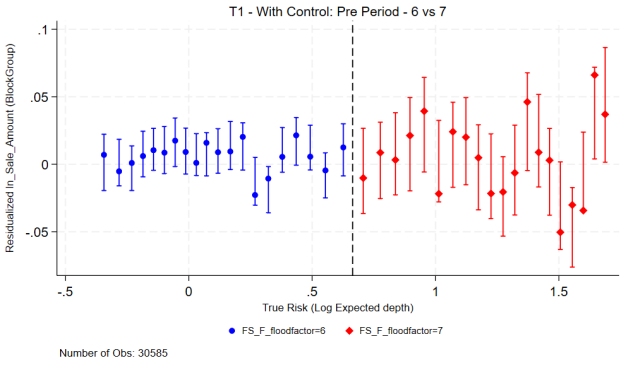
(b) Highest Tercile - Post Period



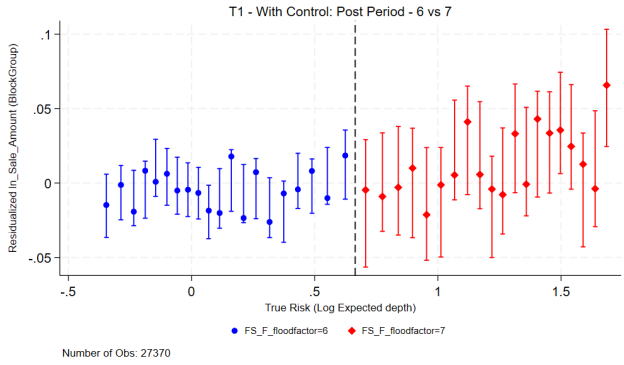
(c) Middle Tercile - Pre Period



(d) Middle Tercile - Post Period

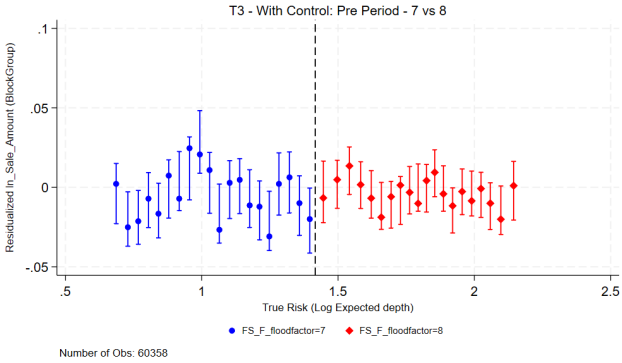


(e) Lowest Tercile - Pre Period

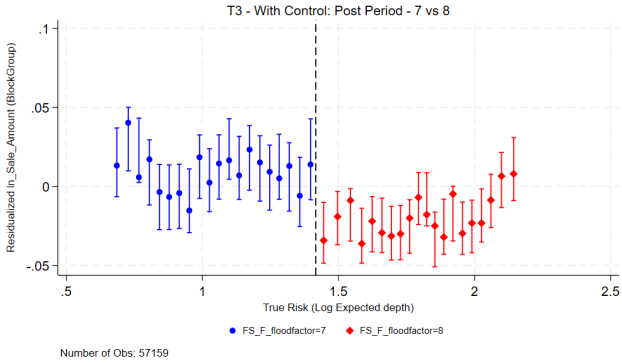


(f) Lowest Tercile - Post Period

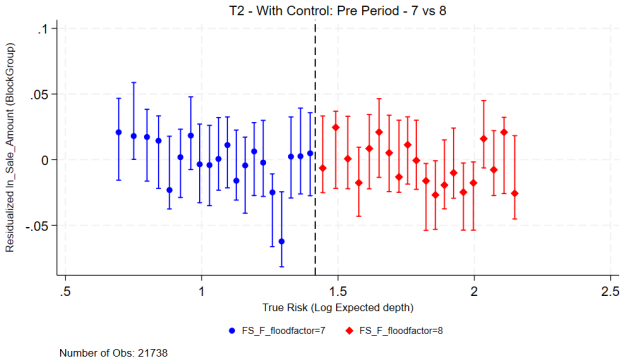
Figure A.2: RD Plot - 7vs8 (Same Score)



