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 friction 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% 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 becoming ever more 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 area), 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). This approach, however, attracts more people and development to floodplains (the so-called "levee-effect") by converting wetlands to habitable land (Pinter 2005, Kousky et al. 2006, Boustan et al. 2012, Collenteur et al. 2015). The fundamental problem is that none of these flood protection structures are perfectly safe. When those engineering structures fail, either due to extreme weather conditions or improper maintenance, flood damage could become even larger than before, with more developments in floodplains (Pinter et al. 2016).[1] Consequently, governments end up spending billions of dollars for disaster relief and recovery even after investing a tremendous amount of resources for flood prevention (CBO 2016). Although some local governments administer policies such as development restrictions to limit exposure, for most places the population in flood-prone areas is expected to grow rapidly (Wing et al. 2018).[2]

This paper studies whether easing information friction on flood risk in the housing market could reduce the number of households in high-risk areas and thus flood damage. Although an official flood map has long been publicly available, numerous earlier studies and anecdotal evidence show a lack of flood risk awareness among home buyers. For instance, Chivers and Flores (2002) find only 14% of home buyers whose property is located in high-risk areas learned about flood risk before closing. Such low awareness hinders home buyers from fully internalizing the flood risk during the real estate transaction and thus makes them consume more than the optimal level of flood risk. Given that a

[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% 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.

potential reason for the friction is information acquisition and processing costs (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, which is composed of yes-or-no check box questions (Lefcoe 2004). Regarding flood risk, a typical question is whether a property is located in the Special Flood Hazard Area (SFHA)—an area with a higher flood risk defined by the official flood map. Home sellers are generally required to deliver the disclosure form to the home buyers before the closing (Stern 2005).

The disclosure requirement is a compelling setting for evaluating the effect of flood risk information for three reasons. First, the policy rolled out across 26 states in the contiguous US with substantial variation in timing between 1992 and 2003, where the variation came primarily from plausibly exogenous state court rulings on the extent of realtor liability for incomplete disclosure (Roberts 2006). In addition, the policy treats properties located in and out of the SFHA differentially, allowing me to credibly estimate policy effects by either implementing a triple difference design or investigating heterogeneous treatment effects. Importantly, in exploiting the staggered adoption, I build on Cengiz et al. (2019) and Brot-Goldberg et al. (2020) and use the stacked approach to overcome potential bias from conventional two-way fixed effect models (Goodman-Bacon 2021).

Second, because the disclosure form considers flood risk in a discontinuous manner, home buyers would receive starkly different flood risk information for two proximate properties located on opposite sides of an SFHA border. This spatial discontinuity of information yields an opportunity to disentangle the information effect from the actual flood risk effect. One potential concern is that being located in the SFHA could invite other treatments such as mandatory flood insurance purchasing. To account for that possibility, I use the difference-in-discontinuity approach following Grembi et al. (2016). Third, there are five states that have implemented a home seller disclosure requirement but without a question on flood. These placebo states are valuable for robustness tests.

To leverage these variations, I combine multiple datasets. To understand household responses to the disclosure, I collect census block-level demographic data from the decennial census, and community-level National Flood Insurance Program (hereafter "flood insurance") policy counts. For flood damage, I use damage records from the flood insurance adjuster report. To account for the distinctive characteristics of the distribution of these outcome variables, namely a mass point at zero with a long right tail, I estimate the extensive and intensive margin separately following suggestions of Chen and Roth (2022). In addition to collecting various data, I also construct community-level past flood events data based on a hydrological measure of flood intensity (Saharia et al. 2017, England Jr et al. 2019). The data overcomes a potential endogeneity problem embedded in the self-reported flood events data such as the National Weather Service Storm Events data (Gall et al. 2009).

Empirical exercises produce two key results. First, the disclosure policy reduces the population in the SFHA. Specifically, I find that it leads to a 7% decline in population for blocks in the SFHA. Further, it lowers the probability of having a positive population by 0.01 (or 1.5% from the baseline of 0.67). Taking these intensive and extensive margin effects together, the 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. Consistent with the population effect, I find that the vacancy rate in high-risk areas increases from 0.095 to 0.109 after the disclosure policy.

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 (or 0.1% from the baseline of 0.83; extensive margin) while insurance counts per housing unit decreases by 0.9% (intensive margin). Investigating these two different margins of household 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).

Second, the disclosure policy reduces the expected probability of having flood damage at the community level by 2.5% (or 33% from the baseline). To show this, I first non-parametrically estimate a 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 on the damage function by leveraging staggered adoption timing and find that the slope of the function is substantially flatter after the policy. Specifically, for each flood size bin, the probability of flood damage is reduced by 4% to 20%, which can be summarized as a 2.5% reduction in the expected probability of flood damage.[3] In doing so, I also find that the disclosure effect is disproportionately larger in the high

[3]This is a probability-weighted average, where probability is coming from the annual likelihood of experiencing a

SFHA fraction communities, which is plausible given that the disclosure policy is primarily affecting properties in the SFHA. This number is likely to be a lower-bound effect because the analysis excludes infrequent but large flood events.

This paper contributes to four different bodies of literature. First, it is related to prior works studying factors that could mitigate climate change damage. Whereas earlier works primarily focused on technology as a driver of adaptation (Miao and Popp 2014, Barreca et al. 2016, Burke and Emerick 2016), I focus on the role of information that facilitates the alignment of private incentives and socially desirable outcomes.

Second, this paper departs from earlier works that have investigated the role of government policies in household adaptation decisions. Although how well-intended policies could backfire by inducing moral hazard has been widely documented (Kousky et al. 2006, 2018, Gregory 2017, Peralta and Scott 2020, Baylis and Boomhower 2022), there is relatively sparse empirical evidence as to how government policies could encourage adaptive behaviors and reduce damage. An exception is a recent study Baylis and Boomhower (2021), which underscores the effectiveness of building code policies in mitigating wildfire damage. The difference is that while Baylis and Boomhower (2021) emphasizes the effectiveness of mandated adaptation, this paper shows how a disclosure requirement can encourage voluntary adaptation. The findings of this paper also have important policy implications as disclosure policies are getting more attention as a flood risk management tool.[4]

Third and more broadly, this paper builds on earlier works that have studied the impact of flood risk on the housing market equilibrium (Hallstrom and Smith 2005, Pope 2008, Bin and Landry 2013, Muller and Hopkins 2019, Hino and Burke 2021, Bakkensen and Barrage 2021). While most of these studies focus on understanding how flood risk information or beliefs affect housing prices, this paper finds evidence that providing flood risk information reduces flood damage. Tracing the effect of flood information up to the damage amount is important because while a change in the price of the high-risk houses, in general, is a transfer between home buyers and sellers, a reduction in flood damage

flood of different size. For instance, the probability of having a flood of size 40–50 in a given year is $\frac{1}{45}$ by definition of flood size. More details are in Section 5.2.

[4]After a series of devastating floods in recent years, both federal and state governments work toward strengthening the disclosure of flood risk. For instance, FEMA has proposed an NFIP reform that conditions flood insurance eligibility on the implementation of a mandatory disclosure policy on flood risk (U.S. Department of Homeland Security 2022, The White House 2023). The House of Representatives passed a bill ("21st Century Flood Reform Act") that made the disclosure of flood risk a prerequisite for joining the National Flood Insurance Program (Committee on Financial Services 2017), although it did not pass the Senate. Texas drastically strengthened its existing disclosure requirement on flood risk after Hurricane Harvey ("TEXAS PROPERTY CODE" 2019).

enhances social welfare.

Fourth and methodologically, this paper contributes to the climate change econometrics literature by constructing a novel measure of flood exposure, which is a critical methodological step in identifying climate effects (Hsiang 2016). My approach leverages hydrological measures of flood intensity, which allows me to objectively document flood events for a wide range of causes including rainfall, snow melt, or storm surge. This complements existing flood damage functions that specialize in capturing the impact of rainfalls 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

A publicly available Flood Insurance Rate Map should inform home buyers whether a property belongs to the SFHA. Also, the Flood Insurance Reform Act of 1994 requires flood insurance purchase as a condition for federally-backed mortgage approval, which should let affected home buyers learn about the associated flood risk. However, prior works show home buyers, in general, are not well aware of the flood risk (Chivers and Flores 2002, Pope 2008, Bin and Landry 2013) either because information acquisition is costly (Kunreuther and Pauly 2004) or compliance with the flood insurance purchase requirement is far from perfect (Tobin and Calfee 2005, Michel-Kerjan 2010, National Research Council 2015, GAO 2021, Wagner 2022).[5]

A statutory disclosure requirement could be a useful policy tool to fill this information gap. It mandates that home sellers provide buyers with a detailed account of known material defects in the listed property by filling out a standardized form. A typical form asks questions about both structural components (e.g., problems with walls, roofs, or plumbing) and surroundings (e.g., natural hazards). In particular, 26 states in the contiguous US implemented the disclosure requirement be-

[5]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% of homeowners in the SFHA purchased flood insurance in 2000.

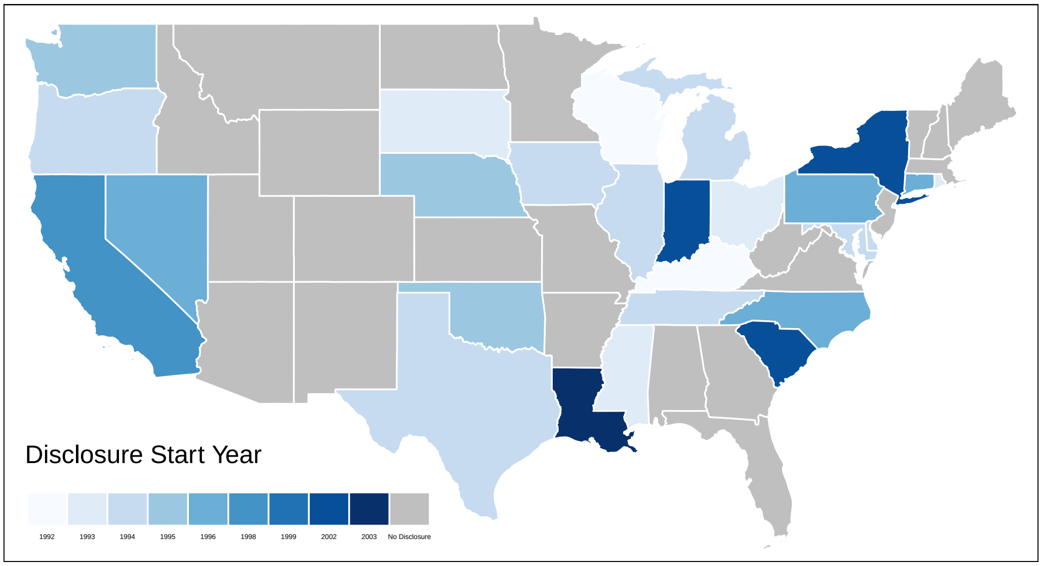


Figure 2.1: The Disclosure Requirement Implementation over Time

tween 1992 and 2003 (see Figure 2.1) with an explicit question on flood risk. Interestingly, five states (ID, ME, MN, NH, and VA) have adopted a disclosure policy, but without a question on flood risk.[6] These "placebo" states are useful to check the robustness of the main results.

