Adaptation to Natural Disasters by Better Information: Evidence from the Home Seller Disclosure Requirement

Seunghoon Lee*

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Abstract

Flood damage is determined by flood intensity and exposure, but the US flood policy has focused on controlling the former with little success. This paper studies if easing information friction in the housing market regarding flood could reduce the risk exposure and thus flood damage. By exploiting the staggered adoption of the Home Seller Disclosure Requirement, I first show this policy reduces property price by 4% and increases vacancy rate by 2%p in high-risk areas, respectively. Further, using a hydrological measure of flood intensity, I find that the policy reduces per capita damage from small-to-moderate-sized floods by at least 6%.

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1 Introduction

Since 1980, floods in the United States have damaged over $1 trillion, making it 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 the exposure (i.e., the number of households 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 (so-called "levee-effect") by creating a false sense of security, which paradoxically increases a society's exposure to flood risk (Pinter 2005, Collenteur et al. 2015).[1] When those engineering structures fail, either due to extreme weather conditions or improper maintenance, flood damage could become even larger than before (Pinter et al. 2016).[2] 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).

This paper studies if 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.[3] Such low awareness hinders home buyers from fully internalizing the flood risk during the real estate transaction, and thus making them consume more than the optimal level of flood risk. Given that a 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

[1] Other shortcomings include (1) spillover of flood in other areas, (2) environmental degradation of the affected areas, (3) the risk of even larger damage when a flood of size exceeding the protection level comes (FEMA 2005).

[2] 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. For instance, Pinter et al. (2016) find that only 1.9% of the levees in the US are rated "Acceptable."

[3] A group of studies has shown the price of properties located in the high flood risk area drops substantially when the perceived level of flood risk increases (Hallstrom and Smith 2005, Bin and Landry 2013, Muller and Hopkins 2019).

alleviate the problem by efficiently delivering risk information embedded in the official flood map.[4] The policy mandates that home sellers must disclose any known property defects using a standardized form (Lefcoe 2004). These forms comprise simple, easy-to-understand checkbox questions that home sellers can answer with a yes-or-no answer. About flood risk, a typical form asks whether a property is located in the Special Flood Hazard Area (SFHA)–an area with higher flood risk defined by the official flood map. Home sellers are generally required to deliver the disclosure to the home buyers before closing on the property (Stern 2005).

The disclosure requirement is a compelling setting for evaluating the effect of providing more information on flood risk to home buyers for two reasons. First, the policy rolled out across 27 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 implement a triple difference design by interacting it with the staggered adoption timing. Importantly, I build on Cengiz et al. (2019) and Brot-Goldberg et al. (2020) and use the stacked DDD approach to overcome potential bias from conventional fixed effect models (Goodman-Bacon 2018). Second, because the disclosure form asks about flood risk status in a binary manner, home buyers would receive starkly different flood risk information for two different properties on opposite sides of an SFHA border even if the actual risk profiles are similar. 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 treatment such as mandatory flood insurance purchase as well. To account for that possibility, I use the difference-in-discontinuity approach following Grembi et al. (2016).

To leverage these variations, I collect and construct a wide range of data on flood damage and its determinants. To explore household responses and housing price change as a result of the disclosure policy, I collect data on individual property transactions and community-level National Flood Insurance Program (hereafter "flood insurance") policy counts, as well as census tract-level demographic data. To measure flood damage, I collect damage records, which are based on the replacement cost net of any depreciation, from the flood insurance adjuster's report. In addition, I construct an objec-

[4] Learning how to read the flood map is a non-trivial task that requires both physical and cognitive effort. Also, people had to make a time-consuming trip to local map repositories, especially in the 1990s.

tive measure of past flood events for each community by conducting flood frequency analysis using the USGS/NOAA gauge records (Saharia et al. 2017b, England Jr et al. 2019). The data overcomes a potential endogeneity problem embedded in the self-reported flood events data, as is the case with the National Weather Service Storm Events data (Gall et al. 2009).

Empirical exercises produce three key results. First, I find that the disclosure policy reduces the price of the properties in the SFHA by 4% in comparison to the non-SFHA properties. At the pre-disclosure average price of the properties located in the SFHA, the reduction in housing price amounts to $13,151 in 2020 dollars. Further, the difference-in-discontinuity analysis that credibly singles out the effect of flood risk information also shows that the price of the affected properties declines. The set of results provide a first pass at the effectiveness of the disclosure policy on flood risk information delivery and its impact on buyers' flood perception.

Second, the disclosure policy increases the vacancy rate by 2%p (or 20%) while reducing the number of households by 3.7%–though statistically insignificant at the conventional level–in the high-risk area relative to the low-risk areas, respectively. I also find suggestive evidence of a moderate increase in the flood insurance take up. Investigating household responses is important because they have different implications for flood damage. Choosing a safer location unambiguously reduces the exposure to flood risk and thus flood damage, but subsidized flood insurance could distort such location adjustment by incentivizing households to take more risk (Peralta and Scott 2020). A substantial increase in the vacancy rate in the high-risk area suggests that the disclosure policy can potentially curb flood damage. It is also worth pointing out that the median income in the risky area declines by 6% after the disclosure policy, implying that the burden of flood risk is bourn disproportionately by poorer households (Bakkensen and Ma 2019).

Third, the disclosure policy reduces the expected annual per capita damage from small-to-moderate-sized floods by at least 6%. To show this, I estimate the change in the damage function as a result of the disclosure policy. Importantly, I take a non-parametric approach to prevent functional form assumptions determine the relationship between flood size and damage. Policy effect comes from a combination of a reduction in the number of damaged properties and also a smaller average damage amount per damaged property, which corroborates a higher vacancy rate. When multiplied with the pre-disclosure average per capita flood damage of $3.78, and the total population of 2020 (330 million), the 6% reduction in per capita damage translates into a $74 million expected reduction in damage from small-to-moderate-sized floods each year.

This paper contributes to three bodies of literature. First, this paper builds on numerous earlier works that have studied the economic impact of flood risk information (Hallstrom and Smith 2005, Pope 2008, Bin and Landry 2013, Muller and Hopkins 2019, Hino and Burke 2020). While most of these studies focused on the capitalization of flood risk information into housing prices, I trace the impact of information up to household responses and resulting flood damage change. This is important because while a reduction in the price of the high-risk houses is a transfer between home buyers and sellers, a reduction in flood damage enhances social welfare. To the best of my knowledge, this is the first paper to report evidence that providing more risk information leads to lower flood damage. It is also worth pointing out that the empirical exercise is enabled by novel data on flood history that I constructed building on a hydrological method.

Second, my work is related to the nascent literature on the economics of climate change adaptation. Whereas earlier works primarily focused on technology as a determinant of adaptation, I focus on the role of information that facilitates the alignment of private incentives and socially desirable outcomes (Miao and Popp 2014, Barreca et al. 2016, Burke and Emerick 2016, Ortiz-Bobea and Tack 2018). This finding indicates that a policy that encourages information flow can be a powerful adaptation tool. Besides, it also has practical importance as information provision policies are getting more attention as a potential flood risk management policy tool.[5]

Lastly, this paper contributes to the literature on disclosure mandate policies. Earlier works have found that information affects school quality, restaurant hygiene, calorie intake, and energy efficiency (Jin and Leslie 2003, Figlio and Lucas 2004, Bollinger et al. 2011, Myers et al. 2019). However, these results are not directly transferable to the natural disaster setting, because key parameters of the disclosure policy effectiveness, such as the accuracy or comprehensibility of information are different. The findings of this paper also have policy implications for managing other environmental risks such as wildfire or earthquake.

The paper proceeds as follows. Section 2 describes households' location choice problem with an option to purchase flood insurance after the disclosure requirement and its implications for housing

[5] After a series of devastating floods in recent years, both federal and state governments work toward strengthening the disclosure of flood risk. For instance, the House of Representatives passed a bill ("21st Century Flood Reform Act") that made the disclosure on 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).

price and flood damage. Section 3 provides background on the Home Seller Disclosure Requirement policy and the Special Flood Hazard Area. Section 4 details the data sources and provides some summary statistics. Section 5 lays out the empirical strategy. Section 6 presents estimation results on housing price changes and household responses while Section 7 shows the disclosure policy effect on flood damage. Section 8 discusses the results, while Section 9 concludes.

2 Conceptual Framework

In this section, I describe a spatial equilibrium in the presence of unaware flood risk following Banzhaf and Walsh (2008) to help guide the empirical analysis.[6] Suppose households' indirect utility function V is defined as $V = V(y, g, p)$, where y is income, g is an index of the amenity level in a community including flood risk, and p is the housing price.[7] Following the literature, I assume household preferences satisfy the "single-crossing" property, which means the indifference curves in the (g, p) plane are strictly increasing in income. Households choose to live in one of two communities, indexed by $j \in \{1, 2\}$.

The single-crossing property implies the equilibrium will exhibit three characteristics (Epple and Platt 1998). First, a household exists that will be indifferent between two communities ("boundary indifference"). Second, households are going to be perfectly stratified in terms of their income ("stratification"). In other words, households with income below the boundary income will prefer the lower-ordered community and vice versa. Third, the rank of communities by amenity must match the rank of the housing price ("ordered bundles").

Now, suppose community 1 is prone to flood risk and 2 is not, but without a disclosure policy, households cannot tell the difference. Also, without loss of generality, suppose the initial overall amenity level of community 2 is higher ($g_1 < g_2$), and thus $p_1 < p_2$. Household income is distributed following a distribution $f(y)$ with continuous support in $[y_L, y_H]$.The boundary indifference condition implies equation (1), where $\tilde{y}$ is the boundary income. For households with income level $\tilde{y}$, both communities yield the same level of utility $\bar{V}$. The boundary condition also determines the initial

[6] For more formal treatment including proofs, see Banzhaf and Walsh (2008).

[7] I abstracted away from the taste parameter for simplicity, but I could either introduce taste parameter α in addition to income y or replace y with α and derive the same result in terms of taste. Sieg et al. (2004), for instance, consider both income and taste, and Epple and Platt (1998) present a two dimensional stratification result.

population share. Specifically, $N_1 = \int_{y_L}^{\tilde{y}} f(y)dy$ and $N_2 = \int_{\tilde{y}}^{y_H} f(y)dy$.

$$V(\tilde{y}, g_1, p_1) = V(\tilde{y}, g_2, p_2) = \bar{V} \tag{1}$$

Suppose a home seller disclosure requirement is implemented and the flood risk is disclosed. In the model's context, the risk information can be interpreted as a negative shock in the level of amenity such that $g_1' < g_1$.[8] As a benchmark case, first suppose the flood insurance does not exist.

As $V' = V(\tilde{y}, g_1', p_1) < V(\tilde{y}, g_2, p_2) = \bar{V}$, home buyers with the boundary income are strictly better off by choosing community 2. In a new equilibrium, N_2 and p_2 will be higher, and $\tilde{y}$ will be lower than the initial equilibrium.

Now, let's introduce an option to purchase flood insurance and explore how it affects the equilibrium. First, it is convenient to introduce the monetized reduction in indirect utility due to the flood risk revelation. Using the equivalent variation, we can define the monetized reduction in utility due to the flood risk as F in the following expression: $V(\tilde{y} - F, g_1, p_1) = V(\tilde{y}, g_1', p_1)$. Further assume $F = f + h$, where f reflects the financial cost and h is the non-financial (e.g., hassle cost) cost. Alternatively, h can be seen as a combination of non-financial and financial costs that go beyond the maximum available coverage.[9]

Reflecting the subsidized premium structure of flood insurance, households can purchase flood insurance at premium $q < f$ and get fully insured for f. Note the insurance is still incomplete in the sense that households are still exposed to h. Importantly, with the insurance, equation (2) holds, and thus the magnitude of migration and housing price adjustment will be smaller than the benchmark (without insurance) case. The intuition is that the insurance is, in effect, a subsidy for living in community 1, reducing the utility gap between V' and V (Peralta and Scott 2020).

$$V' = V(\tilde{y}, g_1', p_1) = V(\tilde{y} - F, g_1, p_1) < V(\tilde{y} - (q + h), g_1, p_1) < V(\tilde{y}, g_2, p_2) = \bar{V} \tag{2}$$

A few additional observations are worth noting. First, p_1 is lower than the initial equilibrium after

[8] Gayer et al. (2000) show that when individuals overestimate health risk in the absence of information, information revelation could reduce the perceived level of risk. This suggests the disclosure requirement could be seen as a positive shock depending on the prior perception. However, earlier works (for review, see Beltrán et al. (2018)) on flood risk information consistently found a negative impact on housing price, which indicates the disclosure of flood risk could be treated as a negative shock.

