Adapting to Natural Disasters through Better Information: Evidence from the Home Seller Disclosure Requirement

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Abstract

While flood damage is determined by both flood intensity and population exposure, the US has primarily focused on managing the former, with little success. This paper studies whether easing information frictions about flood risk could reduce the exposure and thus flood damage. By exploiting plausibly exogenous variations from the Home Seller Disclosure Requirement, I first show this policy lowers the population in high-risk areas. Further, using a hydrological measure of flood intensity, I find that the policy reduces the probability of flood damage by 33 percent from the baseline. These findings suggest that an information policy could facilitate voluntary adaptation.

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1 Introduction

Since 1980, floods in the United States have wrought over $1 trillion in damage, making them the costliest type of natural disaster over the last 40 years (NOAA 2020). Climate scientists predict flooding is likely to happen with higher frequency and intensity in the future (Milly et al. 2002, Ghanbari et al. 2019). Thus, effective adaptation, which is an activity to moderate or avoid harm, is increasingly important (IPCC 2014, Aldy and Zeckhauser 2020).

While flood damage is determined by both flood intensity (i.e., physical characteristics) and exposure (i.e., population size in the high-risk areas), the US flood policy has focused primarily on managing the former by adding engineering structures, such as levees (Changnon et al. 2000, Field et al. 2012, Tarlock 2012, Liao 2014). However, structural responses can attract more people and developments in floodplains (the so-called "levee-effect") by converting wetlands into habitable land (Pinter 2005, Kousky et al. 2006, Boustan et al. 2012, Collenteur et al. 2015). The fundamental problem is that none of these structures are perfectly safe. When those engineering structures fail, either due to extreme weather conditions or improper maintenance, the risk of flood damage is heightened with the increased population exposure (Pinter et al. 2016).[1] Consequently, governments end up spending billions of dollars for disaster relief and recovery on top of the resources devoted to flood prevention (CBO 2016). Although some local governments impose development restrictions and related policies to limit exposure, in most of the US, the population in flood-prone areas is expected to grow rapidly (Wing et al. 2018).[2]

This paper studies whether easing information frictions about flood risk in the housing market could reduce the number of households in high-risk areas and thus flood damage. Although official flood maps have long been publicly available, earlier research and anecdotal evidence suggest a lack of flood risk awareness among home buyers. For instance, Chivers and Flores (2002) find only 14 percent of home buyers in high-risk areas learned about flood risk before closing. Such low awareness hinders home buyers from fully internalizing the costs of flood risk during real estate transactions. Given that a potential reason for the friction is information acquisition and processing costs

[1]Flood protection structures frequently fail. For instance, over 1,000 levees failed during the Midwest Flood of 1993 (LARSON 1996). An important reason is the lack of maintenance. Pinter et al. (2016) find that only 1.9 percent of the levees in the US are rated "Acceptable".

[2]For many local governments, imposing restrictions on development is against the interest of town planners or the mayor because it could hurt the tax base.

(Kunreuther and Pauly 2004), the Home Seller Disclosure Requirement (hereafter "the disclosure requirement") could alleviate the problem by efficiently delivering risk information.

The policy mandates that home sellers must disclose any known property defects using a standardized form (Lefcoe 2004). Regarding flood risk, a typical question is whether a property is located in a Special Flood Hazard Area (SFHA)—an area with elevated flood risk defined by the official flood map. Home sellers are generally required to deliver the disclosure form to home buyers before closing (Stern 2005).

The disclosure requirement was rolled out across 26 states in the contiguous US from 1992–2003. The variation in implementation timing is from plausibly exogenous state court rulings on the extent of realtor liability for incomplete disclosure (Roberts 2006), which facilitates a difference-in-difference research design. In addition, the disclosure requirement treats properties located in and out of the SFHA differentially, which introduces a third difference to further aid in identification. In exploiting the staggered adoption of the disclosure requirement, I use the stacked approach to overcome potential bias from conventional two-way fixed effect models (Cengiz et al. 2019, Brot-Goldberg et al. 2020, Goodman-Bacon 2021).

I also leverage additional identifying variation deriving from the fact that the disclosure form considers flood risk in a discontinuous manner. Specifically, home buyers for two proximate properties located on opposite sides of an SFHA border—over which flood risk is changing continuously—receive starkly different flood risk information. The spatial discontinuity yields an opportunity to identify the information effect holding true flood risk constant. A concern is that being located in the SFHA could invite other treatments such as the mandatory purchase of flood insurance. To account for that possibility, I use the difference-in-discontinuity approach following Grembi et al. (2016).

To leverage these variations, I collect multiple datasets. I collect census block-level demographic data from the decennial census, and community-level flood insurance policy counts from the National Flood Insurance Program (hereafter "flood insurance"). To measure flood damage, I use damage records from flood insurance adjuster reports. I also construct a historical dataset of community-level past flood events based on a hydrological measure of flood intensity (Saharia et al. 2017, England Jr et al. 2019). These data overcomes the potential endogeneity of self-reported flood events, such as from the National Weather Service Storm Events data (Gall et al. 2009). Because main outcome variables used in analysis have a mass point at zero with a long right tail, I estimate the extensive and intensive margin effects separately following suggestions of Chen and Roth (2022).

I analyze the data in two parts that correspond to the two research questions posed earlier. The first part investigates home buyer responses to the disclosure policy. Specifically, building on the insights from Ehrlich and Becker (1972)—households mitigate hazard risk by choosing between self protection and market insurance—I empirically estimate the impact of the disclosure on population distribution and flood insurance take up. The second empirical exercise estimates flood damage function to test if the disclosure policy reduces flood damage.

From the first part, I find that census blocks in the SFHA area (conditional on having a non-zero population) experiences a 7 percent decline in population after the disclosure policy. At the extensive margin, it lowers the probability of a block in the SFHA having any population by 0.01 percentage point (or 1.5 percent from the baseline of 0.67). Taking these intensive and extensive margin effects together, they illustrate the potential for improved information to faciliate voluntary adaptation to flood risk. policy seems to have the potential to discourage not only net population inflow to the existing properties but also developments in previously uninhabited high-risk areas.

In contrast, I find a very small effect of the disclosure policy on insurance purchases: the probability of having a positive number of insurance policies at a community level decreases by 0.001 percentage point (or 0.1 percent from the baseline of 0.83; extensive margin) while insurance counts per housing unit decreases by 0.9 percent (intensive margin). Investigating these two potential responses is important because they have different implications for flood damage. That is, while choosing a safer location to live would reduce the probability of flooding, flood insurance would simply redistribute income from the "dry state" to the "flooding state" without necessarily affecting the probability distribution (Ehrlich and Becker 1972).

From the second part, I find that the disclosure policy reduces the expected probability of having any flood damage at the community level by 2.5 percentage points (or 33 percent of the baseline probability). To show this, I first estimate a non-parametric flood damage function—a mapping between flood size and damage—using community-level flood history and damage data. Then, I estimate the causal effect of the disclosure policy on the damage function and find that the slope of the function is substantially flatter after the policy. This analysis further reveals that the disclosure effect is disproportionately larger in communities with the greatest flood risk.

This paper contributes to four different bodies of literature. First, it is related to prior work on factors mitigate damage from climate change. Whereas earlier studies primarily focus on technology as a driver of adaptation (Miao and Popp 2014, Barreca et al. 2016, Burke and Emerick 2016), I focus on the role information can play in aligning private incentives with socially desirable outcomes.

Second, it contributes to the literature on the role of government in shaping household adaptation behaviors (Kousky et al. 2006, 2018, Gregory 2017, Peralta and Scott 2020, Baylis and Boomhower 2022). Perhaps the closest paper conceptually is Baylis and Boomhower (2021), which shows how building code policies can mitigate wildfire damage. A key difference is that the policies studied by Baylis and Boomhower (2021) directly mandate adaptation, whereas I show how a disclosure requirement can encourage voluntary adaptation.

Third, and more broadly, this paper builds on earlier work on the impacts of flood risk on the housing market (Hallstrom and Smith 2005, Pope 2008, Bin and Landry 2013, Muller and Hopkins 2019, Gibson and Mullins 2020, Hino and Burke 2021, Bakkensen and Barrage 2021). While most of these studies focus on understanding how changes to flood risk information and beliefs affect housing prices, I study their impacts on flood damage. Tracing the effect of flood information up to the damage amount is important because while housing price changes, in general, reflect transfers between home buyers and sellers, a reduction in flood damage enhances social welfare.

Finally, I contribute to the literature methodologically by constructing a novel measure of flood exposure, which is a critical step in identifying climate change effects (Hsiang 2016). My approach leverages hydrological measures of flood intensity, which allows me to document flood events objectively for a wide range of causes including rainfall, snow melt, or storm surge. This measure complements measures from existing flood damage functions that specialize in capturing the impact of rainfall or hurricanes (Strobl 2011, Davenport et al. 2021).

The paper proceeds as follows. Section 2 provides background on the Home Seller Disclosure Requirement and the Special Flood Hazard Area. Section 3 details the data sources and provides some summary statistics. Section 4 presents estimation results on household responses while Section 5 shows the disclosure policy effect on flood damage. Section 6 concludes.

2 Background

2.1 Home Seller Disclosure Requirement

Publicly available Flood Insurance Rate Maps contain the information home buyers need to determine whether a property is located in an SFHA. Also, the Flood Insurance Reform Act of 1994 requires the purchase of flood insurance as a condition for federally-backed mortgage approval for properties in SFHAs, which should inform home buyers of the associated flood risk. However, compliance with the flood insurance mandate is far from perfect (Tobin and Calfee 2005, Michel-Kerjan 2010, National Research Council 2015, GAO 2021, Wagner 2022) and prior work shows home buyers do not have a good understanding of the flood risk they face (Chivers and Flores 2002, Pope 2008, Bin and Landry 2013).[3] A disclosure on flood risk could be a useful apparatus to address this information gap.

Disclosure content. A statutory disclosure requirement mandates that home sellers provide buyers with a detailed account of known material defects in the listed property by filling out a standardized form. Importantly, the disclosure requirement is not exclusively about flood risk. As Illinois Residential Real Property Disclosure Report in Appendix Figure D.1 illustrates, a typical form covers a wide range of property conditions such as structural issues (e.g., problems with walls, roofs, or plumbing) and surroundings (e.g., natural hazards such as flood risk).

The exact language of disclosure policies on flood risk varies slightly from state to state, but some combination of the following three questions usually appears: whether a property is in the SFHA; whether a property had flood damage in the past; and whether a property has flood insurance.[4] Because properties on the SFHA are more susceptible to flood, these questions are highly correlated. Indeed, flood insurance policy and claims data that I acquired through FOIA show that 71 percent (75 percent) of the claims (flood insurance policies) are from properties in the SFHA. Taken together, information from the disclosure may raise home buyers' flood risk awareness for properties in SFHAs relative to those outside.

[3] Anecdotal evidence also suggests that a large number of home buyers are not well aware of flood risk (Flavelle 2017, Satija et al. 2017). Also, Michel-Kerjan (2010) find only 20-30 percent of homeowners in the SFHA purchased flood insurance in 2000.

[4] As of 2021, 5 states ask just the first question about the SFHA status, 15 states ask about SFHA status and past flood experience, and 4 states ask all three questions. MI and TN ask about the latter two only.

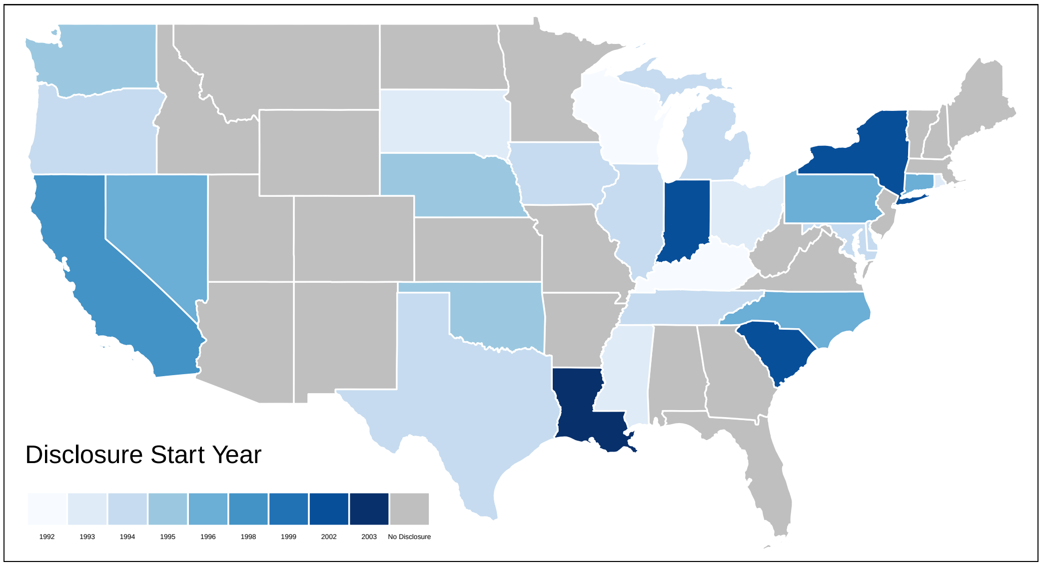
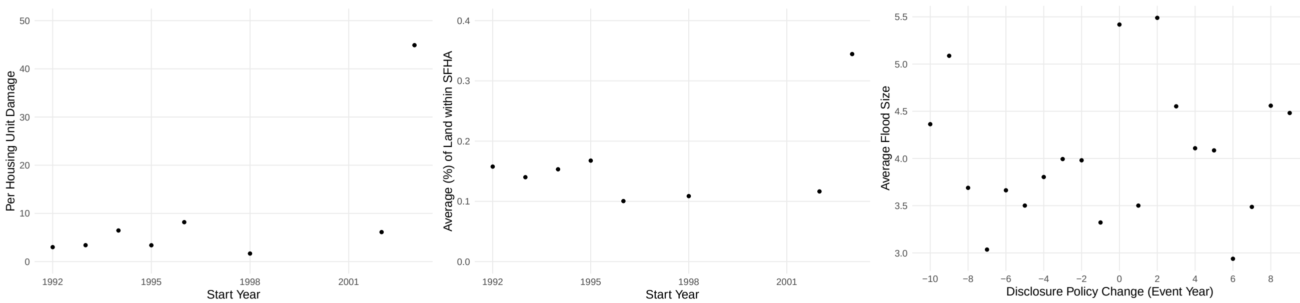


Figure 2.1: The Disclosure Requirement Implementation over Time

Disclosure background. To understand why disclosure requirements were introduced in the first place, it is useful to discuss the evolution of state court rulings on incomplete disclosure cases. Traditionally, home buyers were legally expected to exercise proper caution with regard to potential defects of a property (the so-called "*caveat emptor*" or "let the buyer beware" doctrine). However, with the rise of consumer protectionism (Lefcoe 2004), and with higher public attention to environmental contamination and health issues during the 1980s (Weinberger 1996), state courts increasingly held listing agents responsible for incomplete disclosure cases. In response, the National Association of Realtors issued a resolution in 1991 encouraging state associations to develop and support legislation regarding the statutory disclosure requirement (Tyszka 1995).

Consequently, between 1992 and 2003, 26 states in the contiguous US implemented the disclosure requirement with an explicit question on flood risk (see Figure 2.1). As its historic origin suggests, the disclosure policy was primarily an effort of realtors to deflect potential liability to sellers (Washburn 1995) and the timing of the policy implementation is related to the timing of the change in the state court's view on the *Caveat Emptor* doctrine (Roberts 2006).

Given the background and content of disclosure requirements, the implementation timing of the policy is unlikely to be correlated with each state's underlying flood risk, damage, or history. In Figure 2.2, I plot the relationship between disclosure year and (a) the average flood damage per housing unit and (b) the average proportion of land area inside of the SFHA. If the timing of disclosure pol-



(a) Timing and Flood Damage (b) Timing and (%) of Land in SFHA (c) Timing (in Event) and Flood Size

Figure 2.2: Correlation Between Disclosure Timing and Flood Profiles. These figures illustrate the relationship between the disclosure policy timing and past flood damage (panel (a)) and ex-ante flood risk profile (panel (b)). Panel (c) depicts the relationship between the average flood size and disclosure policy change in event time. Values on the y-axis is pooled across all states with a flood risk disclosure policy. See the text for additional details.

icy implementation is correlated with underlying flood risk, we would expect to see a higher risk profile for early adopters. However, both flood damage and the SFHA ratio are uncorrelated with the implementation year.[5] In contrast to panels (a)-(b) where the x-axis is in calendar years, panel (c) shows the average flood size in event time. If the decision to adopt a disclosure policy were a direct response to devastating flood events, the average flood size would be larger for event years right before 0. The plot shows that flood size is also essentially uncorrelated with policy adoption—if anything, flood size seems to be smaller in event years -1 and -2, which again suggests that the policy implementation is not driven by prior flooding.

States without disclosure requirements on flood. Twenty-two states in the contiguous US (excluding Washington DC) do not mandate home sellers to disclose on flood risk. Interestingly, despite the lack of mandatory requirements, more than 60 percent of these states have seen the formation of voluntary disclosure forms by their respective state realtor associations. In some states, realtor associations even require member realtors to use these forms.[6] Thus, a non-trivial number of home buyers in these "non-disclosure" states might have received information on flood risk. The timing of these realtor-driven behavior is uncertain, as is compliance. For this reason, I do not use non-disclosure states as control states. Rather, I use later-treated states as the control group for earlier-treated

[5] Spikes in Figure 2.2 are due to Louisiana, which has substantially higher flood damage per housing unit and a higher fraction of land area in SFHAs compared to other states.

[6] See Colorado, for instance, from Flood Disclosure Scorecard from NRDC https://www.nrdc.org/flood-disclosure-map (accessed on Sep 8, 2022).

states when I exploit the staggered adoption variation. Indeed, the inclusion of these states seriously attenuates the treatment effect and/or creates a pre-trend (see Appendix Figure B.1 panel (b) and Appendix Table D.5 and accompanying texts).

It is worth noting that five states (out of the 22 states) have adopted a variant of home seller disclosure policy, although it does not have a question on flood risk.[7] These "placebo" states are useful for checking the robustness of the main results.