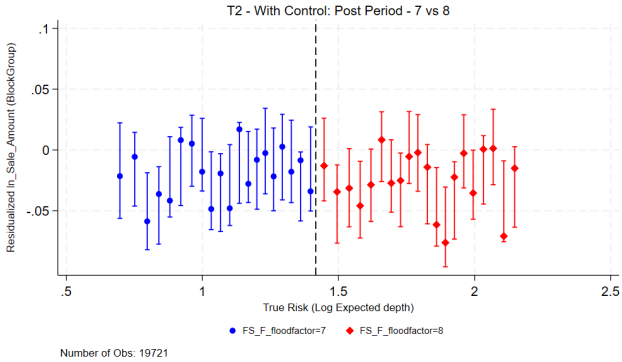
(a) Highest Tercile - Pre Period



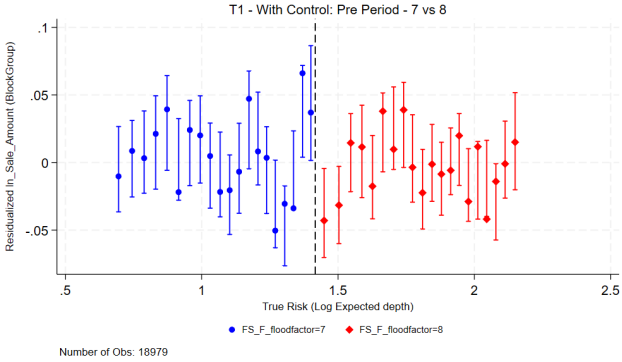
(b) Highest Tercile - Post Period



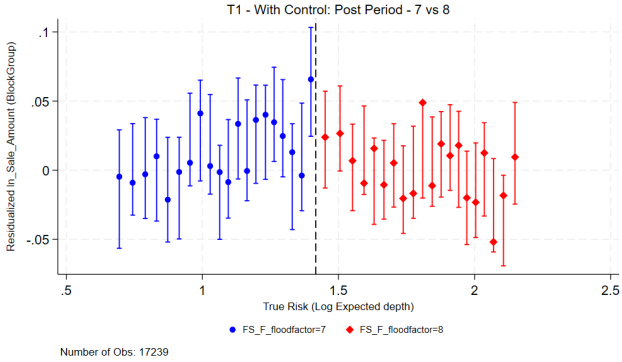
(c) Middle Tercile - Pre Period



(d) Middle Tercile - Post Period

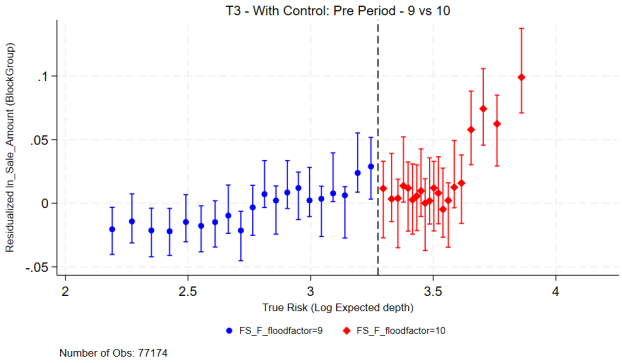


(e) Lowest Tercile - Pre Period

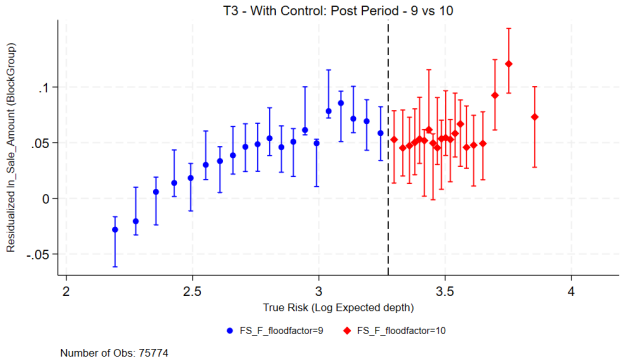


(f) Lowest Tercile - Post Period

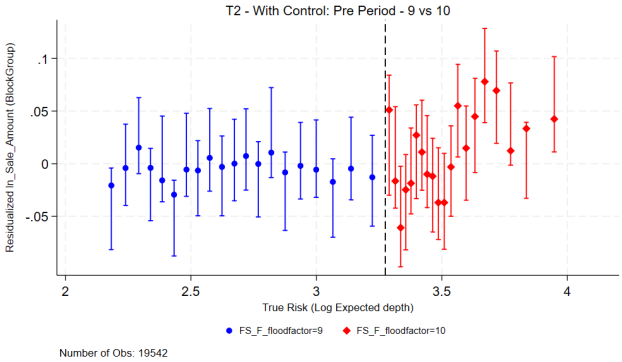
Figure A.3: RD Plot - 9vs10 (Same Score)