[9] For instance, the National Flood Insurance Program covers up to $250,000 for a residential property.

the disclosure in both (with and without insurance) scenarios as long as the disclosure policy successfully increases flood risk awareness ($g_1' < g_1$). N_2, the share of households living in a community with no flood risk, is also higher than the initial level. Conversely, if the disclosure policy is ineffective either because people do not comply or because the information is hard to digest, the housing price will not change. Second, although both migration and insurance increase households' welfare, they could have starkly different implications for flood damage. To see this, observe that flood damage is the foregone stream of utility or rent as a result of flood and such opportunity cost will be smaller when the magnitude of the housing price adjustment for community 1 is larger. Consequently, if households respond to the disclosure policy primarily by purchasing more insurance and choosing to stay in community 1, the flood damage reduction effect will be limited. Third, households are more likely to choose to migrate when the premium subsidy $f - q$ is smaller and when the non-financial cost h is relatively larger than f. Lastly, some home buyers might choose to engage in self-protection investment such as sealing a building at cost c as long as $c \leq f$. This could either replace or supplement flood insurance.

3 Background

3.1 Home Seller Disclosure Requirement

A publicly available Flood Insurance Rate Map should allow home buyers to learn if a specific property belongs to the SFHA. Also, the Flood Insurance Reform Act of 1994 requires flood insurance as a condition for federally-backed mortgage approval, which should let affected home buyers learn about the 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 (Michel-Kerjan 2010).[10]

A statutory disclosure requirement could be a useful policy tool to fill this information gap. It mandates that home sellers provide buyers a detailed account of known material defects about the

[10] In a similar context, Bernstein et al. (2019) show consumer sophistication matters a lot in the capitalization of climate change risk. In particular, they found that sophisticated investors drive the sea level rise exposure discount. Rich anecdotal evidence exists of ill-informed home buyers as well. For instance, see Flavelle (2017) and Satija et al. (2017). Finally, Michel-Kerjan (2010) find only 20%-30% of home owners in the SFHA purchased flood insurance in 2000.

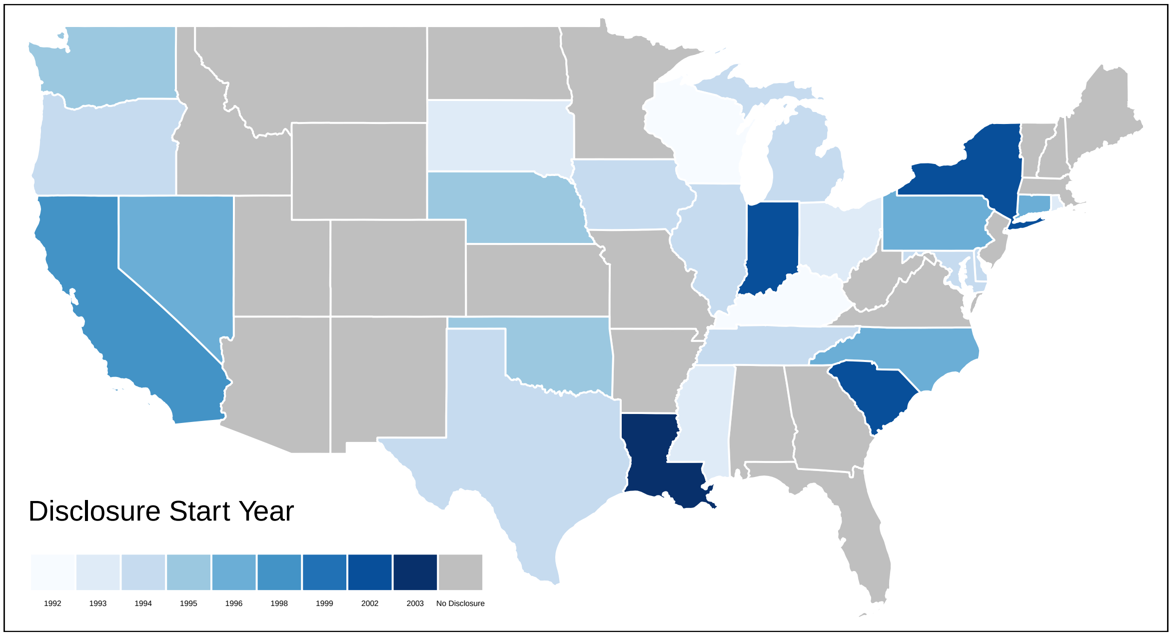

Figure 3.1: The Disclosure Requirement Implementation over Time

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, 27 states in the contiguous US implemented the disclosure requirement between 1992 and 2003 (see Figure 3.1) with an explicit question on flood risk. While the specific language of the requirement varies from state to state, the most prevalent question asks whether a property is located in the SFHA.[11]

The rollout of the disclosure requirement is closely related to the demise of the *caveat emptor* or "let the buyer beware" doctrine in state courts, which increasingly held listing agents responsible for the "failure" to disclose the material facts.[12] In response, the National Association of Realtors issued a resolution in 1991, encouraging state associations to develop and support legislation of the disclosure requirement (Tyszka 1995). It was primarily an effort to deflect potential liability from realtors to sellers (Washburn 1995). Importantly, the disclosure requirement is not exclusively on flood risk, but on a long list of items related to the housing condition. In addition, the timing of the pol-

[11] Other questions include past flood history and the flood insurance premium amount of a property.

[12] Under *caveat emptor*, buyers are expected to exercise proper caution on potential defects of a property. Seller's duty, on the other hand, is limited to not making any false representations or actively concealing any material facts (Washburn 1995). One of the primary factors that initiated this change is higher public attention to environmental and health issues during the 1980s (Weinberger 1996).

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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 3.2: Example of the Home Seller Disclosure Form (IL)

icy implementation was slower in states with *Caveat Emptor* courts (Roberts 2006). Taken together, the difference in policy timing across different states is likely to be uncorrelated with the underlying flood risk level of each state.

Earlier works on disclosure mandates suggest that multiple factors could determine the effectiveness of the disclosure policy on buyer perception. In particular, even if the policy is well-enforced, information has to be easy to understand, salient, accurate, and new to have an effect (Marshall et al. 2000, Figlio and Lucas 2004, Pope 2009, Dellavigna and Pollet 2009). As Figure 3.2 shows, the disclosure forms consist of simple checkbox questions, which deliver straightforward and easy-to-understand information regarding the property.[13] To ensure compliance, many states levy fine or even allow buyers to rescind the agreement without penalty for failure to disclose.[14] While these facts suggest that the disclosure requirement should effectively deliver the information, many states allow waiver upon mutual agreement. Also, the disclosure policy might fail to raise flood risk awareness if home sellers do not provide the form, home sellers provide false information, or home buyers fail to fully grasp the implication of the SFHA. Thus, the effectiveness of the disclosure requirement is an empirical question. While I cannot directly observe how home buyer perceptions on flood risk change due to the disclosure policy, in section 6.1 I conduct indirect tests on the effectiveness of the disclosure policy on buyers' flood awareness using housing price responses.

3.2 Flood Risk and Special Flood Hazard Area (SFHA)

Because the disclosure form delivers flood risk information by informing whether a property is in the SFHA or not, this section briefly discusses it. The SFHA is an area that is going to be inundated with a 100-year flood. It is delineated by Flood Insurance Rate Map, an official community flood map.[15]

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

[13] This feature is in stark contrast to many other disclosures, such as mortgages or automobile leases (White and Mansfield 2002), which could undermine the policy effect due to the information barrier.

[14] As such, the statutory requirements induce higher usage of the disclosure forms. For instance, Lahey and Redle (1997) and Lefcoe (2004) report a dramatic increase in the use of the form after the statutory requirement in Ohio and California, respectively.

[15] 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).

determines the water surface elevation for given water amount; and (3) floodplain mapping, which compares water 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 as well. The continuity of flood risk gives rise to the spatial discontinuity design near the SFHA border because the disclosure form delivers flood risk information in a dichotomous manner for two areas on each side of the border with almost identical actual flood risk. A potential concern, though, is that the flood risk zone status invites other regulations as well.[16] Thus, in section 6, I conduct difference-in-discontinuity analysis, which identifies the difference of two spatial discontinuity estimates before and after the disclosure policy.

It is also worth noting that these maps are updated occasionally. 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 of properties remains constant over the study period. Put it differently, when a flood map is updated, some properties' SFHA status would change, which makes it challenging to determine if an observed policy effect is attributable to the disclosure policy or the map update. Thus, in section 6.1, I check the robustness of the main results by removing properties located in the communities that had a map update over the sample period.

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 a US Census place. Figure B.1 in the appendix shows a sample Flood Insurance Rate Map from a part of the Town of West Hartford, Connecticut. Similar to this community, a typical entity has multiple panels that delineate flood zones. The dark area in the map represents the SFHA, and the light area is the non-SFHA. Most communities have both SFHA and non-SFHA areas within the jurisdiction. Figure B.2 in the appendix is a histogram of the fraction of the SFHA area for 7,306 communities used in the main sample. There is substantial variation in the SFHA ratio across different communities.

[16]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 3.1, 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 used to enforce the elevation requirement (FEMA 2005).

4 Data

4.1 Data Description

I compile a data set from five data sources: individual property transactions, community-level flood insurance takeup, tract-level demographics, and property-level flood damage. I also construct a community-level flood history dataset. In this section, I describe each data source and provide descriptive statistics.

Housing price, flood insurance, and population. For housing prices, I use the Zillow Transaction and Assessment Database (ZTRAX).[17] 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. For flood insurance, I use community-level policy counts data.[18] Demographic characteristics come from the tract level decennial census from Geolytics. The data document the overall population level as well as demographic characteristics such as income, age, race, and education.

Flood damage. I use the damage records from the National Flood Insurance Program adjuster's report, which I acquired through the Freedom of Information Act (FOIA) requests. Damage amount is defined as the actual cash value of flood damage, which is the replacement value net of depreciation, to structures and contents (FEMA 2014). I observe an 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 yearly maximum flood events data.

Flood history.[19] As flood size is a key determinant of flood damage, I need data that documents flood size at each community by year level to estimate the damage function and to explore disclosure policy's impact on flood damage. However, no flood data with an objective measure of size are read-

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

[18] I thank Justin Gallagher for sharing the data. In Gallagher (2014), flood insurance participating communities with non-missing population data are used for the analysis, but I use the entire universe of communities as long as a community is part of the Q3 map.

[19] I especially thank Jonathan J. Gourley at NOAA, Rod Lammers at the University of Georgia, and Tony Ladson at Moroka Pty Ltd for helpful comments and advice.

ily available.[20] Thus, I construct community-level flood history data by conducting flood frequency analysis using daily water volume records from over 3,000 USGS and NOAA stations located within the 27 disclosure requirement states (Milly et al. 2002, Mallakpour and Villarini 2015, Slater and Villarini 2016). Under this approach, flood size is measured by the recurrence interval (Task Committee on Hydrology Handbook of Management Group D of ASCE 1996): the expected number of years before a flood of the same magnitude comes back.[21]

Translating the daily discharge volume at each gauge into the maximum flood size at each community-year involves (1) constructing the gauge-specific frequency distribution by fitting Log-Pearson III distribution using the annual peak flow of each gauge, (2) converting the yearly maximum discharge volume to quantiles of the fitted distribution from step (1) and translating the quantiles into recurrence intervals,[22] and (3) matching each community to the three nearest gauges and calculating community-year-level flood size by taking the average of three gauges' recurrence interval using inverse distance as the weight. More details on flood data construction can be found in Appendix A.

Other data sources. As the disclosure policy differentially treats the properties in and out of the SFHA, I spatially merge individual property, community, and tract with the digitized flood map to determine the SFHA status. Specifically, I use the Q3 flood map, which reflects the flood risk of each community near the disclosure policy change timing.[23] The map 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. Also, the primary data source to track the disclosure requirement legislative history is *Nexisuni* database. I cross-check 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).

[20] An exception is the Unified Flash Flood Database (Gourley et al. 2013), but I choose to construct my own data for reasons described in the data appendix. For an overview of prior approaches, see appendix A.

[21] Flood size is increasing in the recurrence interval. For instance, a 10-year flood is a 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.

[22] 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.

[23] Q3 files are produced by FEMA as an earlier step of its 10-year automation program, by converting the existing hard-copy flood map to machine-readable formats. Approximately 1,300 counties (out of approximately 3,000 counties with the flood map) were chosen for the Q3 Flood Data production (FEMA 1996).

4.2 Summary Statistics

Table 4.1 presents summary statistics for key variables used in the analysis. Except for the number of 10-year flood events, which is plausibly exogenous to the disclosure policy, I present statistics from the pre-disclosure period observations. Also, housing prices and flood damage are inflation-adjusted using 2020 as the base year. For the 10-year flood events variable, I use 10 years of observations around the disclosure policy change.

A few points are worth noting. First, properties located within the SFHA are slightly more expensive than those outside of the SFHA. This price gap could reflect better amenities but also a lack of flood risk awareness before the disclosure requirement. For other variables, I present summary statistics for the entire and above-90%-SFHA-fraction communities. Not surprisingly, the average flood insurance take up, 10-year flood incidents, and flood damage are substantially higher for the high-SFHA communities. Also, a community had on average 0.99 10-year floods during a 10-year period, which partly validates the flood history data I constructed.[24] Lastly, in appendix Table B.2, I also present a balance table for properties located in and out of the SFHA. Results show the property characteristics are well balanced before the disclosure policy.

