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

Seunghoon Lee*

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Abstract

Despite intensifying climate change, population exposure to flood risk in the US remains high. This paper studies whether providing flood risk information to homebuyers can reduce flood exposure, thereby decreasing flood damage. Leveraging two quasi-experimental variations of a Home Seller Disclosure Requirement, I first show that mandating flood risk disclosure lowers the population living in high-risk areas. Further, using a hydrological measure of flood intensity, I find that the policy reduces the probability of flood damage by 38 percent. These findings highlight that easing information frictions can promote voluntary adaptation to natural disasters.

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*Department of Economics, University of Missouri (615 Locust Street Columbia MO 65211, seunghoon.lee@missouri.edu). I am deeply grateful to Ryan Kellogg, Koichiro Ito, and Dan Black for their guidance, mentorship, and patience, and for facilitating access to data. I am also grateful to Eyal Frank and Amir Jina for their comments and encouragement especially during the early stages of this project. I also benefited tremendeously from numerous discussions with Cory Koedel and Peter Mueser. I thank H. Spencer Banzhaf, Lint Barrage, Zarek Brot-Goldberg, Fiona Burlig, Tatyana Deryugina, Justin Gallagher, Jonathan Gourley, Michael Greenstone, Solomon Hsiang, Seojeong Lee, George Lefcoe, Christian Leuz, Meagan McCollum, Philip Mulder, Anant Sudarshan, Richard L. Sweeney, Katherine Wagner, Margaret Walls, Austin Wright, Derek Wu, Siqi Zheng, and seminar participants at the AERE Summer Conference, AREUEA National Conference, FHFA Fall Economic Summit, KDI School of Public Policy and Management, Midwest Energyfest, MIT, NBER Summer Institute, OSWEET (Online Summer Workshop in Environment, Energy, and Transportation), University of Chicago, and University of Missouri for their helpful comments. All errors are my own.

1 Introduction

Since 1980, floods in the United States have caused over $1 trillion in damage, and climate scientists predict flooding is likely to happen with higher frequency and intensity in the future (Milly et al. 2002, NOAA 2020). Despite these warnings, many Americans continue to settle in flood-prone areas, amplifying the economic toll of floods (Weinkle et al. 2018, Redfin 2023, Titus 2023). Previous studies suggest that this seemingly counterintuitive behavior may stem from homebuyers' limited awareness of flood risks, which prevents them from fully internalizing costs associated with their choices (Bakkensen and Barrage 2021, Wagner 2022).[1] Recently, flood risk information policies have gained attention to address this issue, but little is known about their effectiveness.[2]

This paper exploits quasi-experimental variations from a Home Seller Disclosure Requirement (hereafter "the disclosure requirement") to study whether easing information frictions about flood risk can reduce (1) the number of households in high-risk areas and (2) resulting flood damage. The policy mandates that home sellers disclose known property defects using a standardized form (Lefcoe 2004). Regarding flood risk, a typical question is if a property is located in a Special Flood Hazard Area (SFHA)—an area with elevated risk defined by the official flood map. Given that a potential reason for the friction is information acquisition and processing costs (Kunreuther and Pauly 2004), the disclosure requirement could alleviate the problem by efficiently delivering risk information.

The disclosure requirement was rolled out across 26 states in the contiguous US from 1992–2003. The variation in implementation timing is from plausibly exogenous state court rulings on the extent of realtor liability for incomplete disclosure (Roberts 2006), which facilitates a difference-in-differences research design. I also leverage additional variation stemming from the spatial discontinuity in flood risk information at SFHA borders, which allows me to identify the effect of information while holding true flood risk constant (Noonan et al. 2022). A potential concern is that being located in the SFHA could invite other treatments such as the mandatory purchase of flood insurance. Thus, I use the difference-in-discontinuity approach to control for time-invariant confounders (Grembi et al. 2016).

[1] Although official flood maps have long been publicly available, a large body of evidence suggests a lack of flood risk awareness among homebuyers. For instance, Chivers and Flores (2002) find only 14 percent of homebuyers in high-risk areas learned about flood risk before closing.