Does the disclosure requirement matter? Although many states levy fines or even allow buyers to rescind their purchase agreement without penalty to ensure compliance, the disclosure policy might still fail to raise home buyers' flood risk awareness. For example, home sellers might not comply with the regulation. If they furnish the form with inaccurate information or ignore the requirement despite the potential penalty, the disclosure policy's effectiveness could be seriously undermined. Home buyers might also fail to process the new information. While the disclosure forms consist of straightforward check box questions (see Appendix Figure D.1), the implication of living in an SFHA might not be fully understood. Thus, while there are good reasons to expect the disclosure policy to reduce information frictions around flood risk, whether it does is an empirical question.

Unfortunately, I cannot observe home buyers' perceptions of flood risk directly. However, in Appendix B I test whether the disclosure policy affects property values in the SFHA area. I find disclosure reduces housing prices by 4.5 percent, which coincides with existing estimates of the effect of flood risk information on housing prices (e.g., see Hino and Burke (2021)). This finding provides evidence that at least some information is being conveyed to buyers through the disclosure policy. The extent to which this information translates to risk-mitigating behaviors is uncertain and the focus on my empirical work below.

2.2 Flood Map and Special Flood Hazard Area (SFHA)

An official flood map, or the Flood Insurance Rate Map, allows stakeholders to identify the boundary of special flood hazard areas (SFHA), determine a specific property's SFHA status, and determine the Base Flood Elevation among other things (FEMA 2005). The SFHA, which is an area that is

[7] For details regarding the extent of disclosure in these states, see the following. For Idaho: 1994 Ida. HB 825 (1994), Maine: Title 33 Section 173 (1999), Minnesota: CHAPTER 306-—S.F.No. 2697 (2003), New Hampshire: NH. Rev. Stat. Ann. § 477:4-c (1994), and Virginia: VA. CODE ANN. §§ 55.1-704 (2005).

expected to be inundated with a 100-year flood, is a particularly important concept because flood risk communications frequently refer to it.[8]

The flood mapping process involves three key steps (FEMA 2005): (1) hydrologic analysis that determines the water amount in a stream channel for a given weather event; (2) hydraulic analysis that determines the water surface elevation for a given water amount; and (3) floodplain mapping, which compares water surface elevation with the ground elevation to determine the boundary of inundation. The procedure implies that as long as the ground elevation changes continuously, flood risk is continuous. The continuity of flood risk gives rise to the spatial discontinuity design near the SFHA border because the disclosure form treats flood risk discontinuously for two areas on each side of the border with almost identical true flood risk. A potential concern, though, is that the SFHA status invites other regulations as well.[9] Thus, I take advantage of the difference-in-discontinuity design, which exploits the difference between two spatial discontinuity estimates before and after the disclosure policy.

It is also worth noting that these maps are updated occasionally, which could potentially confound the disclosure policy. While the National Flood Insurance Reform Act of 1994 requires that FEMA assess the need to revise and update all flood maps every 5 years, the vast majority of the maps fail to meet the required update cycle (DHS Office of Inspector General 2017). This is favorable for this paper's research design because it ensures flood zone status remains constant over the study period for the majority of properties. Indeed, in Appendix B, I show that excluding properties from communities with map updates does not change the estimated effect of disclosure on the housing price.

The jurisdiction of each flood map is a "community," a local political entity (e.g., village, town, city) defined by the National Flood Insurance Program. These entities are comparable to a US Census place. Appendix Figure D.2 shows a sample Flood Insurance Rate Map from a part of the Bor-

[8]Flood is defined as "a general and temporary condition of partial or complete inundation of two or more acres of normally dry land area or two or more properties from an overflow of inland or tidal waters, from unusual and rapid accumulation or runoff of surface waters from any source, or from mudflow" (FEMA 2005).

[9]Two regulations are worth noting. First, a new development in the SFHA needs to be elevated high enough to withstand the 100-year flood (Horn and Brown 2018). Second, owners of properties in the SFHA are required to purchase flood insurance as a condition of receiving a federally backed mortgage. However, the enforcement of these regulations is imperfect. As briefly mentioned in Section 2.1, Michel-Kerjan (2010) find only 20-30 percent of home owners in the SFHA purchased flood insurance in 2000. Also, a non-trivial number of official flood maps have been created using the "approximate method". These maps do not have the Base Flood Elevation, which is needed to enforce the elevation requirement (FEMA 2005).

ough of Stonington, Connecticut. The dark area on the map represents the SFHA, and the light area is the non-SFHA. A typical entity has both SFHA and non-SFHA areas within the jurisdiction. Appendix Figure D.3 is a histogram of the fraction of area covered by an SFHA for 8,194 communities on the flood map and in the 26 ever-disclosed states. As the histogram shows, there is substantial variation in the SFHA ratio across different communities, which suggests that the fraction of households subject to the disclosure requirement differs across communities.

3 Data

I compile multiple data sets on block and tract level demographics, community-level numbers of flood insurance policies, and flood damage. I also construct a community-level flood history dataset. In this section, I describe each data source and provide descriptive statistics.

Demography and flood insurance. Demographic characteristics come from two sources. I collect census block level population and occupancy data from the 1990, 2000, 2010, and 2020 decennial census. To account for changing block boundaries and resulting one-to-many matches across different decennial census years,[10] I calculate the weighted sum of count variables using interpolation weights from the NHGIS block-to-block crosswalk (Manson et al. 2022).[11]. This creates a geographically standardized time series. For other demographic characteristics such as income, age, race, and education, which are not available at the block level—the smallest census geographic unit—level, I utilize tract-level data from the Geolytics for 1990, 2000, and 2010 decennial census.[12] Data on the number of flood insurance policies by the NFIP community are available from FEMA from 1978–2008.[13]

Flood damage. I use damage records from the National Flood Insurance Program adjuster's report. The damage amount is defined as the actual cash value of flood damage, which is the replacement value net of depreciation, to both structures and contents (FEMA 2014). I observe individual property level damage with loss date, community ID, and building type. I restrict the sample to single-

[10]For instance, block G06000104003003006 in 2000 is matched to five different blocks in 2010 ending in 3010, 3011, 3017, 3020, and 3028.

[11]Interpolation weights represent the expected proportion of the source block's counts (e.g., population or housing units) located in each target block (Manson et al. 2022)

[12]Geolytics data provide tract level data after accounting for changing boundaries across different survey years (for more details, see www.geolytics.com).

[13]I thank Justin Gallagher for graciously sharing this data.

family houses and collapse it to the community-by-year-by-the-largest-flood-event level to match it with the annual maximum flood events data.

Flood history. The measurement of climate exposure is a critical methodological step in identifying climate effects on economic outcomes (Hsiang 2016). In the domain of floods, two different measures have been widely used. The first approach measures flood intensity using outcome variables such as economic cost (for a review, see Felbermayr and Gröschl (2014)). This approach suffers a potential endogeneity problem because the measure is likely to be correlated with economic variables such as income. The second approach uses a meteorological measure, but only for a subset of events such as a hurricane or rainfall (Strobl 2011, Hsiang and Jina 2014, Deryugina 2017, Davenport et al. 2021). Given that rainfall alone explains just one-third of cumulative flood damage in the US (Davenport et al. 2021), such an approach cannot capture the entire scope of floods.

To overcome the limitations of existing approaches, I construct hydrology-based community-level flood history data using daily water volume records from over 3,000 USGS and NOAA stations located within my 26-state sample (Milly et al. 2002, Mallakpour and Villarini 2015, Slater and Villarini 2016). Using this approach, flood size is described by the recurrence interval (Task Committee on Hydrology Handbook of Management Group D of ASCE 1996): the expected number of years for a flood of the same magnitude to come back. Flood size is conveniently increasing in the recurrence interval. For instance, a 10-year flood is the size of a flood that would happen on average once every 10 years, which would be less severe than a 100-year flood that is large enough to happen only once in 100 years on average. This approach objectively measures the intensity of floods from various causes.

Practically speaking, the data is constructed in four steps. First, I estimate a gauge-specific flood frequency distribution by fitting the Log-Pearson III distribution using the annual peak flow records of each gauge. Second, I convert the daily maximum discharge volume at each gauge into quantiles of the fitted distribution from step 1. Third, I translate the quantiles into recurrence intervals and take the maximum recurrence interval for each year. [14] Finally, I match each community to the three nearest gauges and calculate community-year-level flood size by taking the inverse-distance weighted average of three closest gauges' recurrence intervals. More details on the flood data construction

[14] The recurrence interval for quantile q is $\frac{1}{1-q}$. For instance, a discharge volume of the 90th percentile, which means it is the 90th highest among 100 yearly maximum observations, corresponds to a 10-year flood.

procedure and summary statistics are in Appendix A.

Other data sources. As the disclosure policy differentially treats the properties in and out of the SFHA, I spatially merge the NFIP community, block, and tract with the digitized flood map to determine the SFHA status of each geographic unit. Specifically, I use the Q3 map—the first generation of a digitized flood map—reflecting flood risk as of the mid-1990s. The map covers about half of all FEMA communities based on population density and the intensity of past flood incidents, and my main sample consists of these communities (FEMA 1996). Finally, the primary data source to track the disclosure requirement legislative history is the *Nexisuni* database. I cross-validate this database with prior works on the disclosure requirement (Washburn 1995, Pancak et al. 1996, Lefcoe 2004) and reports from the National Association of Realtors (National Association of Realtors 2019).

Summary statistics. Table 3.1 presents summary statistics for key independent (flood size) and dependent (population, number of flood insurance policies per housing unit, and flood damage per housing unit) variables used in the analysis. Population figures are reported for the Census blocks within the optimal bandwidth estimated in Section 4.2, while the last three values are reported from the NFIP communities in my sample.

A notable aspect of the data is the high prevalence of zeros among the dependent variables. For instance, 27 percent of observations for the block population and counts and 17 percent of the observations of flood insurance policy counts are zeros. For the community level flood damage per housing unit variable, 95 percent of observations are zero. Importantly, the prevalence of zeroes in the dependent variables are consistent with external sources (details are in Appendix A.2).

In addition to a mass point at zero, these variables also exhibit substantial skewness (long and thin right tails), as the difference between median and mean values suggests. To account for this, I follow Chen and Roth (2022) and estimate extensive and intensive margin effects separately for these three dependent variables. This approach resonates with a hurdle or two-part model, which is used extensively in modeling health expenditures characterized by a similar distribution (Mullahy and Norton 2022).

Finally, the last row of Table 3.1 indicates that an average community experiences 2.18 10-year flood events over a 20-year period. This is close to the expected value of 2.0.[15]

[15] 2.18 is slightly higher than 2 partly because I used annual peak flow data until 1990. This approach ensures that

Table 3.1: Summary Statistics for Key Variables

Variables	Min.	Q25	Median	Mean	Q75	Max.
Census Block Population	0	0	10	34.4	40	7,597
NFIP Policies Per Housing Unit	0	0.001	0.006	0.03	0.019	6.53
Flood Damage Per Housing Unit	0	0	0	6.97	0	23,991
N of 10-Year Floods (For 20 Years)	0	1	2	2.18	3	15

4 Responses to the Disclosure Requirement

In this section, I investigate how home buyers respond to flood risk information. Building on the insights from Ehrlich and Becker (1972)—households mitigate hazard risk by choosing between self protection and market insurance—I empirically estimate the impact of the disclosure on population distribution and flood insurance take up. Investigating both of these two responses is important because they have starkly different implications for flood damage. That is, while choosing a safer location to live reduces the exposure to risk, flood insurance would simply redistribute income from the "dry state" to the "flooding state" without necessarily affecting the exposure (Ehrlich and Becker 1972).[16]

4.1 Estimation Framework

Spatial Discontinuity. Yes-or-no check box questions on disclosure forms create a spatial discontinuity in flood risk information, which allows me to disentangle the flood risk information effect from the effect of true risk. However, a potential concern is that other policies such as flood insurance requirements also change at the border, which could confound the effect of the change in disclosure requirements. To account for this problem, I leverage a difference-in-discontinuity approach (Grembi et al. 2016). By taking the difference between the two spatial regression discontinuity estimates (for pre and post-disclosure periods), the design controls for time-invariant confounding factors.

Following Grembi et al. (2016), I estimate the policy effect on population and the vacancy rate

flood thresholds remain consistent across different years. However, it does not account for potential large floods beyond 1990, which would raise the threshold and thus reduce the number of floods exceeding the 10-year flood threshold. Further details can be found in Appendix A.

[16] Theoretically, it is possible that a home buyer choose to engage in both self protection and market insurance. The key condition for this complementarity is that investing in self-protection is rewarded by lower insurance premium. However, as Kousky (2019) points out, such a financial reward is limited in this setting given that the NFIP premium is heavily subsidized, and the NFIP premium structure is not comprehensive enough to capture all self-protection measures. Wagner (2022) also finds that substitution between self-protection (property elevation) and flood insurance is prevalent in the flood insurance market.

using block-level decennial census data, which is the smallest Census geographical unit. For states that have implemented disclosure policies between 1990-1999 (2000-2009), I use the 1990, 2000, and 2010 (2000, 2010, and 2020) decennial census. The distance to the border is defined by the distance between a block and the closest SFHA border.

$$\begin{aligned} Y_{bst} =& \delta_0 + \delta_1 X_{bs} + \delta_2 D_{bs} + \delta_3 X_{bs} * D_{bs} + \\ & T_{st}[\delta_4 + \delta_5 X_{bs} + \delta_6 D_{bs} + \delta_7 X_{bs} * D_{bs}] + \epsilon_{bst} \end{aligned} \tag{1}$$

The estimation is conducted in two steps. First, I estimate the optimal bandwidth for each outcome variable. Then, I estimate equation (1) using observations within the optimal bandwidth (Calonico et al. 2014, Cattaneo et al. 2019).[17] In equation (1), Y_{bst} is an outcome variable such as the probability of having any population, log of population conditional on having non-zero population, or the vacancy rate in block b in state s in time t. X_{bs} is the distance from a border in meters (negative if in a non-SFHA area), $D_{bs} = 1$ (i.e., in the SFHA) if $X_{bs} > 0$ is a treatment group indicator variable, and $T_{st} = 1$ if $t > T^*_s$ is a post-period indicator variable, where T^*_s is the policy change date for state s. δ_6 captures the impact of the disclosure policy for blocks located in close proximity to the SFHA border.

A potential concern of using a geographic area such as a block (namely, a polygon) rather than a property (namely, a point) is that a block might contain an SFHA border within it. In this case, the distance from a block to an SFHA border is not well defined. While this might be a serious problem for larger geographical units such as tracts, it will be less of a problem for blocks that are small. For instance, the median size of the census blocks in my sample is 0.009 square miles, and 83 percent of blocks are perfectly contained within or outside an SFHA as an example in Appendix Figure D.4 illustrates. To further alleviate the concern, when calculating the distance between a block and the nearest SFHA border, I take the difference of (1) the distance between block centroids and the closest SFHA border and (2) a block diameter.

Staggered Adoption. Flood insurance policy counts and demographic characteristics such as income and age are observed at either the NFIP community or tract level. As these geographic units are

[17] I estimate the mean squared error optimal bandwidth for 2000 and 2010 separately and use the average of the two similar to Grembi et al. (2016). I ignore 1990 and 2020 because these years have only a subset of the states in the sample.

oftentimes much larger than the SFHA (see Appendix Figure D.4 (b)), the distance from a tract or community to the SFHA border is not well defined. Thus, I employ a version of the triple difference design by combining different policy implementation timing and differential intensity of treatment using equation (2). Specifically, High_{md} is an indicator variable equal to one if geographic unit m in stack d has an above-median fraction of the area covered by an SFHA, which proxies for the proportion of households affected by the disclosure policy. α_3 estimates the differential impact of the disclosure policy for high-intensity geographic units in comparison to low-intensity units.

$$log(Y_{mstd}) = \alpha_1 High_{md} + \alpha_2 D_{mstd} + \alpha_3[High_{md} \times D_{mstd}] + \omega_{td} + \psi_{md} + \epsilon_{mstd} \tag{2}$$

For estimation, I build on Cengiz et al. (2019) and Brot-Goldberg et al. (2020) and use the stacked DDD approach to estimate the policy impact using clean controls, which alleviates concerns over problematic control groups in the staggered adoption design (Goodman-Bacon 2021). I use not-yet-treated states as clean controls and exploit the policy implementation timing among the ever-treated states.

To construct the stacked dataset, I first keep each state's flood insurance policy counts for seven years before and seven years after the policy change. Inclusive of the change year, I use 15 years of data for each state.[18] Each stack consists of geographic units in the treated states, which have implemented the disclosure policy in year d, and geographic units in the control states, which have implemented the policy in year $\tilde{d} > d$.[19] I drop observations from the control states for $t >= \tilde{d}$ because it is no longer "not-yet-treated".

In equation (2), Y_{mstd} denotes various outcome variables on flood insurance and demographic characteristics. D_{mstd} is a dummy variable that takes 1 if a community or tract m in state s in stack d has implemented the disclosure policy at time t. I also include ω_{td}, the time $\times$ stack fixed effect to account for year-specific common shocks and a community or tract $\times$ stack fixed effect ψ_{md}, which captures an unobserved community or tract characteristics. Including fixed effects interacted with stack d ensures that the comparisons are made within each stack.

[18]The data from 1978–2008 are sufficient to cover 15 year window for policy changes in all states except Louisiana, which implemented its policy in 2003, leaving just six post-policy years for analysis.

[19]Stack refers to data that is created for a specific treatment year. A state belongs to either the treatment or control group depending on the stack. For instance, PA and CT, which changed their policy in 1996 are in the "treatment group" for the stack year $d = 1996$. The two states belong to the "control group" when $d < 1996$.

It is worth discussing one additional detail about the tract-level analysis. Because the decennial census is documented once every 10 years, states that implemented the policy after 2000 can be used only as a control group, because there is no control group for them (every ever-treated state is treated in 2010). Therefore α_3 should be interpreted with a caveat that it is estimated from the states that were treated earlier.[20] Also, using two time periods (1990 and 2000 census) implies that there is a single data stack, and thus the estimating equation (2) reduces to a standard triple difference specification with discretized treatment. Throughout the analysis, I use spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference (Newey and West 1987, Conley 1999). When the variance-covariance matrix is not positive-semidefinite, I use eigendecomposition of the estimated variance matrix and convert any negative eigenvalue(s) to zero following Cameron et al. (2011).

4.2 Findings

Self-protection. In Table 4.1 column (1), I report the disclosure policy's extensive margin effect. The estimated coefficient indicates that the disclosure policy reduces the probability of having a positive population in the SFHA area by 0.01 (or 1.5 percent of the baseline value of 0.68). In column (2), I repeat the same exercise as column (1) but with a log of population (using blocks with non-zero population) to separately investigate the intensive margin effect. The result shows the disclosure policy reduces the population in blocks located within the SFHA by 7 percent. Taking these results together, the policy discourages not only population inflow to the existing properties in the SFHA but also developments in previously uninhabited high-risk areas.