5 Empirical Strategy

In this section, I describe a strategy for the first set of empirical exercises that studies the disclosure requirement's impact on housing prices and household behaviors. Specifically, I use the staggered adoption of the disclosure policy as a primary source of variation but also exploit the spatial discontinuity of the disclosure policy to provide additional evidence.

5.1 Staggered Adoption of the Disclosure Requirement

A combination of the different policy implementation timing and the differential treatment of properties located in and out of the SFHA allow me to employ a triple difference design. Specifically, 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 eliminates concerns over problematic control

[24] A 10-year flood is defined as a flood that is large enough to come back every 10 years on average. Thus, for a 10-year period, a community is expected to have one such event on average. For more details, see appendix A.

Table 4.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Mean	Std.Dev.	N
Housing Price	14,723	9,996,495	275,759	300,595	814,131
In SFHA	15,352	9,113,719	327,513	415,040	35,924
Flood Insurance Take Up	0	23.93	0.047	0.422	39,105
(%) SFHA > 90%	0	5.54	0.536	0.865	280
Number of Households	1	11,278	1,314	640	43,550
(%) SFHA > 90%	1	4,056	1,230	662	540
Number 10-Year Floods (For 10 Years)	0	8	0.998	1.07	7,306
(%) SFHA > 90%	0	4	1.38	1.29	56
Annual Flood Damage	0	22,456,066	15,643	312,272	36,530
(%) SFHA > 90%	0	12,670,890	91,119	824,861	280

groups in staggered adoption design (Goodman-Bacon 2018).

I use not-yet-treated states as clean control and thus exploit the policy implementation timing among the ever-treated states. I exclude never-treated states because, as figure B.3 illustrates, the parallel trend assumption for the housing price response is violated when never-treated states are used as a control group. This could bias the causal estimate.[25]

Equation (3) estimates the impact of the disclosure policy on housing price.

$$log(Price_{ijmstd}) = \beta T_{ijmstd} + \theta_{mjhld} + \mu_{jtd} + \lambda_{mtd} + \epsilon_{ijmstd} \tag{3}$$

$Price_{ijmstd}$ 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 Post = Disclosure = SFHA = 1 where Post is a dummy for the post-disclosure period in stack d, Disclosure is a dummy for the treatment group assignment for stack d, and SFHA is a dummy for the SFHA status. Because of the stacked DDD design, every term in equation (8) has a subscript representing the experiment-year d. To construct the stacked data, I first keep each state's observations for five years before and after the disclosure policy change window so that the composition will remain constant in event time. Each stack is consists of the properties in the treated states, which have implemented the disclosure policy in year d, and properties in the control states, which have implemented the policy after year d. I exclude the last experiment-year because there is no control

[25]For more detail, see Section 6.1.

state for this case.

I also include a complete set of two-way fixed effects μ_{jtd}: SFHA × Time, λ_{mtd}: Community × Time, and θ_{mjhld}: Community × SFHA × Building Age × Number of Beds 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 experiment. The identification comes from plausibly exogenous disclosure policy change timings. For building age h, I grouped construction year into 10-years bins (e.g., 2000-2009, 1990-1999, etc.) and for the number of bedrooms l, I grouped it into 1-3, 4-6, 7-10, and 10-or-more bedrooms bins.

I estimate the event study version of equation (3) to check the parallel trends assumption. k in equation (4) indicates event time, namely, the time relative to the disclosure policy change year. In constructing the event study sample, I impose the endpoint restrictions following Ito and Zhang (2020). Specifically, $\beta_k = \underline{\beta}$ for $k < -4$ and $\beta_k = \bar{\beta}$ for $k > 5$, where the unit of k is an year. The main result is reported using the entire set of ever-treated states with housing transaction data five years before and after the disclosure policy change, but it is worth noting that creating a balanced panel for $k = [-4, 5]$ reduces the number of states to 12.[26] I also report results from these 12 states, which is similar to the entire states.[27]

$$log(Price_{ijmstd}) = \sum_{k=-4}^{5} \beta_k T^k_{ijmstd} + \theta_{mjhld} + \mu_{jtd} + \lambda_{mtd} + \epsilon_{ijmstd} \tag{4}$$

Outcome variables other than the housing price are observed at either the community or tract level. Thus, I estimate a continuous treatment version of equation (3), which is in equation (5) below. (%)SFHA$_{md}$ is the proportion of land in the SFHA for community m (or tract m) in stack d, which essentially means that α_1 is the marginal effect of (%)SFHA$_{md}$ and α_3 estimates how the

[26]I do not treat a state as "balanced" when it has zero observations in any of the cells produced by the combination of the SFHA status and event time. I lose DC, DE, IA, IN, KY, MD, MI, MS, NC, NE, NV, OH, SD, and TN out of the 27 ever-disclosed states in the contiguous US. These are states with a smaller population and/or relatively early policy change date.

[27]I apply the following additional 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.

marginal effect changes after the implementation of the disclosure requirement

$$Y_{mstd} = \alpha_1(\%)SFHA_{md} + \alpha_2 D_{mstd} + \alpha_3[(\%)SFHA_{md} \times D_{mstd}] + \omega_{td} + \psi_{md} + \epsilon_{mstd} \tag{5}$$

In equation (5), Y_{mstd} indicates various outcome variables, such as the flood insurance take up in community m at time t in stack d, and the number of households, vacancy rate, median income, and the proportion of senior citizens in tract m at time t in stack d. For the demographic variables, I use the tract level 1990 and 2000 decennial census because the community is often too large, especially for the unincorporated county areas, so that it might mask demographic changes that happen due to the flood risk information. D_{mstd} is a dummy variable that takes a value of 1 if a community or tract m in state s in stack d has implemented the disclosure requirement at time t. I also include ω_{td}, the time by stack fixed effect to account for year-specific common shocks and a community or tract by stack fixed effect ψ_{md}, which captures an unobserved community or tract characteristics. Again, including fixed effects interacted with stack d ensures that the comparisons are made within each stack.

It is worth discussing two important details about the tract-level analysis. First, the decennial census is documented only once in 10 years. Practically, it means that the states that have implemented the policy after 2000 can be used only as a control group. Also, the panel data has two periods only because every ever-treated state is treated in 2010 and the 1980 decennial census covers only urban areas. Second, I keep the tracts that contain the SFHA boundary within it so that I can compare the change in the marginal effect after the disclosure requirement for similar tracts. As appendix Table B.1 shows, tracts with and without the SFHA border could be fundamentally different. This observation makes sense because having the border within a tract means it is near water, which could have a much different amenity level and thus very different types of households. Narrowing focus to the tracts containing the border greatly mitigates the differences in the potential determinants of population flow.

Throughout the analysis, standard errors are clustered at the state level, which corresponds to the level of treatment.

5.2 Difference-in-Discontinuity Analysis at the SFHA Border

I exploit the spatial discontinuity created by the disclosure policy and provide additional evidence on the disclosure policy's effect on housing prices and demographic variables. Importantly, to account for other confounding treatments including flood insurance requirements which change at the SFHA border, I conduct a difference-in-discontinuity analysis. The design allows me to disentangle the information effect from the actual flood risk effect while controlling time-invariant confounding factors.

Following Grembi et al. (2016), I estimate equation (6) for housing prices in three steps. First, I restrict the sample to those near the border In practice, I remove properties beyond 400 meters (0.25 miles) from the border. Next, I estimate the optimal bandwidth using the mean squared error optimal algorithm and subsequently equation (6) using observations within the optimal bandwidth (Calonico et al. 2014, Cattaneo et al. 2019). δ_6 is the coefficient of the interest.[28] In equation (6), $Price_{imt}$ is the housing price of property i in community m in year t, X_{im} is the distance from a border in meters (negative if in non-SFHA area) for property i in community m, treatment group dummy $D_{im} = 1$ (i.e., in the SFHA) if $X_{im} > 0$, and post period dummy $T_t = 1$ if $t > T^*$, where T^* is the policy change date. Importantly, I include community fixed effect ψ_m in both bandwidth and diff-in-disc estimations to account for spatial dispersion of the SFHA boundaries. Standard errors are clustered at the community level.

$$\begin{aligned} log(Price_{imt}) = & \delta_0 + \delta_1 X_{im} + \delta_2 D_{im} + \delta_3 X_{im} * D_{im} + \\ & T_t[\delta_4 + \delta_5 X_{im} + \delta_6 D_{im} + \delta_7 X_{im} * D_{im}] + \psi_m + \epsilon_{imt} \end{aligned} \tag{6}$$

For this exercise, I choose Louisiana for two reasons. First, it is one of the flattest states. A practical implication is that two different properties on opposite sides of an SFHA border are almost indistinguishable in terms of flood risk with the bare eyes. Second, in the stacked DDD analysis, Louisiana serves as a control group only because it is the last state that has implemented the disclosure policy. The diff-in-disc specification allows me to explore the policy effect for Louisiana as well.

I also estimate a version of equation (6) with the number of households as the dependent variable. For this exercise, I use the block group level decennial census data, which is the smallest geographical unit for which the bureau publishes sample data. The distance to the border is defined by the

[28] I estimate the optimal bandwidth for the pre and post period separately and use the average of the two following Grembi et al. (2016).

distance between a block group centroid and the SFHA border. I use either 1990 and 2000 or 2000 and 2010 decennial census for before and after the treatment period depending on the policy change year.

6 Housing Price and Household Response to the Disclosure Requirement

6.1 Housing Price

Housing price response to the disclosure policy is of interest in its own right, but it is also a first pass at the efficacy of the disclosure policy. Admittedly, it is ideal to directly measure how home buyers' flood risk awareness has changed from the disclosure policy. However, no such survey was conducted around the disclosure policy change timing, and thus I (indirectly) establish the disclosure policy's effect on awareness by presenting various housing price effects.

Table 6.1 presents results from equation (3). Column (1) shows that the disclosure requirement reduces the price of the properties in the SFHA by 4% in comparison to those outside of the SFHA. To put these numbers in context, I multiply the estimate from column (1) to the average price of properties located in the SFHA in the pre-disclosure period from Table 4.1 ($327,513), and the reduction in the housing price amounts to $13,151.

Columns (2) and (3) show that the result in column (1) is stable and persistent with different specifications and samples. In column (2), I use a standard two-way fixed effect term (Community $\times$ SFHA) as opposed to a more granular Community $\times$ SFHA $\times$ Building Age $\times$ Number of Beds fixed effect term and find a slightly smaller but similar result to column (1). In column (3), I repeat column (1) using the 12 balanced panel states as opposed to the entire states and again find a similar result. These findings suggest that the result I find in column (1) is not a product or idiosyncratic specification or sample choices.

Column (4) provides additional evidence from a difference-in-discontinuity analysis in equation (6) with an optimal bandwidth estimated by the mean squared error optimal algorithm (Calonico et al. 2014, Cattaneo et al. 2019). As the actual flood risk level near the SFHA border is almost identical, the estimate singles out the effect of flood risk awareness. The magnitude of the reduction is larger

Table 6.1: Effect of Discosure Requirement on Housing Price

	(1)	(2)	(3)	(4)
SFHA × Disclosure × Post	−.040	−.031	−.051	
	(.015)	(.019)	(.015)	
SFHA × Post				−.129
				(.028)
Community × Time × Stack FE	X	X	X	
SFHA × Time × Stack FE	X	X	X	
Community × SFHA × Stack FE		X		
Community × SFHA × Age × N Bed × Stack FE	X		X	
Bandwidth				80.6
Method	Stacked DDD	Stacked DDD	Stacked DDD	Diff-in-Disc
Sample	Entire States	Entire States	Balanced States	Louisiana
Num. obs.	5814108	5814108	4917798	14998

Note: This table is produced from equation (3) and (6). The dependent variable is log(sales price). Columns (1) to (3), which show $\hat{\beta}$ from equation (3) present results from different set of fixed effects and samples. In column (4), I estimate equation (6) and present $\hat{\delta_6}$. Standard errors are clustered at the state (for columns (1) to (3)) and community (column (4)) level.

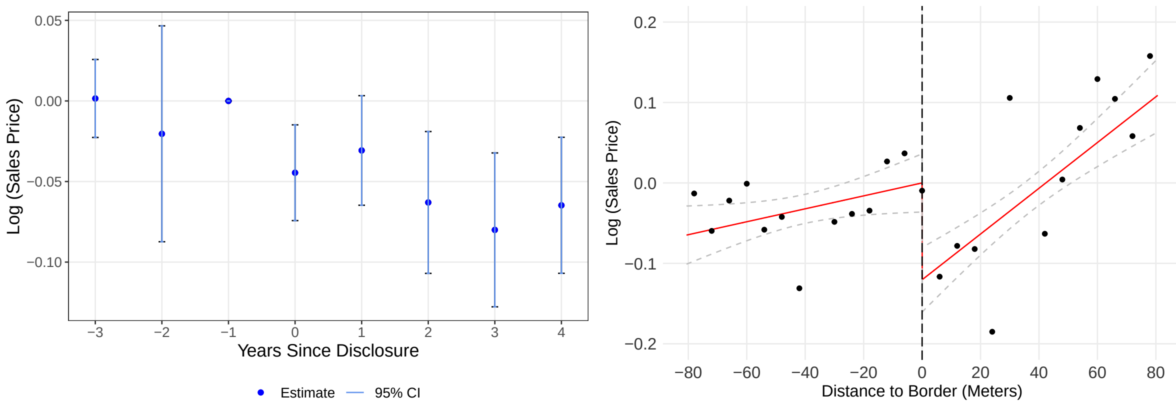
in column (4) at 12.9% in comparison to 4% from column (1), presumably because Louisiana has one of the most stringent and comprehensive disclosure requirements on flood risk.[29] Further, it should also be noted that in estimating column (1), Louisiana served as a control group only, because it is the last state to implement the disclosure policy and thus no states could serve as a control group. Figure B.6 in appendix B shows the policy effect is stable across a wide range of bandwidth choices. Results in Table 6.1 show that the disclosure policy was effective in raising home buyers' flood risk awareness.