The exact language slightly varies from state to state, but the following three questions usually appear in disclosure forms: whether a property is in the SFHA; whether a property had flood damage in the past; and whether a property has flood insurance. 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% of the claims originated from properties in the SFHA while 75% of the flood insurance policies are purchased from properties in the SFHA.

As of 2021, five states ask about the SFHA status only, 15 states ask about the SFHA status and past flood experience, while four states ask all three of them.[7] Taken together, these questions would raise home buyers' flood risk awareness for properties in the SFHA much higher than those outside of it. The policy makes the information provided by sellers credible and verifiable such that overcomes the limitation of voluntary disclosures (see Appendix C for further discussion on potential voluntary disclosure).

To understand why these requirements were introduced in the first place, it is useful to discuss

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

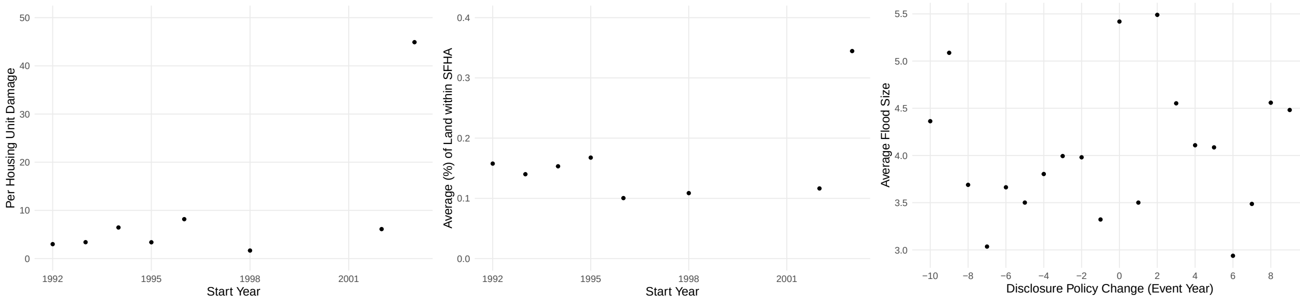
[7] MI and TN ask about the latter two only.

the evolution of state court rulings on incomplete disclosure cases. Traditionally, home buyers were legally expected to exercise proper caution on potential defects of a property (the so-called "*caveat emptor*" or "let the buyer beware" doctrine). However, with the rise of consumer protectionism in general (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). It was primarily an effort to deflect potential liability from realtors 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).

Importantly, the disclosure requirement is not exclusively on flood risk, but on a long list of items covering a wide range of property conditions. Thus, the implementation timing of the disclosure policy is unlikely to be correlated with each state's underlying flood risk, damage, or history. In Figure 2.2 (a) and (b), I plot the relationship between disclosure year and the average flood damage per housing unit and the average proportion of land area inside of the SFHA. If the timing of the disclosure policy implementation is correlated with underlying flood risk, we would expect to see a higher risk profile for early adopters. However, both damage and SFHA ratio are random across different implementation years, which is consistent with the idea that the timing is uncorrelated with the underlying flood profiles.[8] 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 is in 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 essentially random in event time—if anything, flood size seems to be smaller in event years -1 and -2, which again suggests that the policy implementation is not likely to be correlated with floods.

Although many states levy fines or even allow buyers to rescind the agreement without penalty to ensure compliance, the disclosure policy might still fail to raise home buyers' flood risk awareness under certain circumstances. First, home sellers might not comply with the regulation. If they furnish the form with inaccurate information or completely ignore the requirement despite the penalty,

[8]Spikes in the Figure 2.2 are due to Louisiana, which has substantially higher per housing unit and the fraction of land area in the SFHA in comparison to other states.



(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.

the disclosure policy's effectiveness could be seriously undermined. Second, home buyers might not fully grasp the information content. While the disclosure forms consist of straightforward check box questions (see Appendix Figure D.1), the implication of the SFHA might not be easy to comprehend. Thus, the effectiveness of the disclosure requirement is an empirical question.

While I cannot directly observe how home buyers' perceptions of flood risk change due to the disclosure policy, in Appendix B, I test whether the disclosure policy affects property values in the SFHA area. I find a 4.5% reduction in the affected housing prices, which coincides with existing estimates regarding the effect of flood risk information on housing prices (e.g., see Hino and Burke (2021)). This finding provides indirect evidence that the disclosure policy was effective in changing the flood risk awareness of home buyers.

Before further proceeding, it is worth briefly discussing the states without any disclosure requirements. While not mandatory, in over 60% of these states, state realtor associations have formulated voluntary disclosure forms. In some of these states, realtor associations even require member realtors to use these forms,[9]. Further, some states create a disclosure policy on flood for its subgeography.[10] These examples imply that a non-trivial number of home buyers in these "non-disclosure" states might have received information on flood risk. As those forms are not produced by state legislators, it is extremely challenging to pin down the treatment timing, namely the disclosure start year. These

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

[10]For instance, in 1993, Miami-Dade County in Florida implemented a home seller disclosure requirement on the SFHA status through its Ordinance Chapter 11.

complications make it difficult to use these states as a control group. That is, 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). Therefore, I use states that have been treated later rather than never-treated states as a control group whenever I exploit the staggered adoption variation.

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 going to be inundated with a 100-year flood, is a particularly important concept because flood risk communications frequently refer to it.[11]

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 in a discontinuous manner for two areas on each side of the border with almost identical actual flood risk. A potential concern, though, is that the SFHA status invites other regulations as well.[12] 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

[11]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).

[12]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% 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).

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 that the flood zone status remains constant over the study period for the majority of the properties. Indeed, in Appendix B, I show that excluding properties from communities with map updates does not change the estimated effect of disclosure policy on the housing price.

The jurisdiction of each flood map is "community," a local political entity (e.g., village, town, city) defined by the National Flood Insurance Program. These entities are comparable to the US Census place. Appendix Figure D.2 shows a sample Flood Insurance Rate Map from a part of the Borough of Stonington, Connecticut. The dark area on the map represents the SFHA, and the light area is the non-SFHA. Similar to this community, a typical entity has both SFHA and non-SFHA areas within the jurisdiction. Appendix Figure D.3 is a histogram of the fraction of the SFHA area for 8,194 communities that are 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

3.1 Data Description

I compile multiple data sets on block and tract level demographics, community-level number of flood insurance policies, and flood damage. I also construct 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 different sources. First, 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,[13] I calculate the weighted sum of count variables using inter-

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

polation weights from the NHGIS block-to-block crosswalk (Manson et al. 2022).[14]. This resolves one-to-many matches and creates a geographically standardized time series.

Second, for other demographic characteristics such as income, age, race, and education, which are not available at the block—the smallest census geographic unit—level, I utilize tract-level data from the Geolytics for 1990, 2000, and 2010 decennial census.[15] The number of flood insurance policies by the NFIP community for the period of 1978–2008 comes from FEMA.[16]

Flood damage. I use the damage records from the National Flood Insurance Program adjuster's report. 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-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 one-third of cumulative flood damage in the US (Davenport et al. 2021), such an approach has limitations in grasping the entire scope of floods.

To overcome the limitation of existing datasets, I construct hydrology-based community-level flood history data using daily water volume records from over 3,000 USGS and NOAA stations located within the 26 ever-disclosed states (Milly et al. 2002, Mallakpour and Villarini 2015, Slater and Villarini 2016). Under 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

[14]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)

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

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

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, 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 to quantiles of the fitted distribution from step 1. Third, I translate the quantiles into recurrence intervals,[17] and take the maximum recurrence interval for each year, and finally matching each community to the three nearest gauges and calculating 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 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, which is the first generation of a digitized flood map, that reflects the flood risk as of the mid-1990s. The map selectively covers about half of the entire FEMA communities based on population density and the intensity of past flood incidents, and my main sample consists of these communities (FEMA 1996). Also, the primary data source to track the disclosure requirement legislative history is the *Nexisuni* database. I cross-validate it with prior works on the disclosure requirement (Washburn 1995, Pancak et al. 1996, Lefcoe 2004) and the National Realtor Association reports (National Association of Realtors 2019).

3.2 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 band-

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

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

width estimated in Section 4.2, while the last three values are reported from the NFIP communities in my sample.

One of the key characteristics of dependent variables is the presence of a point mass at zero. For instance, about a quarter of observations for both the block population (27%) and flood insurance policy counts per housing unit (17%) variables have zero values. These statistics are consistent with findings from prior studies. Regarding block population, Bureau of the Census (1994) reports that a substantial number of blocks have zero population, with state-level proportions ranging from 14% (RI) to 65% (WY), and a median value of 31% (WA).[18]

For NFIP policy counts per housing unit, 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).[19]

For the community level flood damage per housing unit variable, 95% of observations are zero. Similar to the flood insurance policy counts, no prior studies have cataloged the instances of communities 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%) 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% of communities are likely to have more than one claim in a given year (i.e., 83% of community-year observations

[18] In my sample, the numbers are slightly different at 17% for RI and 26% 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.

[19] 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 3.1).

have zero claims). Note, while 83% is substantially lower than 95%, 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% of community-year observations have zero claims, a figure consistent with the previously reported 83%.

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 distinctive data generating process, 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 model or a two-part model, both extensively employed in modeling health expenditures characterized by a similar distribution (Mullahy and Norton 2022).

Finally, summary statistics for 10-year flood events suggest that over a 20-year period, an average community experiences 2.18 events, which provides validation for the hydrology-based flood events data. To see this, recall that a 10-year flood is defined as a flood that is large enough to come back every 10 years on average, and thus, for a 20-year period, an average community is expected to have two such events.[20]

4 Household Responses to the Disclosure Requirement

In this section, I investigate how households respond to flood risk information due to the disclosure requirement. Building on Ehrlich and Becker (1972), which has investigated household choices under uncertain hazard risk, I focus on two different forms of responses, namely self-protection and market insurance. The distinction between these two is important because they have starkly different implications for flood damage—especially when market insurance replaces self-protection.[21] To measure self-protection and market insurance, I primarily consider population net flow and flood insurance,

[20]The slight discrepancy of 2.18 from the expected 2 arises because I used annual peak flow data until 1990. This approach ensures that 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.