In column (3), I report the estimated effect on the vacancy rate.[21] The disclosure policy increases the vacancy rate in the SFHA area from 0.095 to 0.109, which is consistent with the population reduction effects from columns (1) and (2). These findings suggest that after the disclosure policy, it becomes harder (or takes longer) to sell a house in the SFHA area and a larger fraction of houses remain vacant at any given time.[22] Results in columns (1)-(3) resonate with earlier studies which

[20] Note that the number of flood insurance policies and elevated properties analyses do not have this problem as the observations are community by year.

[21] A property is considered vacant if no one is residing in the unit at the time of enumeration unless its occupants are only temporarily absent (US Census Bureau 2000).

[22] Indeed, New Orleans, which has one of the highest levels of flood risk in the nation, has the highest vacancy rate among the 75 largest MSAs in the US (Fudge and Wellburn 2014).

Table 4.1: Effect of Discosure Requirement on Household Responses

	(1)	(2)	(3)	(4)	(5)
SFHA × Post	−.011***	−.072**	.014***		
	(.003)	(.034)	(.005)		
High Risk × Disclosure × Post				−.001	−.009
				(.006)	(.008)
D.V	Prob. of Non-zero Population	Log Population	Vacancy Rate	Prob. of Non-zero Insurance	Log Insurance Per Housing Unit
Avg D.V.	0.674		0.097	0.826	
Year × Stack FE				X	X
Community × Stack FE				X	X
Bandwidth	136	250	190		
Num. obs.	1465392	1651843	1306372	439822	363476

Note: This table is produced from equation (1) and (2). Columns (1)-(3) are estimated using the decennial census block-level data in 1990, 2000, 2010, and 2020. Columns (4) and (5) are estimated using community-level National Flood Insurance Program data. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

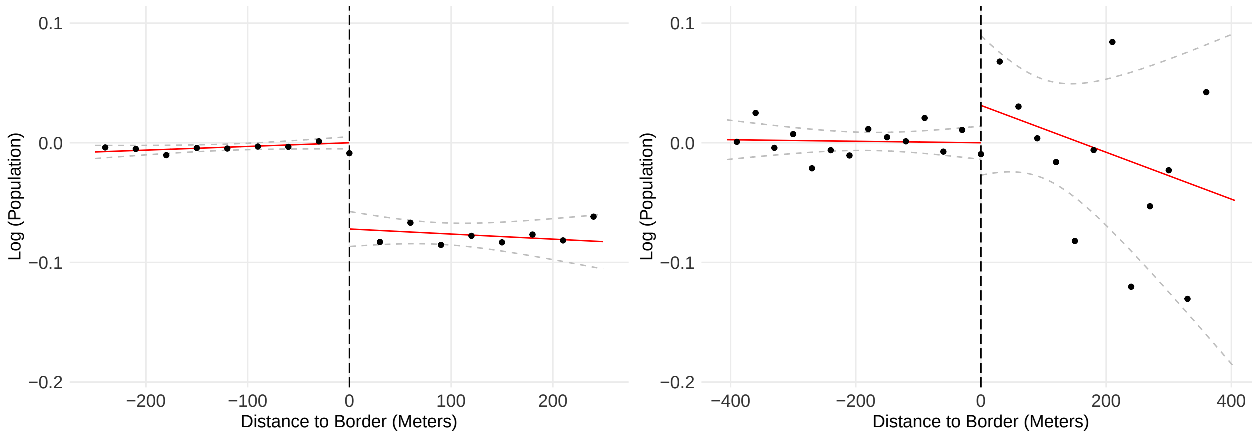
find that people migrate away from negative environmental conditions (Banzhaf and Walsh 2008, Boustan et al. 2012, Hornbeck 2012, Hornbeck and Naidu 2014, Bakkensen and Ma 2020).[23]

To further explore the implication of the change in the population distribution, I investigate the spatial characteristics of the alternative houses buyers choose. If buyers choose a property on outside the SFHA but very close to the border, the risk exposure would remain essentially identical even after the disclosure policy. But if buyers move further away, it would lead to a more substantial decline in flood risk exposure. To gain some insights into the deterrence effect, I repeat the same exercise in columns (1)–(3) of Table 4.1 after removing blocks that are within 20 and 40 meters from the border, respectively. In Appendix Table D.2, I show the directions and magnitudes of my doughnut specification estimates are similar to Table 4.1. Moreover, Appendix Figure D.6 shows that there is no diminishing policy effect as I expand the bandwidth. These findings suggest when home buyers are deterred from an SFHA, they move to a different home that is meaningfully further away. This suggests that the disclosure policy significantly reduces flood exposure.[24]

In Figure 4.1 (a), I present a difference-in-discontinuity plot, which shows the difference of spatial RD estimates before and after the disclosure policy for blocks within the optimal bandwidth. In this

[23] Note, I find that the disclosure policy has an impact on both property value and population distribution. While one might think that price should clear the market without changing population distribution, changes in both price and population distribution can occur when housing supply curves are upward sloping.

[24] Findings of these exercises are useful because it also allows me to test SUTVA assumption violation. If a highly localized location adjustment is prevalent, SUTVA assumption is likely to be violated. Then the effect size from columns (1)-(3) of Table 4.1 is likely to overestimate the true effect of the disclosure policy.



(a) Disclosed States (b) Placebo States

Figure 4.1: The Effect of Disclosure on Population. These figures illustrate difference-in-discontinuity estimates for the log of block population for the treated (Panel (a)) and placebo states (Panel (b)), respectively. The discontinuity at the threshold (0 distance) corresponds to the δ_6 term in equation (1). Dependent variables come from the decennial census block-level data in 1990, 2000, 2010, and 2020. The running variable is defined by the distance between an SFHA border and a census block.

plot, the difference in logged population is normalized such that $\Delta Y^- = 0$. Thus, the effect at the border, which is a 7 percent reduction in population for the blocks in the SFHA, directly corresponds to the effect in column (2) of Table 4.1. Also, note that while the confidence interval for the SFHA areas is wider than the non-SFHA areas, which is not surprising given the difference in the number of observations (Appendix Figure D.5), it is still tight enough to identify a statistically significant disclosure policy effect at the border.

In Appendix Table D.3, I explore the demographic composition change as a result of the disclosure. The estimated coefficients suggest that higher-risk tracts become less affluent and less old in comparison to low-risk tracts. This finding coincides with Bakkensen and Ma (2020) in that those with more resources tend to choose a safer place to live.

A potential concern with the estimates in columns (1)-(3) of Table 4.1 could be that there might be other time-varying policy changes. While the difference-in-discontinuity design controls for time-invariant differences between SFHAs and non-SFHAs, if there is a concurrent policy change at the border, it could bias the results. One such policy is the mandatory flood insurance requirement, which came into effect in 1994. While it has been widely documented that the compliance for this policy was far from perfect, it is still of concern that the policy change timing coincides with disclosure policy timing for early-treated states.[25]

To test for potential confounding policies, I use the five placebo states that have implemented a disclosure policy but without a question about flood risk. If my findings are driven by other policies such as mandatory flood insurance purchase, and not disclosure, I would expect to find a similar effect in the placebo states. In Appendix Table D.1, I show there is no evidence of a reduction in population or an increase in the vacancy rate in the placebo states. If anything, my estimates are either precisely estimated null effects (for the extensive margin population and the vacancy rate) or positive (for the intensive margin population). Figure 4.1 (b) visually confirms this point: in contrast to panel (a), there is no statistically significant reduction in the population after the disclosure policy and if anything, the point estimate is positive.[26]

While choosing a safe location represents an extensive margin self-protection strategy, elevating structures to prevent inundation is one of the most common intensive margin responses (Montgomery and Kunreuther 2018, Mobley et al. 2020). Although data limitations do not allow me to analyze this possibility directly, property elevation is unlikely to be a widely adopted self-protection measure because of its high cost. For instance, the median cost of elevations through the FEMA mitigation program (between 2008 and 2013) is \$166,000 (National Research Council 2015), which is over 50 percent of the average property value in the SFHA area (\$327,171). In addition, elevation takes at least several months to complete, which means that the foregone use value is also substantial.

Market Insurance. In columns (4)-(5) of Table 4.1, I estimate the impact of the disclosure policy on the probability of having positive numbers of flood insurance policies per housing unit and log of flood insurance policy counts per housing unit, respectively. Similar to above, I explore extensive and intensive margin effects separately.

As discussed in Section 4.1, because the level of observation in this exercise is a community, the distance to the SFHA border is not well defined. Therefore, I leverage the staggered adoption of the disclosure policy to study its impact on insurance purchases in a triple difference framework. The

[25] Other examples of potentially time-varying policy changes include (1) enforcement of the mandatory flood insurance requirement could have changed over time and (2) insurance premium could have changed differentially over time for SFHA and non-SFHA properties.

[26] In Appendix Figure D.8, I conduct a more formal test by taking the difference of the diff-in-disc terms for the treated and placebo states by estimating an augmented version of equation (1): $Y_{bmst} = \delta_0 + \delta_1 X_{bms} + \delta_2 D_{bms} + \delta_3 X_{bms} * D_{bms} + T_{st}[\delta_4 + \delta_5 X_{bms} + \delta_6 D_{bms} + \delta_7 X_{bms} * D_{bms}] + H_s[\delta_8 + \delta_9 X_{bms} + \delta_{10} D_{bms} + \delta_{11} X_{bms} * D_{bms} + T_{st}[\delta_{12} + \delta_{13} X_{bms} + \delta_{14} D_{bms} + \delta_{15} X_{bms} * D_{bms}]] + \epsilon_{bmst}$. Here δ_{14} is the coefficient of interest. The estimates suggest that the effect size (in magnitude) is even larger when we consider the trends in the placebo states.

differences are over time, treatment group assignments, and between communities with high versus low exposure to SFHA areas (measured by the fraction of total area covered by an SFHA).[27]

Column (4) shows the disclosure policy reduces the probability of having a positive flood insurance policy per housing unit for high-risk communities by 0.001 percentage point (or 0.1 percent from the baseline of 0.83). Similarly, column (5) suggests the intensive margin effect of the disclosure policy is –0.9 percent. Given tight standard errors and small point estimates, home buyers do not seem to respond to the disclosure policy by purchasing flood insurance.

Why do home buyers engage in self-protection behaviors despite the option to buy flood insurance? One explanation is that the non-insurable cost is large in this setting. Flood insurance covers only up to $250,000 for a residential property, and compensates for replacement rather than market value, and thus is incomplete insurance for potential financial losses. Further, a flood could negatively affect an individual's health (Kahn 2005, Bloom et al. 2009), employment status (Deryugina 2017), or income, which are not covered by flood insurance. Natural disasters also reduce subjective well-being (Rehdanz et al. 2015, Berlemann 2016). Given these non-trivial uninsurable costs, home buyers might adjust their location instead of purchasing insurance and living in risky places.

Findings in this section collectively indicate that households primarily respond to the risk information by selecting a safer location. If instead, the primary response is purchasing more flood insurance (and thus muting self-protection measures), the disclosure policy would have a limited impact on damage reduction.

5 The Effect of the Disclosure Requirement on Flood Damage

5.1 Damage Function Estimation

For a given flood size, how does flood damage change after the disclosure policy? To answer this question, I estimate a damage function, which is a mapping between flood size to damage, and show how the functional relationship changes due to the policy.

Damage functions have been a central object in assessing the cost of climate change, and has been widely used in the economics literature to understand the relationship between heat and economic

[27]While columns (4) and (5) report coefficients of the High Risk × Disclosure × Post term only, I include a full set of interaction terms for estimation.

outcomes.[28] However, relatively little attention has been given to *flood* damage functions specifically, despite severe disruptions caused by floods. That is partly because objective measurement of flood size is challenging. This paper overcomes this limitation by constructing a hydrology-based flood history dataset.

$$\text{Per Housing Unit Damage} = \sum_{k}[\alpha_1^k F^k + \alpha_2^k F^k D] \tag{3}$$

Equation (3) represents the pre-treatment period damage function where the dependent variable is per housing unit flood damage, which is a natural outcome variable given that damage data capture damage to properties. On the right hand side, D is a dummy for the treated group assignment. F^k is a dummy variable that takes 1 when the annual maximum flood size measured by the recurrence interval belongs to flood size bin k where $k \in \{$2-10, 10-20, 20-30, 30-40, 40-50$\}$. I take a non-parametric approach following Barreca et al. (2016) to let the data, rather than the functional form assumption, determine the shape of the function.

There are a couple of points to discuss regarding the F^k variable. First, I use the annual maximum flood size, which mirrors inundation depth, as a proxy for flood exposure for a given community-year. This approach follows a long tradition in the hydrology literature that considers water depth as a primary determinant of flood damage (Smith 1994, Kreibich et al. 2009). Also, while it is true that using the maximum size ignores floods of smaller size that occurred in the same year, this is not likely to be a critical issue given that the majority of the community-years in the dataset had, at most, just one flood. Appendix Figure A.3 (c) shows that conditional on a flood occurrence, 2/3 of community-year have only one flood. Further, when we restrict attention to floods of size over 10 or larger, which cause disproportionately large damage, over 90 percent of community-years have only one such incident (Appendix Figure A.3 (d)).

Second, I focus on flood sizes between 1 and 50 because larger floods are frequently accompanied by multiple, interrelated perils, such as wind and mudslides, and thus measurement error becomes a more serious issue (Kron et al. 2012) Further, as Appendix Figure A.3 (b) shows, the frequency of flood events reduces exponentially as flood size gets larger. This implies that identifying statistical relations for the flood sizes over 50 under the non-parametric approach is challenging. Also, flood sizes ranging from 1 to 50 cover a wide enough band to capture floods of different severity levels

[28] For a review, see Dell et al. (2014), Carleton and Hsiang (2016), and Auffhammer (2018).

including minor, moderate, and major (See Appendix Table A.2 and accompanying text for more details).

Lastly, the key assumption behind binning is the damage per housing unit is identical within each k. While flood sizes of 41 and 49, for example, might have a different effect in reality, I choose a bin size of 10 to strike a balance between flexibility and precision (Barreca et al. 2016).

Flood size between 1 and 2 is the baseline size and is the omitted category. Thus, α_1^k in equation (3) indicates the additional flood damage per housing unit when a community in the control group experiences flood of size k as opposed to the baseline flood. α_2 term in equation (3) allows a different slope between the treated and control groups, which accounts for potential differences in flood exposure or policies between the two groups.

Now posit that a disclosure policy is implemented. Equation (4), which mirrors a canonical difference-in-difference model, shows how equation (3) changes when post period dummy I is included. The coefficient for the interaction term (β_4^k) captures how the damage function changes as a result of the disclosure policy.

$$\text{Per Housing Unit Damage} = \sum_k [\beta_1^k F^k + \beta_2^k F^k I + \beta_3^k F^k D + \beta_4^k F^k ID] \tag{4}$$

For estimation, I use equation (5). Y_{mtd} is either $P(\text{Per Housing Unit Damage} > 0)$ or $log(\text{Per Housing Unit Damage})$ conditional on having positive damage for community m at year t for data stack d. As discussed in Section 3 and Appendix A.2, I estimate the extensive and intensive margin effect separately because the damage variable has a point mass at zero and long right tails. While I report results from both models, I focus more on the extensive margin effect because of greater generalizability—only a small fraction of communities experience more than one non-zero damage—and higher statistical power.

Further, similar to Section 4, I use a stacked approach for the estimation and as such every term in equation (5) has a subscript representing the stack d. One important difference is that I run the stacked DD (i.e., ignoring differences in treatment intensity) to make the estimating equation tractable.[29]

$$Y_{mtd} = \sum_k [\beta_1^k F_{mtd}^k + \beta_2^k F_{mtd}^k I_{mtd} + \beta_3^k F_{mtd}^k D_{mtd} + \beta_4^k F_{mtd}^k I_{mtd} D_{mtd}] + \theta_{md} + \omega_{td} + \epsilon_{mtd} \tag{5}$$

Equation (5) also includes year $\times$ stack (ω_{td}) and community $\times$ stack (θ_{md}) fixed effects, to control for overall time trend and unobserved community characteristics. I use 20 years of observation for each state around the disclosure policy change year. Throughout the analysis, I use spatial-HAC standard errors that allow spatial correlation of up to 500 miles (Newey and West 1987, Conley 1999).[30] Similar to Section 4, when the variance-covariance matrix is not positive-semidefinite, I use eigendecomposition of the estimated variance matrix and convert any negative eigenvalue(s) to zero following Cameron et al. (2011).

Before further proceeding, it is worth discussing the difference between the damage function of this paper and those from earlier engineering studies. A large number of engineering studies have developed damage functions or a "depth-damage functions". As its name suggests, the measure of flood size in these studies is a water depth for an individual property (Meyer et al. 2013). While useful for predicting property-level flood damage, this approach has a few limitations for estimating a more aggregate level flood damage.

First, by focusing on an individual property, it does not directly take into account that a larger flood increases the number of affected properties. That is, estimating flood damage at an aggregate level based on a depth-damage function requires a detailed hydraulic study, which translates weather events into the inundation level for each property (Scawthorn et al. 2006). However, these studies are costly and thus many communities either lack access to them or are reliant on outdated versions (FEMA 2005, Bakkensen and Ma 2020, Weill 2021).

Second, and presumably most importantly, these studies typically lack the capability to account for adaptations at the property level, which is likely to cause a large prediction errors. In theory, this limitation could be addressed by (1) modeling how various defensive measures such as property elevation or the use of waterproof building materials impact damage, and (2) collecting property level data on these defensive measures. However, this approach is impractical due to limitations in

[29] I exploit the differences in treatment intensity by estimating heterogeneous treatment effects.
[30] Weights in this matrix are uniform up to that cutoff distance.

modeling techniques and data availability.[31] This is a major drawback of depth-damage functions given that the main purpose of constructing a damage function is reliable flood damage estimation, which is a key ingredient for the cost-benefit analysis of any flood management policy.

This paper takes a "reduced-form" approach and overcomes these issues. By directly relating flood size, which is measured at the community level using the water gauge records, to the community-level flood damage, this approach can be applied even in areas without up-to-date hydraulic studies. Moreover, the community level damage metric readily factors in the number of properties damaged and the impact of any pre-existing adaptation measures.