[2] For instance, FEMA has proposed a reform to the National Flood Insurance Program (NFIP) that would make a community's eligibility contingent on mandatory flood risk disclosure (U.S. Department of Homeland Security 2022).

I collect multiple datasets to leverage these variations. To explore homebuyer responses to the disclosure requirement, I use census-block-level demographic data from the decennial census. For flood damage, I use damage records from flood insurance adjuster reports. To measure flood size, I use a novel hydrological measure of flood intensity, which objectively documents flood events for various causes (Saharia et al. 2017, England Jr et al. 2019). Because the main outcome variables used in the analysis have a mass point at zero with a long right tail, I estimate the extensive and intensive margin effects separately (Chen and Roth 2022).

The empirical exercise produces two key results. First, by leveraging the spatial discontinuity, I find that census blocks in an SFHA area (provided having a non-zero population) experience a 7 percent decline in population after the disclosure policy. At the extensive margin, disclosure lowers the probability of a block in the SFHA having any population by 0.01, or 1.5 percent from the baseline. I further show that these effects are driven by diverted in-migration (and resulting suppressed development) rather than active out-migration from SFHA areas. These results survive a battery of robustness checks such as allowing for time varying discontinuities at the border.

In the subsequent section, I directly test whether this lower exposure contributes to a reduction in flood damage. To show this, I first estimate a non-parametric flood damage function—a mapping between flood intensity and damage—using community-level flood size and damage data. Then, I estimate the causal effect of the disclosure requirement on the damage function using a stacked difference-in-differences approach to overcome potential bias from conventional two-way fixed effect models (Cengiz et al. 2019, Brot-Goldberg et al. 2020, Goodman-Bacon 2021). I find that the policy substantially flattens the damage curve: the annualized probability of having any flood damage at the community level is reduced by 2.7 percentage points (or 38 percent of the baseline). Additionally, I report that the damage reduction effect is three times larger in high-risk communities, which are subject to higher treatment intensities. Importantly, neither population nor damage reduction effects are observed in the "placebo" states, which had implemented a home seller disclosure requirement but without a question on flood risk.

This paper contributes to four different bodies of literature. First, it is related to prior studies on factors that reduce damage from climate change. While earlier studies primarily focus on technology as a driver of adaptation (Miao and Popp 2014, Barreca et al. 2016, Burke and Emerick 2016), I focus on the role information can play in aligning private incentives with socially desirable outcomes. A recent paper by Fairweather et al. (2023), which experimentally demonstrates that Redfin users are more likely to make offers on properties with lower flood risk when provided with flood risk information, is an important exception. I complement Fairweather et al. (2023) with (1) the ability to estimate changes in flood damage from information provision and (2) a stronger external validity.

Second, I contribute to the literature on the role of government in shaping household adaptation behaviors (Kousky et al. 2006, 2018, Gregory 2017, Peralta and Scott 2020, Baylis and Boomhower 2022). Perhaps the closest papers conceptually are Baylis and Boomhower (2021) and Ostriker and Russo (2023), which show how building-code policies can reduce wildfire damage or flood risk exposure, respectively. A key difference is that the policies studied by these papers directly mandate adaptation, whereas disclosure policies studied in this paper encourage voluntary adaptation such as choosing safer places to live.

Third, and more broadly, I build on earlier work on the impacts of flood risk on the housing market (Hallstrom and Smith 2005, Pope 2008, Bin and Landry 2013, Bosker et al. 2019, Muller and Hopkins 2019, Gibson and Mullins 2020, Hino and Burke 2021, Bakkensen and Barrage 2021). While most prior studies focus on understanding how changes to flood risk information or beliefs affect housing prices, I study their impacts on flood damage.[3] Tracing the effect of flood information up to damage is important because while housing price changes might reflect transfers between homebuyers and sellers, a reduction in flood damage can enhance social welfare.

Finally, I contribute methodologically by constructing a novel measure of flood exposure, which is a critical step in identifying climate change effects (Hsiang 2016). My approach leverages hydrological measures, which allow me to objectively document flood events for various causes including rainfall, snow melt, or storm surge. This extends the existing measures that are either endogenous or more focused in scope (Strobl 2011, Felbermayr and Gröschl 2014, Davenport et al. 2021).