[21]Ehrlich and Becker (1972) points out that when investing in self-protection measures is rewarded by lower insurance premium, self-protection and market-insurance can be complemented. 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.

respectively.

4.1 Estimation Framework

Spatial Discontinuity. Yes-or-no check box questions in disclosure forms create a spatial discontinuity of flood risk information, which allows an analyst to disentangle the flood risk information effect from the actual risk effect. One potential concern, though, is that other policies such as flood insurance requirements also change at the border, which could confound the change in disclosure requirements. To account for the 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 time-invariant confounding factors.

Following Grembi et al. (2016), I estimate the policy effect on population and vacancy rate 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.[22]

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

Practically, the estimation is conducted in two steps. First, I estimate the optimal bandwidth using the mean squared error optimal algorithm for each outcome variable. Then, I estimate equation (1) using observations within the optimal bandwidth (Calonico et al. 2014, Cattaneo et al. 2019).[23] In equation (1), Y_{bst} is various outcome variables such as the probability of having any population, log of population conditional on having a non-zero population, or vacancy rate in block b in state s in time t. Estimating extensive and intensive margin effect separately is useful because 27% of blocks in my sample have zero population.[24] X_{bs} is the distance from a border in meters (negative if in non-SFHA area), treatment group dummy $D_{bs} = 1$ (i.e., in the SFHA) if $X_{bs} > 0$, and post period

[22] Practically, it is defined as the difference of (1) the distance between block centroids and the closest SFHA border and (2) a block diameter.

[23] I estimate the 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.

[24] Bureau of the Census (1994) also documents that the proportion of blocks with zero population at the state level is between 14% (RI) to 65% (WY) with the median value of 31% (WA).

dummy $T_{st} = 1$ if $t > T^*_s$, 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 in it. In this case, the distance from a block to an SFHA border cannot be well defined. While this might be a serious problem for larger geographical units such as tracts, it would not be too much problem for a block as the size is small. For instance, the median size of the census block in my sample is 0.009 square miles, and 83% of them are perfectly contained within either SFHA or non-SFHA areas. Appendix Figure D.4 illustrates this point. The top panel shows that most blocks (black solid lines) are perfectly contained in an SFHA. To further alleviate the concern, as I discussed earlier, I subtract the block diameter when calculating the distance between a block and the nearest SFHA border.

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 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 that takes 1 if a geographic unit m in stack d has above median fraction of the SFHA area, which proxies for the proportion of households affected by the disclosure policy. α_3 estimates the differential impact of the disclosure policy for the high-intensity geographic units in comparison to the 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 control and exploit the policy implementation timing among the ever-treated states.

To construct the stacked data, I first keep each state's flood insurance policy counts for 15 years around the disclosure policy change timing to maintain the composition constant in event time.[25] 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 $\tilde{d} > d$.[26] I drop observations from the control states for $t >= \tilde{d}$ because it is no longer "not-yet-treated".

In equation (2), Y_{mstd} indicates various outcome variables, such as the probability of having a positive number of flood insurance policies per housing unit and log of flood insurance policy counts per housing unit conditional on having non-zero policies in community m in state s at time t in stack d, and median income, the proportion of senior citizens, college graduates, and black population in tract m in state s at time t in stack d. 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.

It is worth discussing one additional detail about the tract-level analysis. Because the decennial census is documented once every 10 years, the states that have 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.[27] 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, 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).

[25] The community-level flood insurance policy data covers 1978–2008. While this dataset provides a sufficient time window to analyze a 15-year time frame around a policy change for most states (seven years in the pre/post disclosure periods), for one state that implemented the policy in 2003 (LA), there are 6 years of post period.

[26] 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 $d < 1996$.

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

4.2 Findings

Self-protection. In Table 4.1 column (1), I report the disclosure policy's extensive margin effect, namely the probability of having a non-zero population. 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% from the baseline of 0.68) for the blocks within the optimal bandwidth. 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 an intensive margin effect. The result shows that the disclosure policy reduces the population in blocks located within the SFHA by 7%. Taking results in columns (1) and (2) together, the policy seems to have the potential to discourage 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.[28] I find that the disclosure policy increases the vacancy rate in the SFHA area from 0.095 to 0.109, which reflects 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.[29] Results in columns (1)-(3) resonate with earlier studies which have found 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).[30]

To further explore the implication of the change in population distribution, I investigate the spatial characteristics of alternative houses home buyers seem to choose—namely, whether home buyers choose a house with meaningfully lower flood risk. For instance, if buyers choose a property on the non-SFHA side but still close to the border, which has effectively non-distinguishable flood risk, the risk exposure would remain identical even after the disclosure policy. If such a highly localized adjustment is prevalent, the effect size from columns (1)-(3) of Table 4.1 is likely to overestimate the true effect of the disclosure policy. In Appendix Table D.2, I repeat the same exercise in columns

[28] 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).

[29] 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).

[30] 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.

Table 4.1: Effect of Discosure Requirement on Household Responses

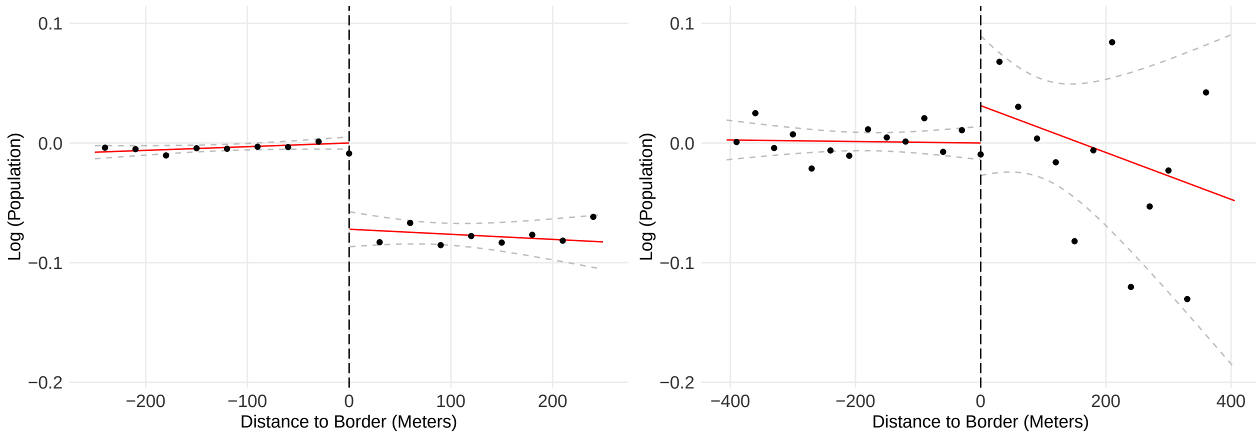
	(1)	(2)	(3)	(4)	(5)
SFHA × Post	$-.011^{***}$	$-.072^{**}$	$.014^{***}$		
	(.003)	(.034)	(.005)		
High Risk × Disclosure × Post				$-.001$	$-.009$
				(.006)	(.008)
D.V	Prob. of Non-zero Population	Log Population	Vacancy Rate	Prob. of Non-zero Insurance	Log Insurance Per Housing Unit
Avg D.V.	0.674		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.

(1)-(3) after removing blocks that are within 20 and 40 meters from the border, respectively. The estimates suggest that the magnitude (as well as the direction) of the effect is very similar to Table 4.1. Similarly, Appendix Figure D.6 shows that there is no diminishing policy effect as I expand the bandwidth, which together suggests that the disclosure policy seems to significantly reduce flood exposure.

In Figure 4.1 (a), I present a diff-in-disc plot, namely the difference of spatial RD estimates before and after the disclosure policy for blocks within the optimal bandwidth. In this plot, the difference in logged population is normalized such that $\Delta Y^- = 0$. Thus, the effect at the border, which is a 7% 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 area is wider than the non-SFHA area, which is not surprising given the difference in the number of observations (Appendix Figure D.5), it is still tight enough to statistically significantly identify the 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. Specifically, median income in the above median SFHA tracts drops by 3% in comparison to below median SFHA tracts after the disclosure requirement. The finding coincides with Bakkensen and Ma (2020) in the sense that those with more resources tend to choose a safer place to live. Also, the proportion of senior people (age above 65) is decreasing by 6%. Reduc-



(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.

tion in the older population is also plausible given that they have less physical capacity to cope with potential flooding (i.e., flood is costlier for them).

One potential concern for 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 SFHA and non-SFHA, if there is a concurrent policy change at the border, it could bias the results. One such policy could be the mandatory flood insurance requirement which changed in 1994. As discussed in Section 2.1, it is mandatory for home buyers to purchase flood insurance when the property is located within the SFHA and they rely on federally-backed mortgages. While it has been widely documented that the compliance for this policy was far from perfect, it could still raise a concern as the policy change timing coincides with disclosure policy timing for early-treated states.[31]

To check the robustness, I use five placebo states that have implemented a disclosure policy but without a question on flood risk. If confounding policy change effects dominate, we should find a similar effect as columns (1)-(3) in Table 4.1. In Appendix Table D.1, I do not find a reduction in population or increase in vacancy rate from these states. If anything, they are either tightly esti-

[31]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.

mated null effect (for the extensive margin population effect and vacancy rate) or positive effect (for the intensive margin population effect). 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 for the blocks in the optimal bandwidth. If anything, the point estimate is positive.[32]

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 limitation does not allow a convincing analysis, 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% 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 blocks, where on average 27% of them in my sample have zero population, 19% of communities in my sample have zero flood insurance policies at a given year. Similar to the empirical exercise on population, 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, where the distance to the SFHA border is not well defined, I leverage the staggered adoption of the disclosure policy to study its impact on insurance purchases. In particular, I split communities into the high versus low SFHA communities (by fraction of the SFHA area out of the entire community area) to capture the difference in the intensity of treatment.[33]

Column (4) shows that disclosure policy reduces the probability of having a positive flood insurance policy per housing unit for high-risk communities by 0.001 (or 0.1% from the baseline of

[32]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.

[33]While columns (4) and (5) report coefficients of the High Risk $\times$ Disclosure $\times$ Post term only, I include a full set of interaction terms in the estimating equation.