5.2 Change in Damage Function from the Disclosure Requirement

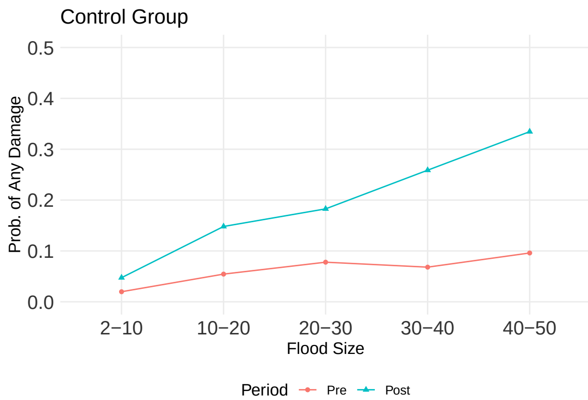
Figure 5.1 (a) and (b) show the damage functions for the control (panel (a)) and treatment (panel (b)) groups for before (red line) and after (blue line) the treatment.[32] Specifically, each line is plotted using the estimated coefficients from equation (5): for instance, the line for the control group in the pre-treatment period plots $\hat{\beta}_1^k$ and the treated group in the pre-treatment period plots $\hat{\beta}_1^k + \hat{\beta}_3^k$ for each k. As the dependent variable in these estimates is the probability of having any damage, the vertical axis indicates the additional probability of having positive per housing unit damage when the baseline flood, which is a flood with a size between 1 and 2, is replaced by a flood of size k.

Before discussing the disclosure policy effect, it is worth evaluating the estimated damage function itself. For that, we limit our attention to the pre-treatment period. In particular, red lines in panels (a) and (b) in Figure 5.1 show that as flood size increases, the probability of having positive flood damage increases monotonically. The largest flood size bin suggests that a community with a flood of size 40-50 is likely to have 10 percentage points (panel (a)) and 20 percentage points (panel (b)) higher chances of having any damage per housing unit in comparison to the baseline floods.

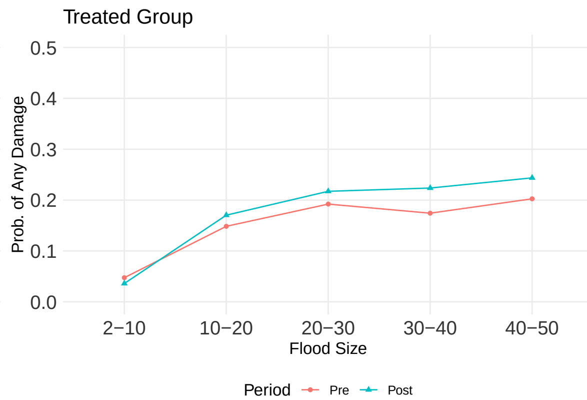
It is also worth mentioning that panels (a)-(b) mask the heterogeneity in the damage function. Even if struck by a flood with the same recurrence interval—the measure of flood size, two communities (for instance, St.Louis, which suffers frequent floods due to its adjacency to the Mississippi River versus Albuquerque which did not have a major flood for nearly 100 years due to its semi-desert

[31] For instance, commonly considered resistance parameters in the engineering literature are building type, building material, and usage of building (Merz et al. 2010). It would be extremely hard to tell differences in the adaptation level across different single family houses using these crude measures.

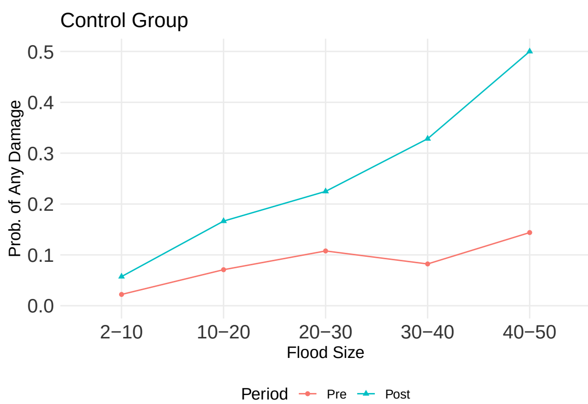
[32] Appendix Figure D.9 reproduces Figure 5.1 with a 95 percent confidence interval.



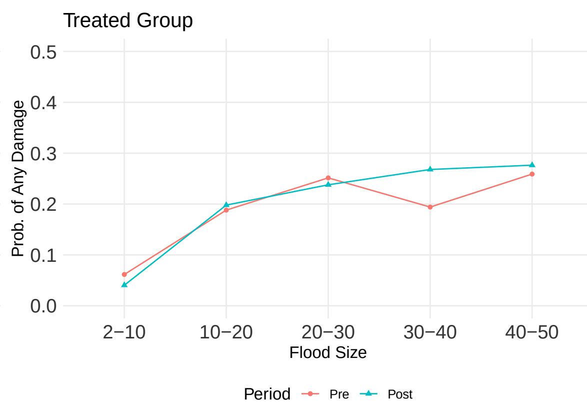
(a) Control Group (All Communities)



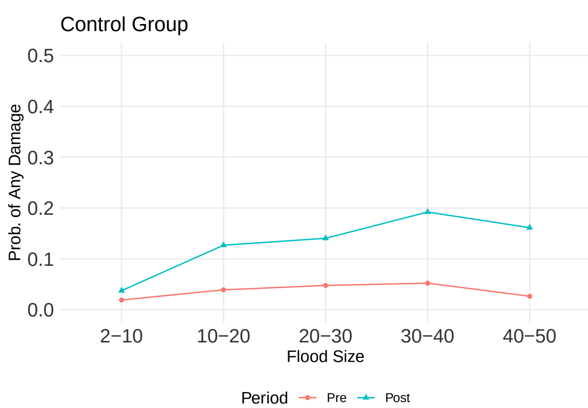
(b) Treatment Group (All Communities)



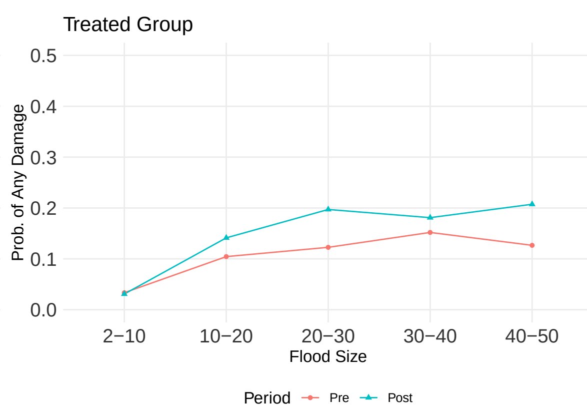
(c) Control Group (High Risk Communities)



(d) Treatment Group (High Risk Communities)



(e) Control Group (Low Risk Communities)



(f) Treatment Group (Low Risk Communities)

Figure 5.1: The Effect of Disclosure on the Damage Function. These plots illustrate a set of estimated damage functions (dep.var: probability of any damage) from equation (5). Panels (a)-(b) are damage functions for all communities. Panels (c)-(d) and (e)-(f) illustrate the damage functions for high (above–median SFHA ratio) and low (below–median SFHA ratio) flood risk communities, respectively. Appendix Figure D.9 reproduces Figure 5.1 with corresponding 95% confidence intervals.

climate) might have a different level of damage depending on the *a priori* flood risk level. To see this, suppose that two hypothetical communities A and B have starkly different risk profiles such that the entire land area in community A (B) is inside (outside) of the SFHA. If two places are hit by a 100-year flood, which is defined based on community-specific thresholds, the entire property in community A will be inundated while no property in community B is under water.

To investigate the heterogeneous relationship between flood size and damage depending on the baseline risk level, in Figure 5.1 (c)-(f), I present two sets of damage functions for the above and below median SFHA fraction communities. Not surprisingly, figures in panels (c) and (d), which are for the above-median communities, have much higher vertical levels and steeper slopes in comparison to the figures in (e) and (f).

Table 5.1 reports the damage reduction effect of the disclosure policy. For the interest of space, I only report $\hat{\beta_4^k}$ from equation (5), which corresponds to the disclosure policy effect for the treated group, but the rest of the estimated coefficients can be found in Appendix Table D.4. In column (1), I estimate the policy effect using the entire set of communities. The results show that the disclosure requirement substantially reduces the probability of having flood damage and flattens the damage function.[33] The effect can be verified visually as well. The gap between two lines in Figure 5.1 panel (a) and (b), which corresponds to the change in the damage amount for each group before and after the policy implementation, is much larger in the control group.

To put the estimated coefficients in Table 5.1 in context, it is useful to summarize coefficients into the annual expected damage reduction effect as equation (6).

$$\sum_k Pr(K = k) \times \beta_4^k \tag{6}$$

This metric takes into account both the probability of each flood bin occurrence and the corresponding damage reduction effect in percentage. Since the flood size is defined using the recurrence interval, the inverse of the size corresponds to $Pr(K = k)$. In practice, I choose the median flood size for each bin and take the inverse of it. Also, because equation (5) is essentially a linear probability model, I can conveniently interpret and summarize the estimated β_4^k coefficients as the estimated change in the probability. Standard errors are calculated using the delta method. Using equation (6),

[33] For per housing unit damage, I divide community-year level damage using the housing stock in 1990.

Table 5.1: Effect of Disclosure Requirement on Flood Damage

	(1)	(2)	(3)	(4)
Post × Disclosure (Size 2-10)	$-.039^{*}$	$-.056^{*}$	$-.021$	$-.063$
	(.023)	(.030)	(.015)	(.325)
Post × Disclosure (Size 10-20)	$-.072^{*}$	$-.086^{*}$	$-.051^{*}$	.189
	(.039)	(.050)	(.029)	(.189)
Post × Disclosure (Size 20-30)	$-.080^{***}$	$-.131^{***}$	$-.018$	.170
	(.029)	(.038)	(.031)	(.562)
Post × Disclosure (Size 30-40)	$-.141^{*}$	$-.172^{**}$	$-.111$	$-.360$
	(.073)	(.072)	(.082)	(.442)
Post × Disclosure (Size 40-50)	$-.197^{***}$	$-.339^{***}$	$-.054$	$-.425$
	(.055)	(.061)	(.068)	(.540)
Annual Expected Effect	-0.025**	-0.036***	-0.013	-0.014
	(0.01)	(0.012)	(0.009)	(0.074)
Dep.Var	$P(Y > 0)$	$P(Y > 0)$	$P(Y > 0)$	$log(Y)$
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	505383	242458	262925	22100

Note: The dependent variable in columns (1) to (3) is the probability of having positive flood damage (per housing unit damage). Column (1) is based on the entire set of communities while in columns (2) and (3), I repeat (1) using the subsample of communities with an above median SFHA ratio and below median SFHA ratio. Dependent variables in columns (4) is log transformed per housing unit damage conditional on non-zero damage for a given community-year. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

I report that the disclosure policy reduces the expected probability of having positive flood damage at a community level by 2.5 percentage points per year for flood sizes less than 50. When I compare this with the average probability of having positive damage conditional on being exposed to a flood of size 2 or larger (7.4 percentage points), the effect size is a 33 percent reduction from the benchmark.

In columns (2) and (3), I split the sample into communities above and below the median SFHA fraction to explore the heterogeneous treatment effect. Given that the disclosure policy should mostly affect properties located in the SFHA, we expect to see that the policy effect is primarily driven by the above-median SFHA communities. Indeed, the annualized effect is three times larger (in terms of point estimates) for above-median SFHA communities at 3.6 percentage points in comparison to 1.3 percentage points of below-median SFHA communities. As such, when compared against the average probability of non-zero damage conditional on being exposed to a flood of size 2 or larger, 3.6 percentage points and 1.3 percentage points translate into 37.5 percent and 25 percent reduction from the benchmark, respectively. Figure 5.1 (c)-(f) mirrors results in columns (2) and (3).

It can be easily seen from the plots that the gap between the control and the treated group before and after the disclosure policy is much larger for the above median SFHA communities. Further, these differences are consistent with more granular sample splits. In Figure 5.2 panel (a), I repeat the same exercise using four quartiles in terms of the SFHA ratio and find that the effect size is monotonically increasing in the SFHA ratio.[34]

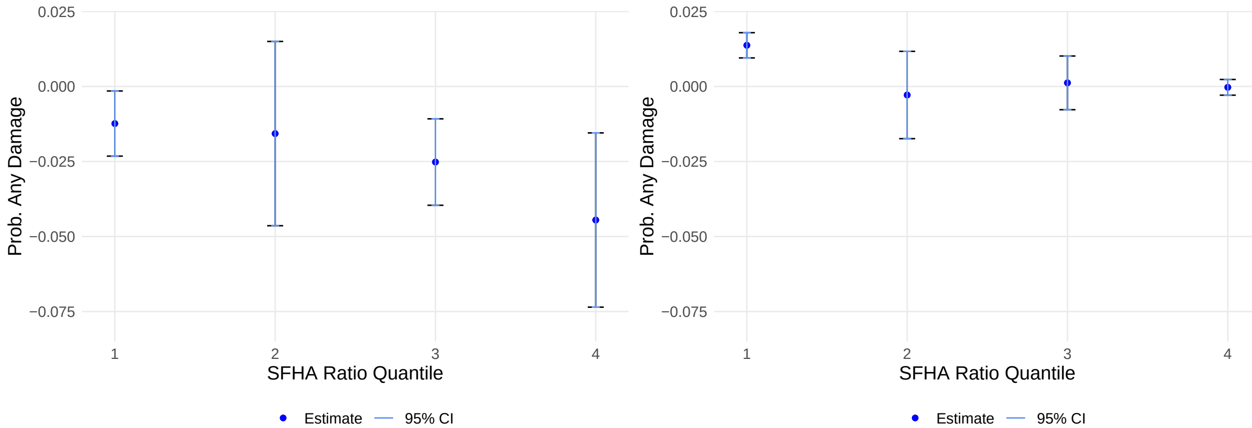
In column (4), I investigate the intensive margin effect. Specifically, I estimate a version of equation (5) that has log transformed per housing unit damage as an outcome variable. As the sample for this exercise is restricted to a community-year with positive damage, the model does not have the power to detect a statistically significant effect. Still, I find suggestive evidence that implies a reduction in flood damage conditional on damage occurrence. Taken together, estimates in Table 5.1 indicate that the disclosure policy reduces damage occurrence at the community level, which is consistent with the disclosure policy's risk exposure reduction effect found in Section 4.2.

While the impact of a simple disclosure policy reported in Table 5.1 is non-trivial, this number is likely to underestimate the true benefit because the analysis excludes floods larger than the 50-year recurrence interval, which incur disproportionately large damage. Besides, I also abstracted away from a potential gain due to a better matching (in terms of flood risk preferences) between properties and home buyers (Bakkensen and Ma 2020).

Rosuteness check. I checked the robustness of the policy effect by conducting a placebo test using five states (ID, ME, MN, NH, and VA) that had implemented the disclosure policy but without a question on the flood risk. The idea is that if flood risk information delivered by the disclosure requirement had reduced flood damage, the disclosure policy in these placebo states should not have such an effect. In Appendix Table D.6, I reproduce Table 5.1 using those five states. As the number of states is substantially smaller in this sample, some of the coefficients under the specification in equation (5) are not identified, and thus I use coarser flood size bins (2-30 and 30-50).

In columns (1) to (3) of Appendix Table D.6, the estimated coefficients suggest that the disclosure policy without flood risk information does not reduce the probability of damage at all. For many of the flood bins, the effect is statistically insignificant and economically small. If anything, the damage seems to *increase* after the disclosure. One exception is the intensive margin effect in column (4),

[34] To compensate for the loss in statistical power due to a more granular sample split, I create coarser flood size bins for this exercise. Specifically, I group them into small (k=2-30) and large (k=30-50).



(a) Disclosed States

(b) Placebo States

Figure 5.2: Annual Expected Damage Reduction Effect by the Ratio of SFHA. These figures show the disclosure policy effect on the annual expected damage reduction effect for communities with different SFHA ratios. I estimated equation (5) for subsample of communities in different quantile of SFHA ratio, and aggregated coefficients using equation (6). See the text for additional details.

but the sample size is too small to draw a strong conclusion. Results in columns (1)-(3) suggest that the disclosure policies without a question on flood risk are not effective in reducing the probability of having positive damage. Such a null effect is consistent with Figure 5.2 panel (b), which shows that a placebo disclosure policy has by and large similar effect on the probability of damage across different communities with different ratios of SFHA. Importantly, the effect is close to zero for all four subsample results for the placebo states.

Having established the result for placebo states, it is worth discussing on the selection of a control group. That is, how would the result change when I use the entire set of no flood risk disclosure states as a control group (recall that this paper uses not-yet-treated observations as a control group)? Appendix Table D.5 repeats the same exercise as Appendix Table D.4 after including non-disclosure states as a control group. Specifically, in creating the data stack, I use both not-yet-treated and never-treated states as controls. When I compare the estimated coefficients in the two tables, two observations emerge. First, the shape of the damage functions coincides: both monotonically increase in size, and post period function is higher in level with a steeper slope. Second, the effect of the disclosure policy is substantially attenuated in Appendix Table D.5. That is, the effect size for the interaction terms has been more than halved after including never-treated states as control units while standard errors remain by and large similar. This is consistent with the discussion in Section 2.1 that a non-trivial number of home buyers in these non-disclosure states are likely to have received some form of information even in the absence of the required disclosure policy. As such, this paper uses not-yet-treated states as a primary control group.

Another robustness check comes from Figure D.10, which is an event study plot illustrating the marginal effect of larger floods. In this exercise, to increase the statistical power, I classified floods into three groups—baseline, small (size 2-30), and medium (size 30-50). Also, I impose an endpoint restriction at -5 and 4. It shows no pre-trend, and more importantly, a clear reduction in the probability of flood damage, after the policy change. This effect corresponds to a flatter damage function after the disclosure policy.

6 Conclusion

Floods are the costliest natural disaster in the US and are expected to become more frequent and severe in the future. Thus, curbing economic loss from these events is of first-order importance. A prevalent policy prescription in the US has been structural flood water control, namely, adding more physical structures. However, this approach discourages adaptation—it rather attracts more people to areas with flood risk, by distorting the location choice.

In this paper, I study whether alleviating information friction regarding flood risk in the housing market can be a more effective way to foster adaptation by exploiting plausibly exogenous variations created by the disclosure requirement. I explore if and how households respond to the disclosure policy and investigate its implications for flood damage. The results show that when property-specific flood risk information is provided, the population in high-risk areas shrinks while the vacancy rate increases. A smaller number of households in flood-risky areas reduces overall exposure to flood risk, which in turn reduces the probability of having any damage from a small to medium-size flood by 2.5 percentage points or a 33 percent reduction from the average probability.