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

[3] For example, Hino and Burke (2021) uses flood map updates as the main source of information shock and tests if the housing market efficiently prices flood risk. In contrast, I study household responses to the information shock—which provide an explanation for price adjustments—and resulting change in flood damage.

2 Background

Disclosure content. A statutory disclosure requirement mandates that home sellers provide buyers with a detailed account of known material defects in the listed property by filling out a standardized form and typically deliver it before closing (Stern 2005). Importantly, the disclosure requirement is not exclusively about flood risk. As Appendix Figure E.3 illustrates, a typical form covers a wide range of property conditions including structural issues (e.g., problems with walls) and surroundings (e.g., flood risks).[4] This implies that the policy adoption decision is likely to be uncorrelated with underlying flood risks. Indeed, Appendix Figures E.2 (a)-(c) show little relationship between the timing of disclosure requirement and recent flood history or ex-ante flood risk levels.

The exact language of disclosure on flood risk varies slightly from state to state, but some combination of the following three questions usually appears: whether a property is in the SFHA; whether a property has flood damage history; and whether a property has flood insurance.[5] Because properties on the SFHA are more susceptible to flooding, answers to these questions are highly correlated. Indeed, flood insurance policy and claims data show that 71 percent (75 percent) of the claims (flood insurance policies) are from properties in the SFHA. Thus, irrespective of the language, the disclosure requirement is likely to raise homebuyers' flood risk awareness for properties in SFHAs relative to those outside.

Background and determinants of policy adoption. Traditionally, homebuyers were expected to practice caution regarding property defects ("*caveat emptor*" or "let the buyer beware" doctrine). However, due to increasing consumer protectionism and public awareness of environmental and health concerns, state courts began holding listing agents accountable for incomplete disclosures (Weinberger 1996, Lefcoe 2004). In response, the National Association of Realtors issued a resolution in 1991 urging state associations to develop and support legislation regarding the statutory disclosure requirement in an effort to deflect potential liability to sellers (Tyszka 1995, Washburn 1995).

Consequently, between 1992 and 2003, 26 states in the contiguous US adopted a disclosure require-

[4]Since the disclosure delivers a bundle of information, discerning treatment mechanism can be challenging especially when there is a positive correlation between flood risk and other property defects. In Appendix Table E.1, I demonstrate that properties in tracts with SFHAs are notably newer compared to those in tracts without SFHAs. As property defects typically emerge over time, this table suggests that SFHA properties are less prone to issues and the disclosure policy's impact stems from flood risk information.

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

ment with an explicit question on flood risk while the remaining 22 states never adopted such a requirement until late 2010s (Appendix Figure E.1). In Appendix Table E.2, I show that (1) the 22 never-adopted states are different in demographic, economic, and political characteristics from the 26 ever-adopted states but (2) such a difference does not appear in the early—14 states that have implemented the policy by 1994—vs. late—12 states implemented after 1994—adopting states comparison. Given this, I use late adopting states as a control group in subsequent empirical exercises.[6]

It is also worth pointing out that five of the 22 non-disclosure states adopted a home seller disclosure mandate without a question on flood risk.[7] These "placebo" states are useful for checking the robustness of the main results.

Flood Map and Special Flood Hazard Area (SFHA). The SFHA, an area designated by an official flood map for potential inundation by a 100-year flood, holds significant importance as it frequently serves as a reference point for flood risk communications (FEMA 2011). The SFHA boundary is determined by comparing water surface elevation with the ground elevation under a 100-year flood scenario (FEMA 2005). This gives rise to the spatial discontinuity design because the disclosure form treats flood risk discontinuously for two areas on different sides of the border with possibly very similar true flood risks (Noonan et al. 2022). It is also worth noting that the flood maps are updated occasionally, albeit much less frequently than legally mandated (DHS Office of Inspector General 2017).[8] Such a map update is a source of information shock (Gibson and Mullins 2020, Bakkensen and Ma 2020, Weill 2021, Hino and Burke 2021), which may confound the disclosure effect. Throughout empirical exercises, I test if my results are robust to the map updates.[9]

3 Data

In this section, I describe data sources. Appendix B provides descriptive statistics.