0.83). Similarly, column (5) suggests that the intensive margin effect of the disclosure policy is -0.9%. Given tight standard errors, it seems that home buyers do not seem to respond to the disclosure policy by purchasing flood insurance.

Why do home buyers engage in self-protection although they have an option to buy flood insurance? One explanation could be that non-insurable cost is large in this setting. The 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 even 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.

A damage function has 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 outcomes.[34] However, relatively little attention has been given to a *flood* damage function despite severe disruptions caused by floods, partly because objective measurement of flood size is challenging.

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

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 the damage data used in this paper captures damage on 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 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 potential 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-year has only one flood. Appendix Figure A.3 (c) shows that conditional on flood occurrence, 2/3 of community-year have only one flood. Further, when we restrict attention to the flood of size over 10 that incurs disproportionately large damage, over 90% of community-year have only one such incident (Appendix Figure A.3 (d)).

Second, I focus on flood size 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 of size over 50 under the non-parametric approach is challenging. Also, flood size ranging from 1 to 50 is wide enough to capture floods of different severity levels including minor, moderate, and major (See Appendix Table A.2 and accompanying text for more details).

Lastly, the key assumption in the binning decision for F^k is that the damage per housing unit remains constant within each bin. While flood sizes of 41 and 49, for instance, 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 flood 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 a flood size of k as opposed to the baseline flood. I also allow 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) shows how equation (3) would change. I is an indicator variable for the post period where 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). As discussed in detail in Section 3.2, the distribution of flood damage has substantial skewness (long and thin right tails) and a point mass at zero. To account for a distinctive data generating process, I follow Chen and Roth (2022) and estimate extensive and intensive margin effects separately, which resonates with a two-part model that is widely used to model health expenditures (Mullahy and Norton 2022). That is, Y_{mtd} in equation (5) are either $P(\text{Per Housing Unit Damage} > 0)$ or log of the per housing unit damage conditional on having positive damage at the community level. While I report results from both models, I focus more on the extensive margin effect. This choice is driven by its greater generalizability—reflecting the fact that only a small fraction of communities experience more than one instance of non-zero damage per year in my panel data—and its enhanced 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 (as opposed to DDD) to make the estimating equation tractable, which effectively ignores treatment intensity differences. However, I separately estimate the policy effect for communities with different ratios of SFHA to show that the effect is indeed driven by the disclosure policy.

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

Equation (5) also includes year × stack (ω_{td}) and community × 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. To account for the correlation in flood occurrence and damage both in space and time, I estimate spatial-HAC standard errors for inference with a cutoff distance of 500 miles (Newey and West 1987, Conley 1999).[35] 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.[36] A large number of engineering studies have developed a damage function or a "depth-damage function". As its name suggests, the measure of flood size in these studies is water depth for an individual property (Meyer et al. 2013). While useful for predicting property-level flood damage, this approach has a few limitations in understanding aggregate (e.g., community) level flood damage.[37]

First, by focusing on an individual property, it does not directly take into account the fact that a larger flood not only makes water depth deeper for a given structure but also increases the number of affected properties. Second, to learn flood damage at an aggregate level using the depth-damage function, a detailed hydraulic study, which translates weather events into the inundation level for each property, is required (Scawthorn et al. 2006). However, as detailed hydraulic studies are costly, many communities have drawn their flood map without such studies (FEMA 2005, Weill 2021). Even the existing ones are oftentimes outdated because map update is costly (Bakkensen and Ma 2020). As such, accurate inundation data are often not available for most areas and are highly susceptible to measurement errors (Freni et al. 2010). Third, and presumably most importantly, these studies could over or underestimate the actual flood damage because it has limitations in considering property-level adaptations. In principle, this issue can be resolved by (1) modeling how each defensive measure (or the "resistance parameter" as it is called in the engineering literature) such as property elevation or using waterproofing building materials would affect damage and (2) collect individual property level data on defensive measures within the jurisdiction of interest. However, this

[35] Weights in this matrix are uniform up to that cutoff distance.

[36] For an overview of the approach taken by the USACE, see National Research Council (2000); USACE (1992).

[37] A few studies have questioned the reliability of existing depth-damage function even for individual property level damage estimation. For instance, see Wing et al. (2020).

is unrealistic given the state of the modeling techniques and data requirements.[38] These are major drawbacks 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 easily applied to places that do not have hydraulic studies. Also, as the approach measures flood damage at the community level, it reflects damage not only due to a higher water depth for a given property but also due to the number of affected properties. Finally, the monetary damage measure, which reflects damage incurred on structures and contents, has incorporated the effect of potential adaptations and thus is closer to the damage that has actually accrued.

5.2 Change in Damage Function from the Disclosure Requirement

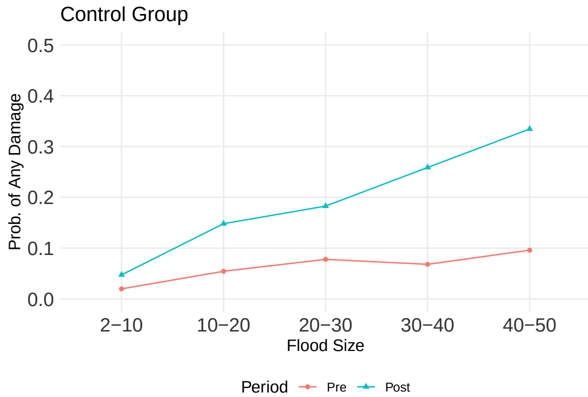
Figure 5.1 (a) and (b) show the damage functions for the control (panel (a)) and treatment (panel (b)) groups for before (red line) and after (blue line) the treatment.[39] Specifically, each line is plotted using the estimated coefficients from equation (5): for instance, the line for the control group 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% (panel (a)) and 20% (panel (b)) higher chances of having any damage per housing unit in comparison to the baseline floods.

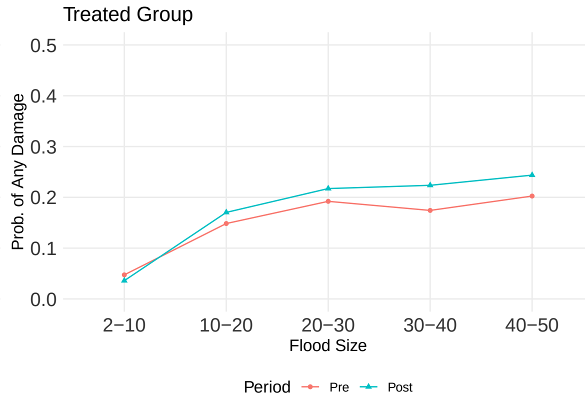
It is also worth mentioning that panels (a)-(b) mask the heterogeneity in the damage function.

[38] 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.

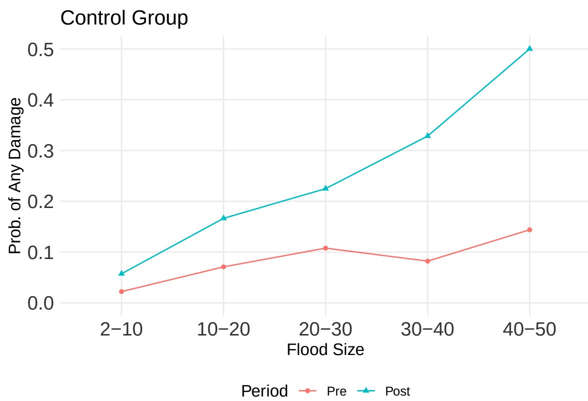
[39] Appendix Figure D.10 reproduces Figure 5.1 with a 95% confidence interval.



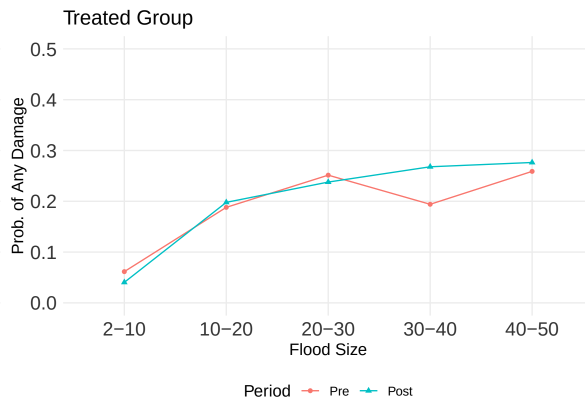
(a) Control Group (All Communities)



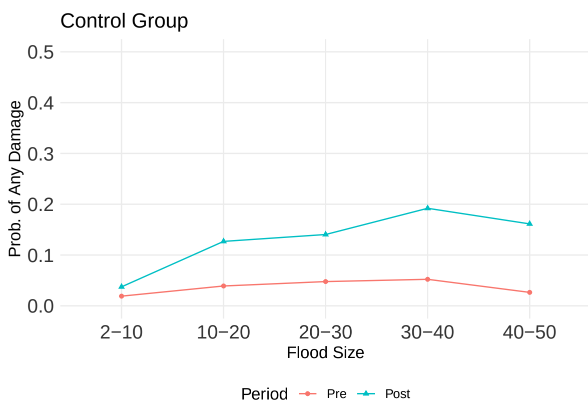
(b) Treatment Group (All Communities)



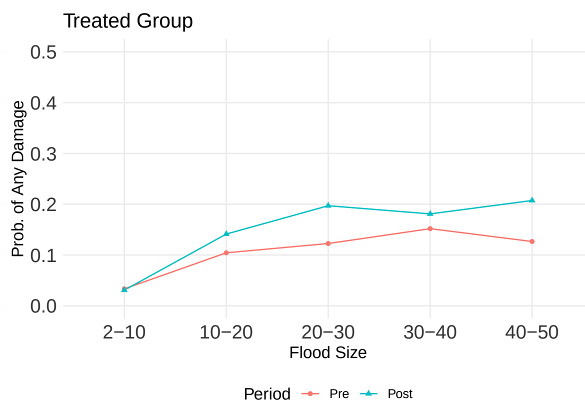
(c) Control Group (High Risk Communities)



(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.10 reproduces Figure 5.1 with corresponding 95% confidence intervals.

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 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.[40] 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

[40]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.