Figure 6.1 (a) presents an event study style graph from equation (4), measuring the policy effect over event time.[30] The estimated coefficients for event time -2 exhibit a small negative effect, but overall, β_k in the pre-disclosure period are stable, satisfying the parallel trend assumption. Since the first year of the policy change, the price of affected properties falls by about 5%. The effect is persistent up until five years after the policy implementation. Figure 6.1 (b) portraits the difference-in-discontinuity term in column (4) of Table 6.1. The negative distance is for properties located outside of the SFHA and it shows a sharp drop in the treated housing price at the SFHA border. Note, the logged sales price is normalized so that $\Delta Y^- = 0$. Figure B.4 shows no evidence exists of bunching at the SFHA border.

While Figure 6.1 (a) adds confidence to the results in Table 6.1, I also show that the main results

[29]In addition to the SFHA classification, Louisiana's disclosure form asks about past flood history, if the property has ever received federal disaster relief, and if the property has flood insurance.

[30]Because of the end-point restriction discussed earlier, I omit $k \in \{-4, 5\}$.



(a) Staggered Adoption (b) Difference-in-Discontinuity

Figure 6.1: The Effect of the Disclosure Requirement on Housing Price. These figures show the disclosure policy effect on the housing price. Panel (a) plots the β_k, the interactions between the SFHA status and disclosure policy dummies in event time from equation (4). Panel (b) plots δ_6, the difference between pre-disclosure and post-disclosure spatial discontinuity estimates from equation (6). The dependent variable is the log of housing price. Standard errors are clustered on state (panel (a)) and community (panel (b)). See the text for additional details.

are robust to occasional flood map updates, which can coincide with the disclosure policy change. In appendix Table B.3, I repeat Table 6.1 after removing 6% of communities that have experienced a flood map update over the sample period. The results are essentially the same as Table 6.1, suggesting that map updates are uncorrelated with the disclosure policy implementation.

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 potential outcome price of the non-SFHA properties. Further, even if that is the case, the estimated housing price would be a policy-relevant parameter because it reflects a real-world housing market response to the flood risk information.

6.2 Flood Insurance Policy Counts and Population Flow

In Table 6.2, I present estimated coefficients of equation (5) on various outcome variables that illustrate how households respond to the flood risk information. Importantly, because the level of observation is at community (tract), the "(%) SFHA" term captures the policy effect from the intensity of treatment, which is defined by the fraction of land in the SFHA for each community (tract). Also,

Table 6.2: Effect of Discosure Requirement on Household Responses

	(1)	(2)	(3)	(4)	(5)
(%)SFHA × Disclosure × Post	.063	2.366	−48	−5272	−.916
	(.049)	(1.083)	(42)	(2962)	(.501)
D.V	Per Household NFIP Counts	(%) Vacant	Household	Median Income	(%) Senior
Avg D.V. (90% > SFHA)	0.237	10.7	1,195	82,122	10.6
Year FE	X	X	X	X	X
Community FE	X				
Tract FE		X	X	X	X
Num. obs.	290699	51204	51204	51204	51204

Note: This table is produced from equation (5). Column (1) is estimated using community-level flood insurance policy counts per capita (base = 1990 population). Columns (2) to (5) are estimated using the decennial census data in 1990 and 2000. Outcome variables and their pre-disclosure period average values for communities with the SFHA area over 90% can be found in the table text. All standard errors are clustered at the state level.

while Table 6.2 reports coefficients of the (%)SFHA × Disclosure × Post term only, I include a full set of interaction terms in the estimating equation. In column (1), I find suggestive evidence that the disclosure requirement leads to a modest increase in the flood insurance take-up for the high-risk communities relative to the low-risk communities. The point estimate indicates that the per capita policy increase for the above 90% SFHA communities is 0.0314 (0.033×0.95) or 13% when compared to the pre-treatment average. For a community with an average SFHA ratio (14.3%), the increase is about 2%.

Part of the reason for the modest effect size on flood insurance take-up could be migration. In column (2), I report how the vacancy rate changes after the disclosure policy. Compared to the pre-treatment average of 10.7%, the vacancy rate increases by 2.25% for the above 90% SFHA communities. This suggests 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.[31]

Column (3) directly investigates the change in the number of households following the disclosure policy. The point estimate suggests that for the above 90% SFHA communities, a reduction in the number of households is 46 (-48.9×0.95). Although statistically insignificant, the magnitude corresponds to the increased vacancy. To see this, consider a community with above 90% SFHA area where each household occupies exactly one unit of the house. Before treatment, there were 1,195 households and 1,323 units (using a vacancy rate of 10.7%). Now, if the vacancy rate goes up by 2.25% due to the policy, it translates into 30 additional vacant units, which is comparable to the 46.

[31]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).

The findings in columns (1) through (3) indicate that the housing price reduction from section 6.1 is driven by a combination of higher insurance take-up and population outflow from the high-risk areas.

In columns (4) to (5), I explore changes in demographic characteristics. Notably, high-risk tracts become less affluent and less old in comparison to the low-risk tracts with non-trivial magnitude. Specifically, the median income of the above 90% SFHA communities drops by $5,008 in comparison to the communities with 0% SFHA area or about 6.1% to the pre-treatment average. The finding corroborates Bakkensen and Ma (2019) that those with more resources tend to choose a safer place to live. Also, the proportion of senior people with age above 65 is decreasing by about 8%. Reduction in the older population is also plausible given that they have less physical capacity to cope with potential flooding. One caveat is that both of the columns are statistically significant at the 90% level, with a p-value of 0.08.

To credibly estimate the causal effect of the disclosure policy on demographic variables, I restrict the sample to the census tracts with a positive SFHA area only.[32] To provide additional credibility, I exploit the spatial discontinuity created by the disclosure policy as equation (6). For this exercise, I use the block group level decennial census data. Block groups in my sample have an average number of households of 463 and an average size of 0.25 square miles. I calculate the distance to the SFHA border from each block group using the distance between a block group centroid and the SFHA border. I remove block groups that have both SFHA and non-SFHA areas because the distance is not defined for those block groups.[33] In appendix Figure B.7, I estimate the diff-in-disc coefficient for a wide range of bandwidths, which present stable effect sizes. Note, the reduction in the number of households is approximately 30 on average, which is a 6.5% reduction compared against the average number of households in the block group. This is an order of magnitude similar effect from column (3) of Table ??, which is 3.8%. Figure B.7 presents additional credibility to the results in Table 6.2.

[32]For more discussion, see section 5.1

[33]In practice, I remove observations that have 5 to 95% of the SFHA area within a block group.

7 The Effect of the Disclosure Requirement on Flood Damage

7.1 Damage Function Estimation

A prediction from the discussion in section 2 is that if more households choose to live in places with a lower level of flood risk, flood damage will decrease. Given the evidence from section 6.2 that the disclosure requirement leads to a smaller number of households and higher vacancy in the high flood risk area, this section empirically investigates if and by how much the disclosure policy reduces flood damage conditional on flood size. Practically, I estimate the change in a damage function, which is a mapping between flood size and damage due to the disclosure policy (Auffhammer 2018). I non-parametrically estimate the relationship between flood size and damage following Barreca et al. (2016) to let the data, rather than the functional form assumption, determine the shape of the function.

$$\text{Per Capita Damage}_{mt} = \sum_{k=1}^{5} [\alpha_1^k F_{mt}^k + \alpha_2^k F_{mt}^k D_{mt}] + u_{mt} \tag{7}$$

Equation (7) represents the pre-treatment period damage function where the dependent variable is per capita flood damage.[34] On the right hand side, F_{mt}^k is a dummy variable that takes 1 when the annual maximum flood size measured by the recurrence interval for community m at time t belongs to flood size bin k where $k \in \{2-10, 10-20, 20-30, 30-40, 40-50\}$.[35] The key assumption in the binning decision is that the damage per capita remains constant within each bin. While flood sizes of 40 and 50, for instance, might have a different effect in reality, I choose the bin size of 10 to strike a balance between flexibility and precision. As Figure A.2 (b) suggests, the number of flood events that exceed the size of 20 and beyond are small and a more granular bin size raises concern about the statistical power. In a similar spirit, I use 15 years of observation for each state around the disclosure policy change year for this exercise. D_{mt} is a dummy for the treated group assignment, which is based on the disclosure policy. Flood size $1-2$ is the baseline flood and is omitted category from the estimating equation. Thus, α_1^k represents the additional flood damage per capita when a community experiences a flood size of k as opposed to the baseline flood. Equation (7) also allows

[34] Per capita damage is calculated using the population level of 1990 (pre-treatment period).

[35] I focus on flood size between 1 and 50 for two reasons. First, the frequency of flood events reduces exponentially as flood size gets larger (Jackson 2013). This implies that identifying statistical relations for the flood of size over 50 under the non-parametric estimation framework is challenging. Second, larger floods are driven by multiple, interrelated perils, such as wind and mudslide (Kron et al. 2012) and thus measurement error becomes a more serious issue.

a different slope between the treated and control group, which accounts for potential differences in flood management policies between the two groups.

Now posit that a disclosure policy is implemented. Equation (8) shows how equation (7) would change. I_{mt} is an indicator variable for the post period where β_4^k estimates how the damage function changes as a result of the disclosure policy.

$$\text{Per Capita Damage}_{mt} = \sum_{k=1}^{5}[\beta_1^k F_{mt}^k + \beta_2^k F_{mt}^k I_{mt} + \beta_3^k F_{mt}^k D_{mt} + \beta_4^k F_{mt}^k I_{mt} D_{mt}] + \epsilon_{mt} \tag{8}$$

The estimating equation mirrors equation (8) with one exception due to the stacked difference-in-difference design. Namely, I estimate how the damage function has changed while using clean controls, which are communities without a disclosure policy within the event window. Because of the stacked DD design, every term in equation (8) has a subscript representing the experiment-year d. I also include year by experiment and community by experiment fixed effects, to ensure that comparisons are made within each experiment. The identification comes from plausibly exogenous disclosure policy change timings.

Before further proceeding, it is worth discussing the difference between the damage function of this paper and those from earlier engineering studies.[36] Indeed, a wide range of engineering studies have developed the "depth-damage function," and as its name suggests, the measure of flood size in the engineering studies is "water depth" at the individual property (Freni et al. 2010, Pistrika et al. 2014). While useful for predicting property-level flood damage, the function does not 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. Further, to learn flood damage at an aggregate level such as community using the depth-damage function, a detailed hydraulic study, which translates flood events into the inundation level, is required.[37] However, as detailed hydraulic studies are costly, many communities have drawn their flood map without such studies (FEMA 2005). This is a major drawback given that flood damage estimation 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

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

[37] Put it differently, the engineering approach needs two steps: (1) translating water gauge data into an inundation map and (2) applying "depth-damage" function by applying inundation map to each property.

size, which is measured at the community level using the water gauges records, to the community level flood damage, this approach does not rely on hydraulic studies. Further, as the approach measures both flood size and damage at the community level, it captures both the intensive (water depth at a given property) and extensive (the number of affected properties) margin effect.

7.2 Change in Damage Function from the Disclosure Requirement

Figure 7.1 show damage functions for the control (panel (a)) and treatment (panel (b)) groups for before (solid line) and after (dotted line) the treatment. Per capita flood damage, which is the dependent variable for columns (1) to (3), is measured by the damage incurred on the properties subscribing to flood insurance from the adjuster's report divided by the population size of 1990 from the decennial census.[38] More specifically, the damage amount reflects "actual cash value," which is replacement cost at the time of loss, less depreciation for depreciation. The age and condition of the item determine the value of physical depreciation (FEMA 2014).