[6]Deshpande and Li (2019) also exploit the timing of treatment because eventual treatment status was predictable based on covariates. Roth and Sant'Anna (2023) also states that in non-experimental contexts, the quasi-randomness in identifying variation may be more plausible when never-treated units are excluded.

[7]For details, see 1994 Ida. 55-2508 (1994), K.S.A. 58-30, 106 (1995), ME Title 33 Section 173 (1999), MN CHAPTER 306-—S.F.No. 2697 (2003), NH. Rev. Stat. Ann. § 477:4-c (1994).

[8]Given that responses to information generally improve with accuracy (Dranove and Jin 2010), the effects of the disclosure policy could be even greater with the use of state-of-the-art flood maps.

[9]293 communities in the 26 disclosure states have experienced at least one update within the 20 years around the change year of the disclosure policy. To generate the list, I use the "L_Comm_Revis" layer from the National Flood Hazard Layer from FEMA (FEMA 2019).

Population and Housing Units. I create census-block-level population and occupancy panel data from the 1990, 2000, 2010, and 2020 decennial censuses. To account for changing block boundaries and resulting one-to-many matches across different decennial census years, I calculate the weighted sum of count variables using interpolation weights from the NHGIS block-to-block crosswalk (Manson et al. 2022).

Flood damage. I use damage records from the flood insurance adjuster's report, which I acquired through Freedom of Information Act requests. The damage amount is defined by the actual cash value—a replacement value net of depreciation (FEMA 2014). I observe individual property level damage with loss date, community ID, and building type. I restrict the sample to damage records from single-family houses that has sustained the largest flood event for a given community-year. Then I collapse the data to the community by year level to merge it with the flood history data.

Flood size. I construct hydrology-based community-year-level flood size data using daily water volume records from over 3,000 USGS and NOAA stations (Gourley et al. 2013, Mallakpour and Villarini 2015, Slater and Villarini 2016). Under this approach, flood size is described by the recurrence interval or the expected number of years for a flood of the same magnitude to come back, which, heuristically, can be considered as deviations from gauge specific averages. Importantly, this objective and comprehensive gauge-based flood data is a major step forward in measuring flood exposure, which is a crucial for estimating credible climate damage functions (Hsiang 2016). Further details on background, procedure, and summary statistics on the flood data are in Appendix A.

Other data sources. To determine the flood risk level of geographic units such as census blocks, I use the Q3 map—the first generation of a digitized flood map—that captures flood risk as of the mid-1990s for over 1,300 counties (FEMA 1996). Also, the primary data source to track the disclosure requirement legislative history is the *Nexisuni* database. I cross-validate this database with prior studies on the disclosure requirement (Washburn 1995, Pancak et al. 1996, Lefcoe 2004) and reports from the National Association of Realtors (National Association of Realtors 2019).

4 The Effect of the Disclosure Requirement on Population

4.1 Estimation Framework

Disclosure requirements create a spatial discontinuity in flood risk information, which allows me to disentangle the information effect from the true flood risk effect. However, a potential concern is that other policies such as flood insurance requirements also change at the border, which could confound the disclosure effect.[10] To account for this, I leverage a difference-in-discontinuity approach as equation (1) following Grembi et al. (2016).

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

Y_{bst} is an outcome variable such as the probability of having any population, log of population conditional on having non-zero population, or the vacancy rate in block b in state s in time t. X_{bs} is the distance between a block border and the closest SFHA border in meters (negative if in a non-SFHA area),[11] $D_{bs} = 1$ if $X_{bs} > 0$ is a treatment group indicator variable, and $T_{st} = 1$ if $t > T_s^*$ is a post-period indicator variable, where T_s^* is the policy change date for s. δ_6 captures the impact of the disclosure policy for blocks located in close proximity to the SFHA border.