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), I report that the disclosure policy reduces the expected probability of having positive flood damage at a community level by 2.5% 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%), the effect size is a 33% 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% in comparison to 1.3% 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% and 1.3% translate into 37.5% and 25% 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.[41]

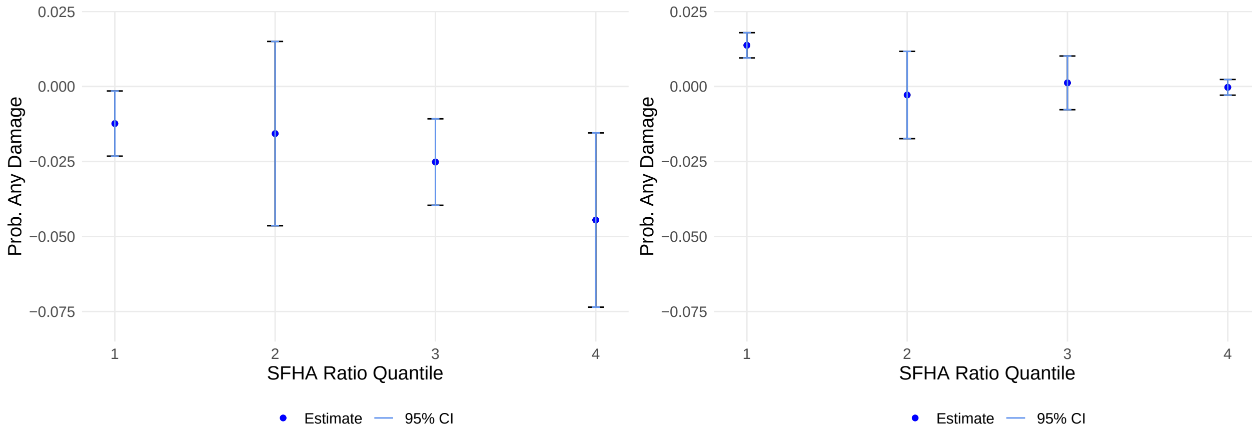
In column (4), I investigate the intensive margin effect. Specifically, I estimate a version of equation (5) that has log transformed per housing unit damage as an outcome variable. As the sample for this exercise is restricted to a community-year with positive damage, the model does not have the power 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),

[41] 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.11, 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% or a 33% reduction from the average probability. These results resonate with recent studies on flood-driven relocation. For instance, using managed retreat projects in the Midwest, Pinter and Rees (2021) shows that the population and housing prices in the affected areas have shrunk, while avoided flood losses are at least 4.3% of pre-retreat values.

The findings of this paper suggest the disclosure policy is an effective flood risk management tool. By alleviating information frictions, it makes home buyers heed flood costs, which in turn facilitates voluntary adaptation (Anderson et al. 2019). The policy yields a double dividend for the government because it can not only save money on flood prevention infrastructure but also reduce post-disaster recovery spending. Also, it is fairer given that a disproportionately large amount of resources are devoted to protecting and relieving people living near water—who tend to be more affluent (GAO 2013). Further, the disclosure policy could contribute to the stability of the housing market and the financial system by preventing home buyers from being overly optimistic about the future housing market and climate exposure (Bakkensen and Barrage 2021).

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A Appendix A: Flood History Data

A.1 Background and Construction Procedure

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).[42]

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% probability in a given year. Alternatively, such an event

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

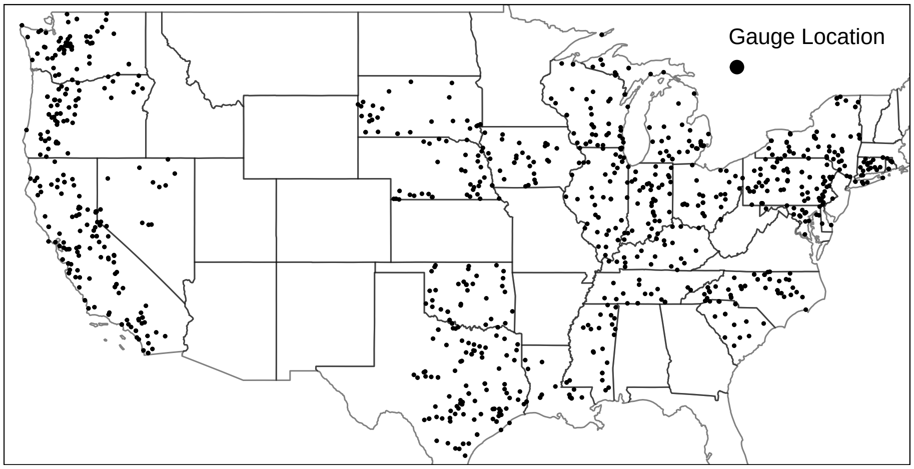


Figure A.1: The Distribution of a Sample of USGS/NOAA Gauges

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.[43] Table A.1 compares the number of stations that have records for at least 80% 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).[44] 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.[45]

[43]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).

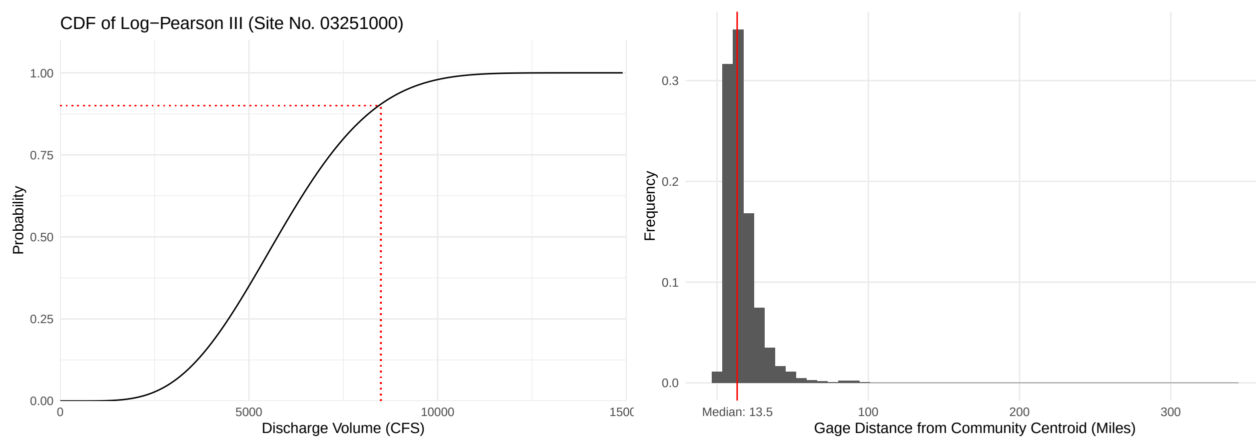
[44]I also did conversion following Sangal (1983), but the error between actual and the estimated IPF was much smaller with Fuller (1913).

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

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

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% 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).

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).

Unified Flash Flood Database

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.[46] 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.

A.2 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.

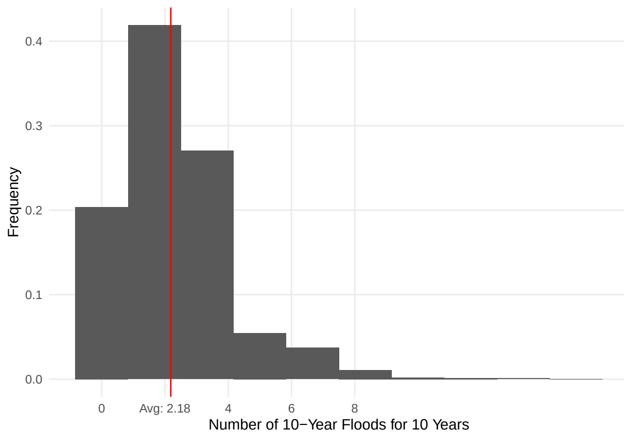
Figure A.3 (b) shows the distribution of flood event size (i.e., recurrence interval), where flood size is truncated at 100 for readability. Note the frequency of low-intensity events dominates the entire distribution. This fact is well-documented in the literature. Jackson (2013) reads "the magnitude 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% 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% of the community-year pairs have only one event.

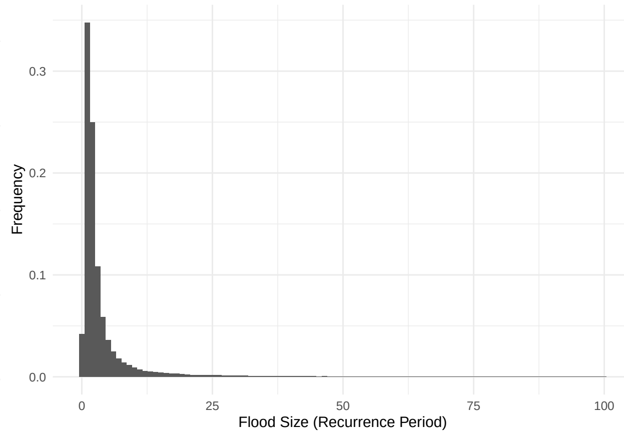
One shortcoming of the estimated coefficient is that it is hard to contextualize it. Namely, how should we think about the magnitude of each flood size (e.g., 10-year flood)? Comparing the estimated flood thresholds with the NWS thresholds can be a useful exercise to this end, because the NWS has defined water stages corresponding to minor, moderate, and major flooding for 3,490 stream gauge locations across the US (Gourley et al. 2013).[47] Specifically, I estimate equation (8) to

[46] 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).

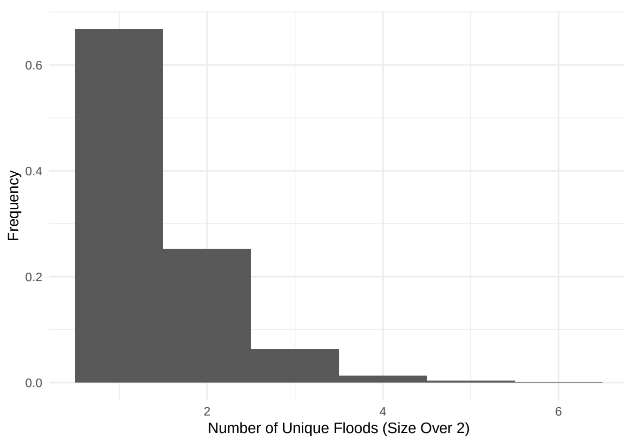
[47] NWS defines each flood category as the following (National Weather Service 2019). Minor: minimal or no property damage, but possibly some public threat (e.g., inundation of roads). Moderate: some inundation of structures and



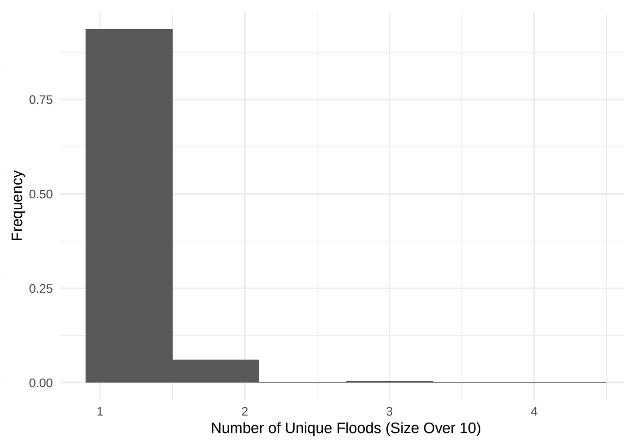
(a) Distribution of N of 10-Year Floods over 10 Years



(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.

connect the thresholds in number to (rough) severity.