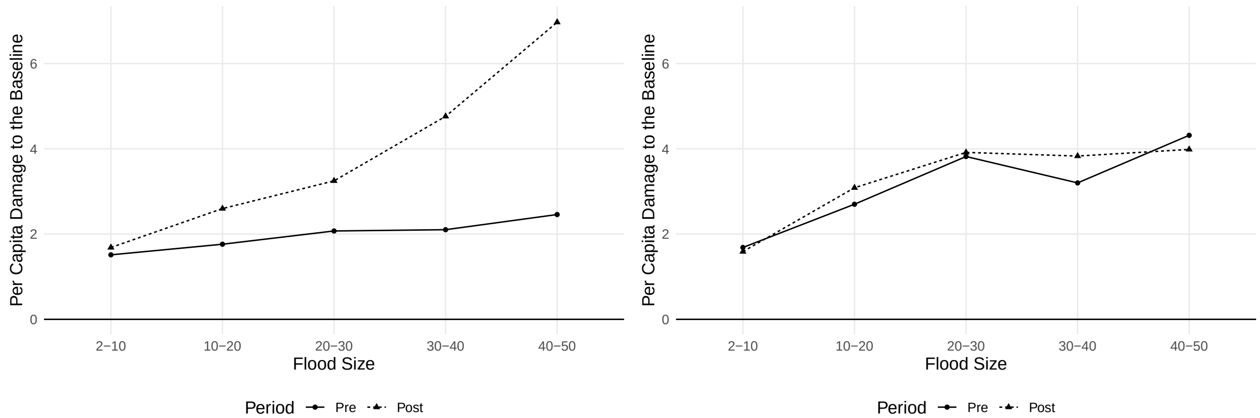
Each line in the figure represents the back-transformed coefficient from equation (8). For instance, the line for the pre-period/control group plots $e^{\hat{\sigma}/2} \times e^{\hat{\beta_1^k}}$ and pre-period/treated group plots $e^{\hat{\sigma}/2} \times (e^{\beta_1^k + \beta_3^k})$ for each k where $\hat{\sigma}$ is the standard error of the regression (Wooldridge 2006). Thus, the vertical axis indicates the additional damage incurred when the baseline flood, which is flood with size between 1 and 2, is replaced by a flood of size k.

The shape of the functions suggests that the damage, in general, is monotonically increasing in flood size. However, there is an important difference between the two groups as well: the gap between two lines, which indicates the change in the damage size for each group before and after the policy change, is much larger in the control group. This indicates that the disclosure policy substantially flattens the damage function.

It is worth mentioning that Figure 7.1 masks the heterogeneous effect of flood size on the damage. Even if struck by the same size of the flood, two communities might have a different level of damage depending on the *a priori* flood risk exposure. For instance, a community with a high level of SFHA area could experience larger damage than its counterpart when a 10-year flood hits. In Figure B.8, I present two sets of damage functions for the above and below median SFHA area communities.[39]

[38] 1990 is the last decennial census before 1992, which is the first year of treatment.

[39] Another possible approach is to multiply the ratio of the SFHA with flood size, which can be viewed as an "effective flood size." However, this pushes the entire distribution toward zero and makes the non-parametric estimation



(a) Control Group (b) Treatment Group

Figure 7.1: The Effect of Disclosure on the Damage Function. These figures show the disclosure policy effect on the damage function. Panel (a) is produced using $\hat{\beta}_1^k$ and $\hat{\beta}_2^k$ from column (1) of Table B.4, which describes the relationship between flood size and log of per capita damage for the control group. Panel (b) plots the damage function for the treated group analogous to the plot (a). The gap between two lines corresponds to the change in per capita damage before and after the disclosure policy for the control and treatment group, respectively. See the text for additional details.

Panels (a) and (b), which are for the above-median communities have a much higher vertical level in comparison to the figures in panels (c) and (d), corroborating that the damage size is much larger for a given flood size and also increasing much faster as flood size gets larger for high flood risk communities.

Table 7.1 confirms the graphical illustration in Figure 7.1. For the interest of space, I only report $\hat{\beta}_4^k$ from equation (8) here, which corresponds to the disclosure policy effect for the treated group, but the rest of the estimated coefficients can be found in appendix table B.4. In column (1), I estimate the damage function using the entire communities. The results show that the disclosure requirement flattens the damage function substantially across different flood sizes for an average community in the treated states.

One potential shortcoming of the approach taken in column (1) is that it abstracts away from the treatment intensity by the proportion of the SFHA within the community. In columns (2) and (3), I split the sample into communities above and below the median level of (%) SFHA to explore the heterogeneous effect. If the damage reduction is driven by the disclosure policy, we should see a larger effect from the higher SFHA communities, which are disproportionately affected by the policy. The

infeasible. For instance, 90% of the community-year observations have effective flood size below 1 after the transformation.

Table 7.1: Effect of Disclosure Requirement on Flood Damage

	(1)	(2)	(3)	(4)	(5)
Post × Disclosure (Size 2-10)	−.167	−.229	−.096	−.492	−.189
	(.076)	(.117)	(.029)	(.179)	(.078)
Post × Disclosure (Size 10-20)	−.254	−.252	−.248	−.822	−.316
	(.246)	(.397)	(.143)	(.522)	(.191)
Post × Disclosure (Size 20-30)	−.424	−.724	−.059	−1.018	−.418
	(.221)	(.391)	(.213)	(.467)	(.188)
Post × Disclosure (Size 30-40)	−.638	−.909	−.413	−1.686	−.657
	(.382)	(.557)	(.293)	(.947)	(.355)
Post × Disclosure (Size 40-50)	−1.122	−1.676	−.590	−2.734	−1.031
	(.443)	(.527)	(.372)	(.833)	(.333)
Dep.Var.	Per Capita Damage	Per Capita Damage	Per Capita Damage	Average Per Capita Damage	Damage Counts
Year FE	X	X	X	X	X
Community FE	X	X	X	X	X
Sample	All	Above Median SFHA	Below Median SFHA	All	All
Num. obs.	369956	178950	191006	369956	369956

Note: The dependent variable in columns (1) to (3) is the inflation-adjusted (base = 2020) log per capita damage at community-year. Column (1) corresponds to equation (8). 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) and (5) are log average per capita damage size and the log number of damaged properties. All standard errors are clustered at the state level.

estimated coefficient in columns (2) and (3) show the damage reduction effect is primarily driven by the above-median SFHA communities.

In columns (4) and (5) I investigate the intensive versus extensive margins of the per capita damage reduction by studying the policy effect on the average size of the per capita damage and the number of damaged properties. For the first measure, I divide the total per capita damage by the number of claims. The estimates suggest that the disclosure requirement reduces both the intensive and extensive margin of flood damage. It is straightforward that the increased vacancy will lead to a smaller number of damage counts as these properties would not subscribe to flood insurance. Further, the reduction in average per capita damage can also be partly explained by the increased vacancy because unoccupied properties lead to smaller average damage for two reasons. First, vacant properties do not have personal belongings to be damaged. Second, the actual cash value of the vacant properties will be lower because those houses are not as well-maintained (White 1986).[40]

In section 6, the difference-in-discontinuity exercise showed the robustness of the main results.

[40] There are other potential channels as well. The disclosure policy might have induced households to engage in self-protection such as insulating their houses. Adverse selection in the flood insurance market could also explain the reduction in the average damage size. Namely, if the riskiest households were buying insurance before the disclosure policy, and if the new subscribers have lower risk profile than existing subscribers, we could experience lower average damage size (Wagner 2019).

Table 7.2: Effect of Disclosure Requirement on Flood Damage (Placebo States)

	(1)	(2)	(3)	(4)	(5)
Post × Disclosure (Size 2-10)	−.087	−.182	.030	−.060	−.110
	(.064)	(.100)	(.021)	(.043)	(.066)
Post × Disclosure (Size 10-20)	.655	.318	1.094	.386	.542
	(.186)	(.229)	(.245)	(.128)	(.157)
Post × Disclosure (Size 20-30)	−.256	−.724	.443	−.307	−.060
	(.364)	(.800)	(.407)	(.255)	(.212)
Post × Disclosure (Size 30-40)	.710	.646	.985	.348	.542
	(.162)	(.223)	(.266)	(.106)	(.188)
Post × Disclosure (Size 40-50)	.348	.117	1.283	.198	.381
	(.191)	(.224)	(.206)	(.124)	(.183)
Dep.Var.	Per Capita Damage	Per Capita Damage	Per Capita Damage	Average Per Capita Damage	Damage Counts
Year FE	X	X	X	X	X
Community FE	X	X	X	X	X
Sample	All	Above Median SFHA	Below Median SFHA	All	All
Num. obs.	72048	39894	32154	72048	72055

Note: This table repeats Table 7.1 using the placebo states. The dependent variable in columns (1) to (3) is the inflation-adjusted (base = 2020) log per capita damage at community-year. Column (1) corresponds to equation (8). 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) and (5) are log average per capita damage size and the log number of damaged properties. All standard errors are clustered at the state level.

This exploited individual or block group level datasets. For the damage function, however, I do not have such a luxury because the data is documented at the community level. Thus, I check the robustness of the results by conducting a placebo test by leveraging five states (ME, MN, NH, NJ, 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 an effect.

To produce Table 7.2, I repeat the stacked DD approach described in section 7.1 using the five states. The sign and magnitude of the triple difference terms in Table 7.2 indicate that we do not find a comparable damage reduction effect to Table 7.1 when a disclosure policy does not cover flood risk.

Figure B.9, which is an event study plot that corresponds to equation (8), provides further assurance to the estimation. Here, $\hat{\beta}_4$ for each event time for flood size 30-50 is plotted, which is the marginal effect of flood size on the log of per capita damage for five years before and after the policy change. To increase the statistical power, I classified floods into three groups–baseline, small, and large–for this exercise. Also, I impose an endpoint restriction at -5 and 4 and code event time smaller than -5 as -5 and larger than 4 as 4.[41] It shows no pre-trend, and more importantly, a clear reduction in the per capita damage, after the policy change. This effect corresponds to a flatter damage function after the disclosure policy.

8 Discussion

8.1 Interpreting the Damage Reduction Effect

The estimates in Table 7.1 can be summarized into an annual expected damage reduction from the disclosure policy. This metric takes into account both the probability of each flood size occurrence and corresponding damage reduction effect as equation (9).

$$\sum_{k=1}^{5} Pr(K = k) \times (e^{\hat{\beta_4^k}} - 1) \tag{9}$$

Table 8.1 shows how equation (9) works in practice. The first column presents $\hat{\beta_4^k}$ and is identical to the column (1) of Table 7.1. As coefficients in the first column are large changes in magnitude to use the first-order Taylor expansion, I make adjustments accordingly to report the percentage reduction in flood damage in the second column where standard errors are calculated using the delta method. The third column reports the probability of occurrence for each flood size bin. Since the flood size is defined using the recurrence interval, the inverse of the size corresponds to $Pr(K = k)$.[42] In the fourth column, I multiply the second column with the $Pr(K = k)$ to calculate the expected reduction. However, the results in the $E[Reduction]$ column do not take into account the fact that the coefficient for size 10-20 in the second column is not statistically significant at the conventional level. In the last column, I take a conservative stance and replace the point estimate of 10-20 bin with the corresponding upper limit of the 95% confidence interval. The sum of the last column indicates that the disclosure reduces per capita flood damage by at least 6%.

Using the average pre-disclosure per capita damage for flood size between 2 and 50 (\$3.78) and by multiplying it to the total population in the US, I can calculate the annual expected damage reduction effect in dollars. Since the US population in 2020 is 330 million, $\$3.78 \times 330,000,000 \times 6\%$ yields

[41] Thus the estimates in event time -5 and 4 are omitted from the graph.
[42] For this exercise, I choose the mean flood size for each bin and take the inverse of it.

$74 million reduction in expected annual flood damage. While the effect size is non-trivial, this number is likely to underestimate the true effect because the analysis excludes floods larger than the 50-years 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 2019).

For a complete welfare analysis, we need an estimate for the social cost of the disclosure policy as well. However, to the best of my knowledge, there is no such estimate. Nonetheless, given the nature of the policy, the cost is likely to be fairly low. For instance, in terms of the administrative cost, creating the form incurs a small one-time cost. The compliance cost imposed on home sellers–the time and effort required to furnish the form–is likely to be small as well. One survey result shows that home sellers on average spend less than 40 minutes to fill out the form (Moore and Smolen 2000). Combining this with the reduced flood damage, the policy produces a substantial welfare gain.

The findings are driven by the population reduction in high-risk areas. But why do home buyers engage in self-protection, namely choosing a safer place to live, although they have an option to buy flood insurance? One of the predictions of section 2 is that when the non-insurable cost is large, households will change the location. The flood insurance covers up to $250,000 for a residential property, and the premium on average is lower than the actuarially fair premium, but it is still incomplete insurance. A flood could negatively affect an individual's health (Kahn 2005, Bloom et al. 2009), employment status (Deryugina 2017), or income, which is not covered by the flood insurance.[43] Also, cleaning up and finding a new living arrangement incurs huge time and cognitive costs. Natural disasters even reduce subjective well-being (Rehdanz et al. 2015, Berlemann 2016). Given these non-trivial uninsurable costs, people might choose to migrate instead of purchasing insurance and living in risky places.

8.2 Why Do Home Sellers 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,

[43] Anecdotal evidence shows floods could impose serious health threats. For instance, Hurricane Harvey disrupted operations at 40 wastewater treatment plants, which caused at least 25,000 gallons of sewage-tainted water to flood streets and waterways (Constible 2018).