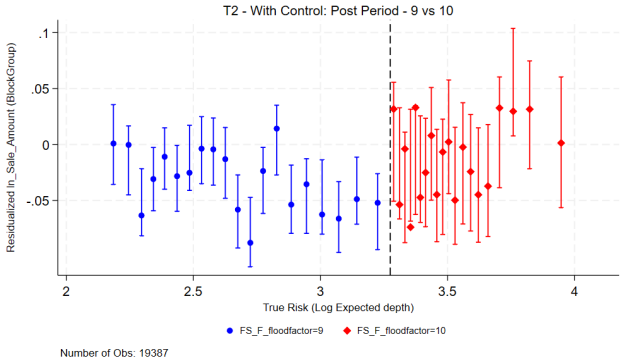
(a) Highest Tercile - Pre Period



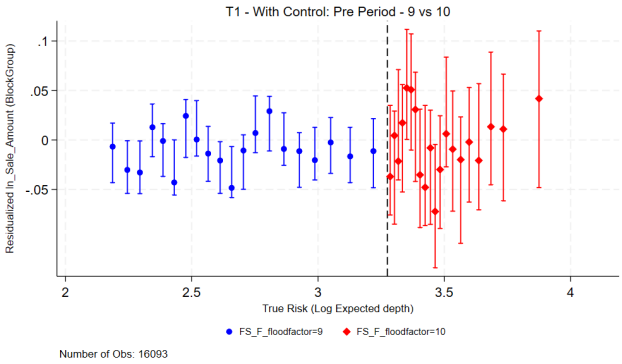
(b) Highest Tercile - Post Period



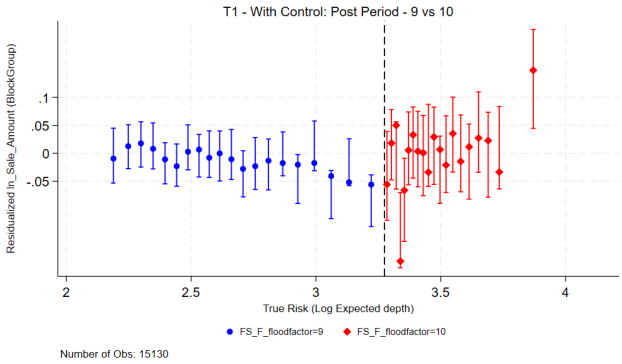
(c) Middle Tercile - Pre Period



(d) Middle Tercile - Post Period



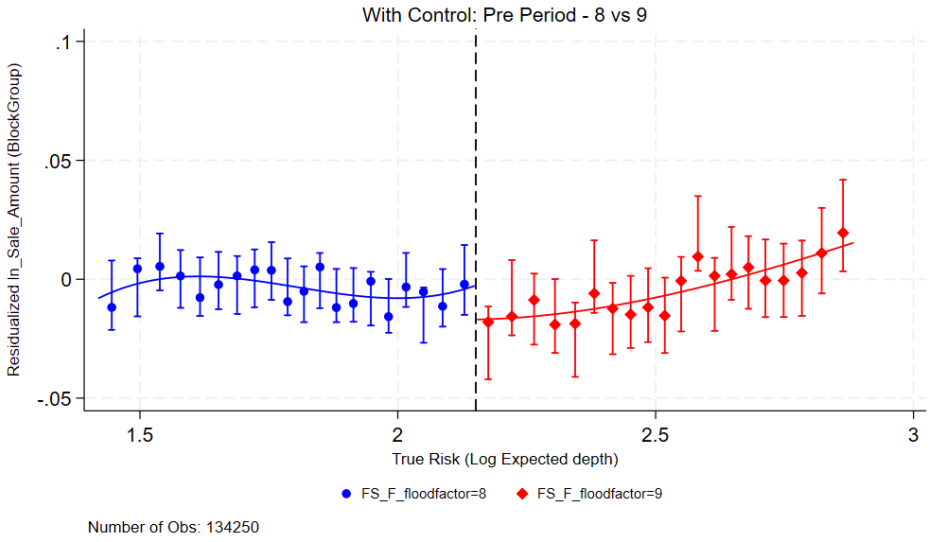
(e) Lowest Tercile - Pre Period



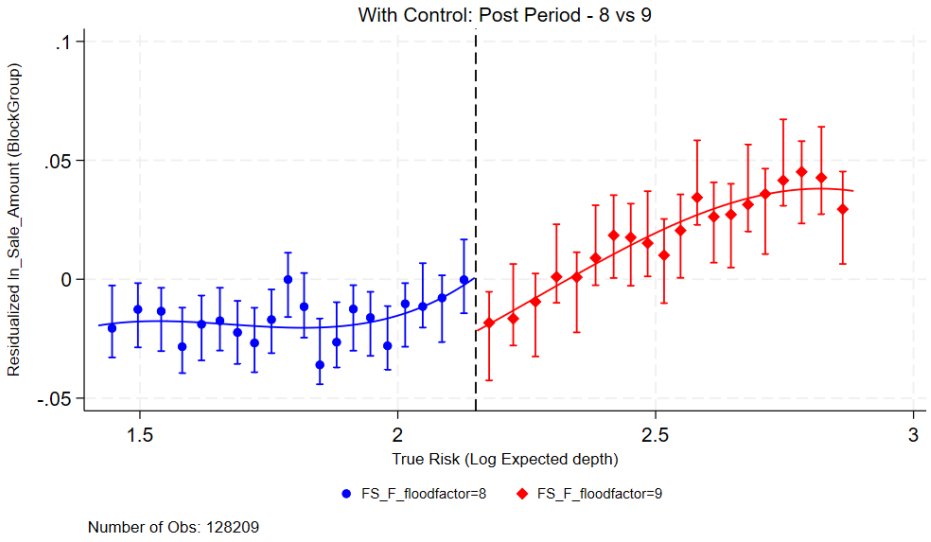
(f) Lowest Tercile - Post Period

A.4 RD combined for 8 vs 9

Figure A.4: No Terciles (8 vs 9) [Same Score Sample]