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 $j \in \{\text{minor, moderate, major}\}$. 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.

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.

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).[48] 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.[49]

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 × Time × Stack, λ_{mtd}: Community × Time × Stack, and θ_{mjhld}: Community × SFHA × Building Age × Number of Beds × 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.

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

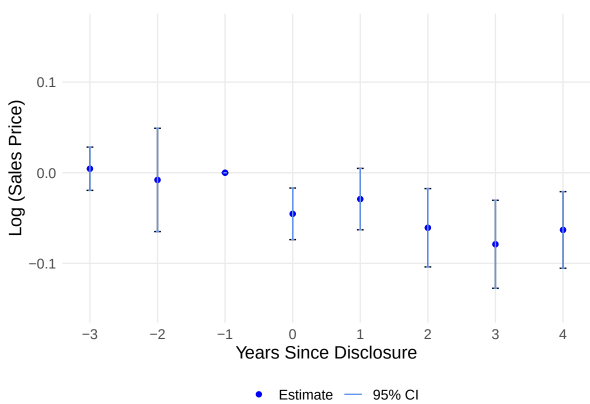
	(1)	(2)
SFHA × Disclosure × Post	$-.045^{***}$	$-.046^{**}$
	(.015)	(.018)
Sample	Entire Communities	No-Revision Communities
Stack × Community × Year FE	X	X
Stack × Community × Year FE	X	X
Stack × Community × SFHA × Year Built × N Beds FE	X	X
Num. obs.	6249070	5931016

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.

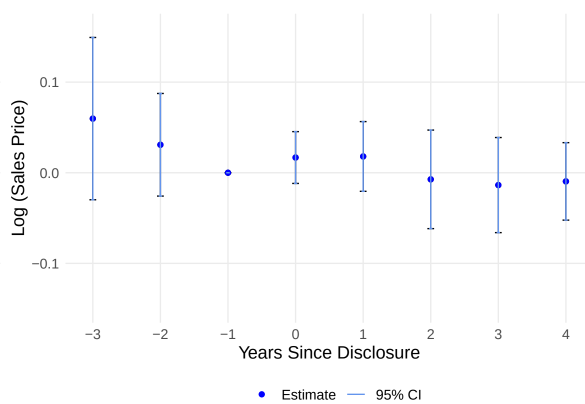
[48] I thank Eyal Frank for his generous help with data access.

[49] 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.

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% 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% 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 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%. 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% (average: 4.8%) 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.

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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.

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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 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.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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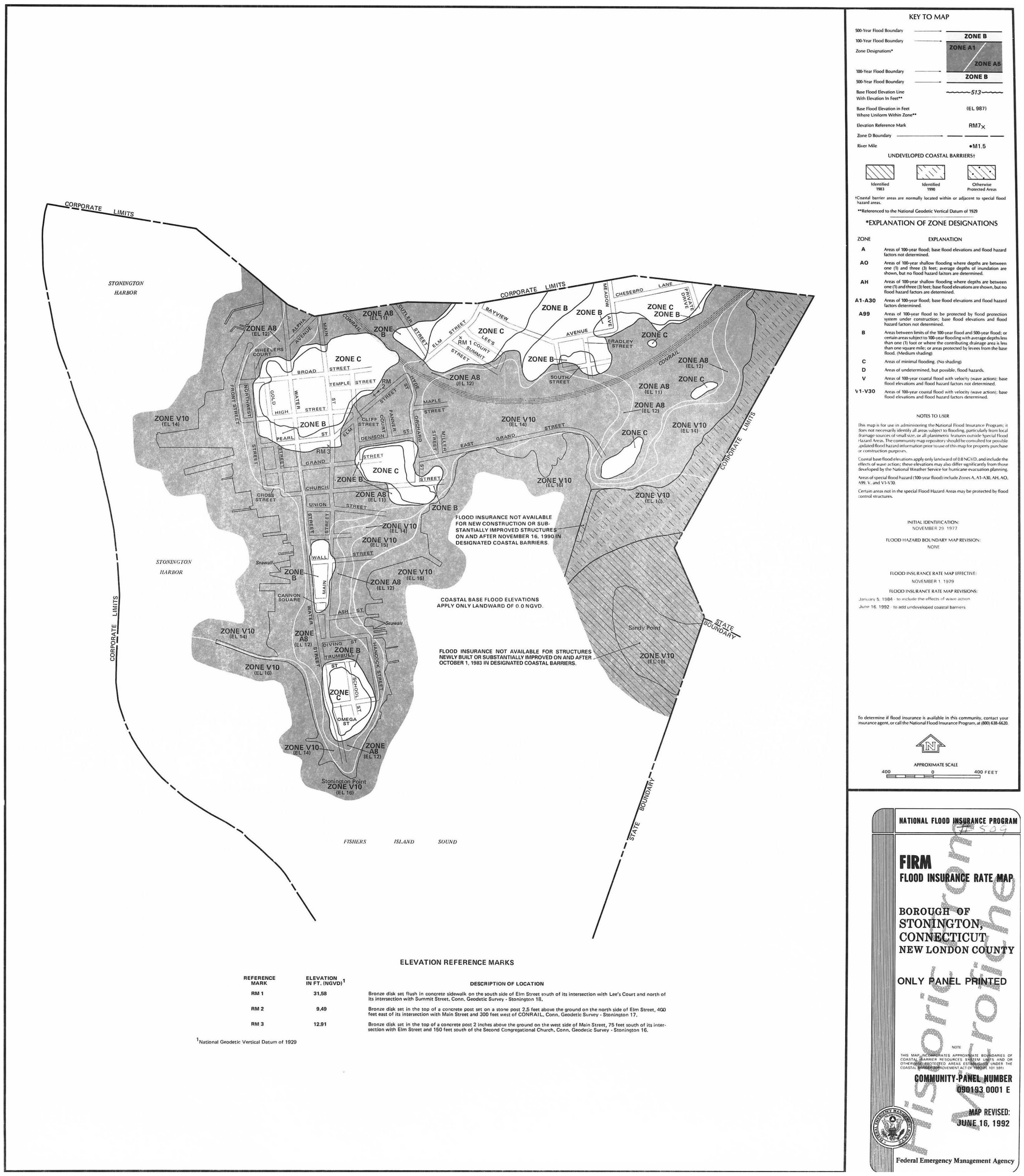

Figure D.2: Sample Flood Insurance Rate Map (Borough of Stonington, CT)

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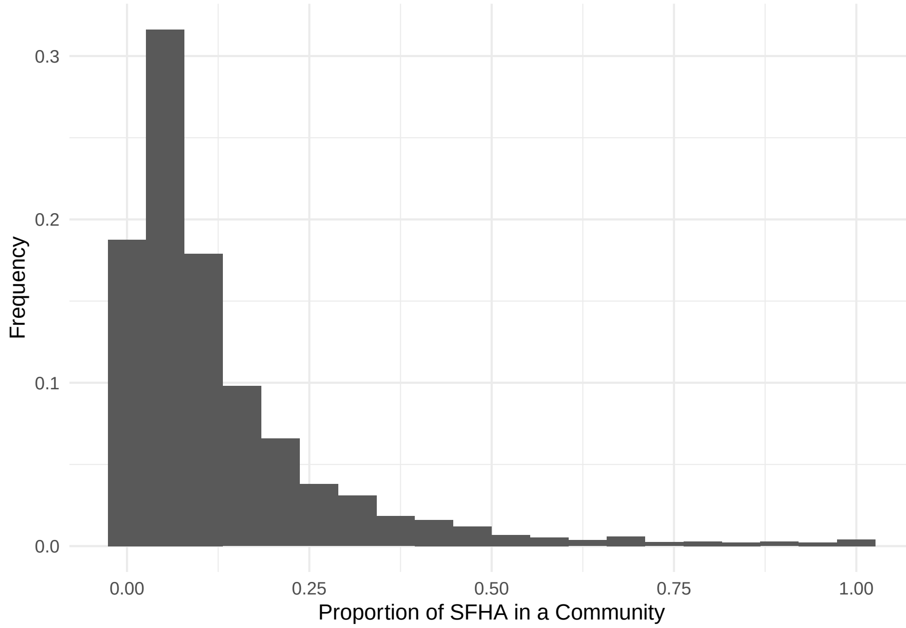
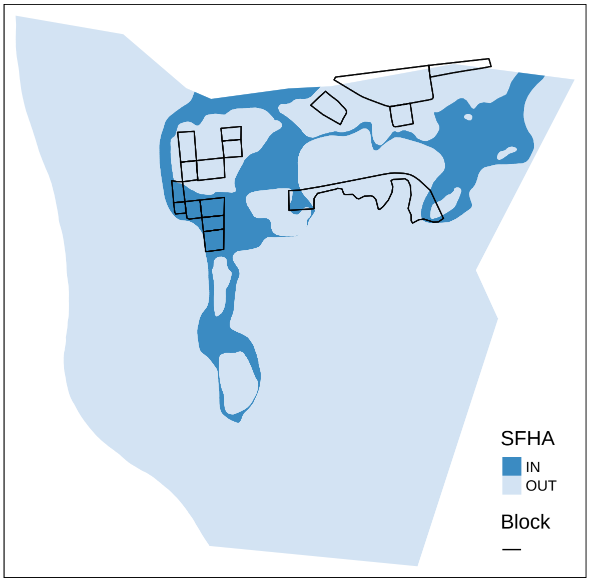
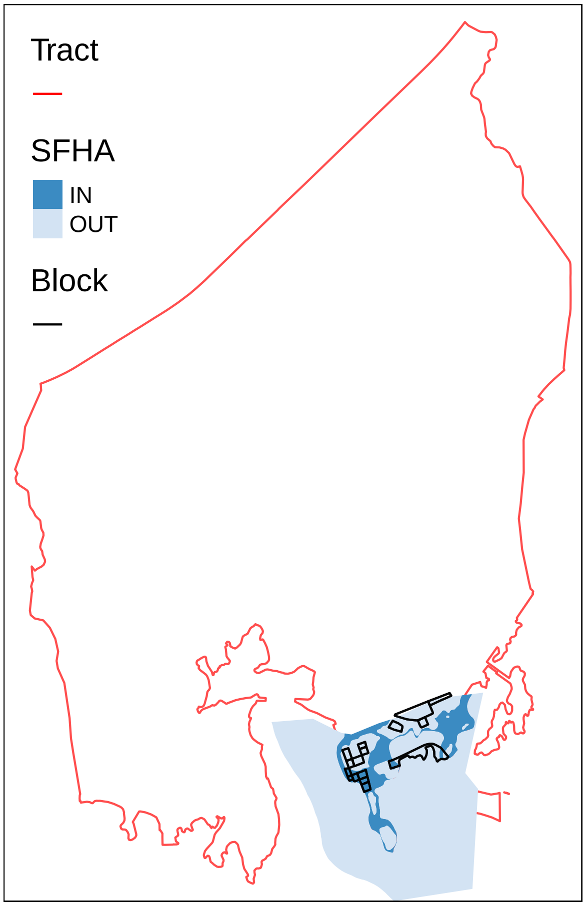


Figure D.3: Histogram of the Proportion of the SFHA at the Community Level. The plot shows the distribution of the SFHA ratio for the 8,194 communities that are on the Q3 map and in the 26 ever-disclosed states.