Table 8.1: Annual Expected Damage Reduction

	$\hat{\beta}_4^k$	$e^{\hat{\beta}_4^k} - 1$	$Pr(K = k)$	$E[Reduction]$	$E[Reduction]^*$
Post × Disclosure (Size 2-10)	−.167	−.153	.182	−.028	−.028
	(.076)	(.064)			
Post × Disclosure (Size 10-20)	−.254	−.225	.067	−.015	.010
	(.246)	(.191)			
Post × Disclosure (Size 20-30)	−.424	−.346	.040	−.014	−.014
	(.221)	(.144)			
Post × Disclosure (Size 30-40)	−.638	−.472	.029	−.013	−.013
	(.382)	(.202)			
Post × Disclosure (Size 40-50)	−1.122	−.674	.022	−.015	−.015
	(.443)	(.144)			

Note: The first column reproduces column (1) of Table 7.1. The second column adjusts the first column coefficients to express in percentage terms. The third column indicates the annual probability of each flood size occurence. The fourth column multiplies the second and third column while the last column multiplies the third column with the second column where the flood size 10-20 estimate is replaced with the corresponding upper 95% CI.

voluntary disclosure is going to happen (Milgrom 1981, Grossman 1981). Under this circumstance, 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 physical characteristics (e.g., number of bedrooms) and amenities such as crime rate, school quality, and pollution. Thus, vertically differentiating a house along a single dimension is not easy.

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 subscription status or premium? Or the SFHA status? The disclosure policy standardizes risk communication, thus facilitating information flow.

9 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 is criticized for disincentivizing people to adapt–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 the staggered adoption of the disclosure requirement across different states and spatial discontinuity in flood information. The policy mandates that sellers disclose property defects, and 27 states in the contiguous US have an explicit question on flood risk. 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, housing prices of the affected properties drop by 4%, indicating the policy is binding and effective in delivering flood risk information. The price adjustment is driven by a combination of additional flood insurance purchases and increased vacancy in a flood risky area. A fewer number of households in flood risky areas reduce overall exposure to flood risk, which in turn reduces damage from a small to moderate flood by at least 6%.

The findings of this paper suggest the disclosure policy is an effective flood risk management tool. By removing market frictions, it makes home buyers heed flood costs, which in turn facilitates voluntary adaptation. The policy yields a double dividend for a government because it can not only save money on flood management infrastructure but also reduce post-disaster recovery spending. Also, it is fairer from the taxpayer's perspective given that a disproportionately large amount of resources are devoted to protect and relieve people living near water–who are also more affluent–under the current system (GAO 2013). Further, the disclosure policy could contribute to the stability of the housing market and the financial system by preventing home buyers to be overly optimistic about the future housing market and climate exposure (Bakkensen and Barrage 2017). Finally, it is worth pointing out that the disclosure policy effect could be larger when the flood insurance premium subsidy is removed and the premium reflects the true flood risk level.

Lastly, though this paper has exploited one of the best available data sets on direct flood damage, the measurement is still incomplete. A more comprehensive measure should also include indirect losses from floods, such as loss of income, business disruption, and use time loss (Gall et al. 2011). Developing a measure for these costs and examining whether a disclosure policy could reduce the indirect cost of a flood would be an important future research area.

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A Appendix A: Flood History Data

A.1 Background and Construction Procedure

Background

One of the major difficulties in studying the economic impact of floods is that no single repository or database objectively documents past flood events in the US. For instance, the National Weather Service (NWS) Storm Events Database, one of the most widely used databases, documents county-level flood incidents with information on the meteorological environment, monetary damage estimates, and the number of fatalities. A critical feature of these data–which many other flood datasets share–is that they are self-reported by local offices.[44] In other words, two events of the same magnitude could and could not be included in the dataset, depending on the local officer's judgment. This feature creates potential bias from missing data (Gallagher 2013, Gourley et al. 2013).

Earlier studies focused on a single event, relatively well-documented flood type, used the Presidential Disaster Declaration (PDD) floods, or water-depth data from the flood insurance claims data (Bin and Landry 2013, Gallagher 2014, Deryugina 2017, Wagner 2019, Muller and Hopkins 2019). However, these measures do not cover the entire extent of past floods in an objective manner. For instance, focusing on Hurricanes only leaves out devastating inland floods like The Great Flood of 1993. Using PDD floods is also problematic because the declaration, which is the discretion of the president, not only reflects the size of the flood, but also political interests (Reeves 2011). Water-depth from the flood insurance claims data is a function of flood size and any property level flood protection measures, thus can be different from the physical size of a flood.

An alternative is to construct flood history data by combining objective records with physical characteristics of floods. Floods, like other natural disasters, can be characterized by their magnitude, which can be measured by the likelihood of exceedance, such as a flood having a 10% chance of being exceeded in any year (Task Committee on Hydrology Handbook of Management Group D of ASCE 1996).[45] The reciprocal of annual exceedance probability, which is also called the recurrence interval, defines an average length of time in years, between the occurrences of floods of a specified magnitude or larger. Therefore, referring to a 10% AEP as a 10-year flood and flood with a 1% AEP as a 100-year flood has become common. To know the quantile, we need to calibrate a distribution.

The newly constructed flood history data have two important advantages. First, they provide an objective and consistent documentation of flood events at the national level for a long period. Second, the measure of flood size–the recurrence interval–is flexible enough to allow for building flood events data of varying size.

Procedure

Following England Jr et al. (2019), I implemented the following steps using USGS discharge data from 3,507 gauge stations in the 27 contiguous ever-disclosed states retrieved using the USGS official R package "dataRetrieval" (Cicco et al. 2018). First, I estimate the parameters of Log-Pearson Type III Distribution using the annual peak discharge data at each gauge station. I keep stations with at least 10 or more annual peak observations following the USGS guideline (England Jr et al. 2019). Also, I use annual peak data until 1990 to reflect flood thresholds around the disclosure policy change.

[44] See Gall et al. (2009) and Saharia et al. (2017a) for review of the existing natural disaster data.

[45] Another common measure is discharge, that is the volume of water flowing at a point for instantaneous time. However, the absolute value of discharge is not useful for comparing floods using different stations, because the baseline discharge is much different from station to station.

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 estimate the maximum daily flow from the mean daily flow data. 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). However, 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. Table A.1 illustrates this point. It 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 IPF from MDF by constructing a relationship between the ratio of instantaneous peak and the corresponding mean daily flow, with physiographic characteristics of the basin such as the size of the drainage area (Fuller 1913).[46] Third, I compare the estimated daily maximum discharge volumes with fitted distribution to identify their quantile in terms of the annual peak flow. 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.

Figure A.1 (a) shows 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.

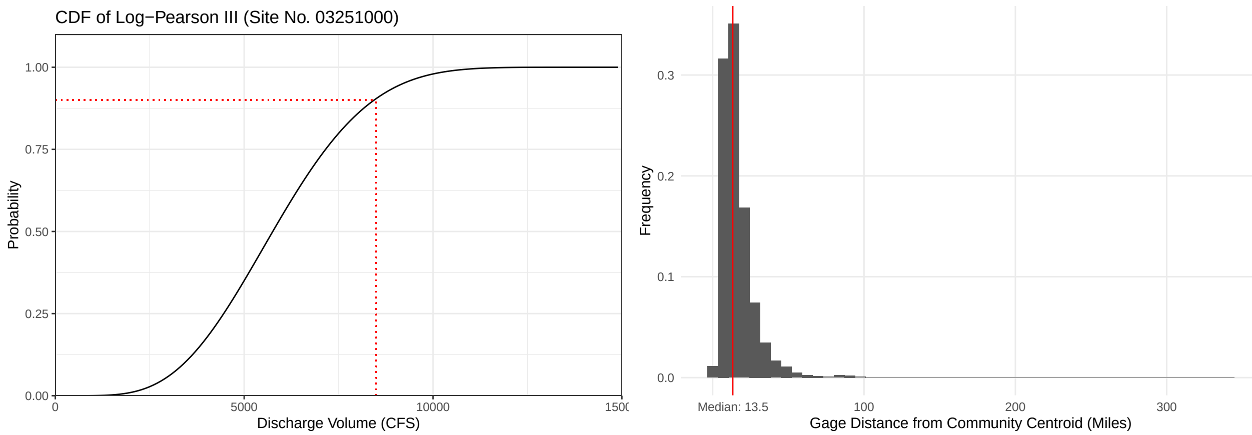
Note, because the USGS gauge stations rarely cover coastal areas, I add 45 additional NOAA sites in the gauge station data. Zervas (2013) documents the flood threshold for the entire NOAA sites, so I adopt them directly. NOAA water level data are retrieved using the R package "Rnoaa" (Edmund et al. 2014).

Finally, to translate gauge-level flood events to the community-level floods, I match each community to the three nearest gauges using the distance between a centroid of community and gauge stations. Then, I calculated the average flood size for a community using the inverse distance as a weight. Figure A.1 (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.

Unified Flash Flood Database

The Unified Flash Flood Database (Gourley et al. 2013) is an existing database that is constructed by the procedure outlined above using the USGS gauge records. It is a comprehensive and objective measure of flood events that can present the overall trend of flood events for the contiguous US. 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,

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



(a) Flood Frequency Analysis

(b) Distance between Gauge and Community Centroids

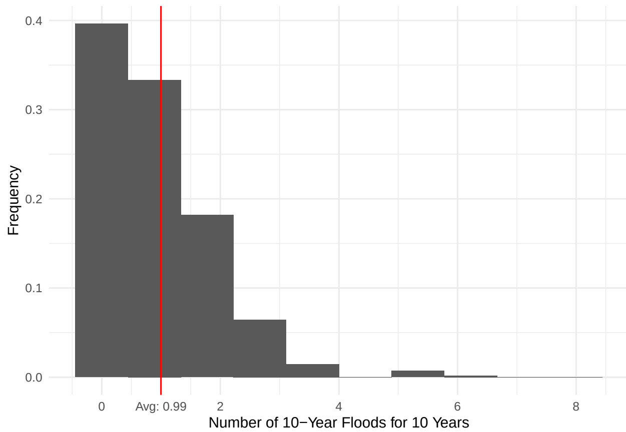
Figure A.1: Flood Frequency Analysis and Gauge Matching. Plot (a) is an example of flood frequency analysis. The black solid line represents the CDF of the fitted Log-Pearson III distribution from the USGS site 03251000. If daily discharge volume is 8,500 CFS, it corresponds to the 90th quantile or a 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.

and major.[47] These categories are defined by NWS in collaboration with local stakeholders, which makes comparisons across different stations harder. Second, the data are constructed based on the instantaneous peak flow data thus, a potential bias arises due to the missing records, which can be especially problematic for the years before the 2000s.

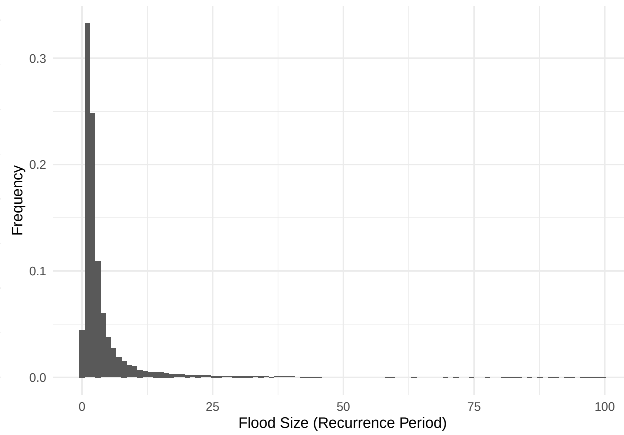
A.2 Validation and Summary Statistics

To validate the data, I check the number of the average 10-year flood events over 10 years for the 8,194 communities. These communities are from the 27 ever-disclosed states that are on the Q3 map. By definition, a 10-year flood is going to happen once in a 10-year period around the disclosure policy change date on average. Figure A.2 (a) shows that most communities had 0, 1, or 2 10-year floods over the 10 years whereas the average number of the 10-year flood is 0.99.

Figure A.2 (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."



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



(b) Distribution of Flood Size

Figure A.2: Flood Frequency Analysis and Gauge Matching. Plot (a) shows that on most communities had 0, 1, or 2 10-year floods over the 10 years whereas the average number of 10-year flood is 0.99. Plot (b) shows the distribution of flood event size (i.e., recurrence interval), where flood size is truncated at 100 for readability.

B Appendix B: Additional Tables and Figures

[47] 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).

Table B.1: Balance Table (Tracts With/Without the SFHA)

	No SFHA		With SFHA		Difference	
Variables	Mean	SE	Mean	SE	Mean	t-stat
Population	3510	15	3492	9.99	-17	-0.2311
Median Inc	85280	409	91038	271	5758	2.3
(%) 65+	12.13	0.063	11.97	0.0395	-0.1557	-0.2662
(%) BA	19.25	0.1421	20.89	0.091	1.64	2.69
(%) Black	20.73	0.2971	9.77	0.1178	-11	-3.26
N Housing Unit	1377	6.31	1408	4.2	32	1.2
(%) Home Age Below 6	0.078	0.0012	0.1296	0.0009	0.0517	4.1
(%) Home Age Above 42	0.3961	0.0028	0.2337	0.0014	-0.1624	-3.8
N Home Age Below 6	92	1.58	160	1.14	68	4.64
N Home Age Above 42	558	5.09	343	2.44	-216	-3.7

Note:
For each variable, I show the mean and standard error for tracts with and without the SFHA border. The last column shows the difference in the mean with the standard error of the difference. I cluster standard error at the state level.