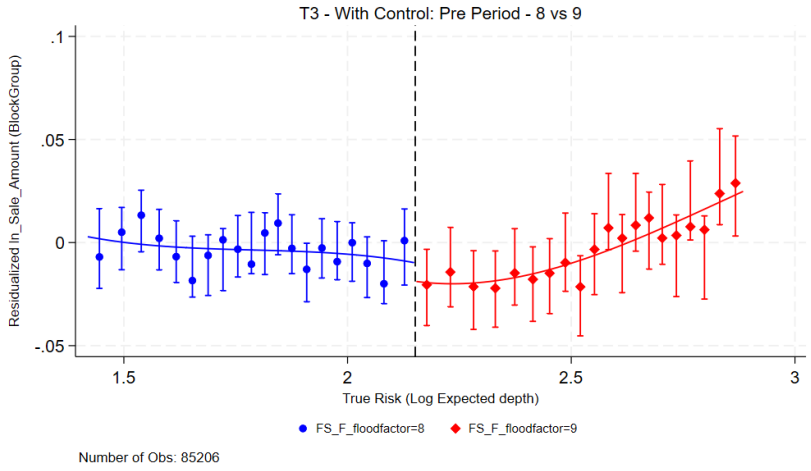


(a) Pre Period: Full Sample

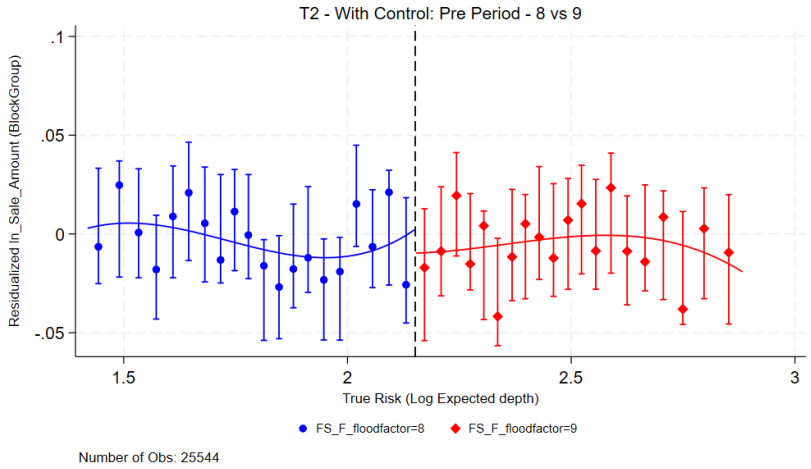


(b) Post Period: Full Sample

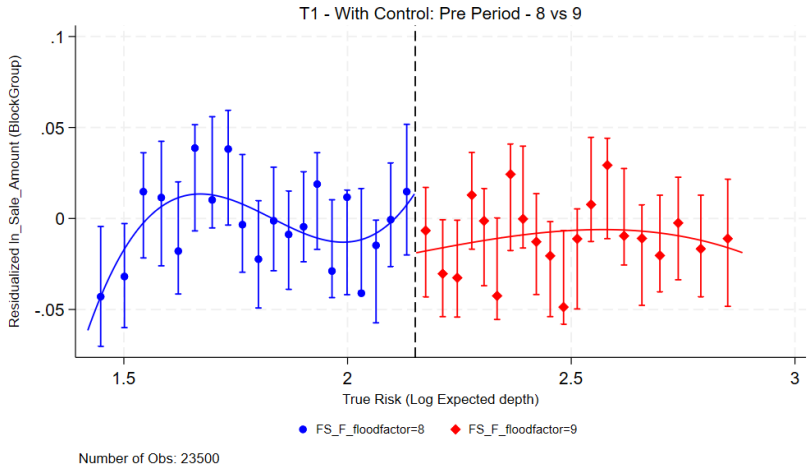
Figure A.5: Pre-Period: Tercile by county-level Risk Exposure(8 vs 9)



(a) Highest Tercile - Pre Period(2018-2020)

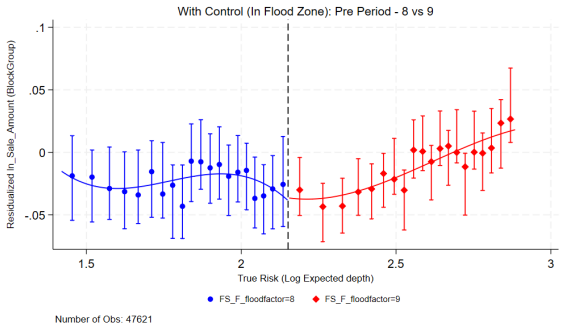


(b) Middle Tercile - Pre Period(2018-2020)