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)

Back to 4.1.

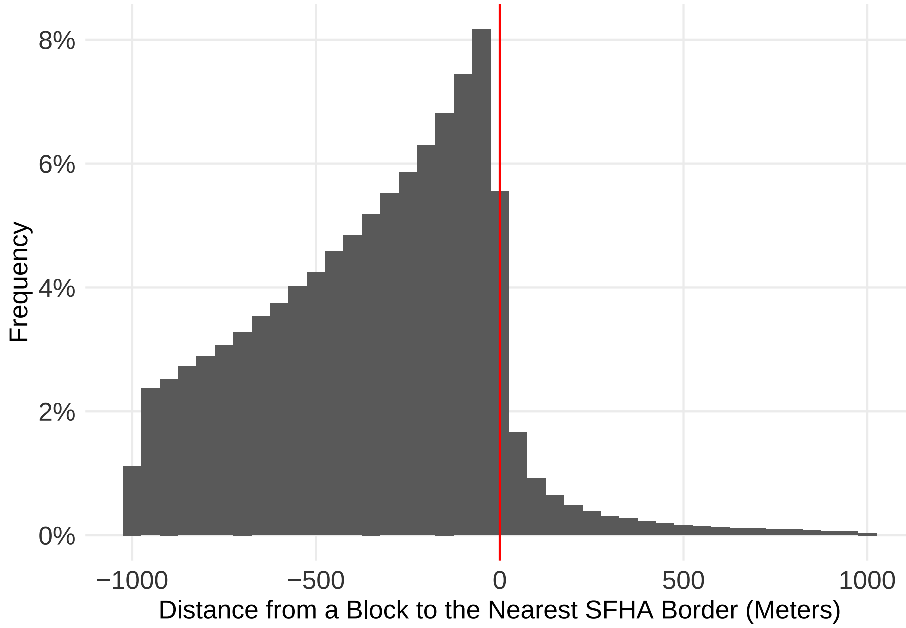
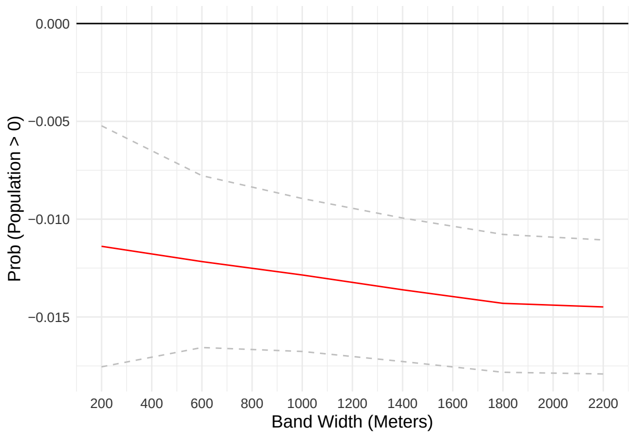
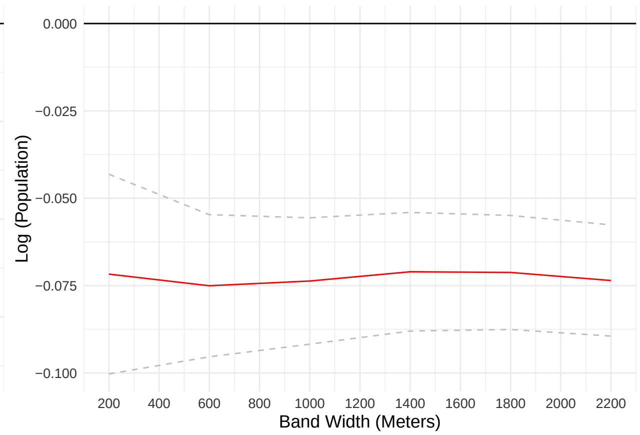


Figure D.5: Histogram of Running Variable (Distance to the SFHA Border)

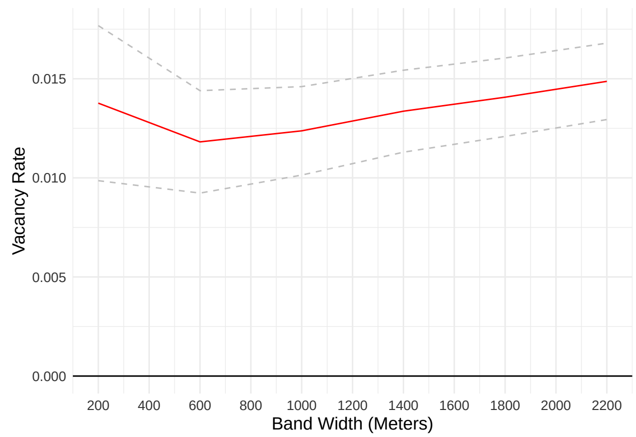
Back to 4.2.



(a) Prob. of Positive Population



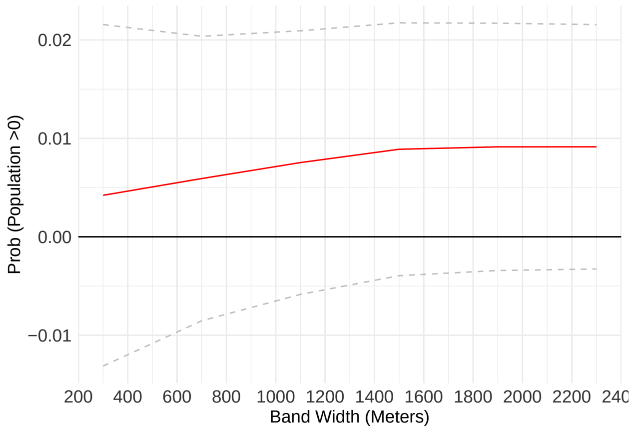
(b) Log Population



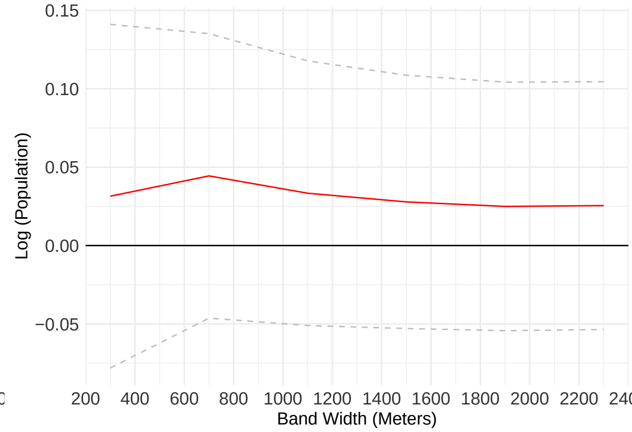
(c) Vacancy Rate

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

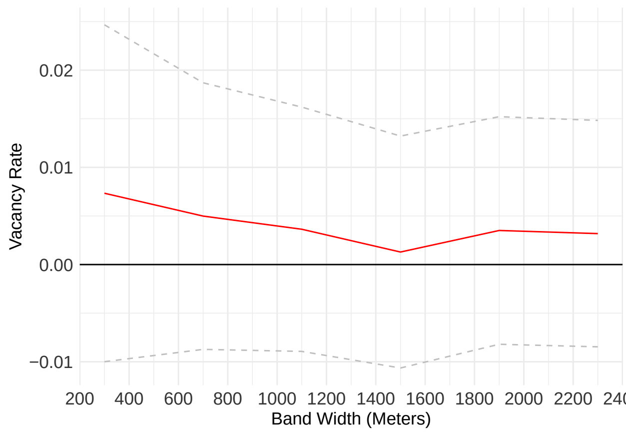
Back to 4.2.



(a) Prob. of Positive Population



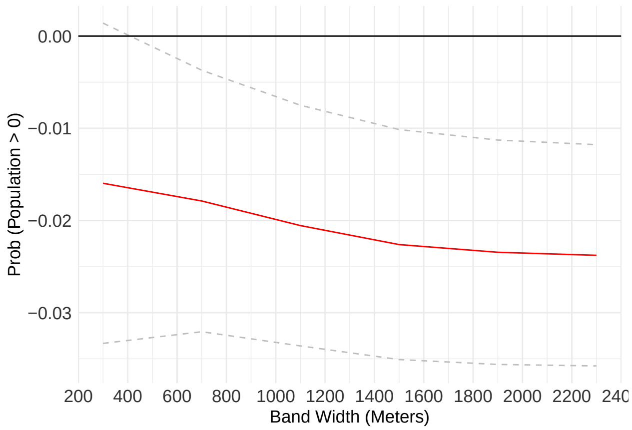
(b) Log Population



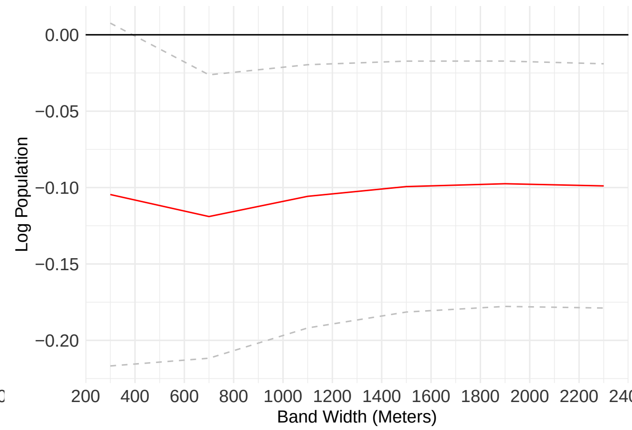
(c) Vacancy Rate

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.