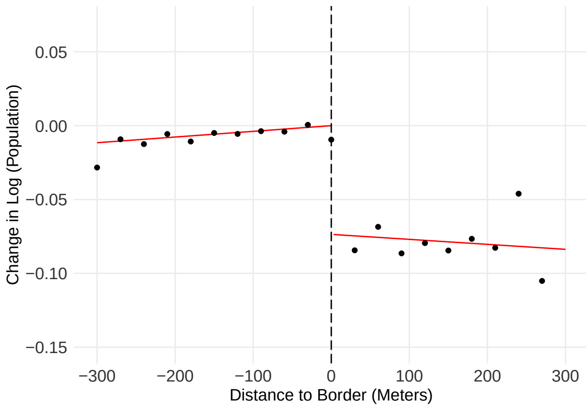
To estimate δ_6, I first estimate the optimal bandwidth for each outcome variable. Then, I estimate equation (1) using blocks within the optimal bandwidth (Calonico et al. 2014, Cattaneo et al. 2019).[12] For states that have implemented disclosure policies between 1990-1999 (2000-2009), I use the 1990, 2000, and 2010 (2000, 2010, and 2020) decennial census. Throughout the analysis in Section 4, standard errors are clustered at state—the level of disclosure treatment. Also, I remove 17% of blocks that contain SFHA borders from the analysis because X_{bs} may not be well defined for them.

[10] While Noonan et al. (2022) shows that flood risk changes continuously at the border in Texas, it is possible that land contour changes rather abruptly for other states in my sample. However, because land contour is likely time invariant, such differences will also be controlled by the difference-in-discontinuity approach.

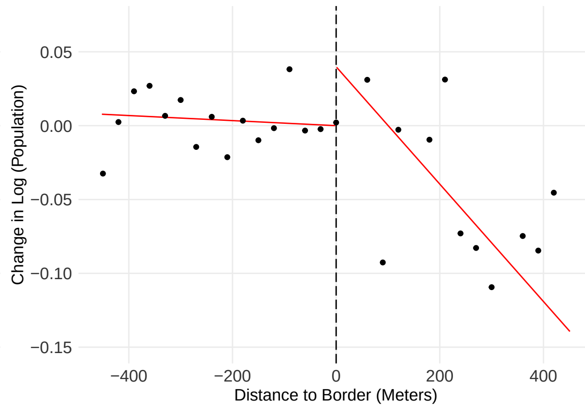
[11] X_{bs} is approximated by taking the difference of (1) the distance between block centroids and the closest SFHA border and (2) a block diameter.

[12] I estimate the mean squared error optimal bandwidth for 2000 and 2010 and take the average of them following Grembi et al. (2016). I ignore 1990 and 2020 because these years have only a subset of the states in the sample.