This paper also have important policy implications as disclosure policies are getting more attention as a flood risk management tool. For instance, FEMA has recently proposed an NFIP reform that conditions a community's flood insurance eligibility on the implementation of a mandatory flood risk disclosure (U.S. Department of Homeland Security 2022, The White House 2023). My analysis shows that such a disclosure policy can facilitate voluntary adaptation by alleviating information frictions and thus making home buyers heed flood costs (Anderson et al. 2019).

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A Appendix A: Data Appendix

A.1 Flood History Data

Background

To estimate flood damage function, a key input is flood size data. An ideal data should satisfy at least four conditions. First, it should be a continuous measure that can capture both extensive and intensive margin of flood events. This will not only reduce measurement error that is prevalent in binary measures, but allow estimating a non-linear relationship that has shown to be important (Burke et al. 2015, Hsiang 2016).

Second, it should objectively measure flood intensity. For instance, EM-DAT, which has been frequently used for a country-level analysis, measures flood size using economic cost or death tolls, which are likely to be correlated with economic variables such as income (Felbermayr and Gröschl 2014). Another example is Gallagher (2014) that has used an occurrence of the Presidential Disaster Declaration (PDD) floods. This data also suffers potential endogeneity because the declaration depends on the discretion of the president and thus could reflect political interests (Reeves 2011).

Third, it should comprehensively measure flood events. A few existing studies have leveraged meteological measures to objectively measure disasters, but most of them focus on a subset of events. For instance, Deryugina (2017), Hsiang and Jina (2014), and Strobl (2011) have used physical measure of hurricane intensity while Davenport et al. (2021) leveraged precipitation data. Despite objectivity, such an approach has limits in comprehensively capturing the extent of flood events. This could be problematic given that precipitation changes alone can explain one-third of cumulative flood damages (Davenport et al. 2021).

Lastly, as flood damage is measured at a community level, flood exposure should also be measured at community. This is not trivial because most climate data are collected to answer physical science questions, and thus are not readily mapped into an administrative unit such as community (Carleton and Hsiang 2016).

To the best of my knowledge, no existing dataset satisfies all of the properties discussed above. In this paper, I construct an objective measure of past flood events by applying a hydrologic method to the USGS/NOAA water gauge records. This approach does not distinguish the cause of floods—hurricane, rainfall, snowmelt, etc, as long as it is reflected in the water gauge level. Flood size is defined and recorded by a recurrence interval, which represents the expected number of years for a flood of given size (or larger) to come back, and thus is continuous by construction. Also, by matching gauge stations to a community, I can measure flood exposure at the community level.

Procedure

Following the USGS guideline (England Jr et al. 2019), I implemented the following steps using USGS/NOAA discharge data from 3,505 gauge stations distributed in the 26 ever-disclosed states in the contiguous US (Appendix Figure A.1).[35]

First, I construct a site-specific flood size distribution. For this, I retrieved annual peak flow records using the R package "dataRetrieval" and fit the Log-Pearson III distribution using the annual peak records to estimate gauge-specific parameters (Cicco et al. 2018). Importantly, as I use annual peak discharge data to fit the distribution, the quantile of the distribution has an intuitive interpretation. For instance, if a certain water level is the 95th percentile of the distribution, it means that such an event would happen with a 5 percent probability in a given year. Alternatively, such

[35] I randomly sampled 1000 sites in Appendix Figure A.1 for visibility.

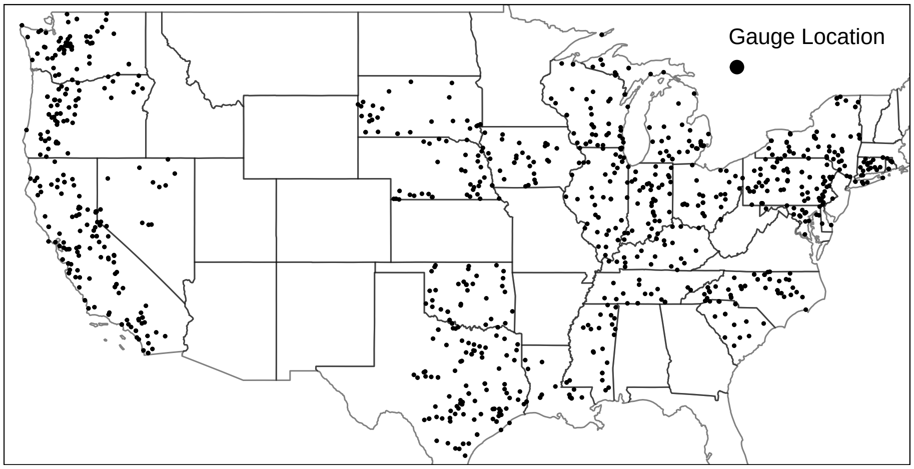


Figure A.1: The Distribution of a Sample of USGS/NOAA Gauges

an event is called a 20-year ($\frac{1}{0.05} = 20$) flood. I keep stations with at least 10 or more annual peak observations again following the USGS guideline. Also, I use annual peak data until 1990 to reflect flood thresholds around the disclosure policy change.

Table A.1: Number of MDF Stations vs. IPF Stations in Iowa

name	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
N Gauges (Mean Daily Flow)	112	112	105	107	109	109	105	109	112	111
N Gauges (Maximum Daily Flow)	3	8	40	72	34	31	29	34	59	95

Second, I convert daily water level records into the recurrence interval. For that, I back out the quantile using the fitted flood size distribution from step 1. For this, I need a daily maximum flow, but for most of the stations, the maximum daily flow (or more precisely the instantaneous peak flow which enables calculating maximum daily flow) data have too many missing values.[36] Table A.1 compares the number of stations that have records for at least 80 percent of the days (i.e., 292 days or more) for a given year in Iowa and the number of mean daily flow sites outnumber maximum daily flow sites substantially for most years.

This is problematic because, with many missing observations, flood events will be significantly under-recorded. To solve this problem, I estimate a projected instantaneous peak flow from the *mean* daily flow using the Fuller method (Fuller 1913). Specifically, for a given geographical unit, I estimate Fuller coefficients by regressing instantaneous peak flow (Q_{it}^{IPF}) for site i in time t on mean daily flow (Q_{it}^{MDF}) and the size of the drainage area (A) as equation (7) (Fuller 1913).[37] I use three different levels of geographic units, namely state, HUC4, and HUC2 and separately estimate Fuller coefficients. Using the estimated coefficients, I calculate projected instantaneous peak flow, and compare that with the actual instantaneous peak flow to pick the geographic unit that minimizes the prediction error.[38]

[36]Conceptually, maximum daily flow is an appropriate discharge measure to identify flood events (as opposed to the mean daily flow), because the maximum could be significantly higher than the mean, especially for gauges with a smaller basin area (Chen et al. 2017).

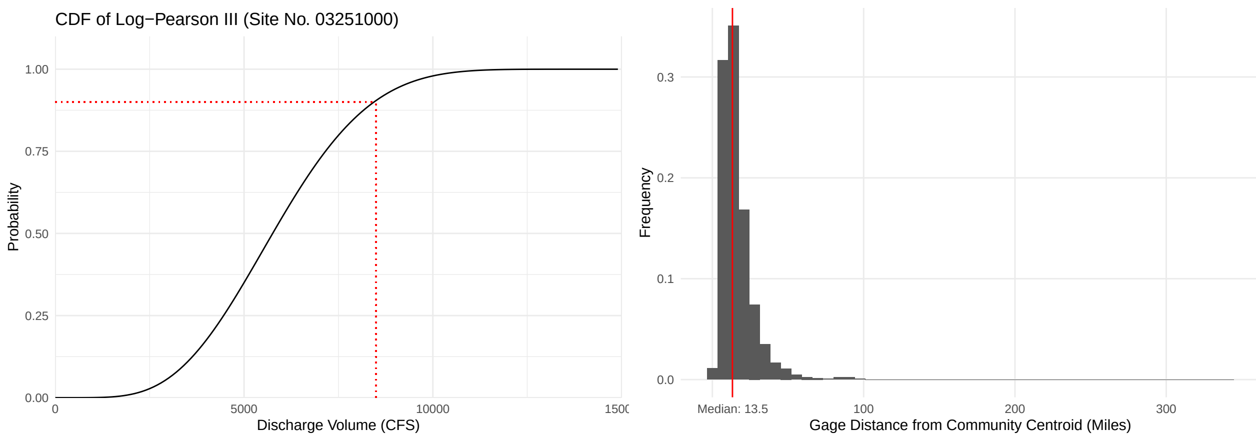
[37]I also did conversion following Sangal (1983), but the error between actual and the estimated IPF was much smaller with Fuller (1913).

[38]Practically, I apply the following hierarchy among state, HUC4, and HUC2 models: (1) When a site has the best

$$Q_{it}^{IPF} = Q_{it}^{MDF}(1 + \alpha A^{\beta}) \quad (7)$$

Now, by converting the estimated instantaneous peak flow to the quantile of the estimated Log-Pearson III CDF, I identify each day's flood size. This has an intuitive interpretation. Suppose, the maximum discharge volume for Oct 1, 1995, is at the 99%th quantile of the fitted distribution. It means that this day's discharge volume is large enough to exceed 99 *annual* maximum volumes out of 100 observations and thus interpreted as (once in) a 100-year flood.

Finally, to translate gauge-level flood events to the community-level floods, I match each community to the three nearest gauges based on the distance between a centroid of community and gauge station. Then, I calculate the average flood size for a community using the inverse distance as a weight. Figure A.2 (b) presents the distribution of the average distance between gauges and community centroid. Over 90 percent of them are within 20 miles with a median distance of 13.5 miles.



(a) Flood Frequency Analysis (b) Distance between Gauge and Community Centroids

Figure A.2: Flood Frequency Analysis and Gauge Matching. Plot (a) is an example of flood frequency analysis. The black solid line represents the CDF of the fitted Log-Pearson III distribution from the USGS site 03251000. If daily discharge volume is 8,500 CFS, it corresponds to the 90th quantile or a 10-year flood. Plot (b) presents the distribution of the average distance between gauges and community centroid. Over 90% of them are within 20 miles with the median distance 13.5 miles.

Figure A.2 (a) illustrates step 1 and 2 described above. The black solid line is the fitted Log-Pearson III CDF from the USGS site 03251000. To fit the distribution, I use the annual peak flow data from 1947 to 1990 to calculate the mean, standard deviation, and skewness parameters. Now suppose that on a given day, the daily discharge volume is 8,500 CFS. It corresponds to the 90th percentile of the CDF, it corresponds to the 90th quantile or a 10-year flood.

Note, because the USGS gauge stations rarely cover coastal areas, I add 45 additional NOAA sites to the gauge station data. Zervas (2013) documents the flood threshold for the entire NOAA sites by fitting GEV distribution, so I adopt them directly. NOAA water level data are retrieved using the R package "Rnoaa" (Edmund et al. 2014).

Unified Flash Flood Database

match (which means that a site has both daily mean flow and instantaneous flow records), I use it. (2) If a site does not have site-specific match (meaning that this site did not have instantaneous flow records), I use prioritized HUC4, HUC2, and State, because HUC4 had the least overall prediction error. I also remove the cases where a site does not have drain area (and thus Fuller coefficients cannot be estimated).

The Unified Flash Flood Database (Gourley et al. 2013) is USGS-gauge record based dataset constructed following a similar procedure outlined. It is a comprehensive and objective measure of flood events that can present the overall trend of flood events for the contiguous US, which overcomes the limits of the existing data. However, I decided not to use this database for a couple of reasons. First, the primary flood threshold used in the unified data is the NWS flood thresholds, which have four categories: action, minor, moderate, and major.[39] The threshold for each category is defined by NWS local officers in collaboration with local stakeholders, which makes comparisons across different stations hard. Second, the data are constructed based on the instantaneous peak flow data, and thus a potential bias arises due to the missing records.

Validation and Summary Statistics

To validate the data, I check the number of the average 10-year flood events over a 20-year period for the 8,194 communities. These communities are from the 26 ever-disclosed states that are on the Q3 map. By definition, a 10-year flood is going to happen twice in a 20-year period on average. Figure A.3 (a) shows that most communities had 1 or 2 10-year floods over the 20 years whereas the average number of the 10-year flood is 2.18. While this is slightly higher than 2, it is plausible given that I use the annual peak flow data until 1990. Fixing flood threshold is necessary to compare floods across different times (namely, a 10-year flood should have the same magnitude whether it is in 1990 or 2000). Although this approach can be problematic as the period in consideration gets longer, it should not be a major problem for this paper as the longest sample period is 20 years.

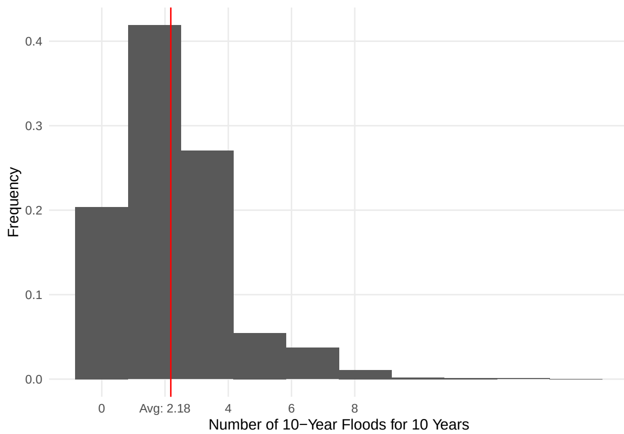
Figure A.3 (b) shows the distribution of flood event size (i.e., recurrence interval), where flood size is truncated at 100 for readability. Note the frequency of low-intensity events dominates the entire distribution. This fact is well-documented in the literature. Jackson (2013) reads "the magnitude of a natural hazard event and its frequency is often depicted as log-normal where the magnitude increases linearly (e.g., 1, 2, 3, . . .) whereas the frequency decreases as an inverse power function (e.g., 1/3, 1/9, 1/81) with increasing magnitude." I focus on flood events between size 1 and 50 because of power issues. Namely, there are too small number of floods beyond size of 50.

In panel (c), I plot the number of unique floods for each community-year pair, conditional on a community-year had a flood (most of community-year do not have a flood). Also, I removed community-year pairs that had a flood with maximum size exceeding 50. The histogram shows that about 70 percent of the community-year had exactly one flood event. This alleviates concern that communities are exposed to multiple floods per year. More importantly, when I limit attention to floods with size over 10, which incurs disproportionately large damage, over 90 percent of the community-year pairs have only one event.

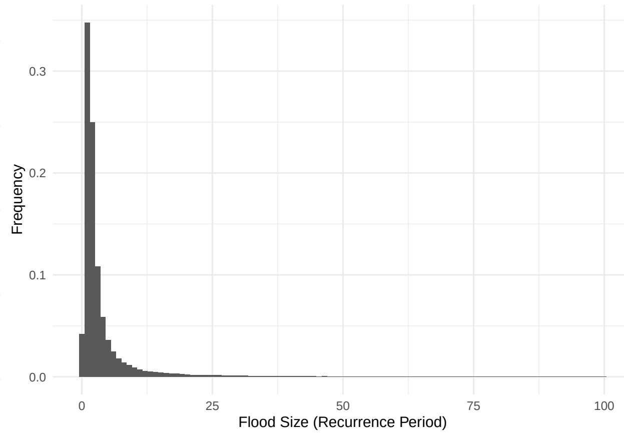
One shortcoming of the estimated coefficient is that it is hard to contextualize it. Namely, how should we think about the magnitude of each flood size (e.g., 10-year flood)? Comparing the estimated flood thresholds with the NWS thresholds can be a useful exercise to this end, because the NWS has defined water stages corresponding to minor, moderate, and major flooding for 3,490 stream gauge locations across the US (Gourley et al. 2013).[40] Specifically, I estimate equation (8) to connect the thresholds in number to (rough) severity.

[39] Each is defined as minor: minimal or no property damage, but possibly some public threat (e.g., inundation of roads); moderate: some inundation of structures and roads near the stream, evacuations of people and/or transfer of property to higher elevations; major: extensive inundation of structures and roads, significant evacuations of people and/or transfer of property to higher elevations (National Weather Service 2019).

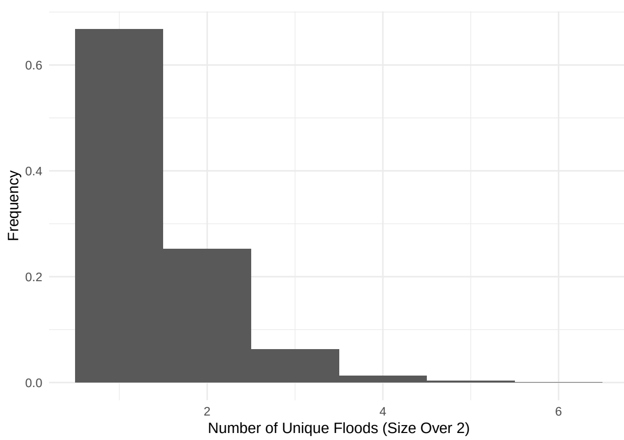
[40] NWS defines each flood category as the following (National Weather Service 2019). Minor: minimal or no property damage, but possibly some public threat (e.g., inundation of roads). Moderate: some inundation of structures and roads near stream, evacuations of people and/or transfer of property to higher elevations. Major:extensive inundation of structures and roads, significant evacuations of people and/or transfer of property to higher elevations.



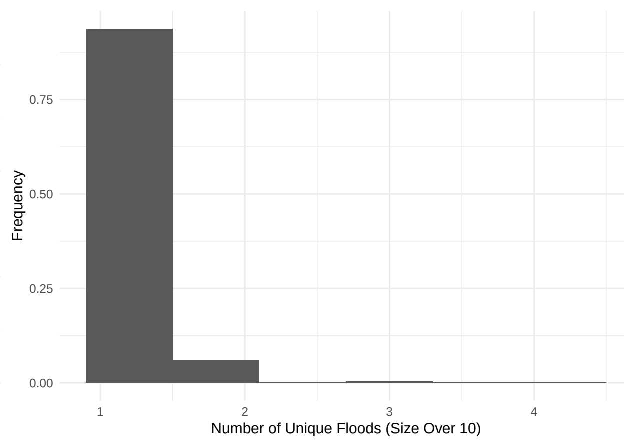
(a) Distribution of N of 10-Year Floods over 10 Years



(b) Distribution of Flood Size



(c) N of Unique Floods (size over 2) by Community-year



(d) N of Unique Floods (size over 10) by Community-year

Figure A.3: Flood Data Summary Information. Panel (a) shows that on most communities had 1 or 2 10-year floods over the 20 years whereas the average number of 10-year flood is 2.18. Panel (b) shows the distribution of flood event size (i.e., recurrence interval), where flood size is truncated at 100 for readability. Panel (c) illustrates the number of unique floods (size over 2) for community-year. Panel (d) repeats panel (c) for floods with size over 10.