Table B.2: Balance Table (Properties in/out the SFHA)

	No SFHA		With SFHA		Difference	
Variables	Mean	SE	Mean	SE	Mean	t-stat
Staggered Adoption Sample						
log(Price)	12.29	0.0047	12.22	0.0009	0.0663	0.8625
House Age	33.94	0.1853	35.78	0.0361	-1.85	-0.58
Sqft	3295	15.4	3395	3.29	-101	-0.4024
N Stories	1.52	0.003	1.55	0.0006	-0.0297	-1.25
Diff-in-Disc Sample						
log(Price)	11.58	0.01	11.65	0.0052	-0.0746	-0.899
Sqft$	1868	16.77	1919	7.96	-51.24	-1.12

Note:
Note: For each variable, I show the mean and standard error for properties inside and outside of the SFHA. The last column shows the difference in the mean with the standard error of the difference. I cluster standard error at the state (for the top panel) and community (for the bottom panel) level.

Table B.3: Effect of Discosure Requirement on Housing Price (No FIRM Revision Communities)

	(1)	(2)	(3)
Treated	$-.041$	$-.039$	$-.052$
	(.018)	(.021)	(.016)
Community $\times$ Time $\times$ Stack FE	X	X	X
SFHA $\times$ Time $\times$ Stack FE	X	X	X
Community $\times$ SFHA $\times$ Stack FE		X	
Community $\times$ SFHA $\times$ Age $\times$ N Bed $\times$ Stack FE	X		X
Method	Stacked DDD	Stacked DDD	Stacked DDD
Sample	Entire States	Entire States	Balanced States
Num. obs.	5496054	5496054	4609387

Note: This table is produced from equation (3), with different sample. In particular, communities that have experienced Flood Insurance Rate Map, or an official flood map, update during the sample period were removed. The dependent variable is log(sales price). All standard errors are clustered at the community level.

Table B.4: Effect of Disclosure Requirement on Flood Damage (Entire Coefficients)

	(1)	(2)	(3)	(4)	(5)
Flood Size 2-10	.071	.080	.070	.212	.070
	(.032)	(.045)	(.025)	(.105)	(.041)
Flood Size 10-20	.223	.297	.150	.532	.198
	(.074)	(.111)	(.034)	(.195)	(.083)
Flood Size 20-30	.386	.567	.193	.835	.328
	(.142)	(.233)	(.056)	(.295)	(.122)
Flood Size 30-40	.400	.539	.209	.795	.340
	(.133)	(.197)	(.080)	(.234)	(.104)
Flood Size 40-50	.556	.813	.152	1.158	.471
	(.203)	(.289)	(.105)	(.374)	(.162)
Disclosure × Size 2-10	.108	.164	.042	.266	.108
	(.041)	(.064)	(.019)	(.101)	(.045)
Disclosure × Size 10-20	.427	.553	.276	.961	.376
	(.093)	(.139)	(.071)	(.239)	(.096)
Disclosure × Size 20-30	.611	.810	.336	1.320	.517
	(.134)	(.225)	(.101)	(.290)	(.107)
Disclosure × Size 30-40	.420	.537	.313	.999	.369
	(.150)	(.229)	(.126)	(.323)	(.125)
Disclosure × Size 40-50	.563	.675	.475	1.264	.438
	(.196)	(.245)	(.127)	(.427)	(.165)
Post × Size 2-10	.107	.149	.062	.285	.109
	(.041)	(.058)	(.023)	(.092)	(.039)
Post × Size 10-20	.388	.418	.348	.982	.382
	(.112)	(.199)	(.068)	(.290)	(.108)
Post × Size 20-30	.449	.516	.387	1.069	.395
	(.135)	(.267)	(.079)	(.346)	(.139)
Post × Size 30-40	.817	1.128	.591	1.873	.734
	(.236)	(.328)	(.220)	(.601)	(.242)
Post × Size 40-50	1.042	1.475	.739	2.522	.909
	(.272)	(.358)	(.232)	(.571)	(.230)
Post × Disclosure × Size 2-10	−.167	−.229	−.096	−.492	−.189
	(.076)	(.117)	(.029)	(.179)	(.078)
Post × Disclosure × Size 10-20	−.254	−.252	−.248	−.822	−.316
	(.246)	(.397)	(.143)	(.522)	(.191)
Post × Disclosure × Size 20-30	−.424	−.724	−.059	−1.018	−.418
	(.221)	(.391)	(.213)	(.467)	(.188)
Post × Disclosure × Size 30-40	−.638	−.909	−.413	−1.686	−.657
	(.382)	(.557)	(.293)	(.947)	(.355)
Post × Disclosure × Size 40-50	−1.122	−1.676	−.590	−2.734	−1.031
	(.443)	(.527)	(.372)	(.833)	(.333)
Dep.Var.	Per Capita Damage	Per Capita Damage	Per Capita Damage	Average Per Capita Damage	Damage Counts
Year FE	X	X	X	X	X
Community FE	X	X	X	X	X
Sample	All	Above Median SFHA	Below Median SFHA	All	All
Num. obs.	369956	178950	191006	369956	369956

Note: The dependent variable in columns (1) to (3) is the inflation-adjusted (base = 2020) log per capita damage at community-year. Column (1) corresponds to equation (**??**). 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) and (5) are log average per capita damage size and the log number of damaged properties. All standard errors are clustered at the state level.

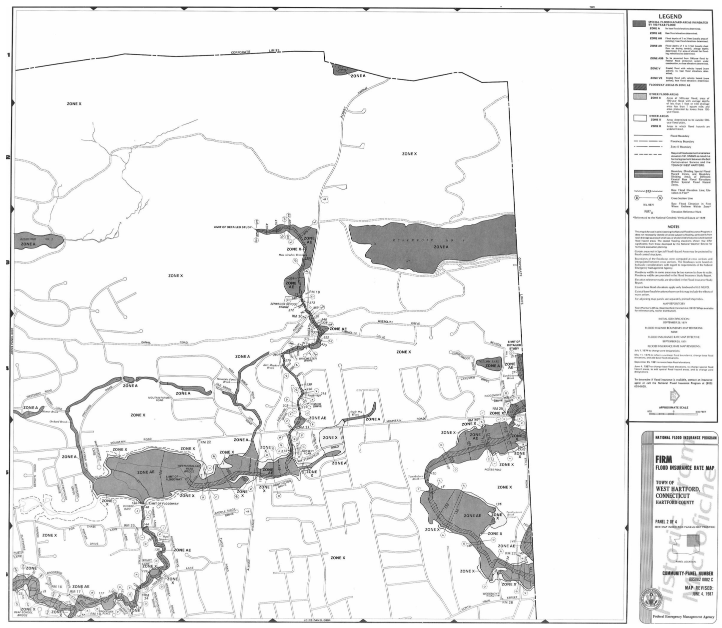


Figure B.1: Sample Flood Insurance Rate Map (West Hartford, CT)

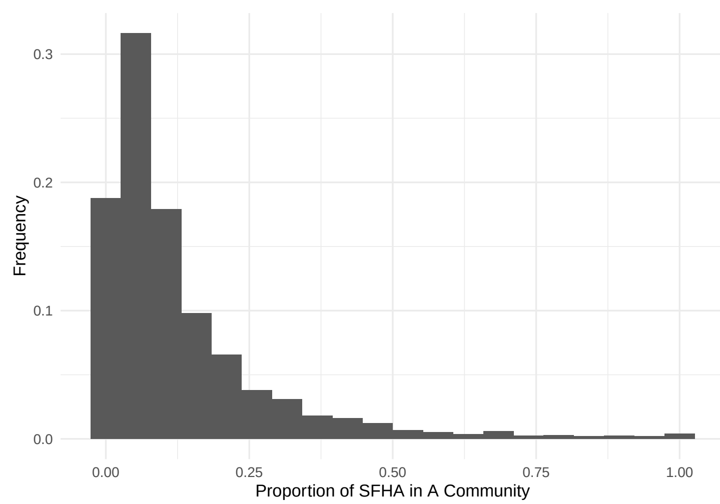


Figure B.2: Histogram of the Proportion of the SFHA for Each Community. The plot shows the distribution of the SFHA ratio for the 8,194 communities that are on the Q3 map and in the 27 ever-disclosed states.

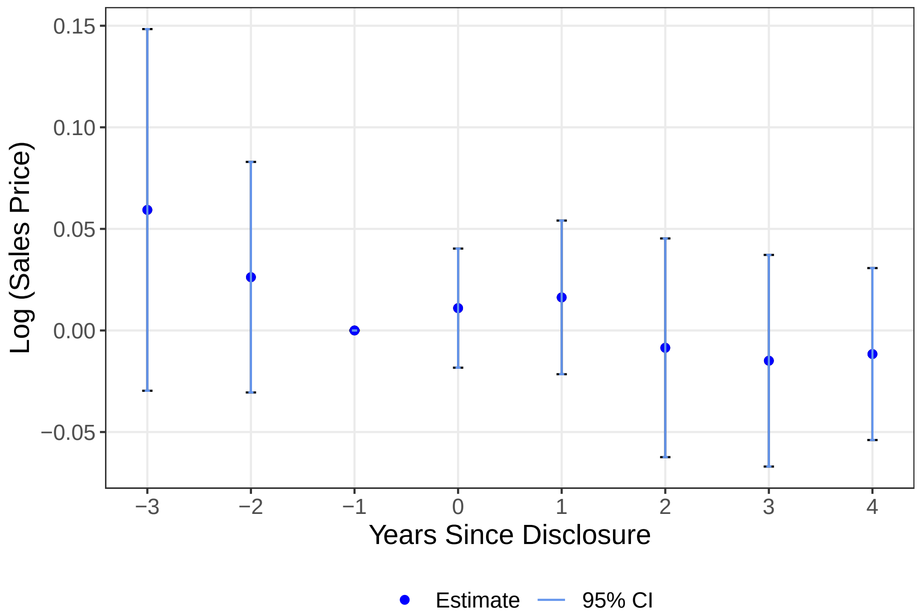


Figure B.3: This figure plots the β_k, the interactions between the SFHA status and disclosure policy dummies in event time from equation (4) from the 25 ever-treated states and never-treated states. Event time unit in this figure is year. The dependent variable is the log of housing price. Standard errors are clustered on state. Dotted line corresponds to a 95% confidence interval.

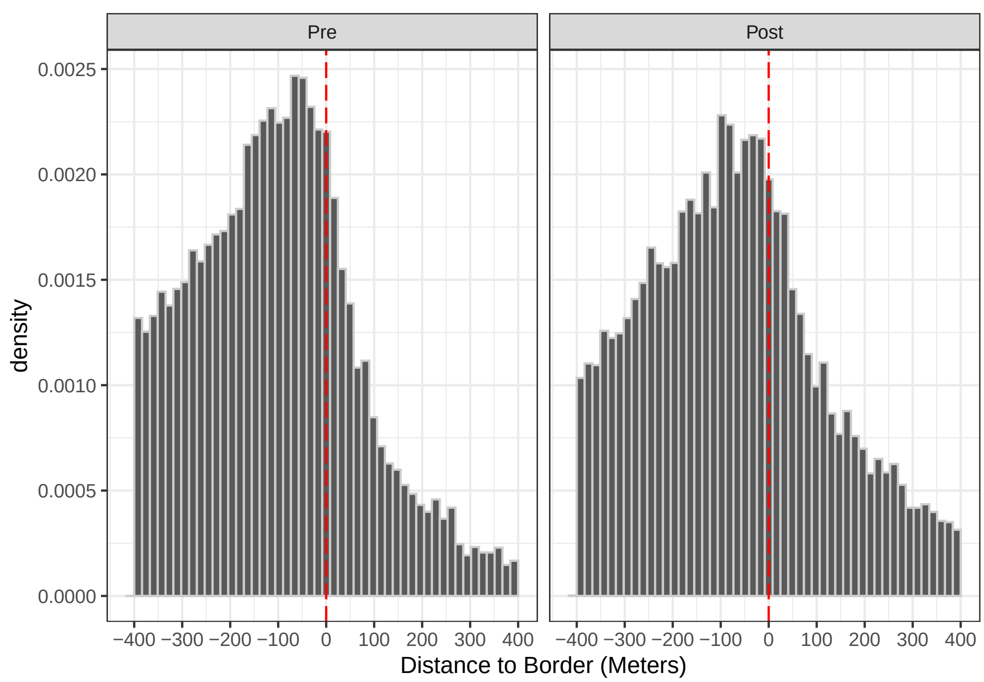
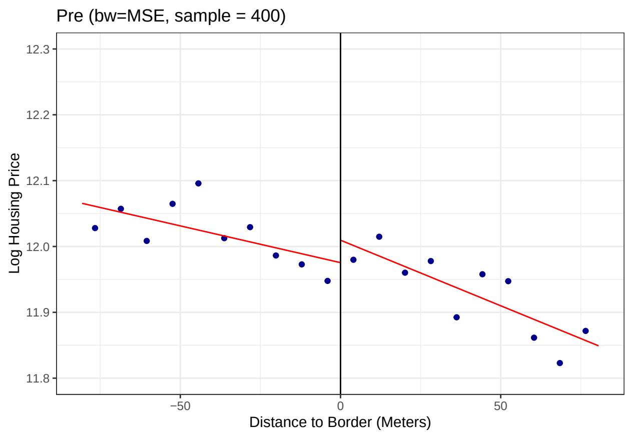
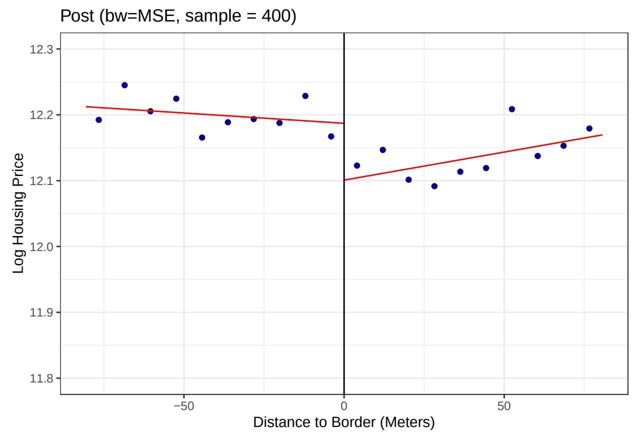


Figure B.4: Density of Houses Regarding Distance to the SFHA Border. This plot shows the distribution of property locations with respect to the SFHA border in Louisiana before and after the disclosure policy. The dotted vertical line represents the SFHA border. Negative and positive distance represent outside and inside of the SFHA, respectively. The histograms present no evidence of sorting.