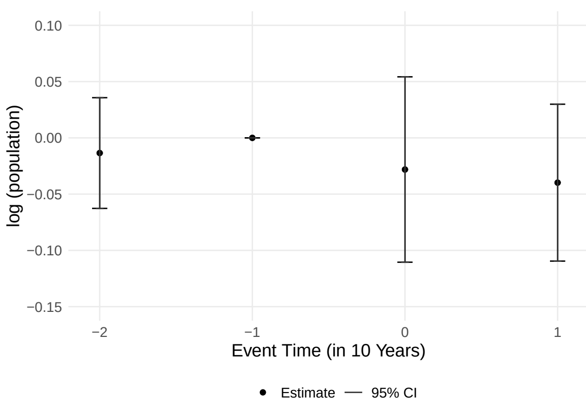
4.2 Findings



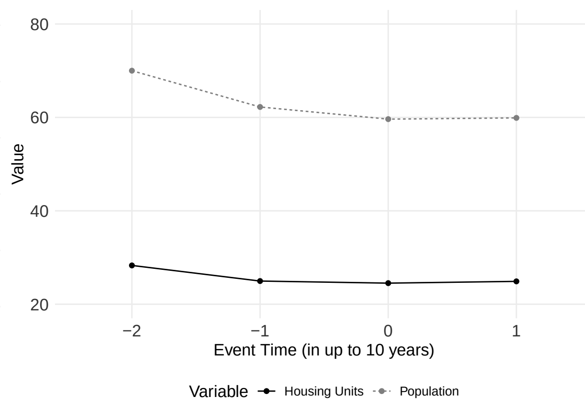
(a) Disclosed States



(b) Placebo States



(c) Event Study



(d) Raw Trends for SFHA Blocks

Figure 4.1: The Effect of Disclosure on Population. Panels (a) and (b) illustrate difference-in-discontinuity estimates for the disclosed and placebo states, respectively. The dependent variable is the change in log of population after the disclosure. The running variable is defined by the distance between a census block and the nearest SFHA border. The discontinuity at the threshold (dashed vertical line) represents δ_6 in equation (1). Panel (c) plots coefficients from an event study version of equation (1). Panel (d) plots population and housing unit trends (in absolute terms) in event time for SFHA blocks. For panels (c) and (d), I limit the sample to blocks that are observed in at least four decennial censuses.

Figure 4.1 (a) illustrates the impact of disclosure policy on the population. The horizontal axis is the distance between a block and the nearest SFHA border. The blocks within (outside of) an SFHA are presented on the right-hand (left-hand) side of the border (the vertical dashed line). The solid lines represent the regression fit from equation (1) and points are the difference in log population between pre and post treatment periods for each distance bin. δ_2 from equation (1) is normalized to 0 to enhance readability.

The figure indicates there is a sharp drop—approximately 0.07 log points—in the population for

SFHA blocks relative to non-SFHA blocks at the SFHA boundary after the disclosure requirement. The tight fit of the regression line to the scatter plot suggests that the choice of functional form for the running variable likely has minimal impact on the estimates. Importantly, as Figure 4.1 (b) shows, no such population change is observed when a disclosure requirement does not provide information on flood risk.

Table 4.1 reports the disclosure policy effects more formally. In column (1), which corresponds to Figure 4.1 (a), I limit the sample to blocks with non-zero population and find that the disclosure reduces the population in SFHA blocks by 7 percent relative to non-SFHA blocks. In column (2), I report the extensive margin effect—the disclosure reduces the probability of having any population in an SFHA block by 0.01 relative to a non-SFHA block (or 1.5 percent of the baseline value of 0.68). Taking these extensive and intensive margin effects together, the policy seems to discourage both in-migration into SFHA blocks with existing populations and new developments in previously uninhabited SFHA blocks.

In column (3), I report that the disclosure increases the vacancy rate for the blocks in an SFHA from 0.095 to 0.109. This finding suggests that after the disclosure, selling properties in the SFHA becomes harder (or takes longer) and a larger share of them are vacant at any given time.[13] These findings are consistent with evidence that people migrate away from negative environmental conditions (Banzhaf and Walsh 2008, Boustan et al. 2012, Hornbeck 2012, Hornbeck and Naidu 2014).

In Figure 4.1 (c), I show the log of population change in event time.[14] The analysis focuses on blocks that appear in at least four decennial censuses, with 80% of observations excluded due to the 1980 census covering only urban or metropolitan areas. Although the results are underpowered, the event study indicates no pre-trend in log population, with a 3-4% relative decline in SFHA areas after the disclosure requirement compared to non-SFHA areas. Interestingly, as shown in Figure 4.1 (d), the absolute level of log of average population and housing units in SFHA blocks did not decline over the same period, suggesting that the population adjustments stem from diverted in-migration and suppressed development, rather than active out-migration. This is consistent with the policy's role in informing prospective buyers rather than existing homeowners.

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

[14] I replace the post period indicator in equation (1) with event time indicators. Event time is defined as -2 (-1) for 19 to 10 (9 to 1) years before the policy change and 0 (1) for 0 to 9 (10 to 19) years after the policy change.

Table 4.1: Effect of Discosure Requirement on Net Population Flow

	Log Population	Prob. of Any Population	Vacancy Rate
	(1)	(2)	(3)
SFHA × Post	$-.074^{**}$	$-.011^{***}$	$.014^{***}$
	(.030)	(.003)	(.004)
Avg D.V.		0.675	0.095
Bandwidth	301	138	262
Num. obs.	1915717	1483356	1700002

Note: Columns (1)–(3) are estimated based on equation (1) using the decennial census block-level data in 1990, 2000, 2010, and 2020. Standard errors are clustered at the state level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Two potential concerns regarding internal validity—treatment spillover and concurrent policy changes—merit attention. In Appendix D, I show that my main results survive a battery of robustness checks such as allowing for time varying discontinuities at the border.