Table A.2: Comparing the Estimated Flood Size Thresholds with the NWS Threshold

	2 Yrs Flood	10 Yrs Flood	50 Yrs Flood	100 Yrs Flood
Minor	0.778	1.285	1.74	1.944
	(0.052)	(0.071)	(0.102)	(0.124)
Moderate	0.594	0.994	1.36	1.526
	(0.042)	(0.06)	(0.085)	(0.103)
Major	0.45	0.771	1.081	1.226
	(0.034)	(0.043)	(0.051)	(0.06)

Note:
Note: The entries report the results from 12 separate regressions where each column represents four different dependent variables and each row represents three different regressors. Standard errors are clustered at the gauge level. See text for additional details.

Q_{ik} is the estimated flood threshold for site i for flood size k where $k \in \{2, 10, 50, 100\}$. NWS_{ij} is flood thresholds from the NWS for site i for flood severity j where $j \in$ {minor, moderate, major}. β is the coefficient of interest which illustrates how comparable two thresholds are. Namely, the closer β is to 1, the more comparable two thresholds are. For this analysis, I use 2,093 sites that have both estimated and the NWS flood thresholds.

$$Q_{ik} = \beta NWS_{ij} + \epsilon_{ijk} \tag{8}$$

Table A.2 reports the estimated β for 12 separate regressions and provides useful insights. First, an average 2-year flood incurs smaller than "minor" impact. When minor threshold increases by 1 unit, Q2 is increasing by only 0.78 units, indicating that reaching a 2-year flood threshold requires smaller amount of water. In contrast, a 10-year flood is comparable to a flood that incurs moderate damage. Indeed, the two thresholds behave very similarly as the regression coefficient (0.994) suggests. Similarly, a 50-year flood closely matches with a flood with major impact. Note, a 100-year flood is larger than a major flood and this is plausible given that a 50-year flood is comparable to the major flood threshold.

A.2 Validation of Key Dependent Variables

Table 3.1 shows that key dependent variables in this paper have prevalence of zeros. These statistics are consistent with findings from external sources.

Block population. Bureau of the Census (1994) reports that a substantial number of blocks have zero population, with state-level proportions ranging from 14 percent (RI) to 65 percent (WY), and a median value of 31 percent (WA). In my sample, the numbers are slightly different at 17 percent for RI and 26 percent for WA (WY is a non-disclosure state). A minor discrepancy is not surprising given that blocks not included in the digitized flood map are excluded from the analysis.

Flood insurance counts. There is no prior work that has documented the fraction of communities with zero insurance policies. However, when I compare the total number of insurance policies by state in my sample with other studies, I find them highly congruent. For instance, in my sample, Louisiana had 504,641 policies as of 2007, a figure closely matching the documented 502,085 flood insurance policies as of December 2007 in Michel-Kerjan and Kousky (2010). Other disclosing states listed in Michel-Kerjan and Kousky (2010) Table 1 are also well matched: CA (258,808 vs. 266,171), NC (123,949 vs. 133,955), NY (141,525 vs. 144,253), SC (190,997 vs 197,334), and TX (508,348 vs. 666,920) where the first number is from my sample and the second number is from Michel-Kerjan and Kousky (2010). Note, for TX, there is a noticeable gap primarily because Harris County is not in my sample (the county is not included in the digitized flood map described in Section 3).

Flood damage. Similar to the flood insurance policy counts, no prior studies have cataloged the fraction of community-years with zero flood damage. However, a back-of-the-envelop calculation suggests that this statistic is in line with existing works. For that, I take the average probability (1.45 percent) of filing a claim per policy over 1980–2012 from Kousky and Michel-Kerjan (2015) and multiply it with the number of flood insurance policies by the community in my sample. The result reveals that 17 percent of communities are likely to have more than one claim in a given year (i.e., 83 percent of community-year observations have zero claims). Note, while 83 percent is substantially lower than 95 percent in Table 3.1, this is a direct consequence of sample restriction: as I discuss in detail in Section 5.1, I remove extreme values—flood events with a size of 50 and above—from my analysis due to various economic and statistical reasons. When I undertake the same calculation without imposing these sample restrictions, I find that 86 percent of community-year observations have zero claims, a figure consistent with the previously reported 83 percent.

B Appendix B: Disclosure Requirement and Housing Price

Housing price change to the disclosure policy is of interest in its own right, but it is also a first pass at testing the efficacy of the disclosure policy. For housing prices, I use the Zillow Transaction and Assessment Database (ZTRAX).[41] It documents transaction dates, sales prices, and housing characteristics such as type (e.g., single house, condominium, etc.), exact longitude and latitude, year built, and the number of bedrooms.[42]

A combination of the different policy implementation timing and the differential treatment of properties located in and out of the SFHA allows me to employ a triple difference design using the stacked DDD approach. Similar to earlier sections, I use not-yet-treated states as clean control and exploit the policy implementation timing among the ever-treated states.

Equation (9) estimates the impact of the disclosure policy on the housing price.

$$log(Price_{ijmstd}) = \beta T_{ijmstd} + \theta_{mjhld} + \mu_{jtd} + \lambda_{mtd} + \epsilon_{ijmstd} \tag{9}$$

$Price_{ijmstd}$ is the housing price for a property i with SFHA status j in community m in state s at time t in stack d and T_{ijmstd} is the treatment status dummy, which takes 1 when SFHA $=$ Post $=$ Disclosure $=$ 1 where SFHA is a dummy for the SFHA status, Post is a dummy for the post-disclosure period, and Disclosure is a dummy for the treatment group assignment. Importantly, Post and Disclosure dummies are specific for each stack.

I also include a complete set of two-way fixed effects μ_{jtd}: SFHA $\times$ Time $\times$ Stack, λ_{mtd}: Community $\times$ Time $\times$ Stack, and θ_{mjhld}: Community $\times$ SFHA $\times$ Building Age $\times$ Number of Beds $\times$ Stack to estimate β. These fixed effects allow me to estimate the policy effect using the sales price variation before and after the disclosure policy, inside and outside of the SFHA while controlling for the community by SFHA specific property characteristics. Further, these fixed effects are interacted with the stack d, to ensure that comparisons are made within each stack. For building age h, I group construction years into 10-year bins (e.g., 2000-2009, 1990-1999, etc.) and for the number of bedrooms l, I group them into 1-3, 4-6, 7-10, and 10-or-more bedrooms bins. The identification comes from plausibly exogenous disclosure policy change timings after conditioning on the set of fixed effects.

In Table B.1 column (1), I report the estimated coefficients of equation (9) to find that the disclosure requirement reduces the price of the properties in the SFHA by 4.5 percent in comparison to those outside of the SFHA. To put this number in context, I multiply the estimate from column (1) to the average price of properties located in the SFHA in the pre-disclosure period ($327,171), and the reduction in the housing price amounts to $14,598. Importantly, community by year level potential confounders such as flood exposure, flood insurance take up rates, or flood insurance premiums are controlled by the community by year fixed effects in this specification. In column (2), I show that the estimate in column (1) is robust to occasional flood map updates, which can coincide with the disclosure policy change. Specifically, I repeat column (1) after removing 6 percent of communities that have experienced a flood map update over the sample period. The estimate in column (2) is essentially identical, suggesting that map updates are uncorrelated with the disclosure policy implementation. In column (3), I control for flood exposure to control for potential impact of direct flood damage, which could potentially affect the housing price. The estimate is essentially identical to the column (1). This is not surprising because the timing of a given flood event and a disclosure policy

[41] I thank Eyal Frank for his generous help with data access.

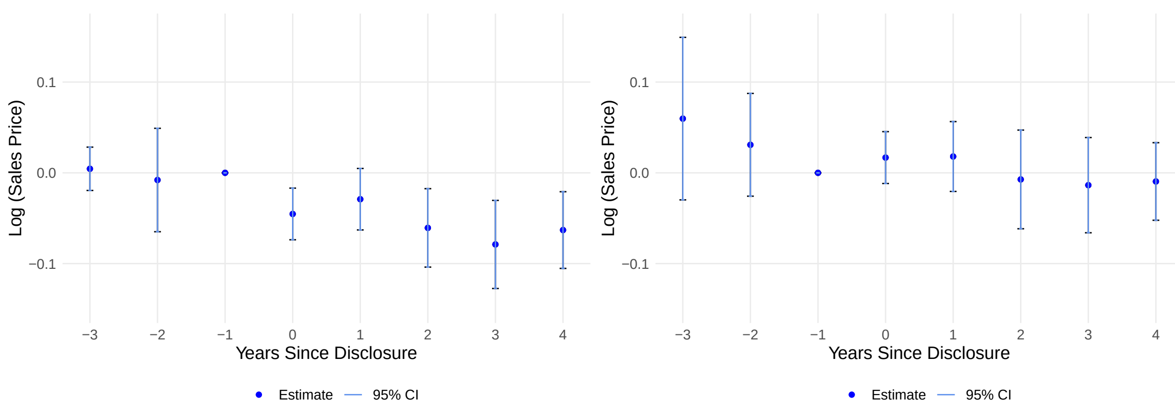
[42] I apply the following sample restrictions. First, I drop observations without longitude and latitude information. Second, I keep only single-family houses in the sample, reflecting the fact that the disclosure requirement in many states is applied only to one to four dwelling units. Third, I restricted the transaction price (before CPI adjustment) to be between $10,000 and $100,000,000.

Table B.1: Effect of Disclosure Requirement on the Housing Prices

	(1)	(2)
SFHA × Disclosure × Post	$-.045^{***}$	$-.046^{**}$
	(.015)	(.018)
Sample	Entire Communities	No-Revision Communities
Stack × Community × Year FE	X	X
Stack × Community × Year FE	X	X
Stack × Community × SFHA × Year Built × N Beds FE	X	X
Num. obs.	6249070	5931016

Note: Column (1) shows $\hat{\beta}$ from equation (9) from the 26 ever-disclosed states. In column (2), I remove observations from communities that have experienced Flood Insurance Rate Map, or an official flood map, update during the sample period. The dependent variable is log(sales price). All standard errors are clustered at the state level.

change is likely to be orthogonal.



(a) Early vs. Late (b) Ever vs. Never

Figure B.1: The Effect of the Disclosure Requirement on Housing Price. These figures plot the coefficients of interaction terms between the SFHA status and disclosure policy dummies in event time. The dependent variable is the log of housing price. Panel (a) uses late-treated states as a control group whereas panel (b) uses never-treated states as a control group. Standard errors are clustered on state. See the text for additional details.

Figure B.1 (a) presents an event study style graph, measuring the policy effect over event time. $\hat{\beta}_k$ in the pre-disclosure periods are almost zero, satisfying the parallel trend assumption. Since the first year of the policy change, the price of affected properties has fallen by about 4 percent. The effect is persistent up until five years after the policy implementation.

Importantly, this is a notable contrast to the figure in Panel (b), which has included never-treated (namely, states that have not implemented a home seller disclosure requirement on flood risk) states as a control group. In contrast to Panel (a), the plot exhibits a clear pre-trend. Further, the impact of the disclosure policy on the treated properties is null, which is consistent with an earlier discussion that realtor associations in no-requirement states have widely adapted disclosure forms even in the absence of state legislation. Further, these attenuation effects also reflect mandatory flood risk disclosure requirements implemented by local jurisdictions.

Finally, it is worth pointing out that the violation of the SUTVA assumption would not be a major concern in this setting because such an effect is likely to be small. The number of properties inside of the SFHA is equal to or less than 10 percent (average: 4.8 percent) for every state except Louisiana. Thus even if home buyers sort into the non-SFHA area after the disclosure policy, the effect would not be large enough to change the counterfactual price of the non-SFHA properties. Further, even if the SUTVA assumption is violated, the estimated housing price change can still show that the disclosure policy is effective and would be a policy relevant parameter because it reflects an actual housing market response to the flood risk information.

C Appdndix C: Why Home Sellers Do Not Disclose Voluntarily?

Given the disclosure requirement's significant impact on housing prices, home buyers clearly care about flood risk. Earlier works on "unraveling" have pointed out that when a seller has better information about the product quality than consumers, and the cost of verifiable disclosure is zero, voluntary disclosure is going to happen (Milgrom 1981, Grossman 1981). With voluntary disclosure, a mandatory disclosure policy would have no or small effect because the information is already provided to home buyers. Why it was not the case for flood risk?

There are a couple of potential explanations. First, making a credible disclosure on flood risk could be costly for home sellers. What the disclosure requirement effectively does is similar to a product guarantee. It delivers the best available and truthful information a home seller has to a home buyer, and if the information is significantly misleading or false, home sellers can be held responsible later (Lefcoe 2004). Without an institution like the disclosure requirement, delivering credible information could induce a non-trivial cost (e.g., third-party certification). Conversely, self-generated information from a home seller might have little effect on home buyers if the information is not deemed credible or easily verifiable (Stern 2005).

Second, one of the key assumptions for unraveling is that a product is vertically differentiated along a single, well-defined dimension of quality because it allows consumers to interpret the lack of disclosure as inferior quality, which in turn induces voluntary disclosure from the producers (Dranove and Jin 2010). However, a house is a bundle of attributes with various physical characteristics (e.g., number of bedrooms) and amenities (e.g., crime rate, school quality, and pollution). Thus, it is not straightforward to vertically differentiating a house along a single dimension.

Third, voluntary disclosure might not happen when the standard is unclear (Harbaugh et al. 2011), which can be true with flood risk. In what language should home sellers and buyers communicate concerning flood risk? Using past flood experience? If so, for how many past years? Or should they use the flood insurance purchase status or premium? Or the SFHA status? The disclosure policy standardizes risk communication, thus facilitating information flow.

D Appendix D: Additional Tables and Figures

Table D.1: Effect of Discosure Requirement on Household Responses (Placebo States)

	(1)	(2)	(3)
SFHA × Post	.004	.031	.004
	(.004)	(.062)	(.010)
D.V	Prob (Pop > 0)	Log Population	Vacancy Rate
Avg D.V. (Within BW)	0.602		0.095
Bandwidth	494	406	477
Num. obs.	357459	188304	209918

Note: This table is produced from equation (1). Columns (1)-(3) are estimated using the decennial census block-level data in 1990, 2000, 2010, and 2020. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

Back to 4.2.

Table D.2: Effect of Discosure Requirement on Population and Vacancy Rate (Donut Specification)

	(1)	(2)	(3)	(4)	(5)	(6)
SFHA × Post	$-.011^{***}$	$-.077^{**}$	$.013^{***}$	$-.007^{*}$	$-.079^{**}$	$.015^{**}$
	(.003)	(.035)	(.005)	(.003)	(.038)	(.006)
D.V	P(Pop > 0)	Log Population	Vacancy Rate	P(Pop > 0)	Log Population	Vacancy Rate
Avg D.V. (Within BW)	0.691		0.095	0.703		0.094
Doughnut Size	20	20	20	40	40	40
Num. obs.	1209186	1499805	1155519	966183	1343715	1000621

Note: This table is produced from equation (1) after excluding observations closest to the SFHA border. In columns (1)-(3), doughnut sizes are 20 meters and in columns (4)-(6) doughnut sizes are 40 meters. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

Back to 4.2.

Table D.3: Effect of Discosure Requirement on Demographic Compositions

	(1)	(2)	(3)	(4)
High × Disclosure × Post	$-.034^{***}$	$-.770^{***}$	.512	$-.004$
	(.012)	(.268)	(.376)	(.657)
D.V	log(Median income)	(%) 65+	(%) BA	(%) Black
Avg D.V.		12.3	24	14.8
Year FE	X	X	X	X
Tract FE	X	X	X	X
Num. obs.	73702	73702	73702	73702

Note: This table is produced from equation (2) using the decennial census data in 1990 and 2000. Outcome variables and their average values can be found in the table text. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

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Table D.4: Effect of Disclosure Requirement on Flood Damage

	(1)	(2)	(3)	(4)
Flood Size 2-10	.020***	.022***	.019**	.223***
	(.007)	(.008)	(.008)	(.054)
Flood Size 10-20	.054***	.071***	.039***	1.140***
	(.012)	(.016)	(.010)	(.104)
Flood Size 20-30	.078***	.108***	.048***	2.095***
	(.023)	(.032)	(.013)	(.419)
Flood Size 30-40	.068***	.082***	.052*	1.584***
	(.024)	(.031)	(.027)	(.338)
Flood Size 40-50	.096**	.144***	.026	1.850***
	(.042)	(.046)	(.040)	(.254)
Disclosure × Size 2-10	.028***	.039***	.014***	.087
	(.009)	(.015)	(.005)	(.164)
Disclosure × Size 10-20	.094***	.117***	.065***	−.003
	(.017)	(.026)	(.009)	(.086)
Disclosure × Size 20-30	.114***	.144***	.075***	−.164
	(.018)	(.028)	(.017)	(.138)
Disclosure × Size 30-40	.106***	.112***	.100***	.077
	(.030)	(.033)	(.030)	(.156)
Disclosure × Size 40-50	.107**	.115**	.100***	−.048
	(.044)	(.054)	(.031)	(.406)
Post × Size 2-10	.028**	.035***	.018*	.452**
	(.012)	(.012)	(.010)	(.184)
Post × Size 10-20	.094***	.096***	.088***	.086
	(.030)	(.034)	(.030)	(.076)
Post × Size 20-30	.105***	.117***	.093***	−.349
	(.028)	(.032)	(.032)	(.326)
Post × Size 30-40	.191***	.246***	.140*	.668*
	(.054)	(.044)	(.078)	(.361)
Post × Size 40-50	.239***	.356***	.135***	.629**
	(.040)	(.042)	(.046)	(.312)
Post × Disclosure × Size 2-10	−.039*	−.056*	−.021	−.063
	(.023)	(.030)	(.015)	(.325)
Post × Disclosure × Size 10-20	−.072*	−.086*	−.051*	.189
	(.039)	(.050)	(.029)	(.189)
Post × Disclosure × Size 20-30	−.080***	−.131***	−.018	.170
	(.029)	(.038)	(.031)	(.562)
Post × Disclosure × Size 30-40	−.141*	−.172**	−.111	−.360
	(.073)	(.072)	(.082)	(.442)
Post × Disclosure × Size 40-50	−.197***	−.339***	−.054	−.425
	(.055)	(.061)	(.068)	(.540)
Dep.Var	$P(Y>0)$	$P(Y>0)$	$P(Y>0)$	$log(Y)$
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	505383	242458	262925	22100