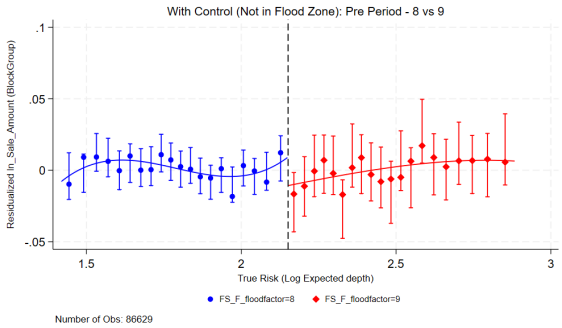


(c) Lowest Tercile - Pre Period(2018-2020)

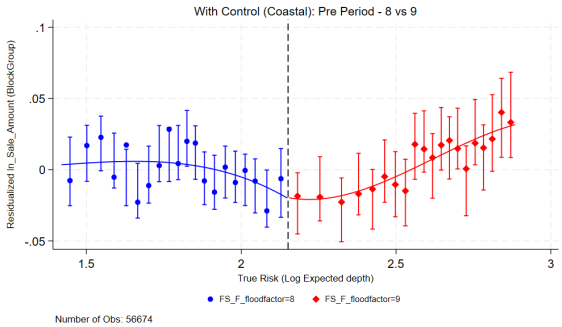
Figure A.6: Pre-period: RD Subsample Analysis



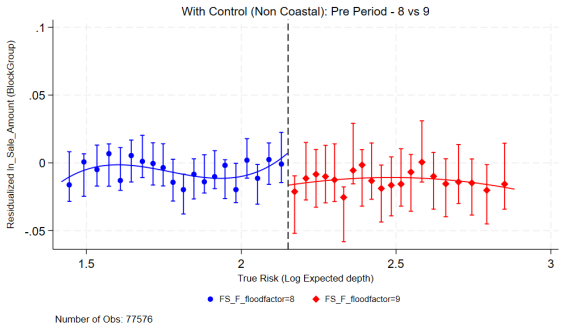
(a) Pre Period: In FEMA Flood Zone



(b) Pre Period: Not In FEMA Flood Zone



(c) Pre Period: Coastal



(d) Pre Period: Non Coastal