(a) Pre



(b) Post

Figure B.5: The Effect of the Disclosure Requirement on Flood Damage. Panel (a) plots δ_2, which is the pre-disclosure log housing price difference at the SFHA border from equation (6) using the estimated optimal bandwidth. Panel (b) plots the post-disclosure log housing price difference at the SFHA border, which corresponds to $\delta_2 + \delta_6$ from equation (6) using the estimated optimal bandwidth. The dependent variable is the log of housing price and standard errors are clustered on community.

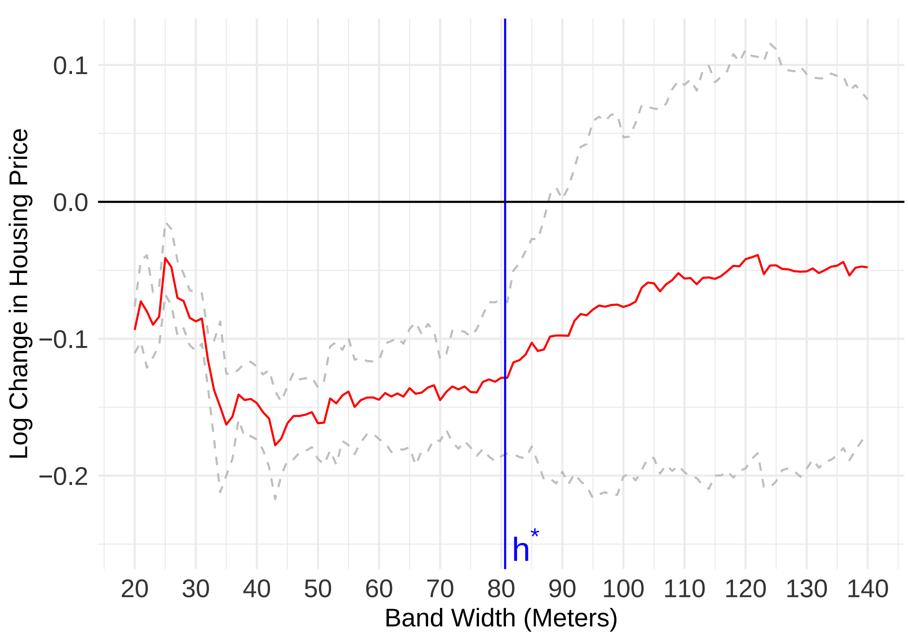


Figure B.6: The Effect of the Disclosure Requirement on Housing Price for Different Bandwidth. This figure plots δ_6 from equation (6) for a range of bandwidths around the estimated optimal bandwidth. The dependent variable is the log of housing price and standard errors are clustered on community.

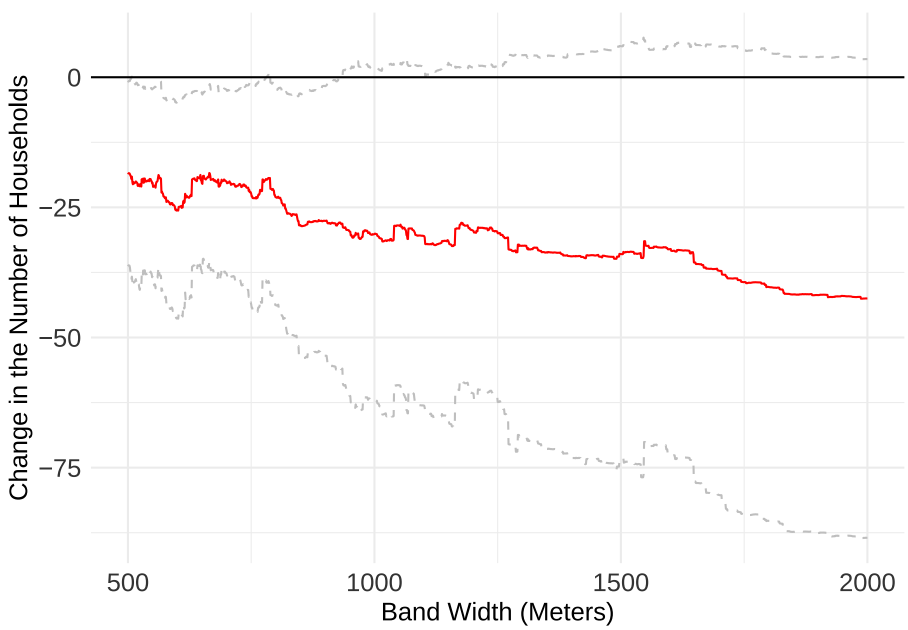
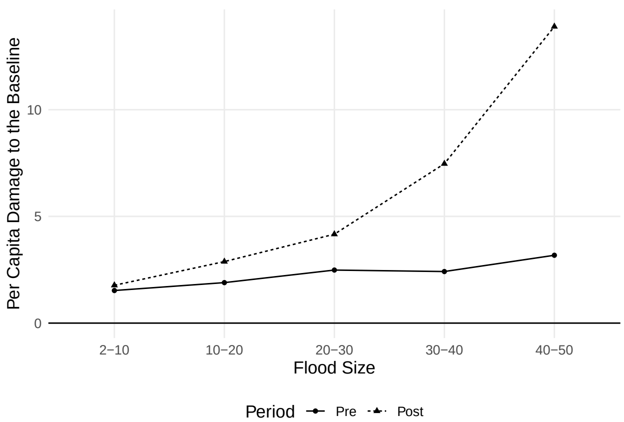
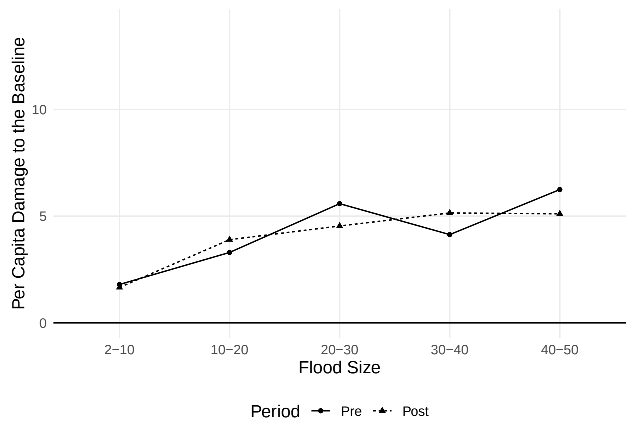


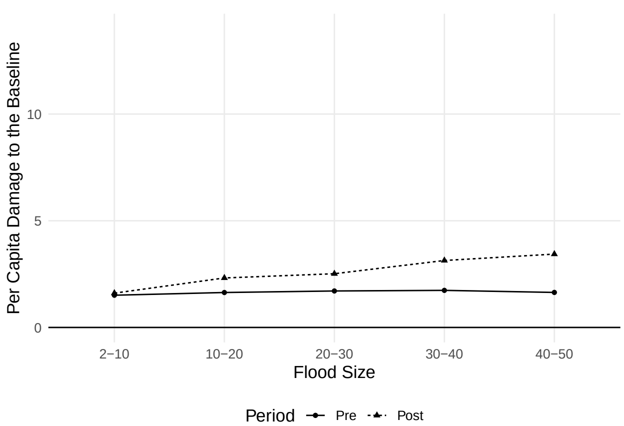
Figure B.7: The Effect of the Disclosure Requirement on Number of Households for Different Bandwidths. The figure plots δ_6 from equation (6) on demographic variables for a range of bandwidths. The level of observation is census block groups, which is the smallest geographical unit for which the bureau publishes sample data. Standard errors are clustered on state. See the text for additional details.



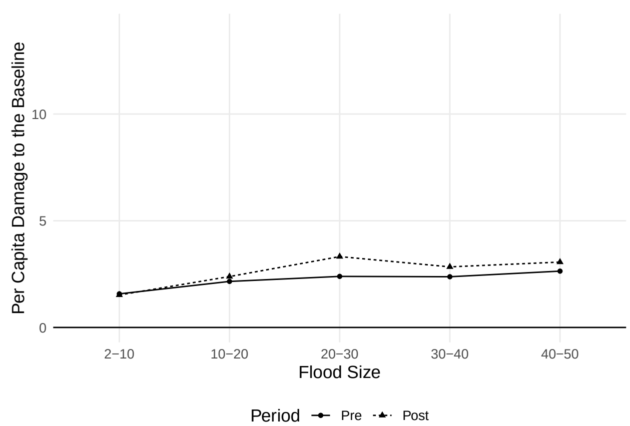
(a) Above Median SFHA (Control Group)



(b) Above Median SFHA (Treatment Group)



(c) Below Median SFHA (Control Group)



(d) Below Median SFHA (Treatment Group)

Figure B.8: The Effect of Disclosure on the Damage Function (Above vs. Below the median SFHA Ratio). These figures show the disclosure policy effect on the damage function for the control and treated communities and for the above and below median SFHA area communities, respectively. Panel (a) is produced using $\hat{\beta}_1^k$ and $\hat{\beta}_2^k$ from column (2) of Table B.4, which describes the relationship between flood size and log of per capita damage for the control group among the above median SFHA communities. Panel (b) plots the damage function for the treated group among the above median SFHA communities analogous to the plot (a). Panel (c) and (d) repeats panel (a) and (b) for the below median SFHA communities. The gap between two lines corresponds to the change in per capita damage before and after the disclosure policy. See the text for additional details.

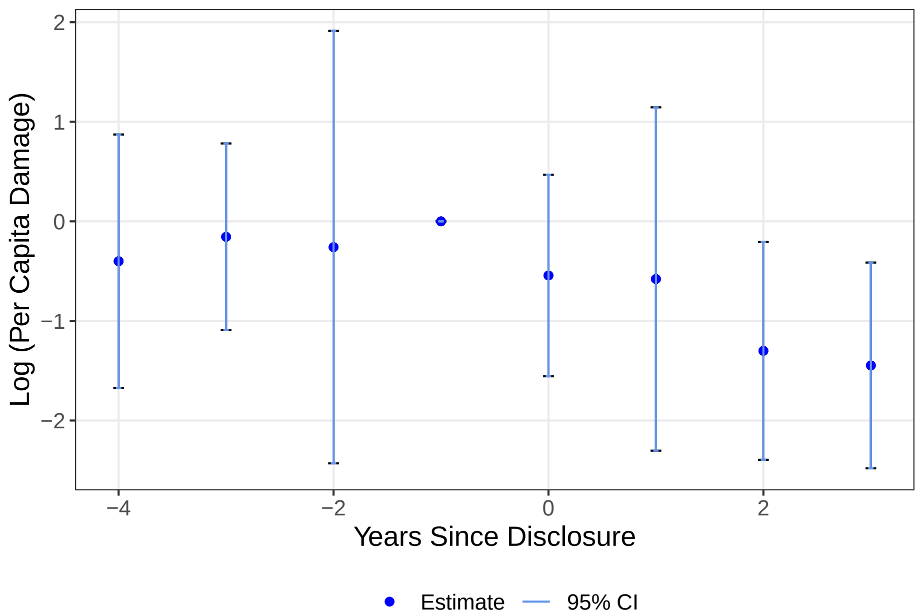


Figure B.9: The Effect of Disclosure on the Damage Function (Event Study). This figure depicts $\hat{\beta}_4$ for flood size of 30-50 in event time. The error bar represents the 95% confidence interval. See text for more details.