Note: The dependent variables in columns (1) to (3) are the probability of having positive flood damage (per housing unit damage). Column (1) is based on the entire set of communities while in columns (2) and (3), I repeat (1) using the subsample of communities with an above median SFHA ratio and below median SFHA ratio. Dependent variables in columns (4) is log transformed per housing unit damage conditional on non-zero damage. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

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Table D.5: Effect of Disclosure Requirement on Flood Damage (Including Never Disclosed States)

	(1)	(2)	(3)	(4)
Flood Size 2-10	.026***	.035***	.019***	.146
	(.005)	(.006)	(.004)	(.130)
Flood Size 10-20	.091***	.116***	.064***	.531***
	(.009)	(.015)	(.008)	(.192)
Flood Size 20-30	.132***	.169***	.094***	.841***
	(.012)	(.015)	(.017)	(.296)
Flood Size 30-40	.154***	.179***	.123***	1.394***
	(.022)	(.029)	(.017)	(.133)
Flood Size 40-50	.191***	.251***	.119***	1.776***
	(.022)	(.027)	(.019)	(.199)
Disclosure × Size 2-10	.019**	.022**	.016***	.046
	(.009)	(.011)	(.006)	(.200)
Disclosure × Size 10-20	.058***	.066***	.049***	.534***
	(.017)	(.023)	(.012)	(.114)
Disclosure × Size 20-30	.060***	.084***	.034**	.995***
	(.020)	(.031)	(.015)	(.241)
Disclosure × Size 30-40	.028	.022	.037	.271***
	(.021)	(.023)	(.030)	(.104)
Disclosure × Size 40-50	.025	.031	.015	.052
	(.022)	(.033)	(.023)	(.328)
Post × Size 2-10	.020**	.025***	.013*	.440***
	(.008)	(.009)	(.007)	(.131)
Post × Size 10-20	.062**	.062**	.059**	.563***
	(.026)	(.027)	(.026)	(.105)
Post × Size 20-30	.080**	.078*	.082***	.593**
	(.037)	(.046)	(.030)	(.234)
Post × Size 30-40	.103***	.100***	.107**	.373***
	(.038)	(.034)	(.048)	(.104)
Post × Size 40-50	.119**	.119**	.117***	.374**
	(.047)	(.058)	(.033)	(.165)
Post × Disclosure × Size 2-10	−.016	−.022	−.009	.113
	(.011)	(.015)	(.010)	(.158)
Post × Disclosure × Size 10-20	−.017	−.022	−.005	−.174*
	(.020)	(.032)	(.020)	(.101)
Post × Disclosure × Size 20-30	−.028	−.057	.010	−.599**
	(.030)	(.038)	(.036)	(.234)
Post × Disclosure × Size 30-40	−.028	.008	−.055	.095
	(.046)	(.042)	(.052)	(.240)
Post × Disclosure × Size 40-50	−.055	−.068	−.020	−.183
	(.040)	(.050)	(.050)	(.260)
Dep.Var	$P(Y > 0)$	$P(Y > 0)$	$P(Y > 0)$	$log(Y)$
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	1084023	542442	541581	57343

Note: This table repeats Appendix Table D.4 after including states without a disclosure policy on flood risk as control group. The dependent variables in columns (1) to (3) are the probability of having positive per housing unit flood damage. Dependent variables in columns (4) is log transformed per housing unit damage conditional on non-zero damage. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

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Table D.6: Effect of Disclosure Requirement on Flood Damage (Placebo States)

	(1)	(2)	(3)	(4)
Post × Disclosure (Size 2-30)	.007	.003	.010	−.060
	(.006)	(.006)	(.008)	(2.812)
Post × Disclosure (Size 30-50)	.045	−.046	.175	−.696
	(.138)	(.152)	(.132)	(3.113)
Dep.Var	$P(Y > 0)$	$P(Y > 0)$	$P(Y > 0)$	$log(Y)$
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	29626	14864	14762	515

Note: This table repeats Table 5.1 using the placebo states. The dependent variables in columns (1) to (3) are the probability of having positive flood damage (per housing unit damage). Column (1) is based on the entire set of communities while in columns (2) and (3), I repeat (1) using the subsample of communities with an above median SFHA ratio and below median SFHA ratio. Dependent variables in columns (4) is log transformed per housing unit damage conditional on non-zero damage. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference for columns (1)-(3). For column (4), I impose a more conservative standard error (IID) because the eigendecomposition approach used for fixing non positive-semidefinite variance-covariance matrix for Spatial-HAC standard error is producing zero standard errors.

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Illinois REALTORS®
RESIDENTIAL REAL PROPERTY DISCLOSURE REPORT
(765 ILCS 77/35)

NOTICE: THE PURPOSE OF THIS REPORT IS TO PROVIDE PROSPECTIVE BUYERS WITH INFORMATION ABOUT MATERIAL DEFECTS IN THE RESIDENTIAL REAL PROPERTY. THIS REPORT DOES NOT LIMIT THE PARTIES' RIGHT TO CONTRACT FOR THE SALE OF RESIDENTIAL REAL PROPERTY IN "AS IS" CONDITION. UNDER COMMON LAW, SELLERS WHO DISCLOSE MATERIAL DEFECTS MAY BE UNDER A CONTINUING OBLIGATION TO ADVISE THE PROSPECTIVE BUYERS ABOUT THE CONDITION OF THE RESIDENTIAL REAL PROPERTY EVEN AFTER THE REPORT IS DELIVERED TO THE PROSPECTIVE BUYER. COMPLETION OF THIS REPORT BY THE SELLER CREATES LEGAL OBLIGATIONS ON THE SELLER; THEREFORE SELLER MAY WISH TO CONSULT AN ATTORNEY PRIOR TO COMPLETION OF THIS REPORT.

Property Address: ______________________________

City, State & Zip Code: ______________________________

Seller's Name: ______________________________

This Report is a disclosure of certain conditions of the residential real property listed above in compliance with the Residential Real Property Disclosure Act. This information is provided as of ______________________________, 20___, and does not reflect any changes made or occurring after that date or information that becomes known to the seller after that date. The disclosures herein shall not be deemed warranties of any kind by the seller or any person representing any party in this transaction.

In this form, "am aware" means to have actual notice or actual knowledge without any specific investigation or inquiry. In this form, a "material defect" means a condition that would have a substantial adverse effect on the value of the residential real property or that would significantly impair the health or safety of future occupants of the residential real property unless the seller reasonably believes that the condition has been corrected.

The seller discloses the following information with the knowledge that even though the statements herein are not deemed to be warranties, prospective buyers may choose to rely on this information in deciding whether or not and on what terms to purchase the residential real property.

The seller represents that to the best of his or her actual knowledge, the following statements have been accurately noted as "yes" (correct), "no" (incorrect), or "not applicable" to the property being sold. If the seller indicates that the response to any statement, except number 1, is yes or not applicable, the seller shall provide an explanation, in the additional information area of this form.

	YES	NO	N/A	
1.	___	___	___	Seller has occupied the property within the last 12 months. (No explanation is needed.)
2.	___	___	___	I am aware of flooding or recurring leakage problems in the crawl space or basement.
3.	___	___	___	I am aware that the property is located in a flood plain or that I currently have flood hazard insurance on the property.
4.	___	___	___	I am aware of material defects in the basement or foundation (including cracks and bulges).
5.	___	___	___	I am aware of leaks or material defects in the roof, ceilings, or chimney.
6.	___	___	___	I am aware of material defects in the walls, windows, doors, or floors.
7.	___	___	___	I am aware of material defects in the electrical system.
8.	___	___	___	I am aware of material defects in the plumbing system (includes such things as water heater, sump pump, water treatment system, sprinkler system, and swimming pool).
9.	___	___	___	I am aware of material defects in the well or well equipment.
10.	___	___	___	I am aware of unsafe conditions in the drinking water.
11.	___	___	___	I am aware of material defects in the heating, air conditioning, or ventilating systems.
12.	___	___	___	I am aware of material defects in the fireplace or wood burning stove.
13.	___	___	___	I am aware of material defects in the septic, sanitary sewer, or other disposal system.
14.	___	___	___	I am aware of unsafe concentrations of radon on the premises.
15.	___	___	___	I am aware of unsafe concentrations of or unsafe conditions relating to asbestos on the premises.
16.	___	___	___	I am aware of unsafe concentrations of or unsafe conditions relating to lead paint, lead water pipes, lead plumbing pipes or lead in the soil on the premises.
17.	___	___	___	I am aware of mine subsidence, underground pits, settlement, sliding, upheaval, or other earth stability defects on the premises.
18.	___	___	___	I am aware of current infestations of termites or other wood boring insects.
19.	___	___	___	I am aware of a structural defect caused by previous infestations of termites or other wood boring insects.
20.	___	___	___	I am aware of underground fuel storage tanks on the property.
21.	___	___	___	I am aware of boundary or lot line disputes.
22.	___	___	___	I have received notice of violation of local, state or federal laws or regulations relating to this property, which violation has not been corrected.
23.	___	___	___	I am aware that this property has been used for the manufacture of methamphetamine as defined in Section 10 of the Methamphetamine Control and Community Protection Act.

Note: These disclosures are not intended to cover the common elements of a condominium, but only the actual residential real property including limited common elements allocated to the exclusive use thereof that form an integral part of the condominium unit.

Note: These disclosures are intended to reflect the current condition of the premises and do not include previous problems, if any, that the seller reasonably believes have been corrected.

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Figure D.1: Example of the Home Seller Disclosure Form (IL)

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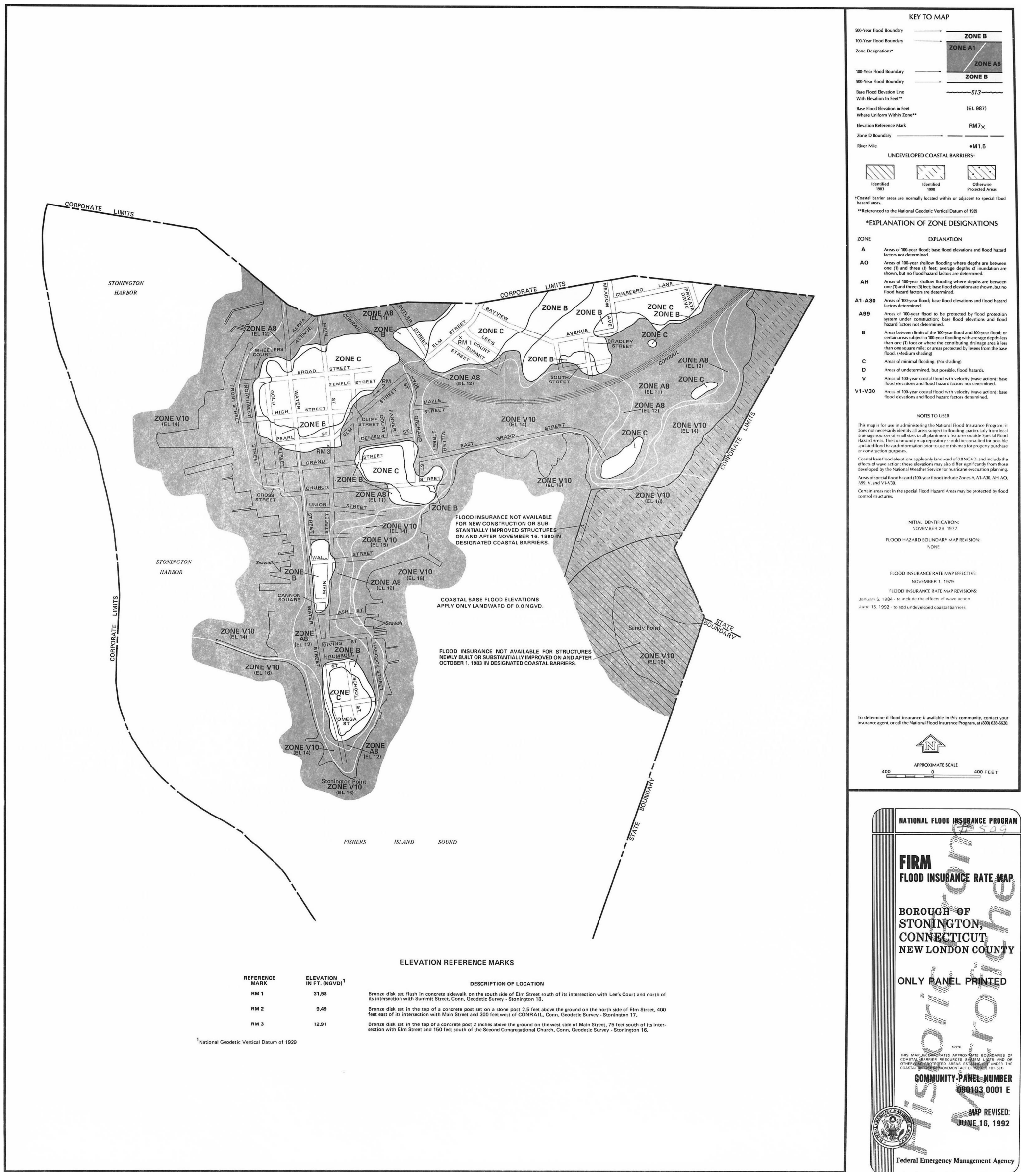


Figure D.2: Sample Flood Insurance Rate Map (Borough of Stonington, CT)

Back to 2.2.

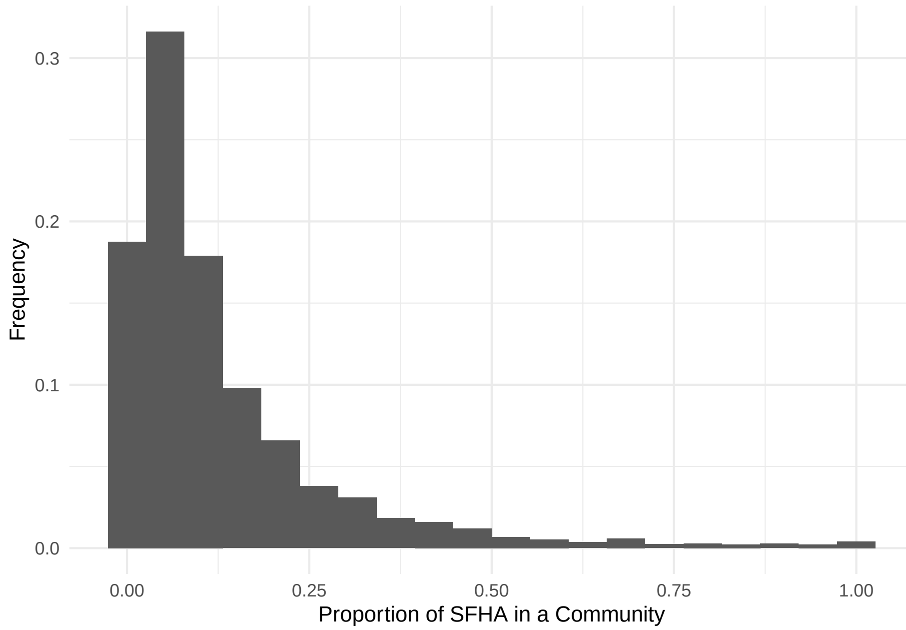
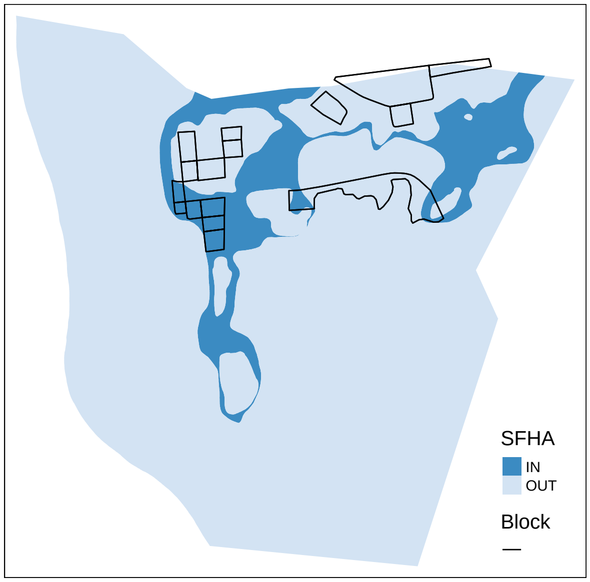
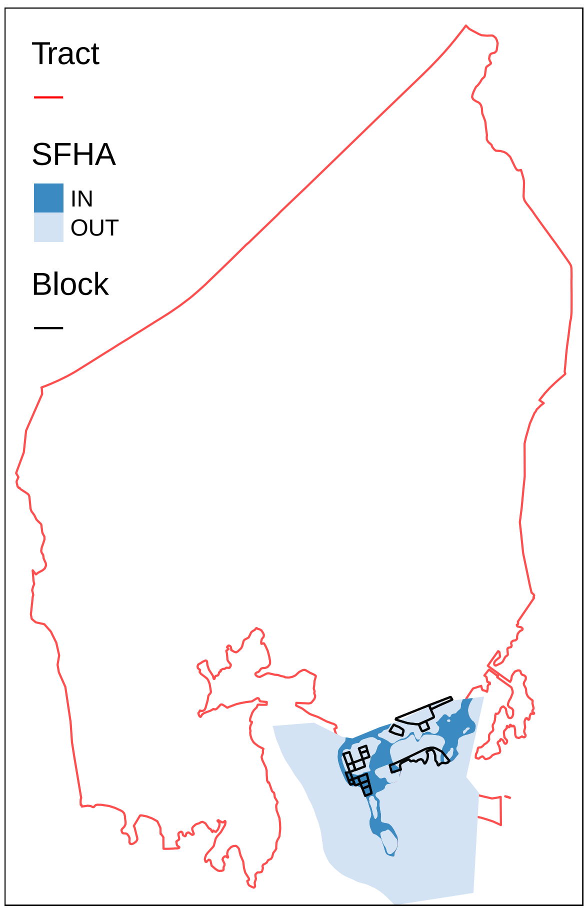


Figure D.3: Histogram of the Proportion of the SFHA at the Community Level. The plot shows the distribution of the SFHA ratio for the 8,194 communities that are on the Q3 map and in the 26 ever-disclosed states.