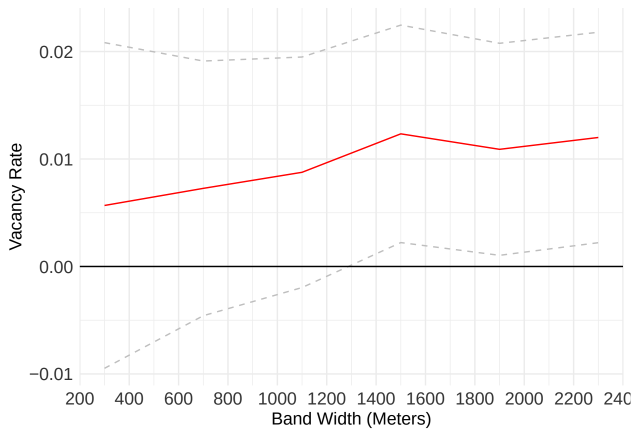
Back to 4.2.



(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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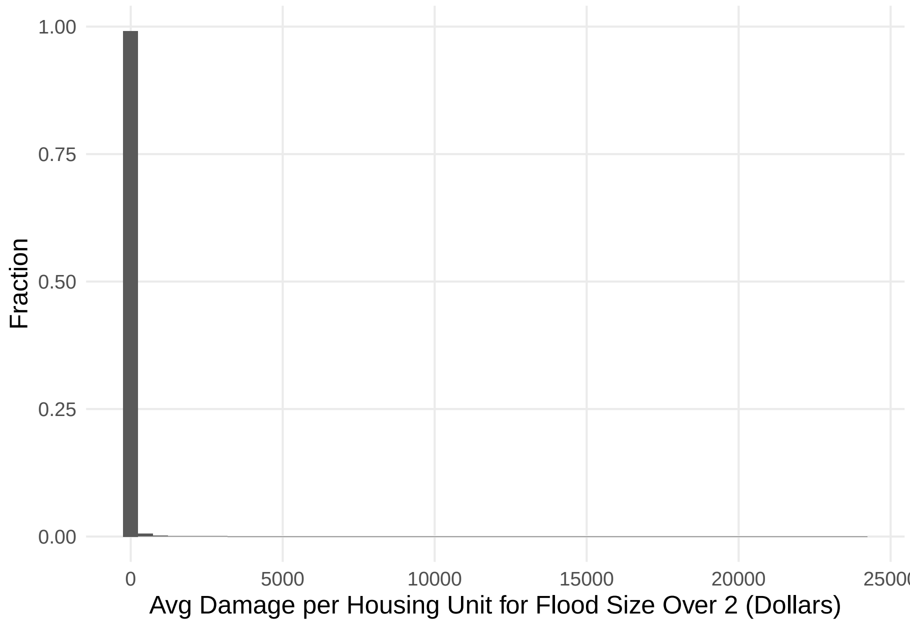
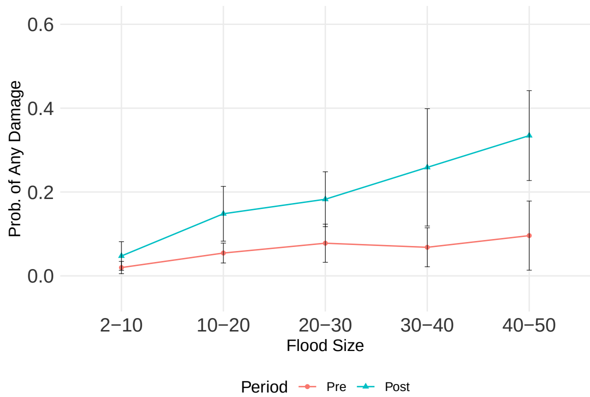
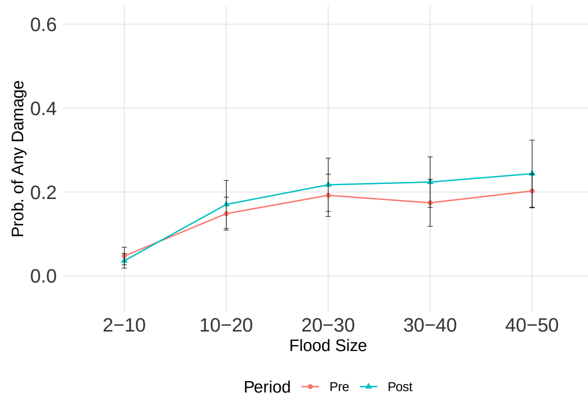


Figure D.9: The Distribution of Flood Damage (for communities with flood size 2 or larger). The plot shows the distribution of flood damage (per housing unit damage) for community-year pairs that are exposed to flood of size 2 or larger.

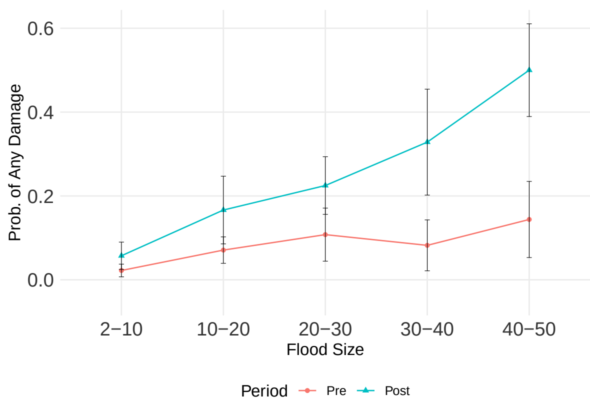
Back to 5.1.



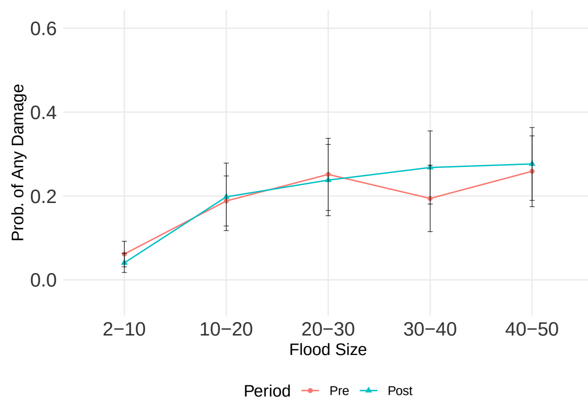
(a) Control Group (All Communities)



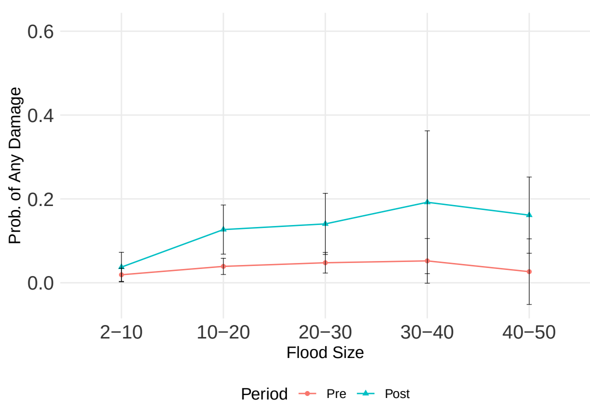
(b) Treatment Group (All Communities)



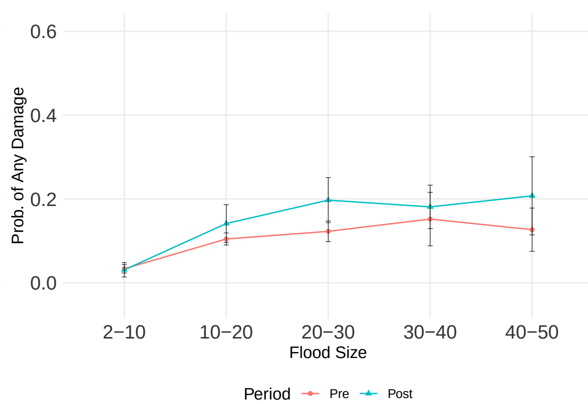
(c) Control Group (High Risk Communities)



(d) Treatment Group (High Risk Communities)



(e) Control Group (Low Risk Communities)



(f) Treatment Group (Low Risk Communities)

Figure D.10: 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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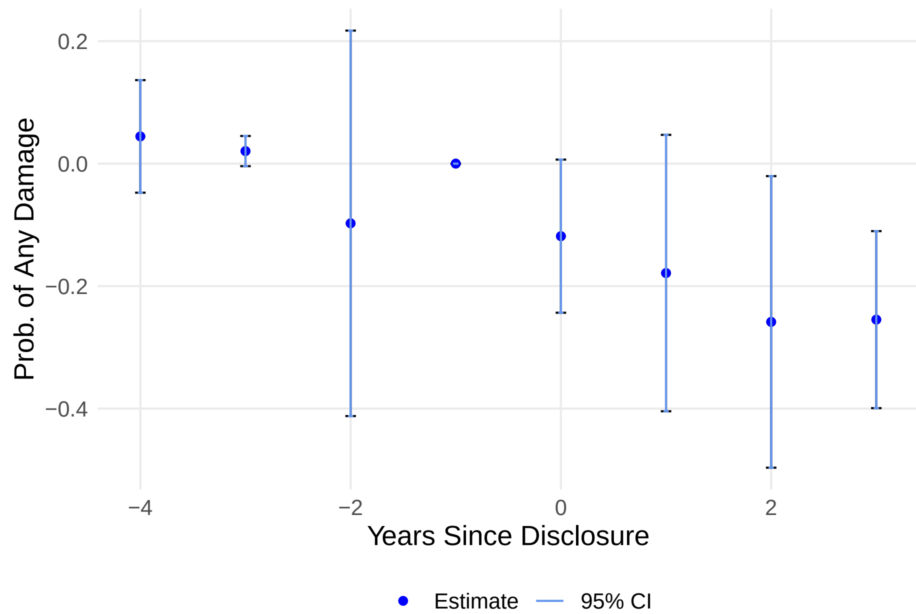

Figure D.11: The Effect of Disclosure on the Damage Function (Event Study). This figure depicts $\hat{\beta}_{4,t}^{30-50}$ for flood size of 30-50 in event time t. The error bar represents the 95% confidence interval. See text for more details.

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