Back to 2.2.



(a) Census Block vs. SFHA Status



(b) Census Tract vs. SFHA Status

Figure D.4: Census Geographies and the SFHA Status (Borough of Stonington, CT)

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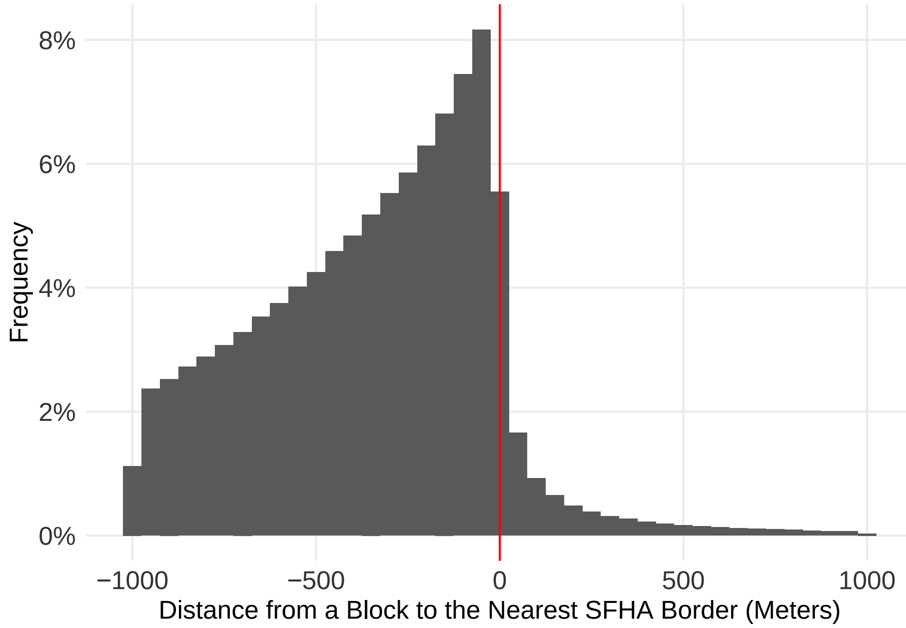
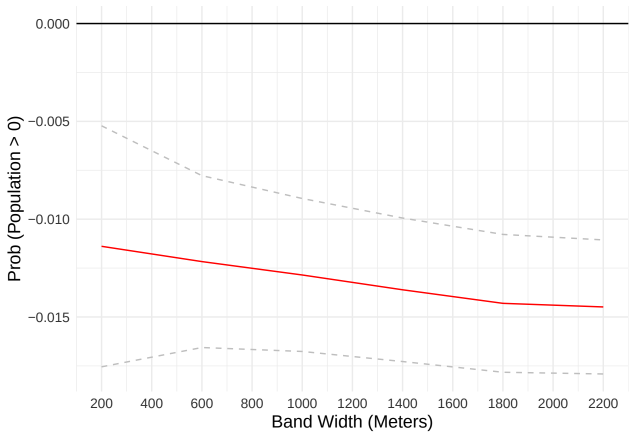
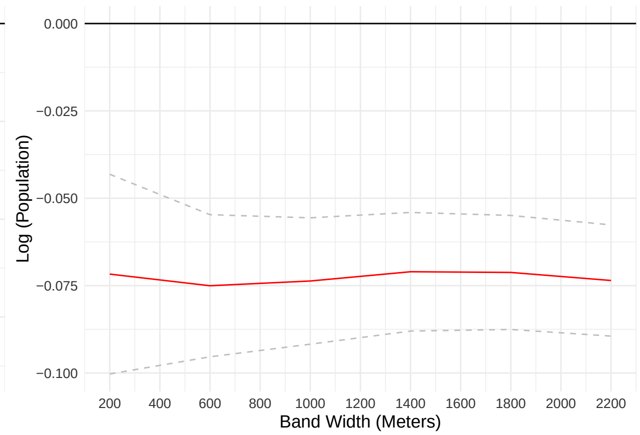


Figure D.5: Histogram of Running Variable (Distance to the SFHA Border)

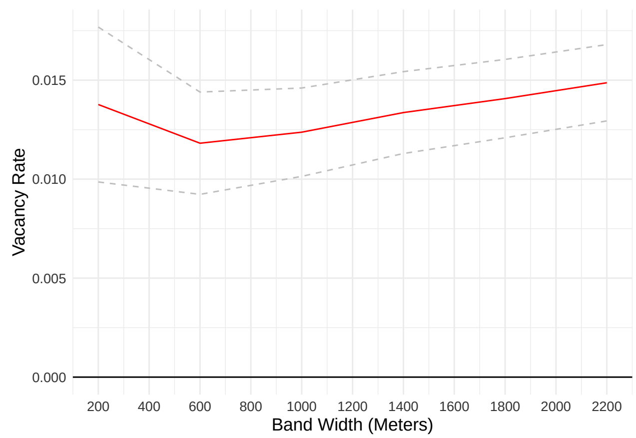
Back to 4.2.



(a) Prob. of Positive Population



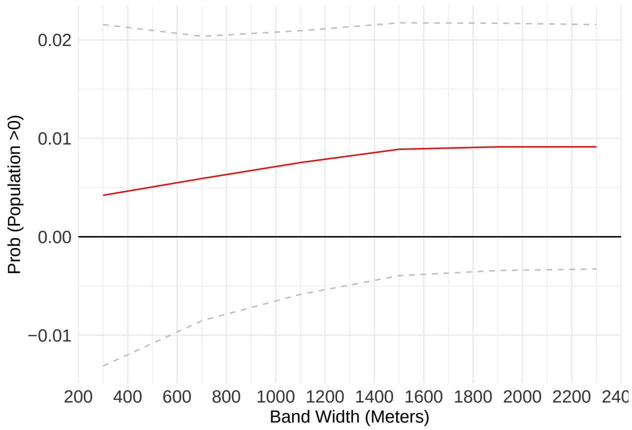
(b) Log Population



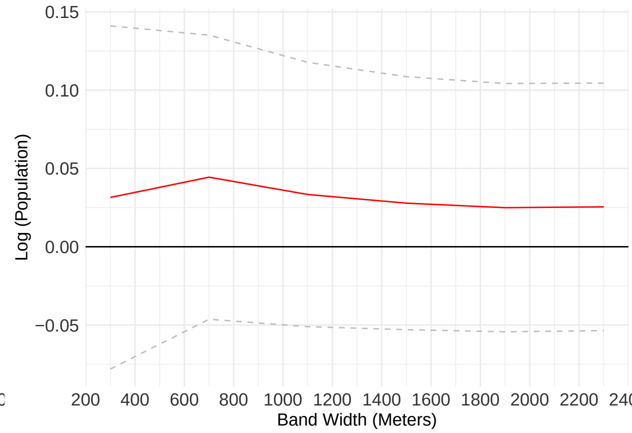
(c) Vacancy Rate

Figure D.6: The Effect of the Disclosure Requirement on Population and Vacancy Rate for Different Bandwidths. The figure plots $\hat{\delta_6}$ from equation (1) for a range of bandwidths. The level of observation is census block, which is the smallest census geographical unit. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference

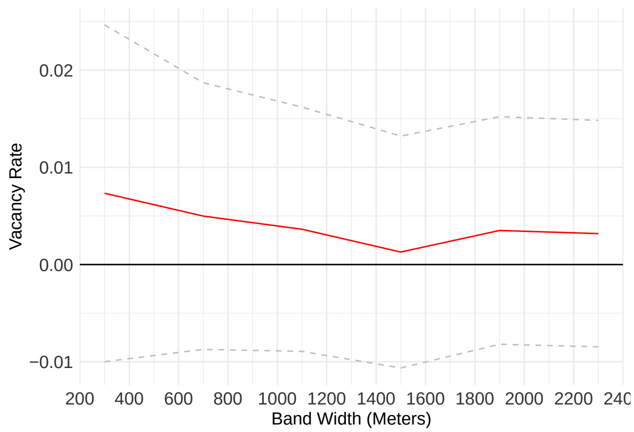
Back to 4.2.



(a) Prob. of Positive Population



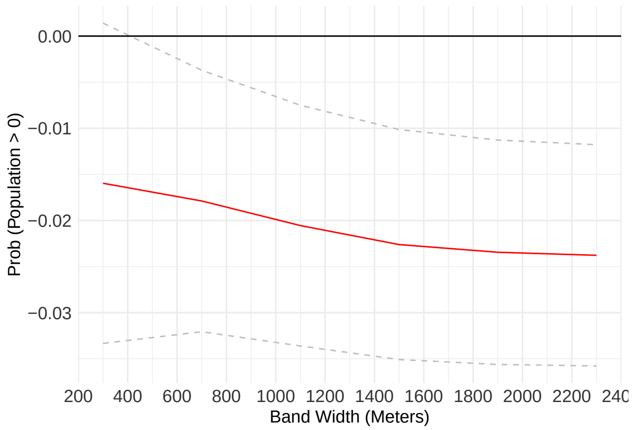
(b) Log Population



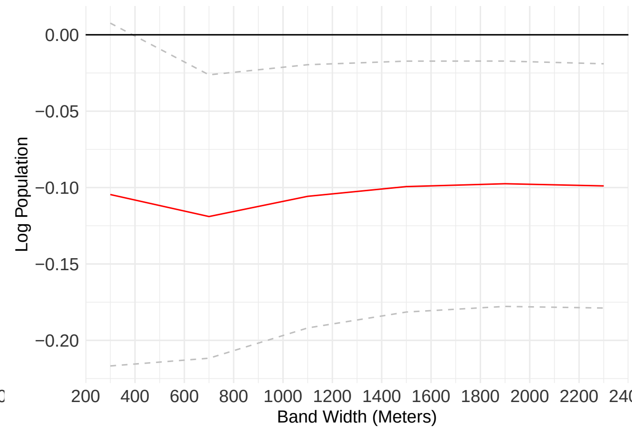
(c) Vacancy Rate

Figure D.7: The Effect of the Disclosure Requirement on Population and Vacancy Rate for Different Bandwidths (Placebo States). The figure plots $\hat{\delta}_6$ from equation (1) for a range of bandwidths for the placebo states. The level of observation is census block, which is the smallest census geographical unit. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference.

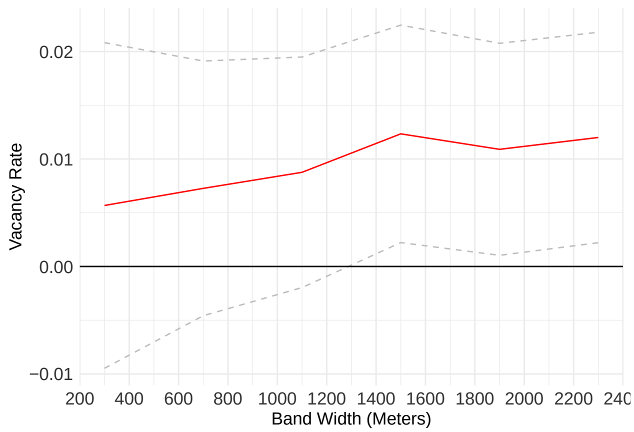
Back to 4.2.



(a) Prob. of Positive Population



(b) Log Population



(c) Vacancy Rate

Figure D.8: The Difference in Diff-in-Disc Estimates Between Treated and Placebo States. These figures plot the difference in diff-in-disc estimates between the treated and placebo states for a range of bandwidths. The level of observation is census block, which is the smallest census geographical unit. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference. See the text for additional details.

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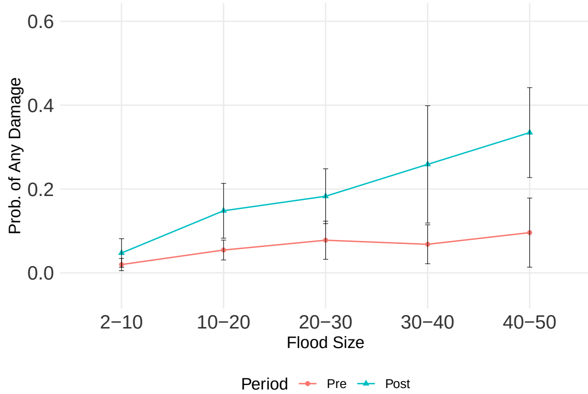
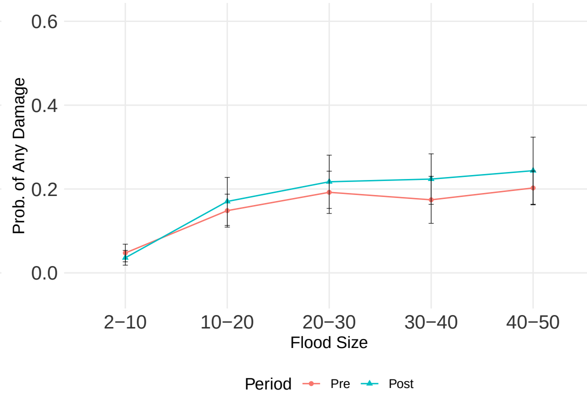
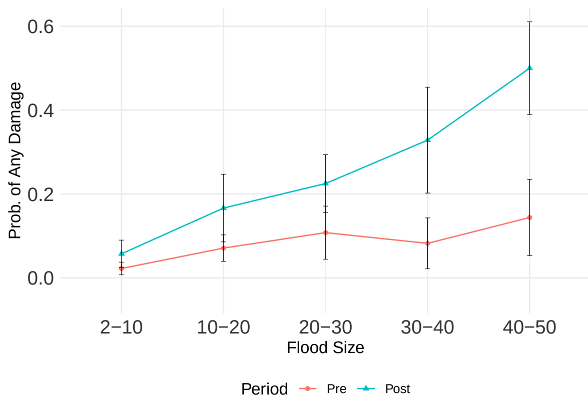


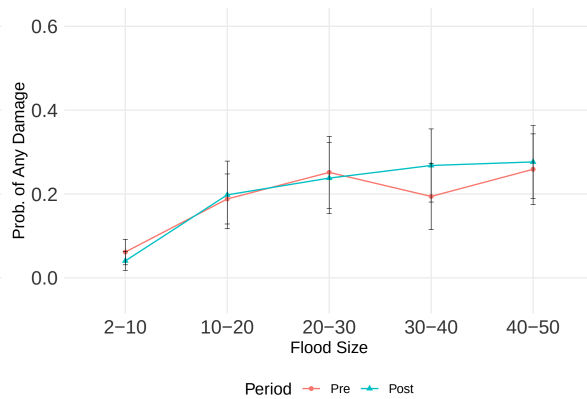
(a) Control Group (All Communities)



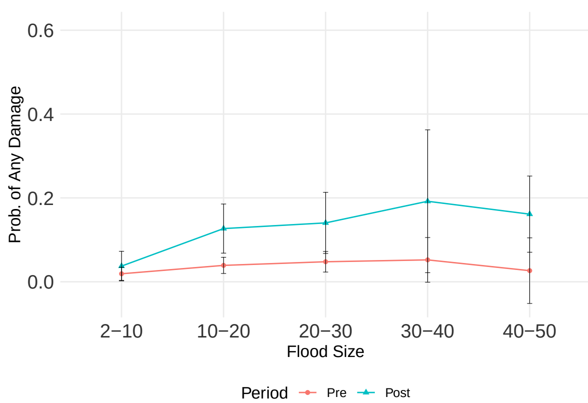
(b) Treatment Group (All Communities)



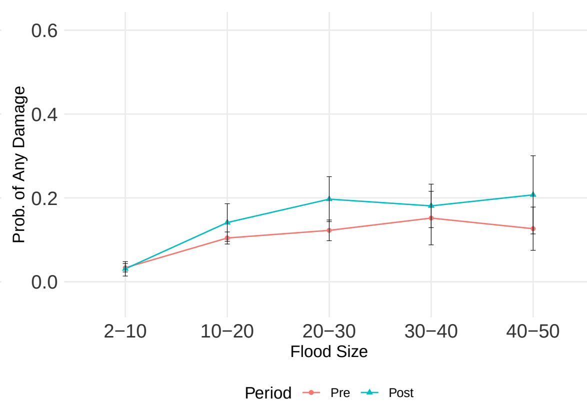
(c) Control Group (High Risk Communities)



(d) Treatment Group (High Risk Communities)



(e) Control Group (Low Risk Communities)



(f) Treatment Group (Low Risk Communities)

Figure D.9: The Effect of Disclosure on the Damage Function with Corresponding 95% Confidence Intervals. These plots reproduce Figure 5.1 with confidence intervals.

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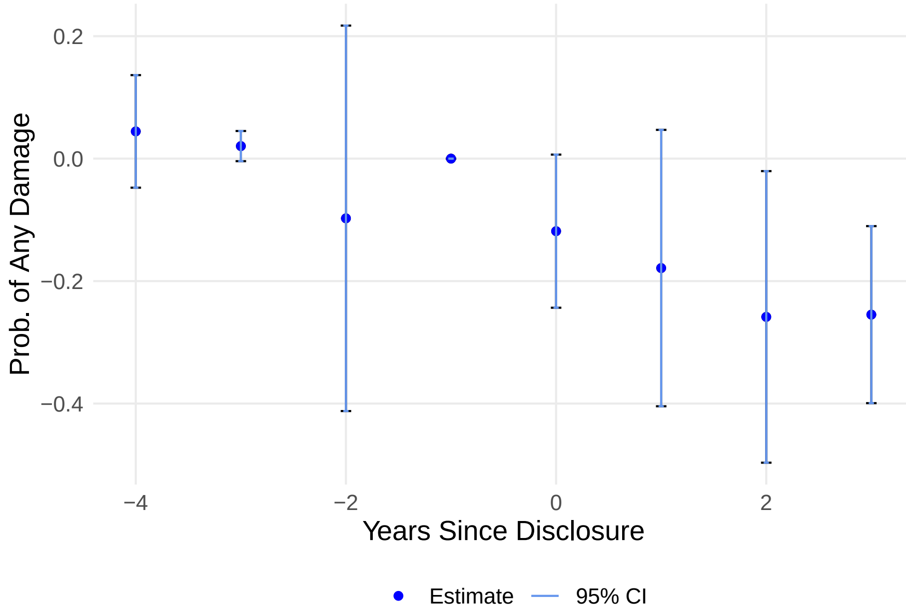

Figure D.10: The Effect of Disclosure on the Damage Function (Event Study). This figure depicts $\hat{\beta_{4,t}^{30-50}}$ for flood size of 30-50 in event time t. The error bar represents the 95% confidence interval. See text for more details.

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