Given that purchasing insurance is a potential alternative to self-protection, namely choosing a safer location (Ehrlich and Becker 1972), in Appendix C, I investigate the disclosure policy's impact on flood insurance take up.[15] The results suggest that homebuyers primarily respond to the flood risk information by choosing a safer location to live, which indicates that the disclosure requirement has the potential to substantially reduce flood damage. But why do homebuyers engage in self-protection despite having access to flood insurance? One possibility is that the cost of location adjustment is substantially lower for homebuyers especially compared to households not intending to move. Indeed, Zumpano et al. (2003) documents that homebuyers actively search across alternatives, and an average buyer visits 17 properties before closing. Moreover, the NFIP coverage may be considered incomplete: it does not (1) cover asset losses exceeding $250,000 and (2) compensate for numerous economic costs (e.g., loss of income or use value) beyond asset losses (Lee et al. 2024).

[15] Investigating both margins is important because they have starkly different implications for flood damage—self protection can reduce flood risk exposure whereas buying insurance simply redistribute income from "dry" to "flood" state without necessarily affecting exposure. Ehrlich and Becker (1972) suggests that, when self-protection is financially rewarded, self-protection and market insurance are complements. However, as Kousky (2019) points out, the NFIP premium is heavily subsidized and the NFIP premium structure is too coarse to account for all self-protection measures. Wagner (2022) also finds that substitution between self-protection (property elevation) and flood insurance is prevalent in the flood insurance market.

5 The Effect of the Disclosure Requirement on Flood Damage

5.1 Estimation Framework

Conditional on flood size, how does flood damage change after the disclosure requirement? To answer this question, I estimate a damage function, which is a mapping between flood size and damage, and show how the functional relationship changes due to the policy. As Hsiang (2016) notes, a crucial step in estimating any damage function is constructing an objective and continuous measure of exposure, and I leverage the hydrology-based flood history dataset described in Section 3.

$$\text{Per Housing Unit Damage} = \sum_k [\alpha_1^k F^k + \alpha_2^k F^k D] \tag{2}$$

Consider equation (2), where the dependent variable is flood damage per housing unit, D is an indicator variable for the treated (i.e., disclosed) group assignment and F^k is an indicator variable equal to 1 when the annual maximum flood size is in bin k where $k \in \{$2-5, 5-10, 10-20, 20-30, 30-50$\}$.[16]

Here, flood sizes between 1–2 serve as the omitted category, and thus α_1^k is the additional damage per housing unit when a community in the control group experiences a flood of size k as opposed to a flood size between 1–2. α_2^k allows a different damage function slope for the treated group for flood size k. Note, equation (2) follows a non-parametric approach of Barreca et al. (2016), which lets the data rather than the functional form assumption, determine the shape of the damage function.

$$\text{Per Housing Unit Damage} = \sum_k [\beta_1^k F^k + \beta_2^k F^k I + \beta_3^k F^k D + \beta_4^k F^k I D] \tag{3}$$

Equation (3), which mirrors a canonical difference-in-differences model, shows how equation (2) changes when the post disclosure indicator I is introduced. The coefficient for the interaction term (β_4^k) captures the treatment effect.

$$Y_{mtd} = \sum_k [\beta_1^k F_{mtd}^k + \beta_2^k F_{mtd}^k I_{mtd} + \beta_3^k F_{mtd}^k D_{mtd} + \beta_4^k F_{mtd}^k I_{mtd} D_{mtd}] + \theta_{md} + \omega_{td} + \epsilon_{mtd} \tag{4}$$

For estimation, I use equation (4). Y_{mtd} is either an indicator variable for positive flood damage in community m (extensive margin), or log(Per Housing Unit Damage) conditional on having posi-

[16] I focus on flood sizes between 1 and 50 for main analysis because of statistical power. However, I show that the results are robust to different cutoff choices (e.g., 100). See Appendix A.3 for additional details on the binning decision.

tive damage for community m (intensive margin), in year t for data stack d. While I report both the extensive and intensive margin effects, an emphasis is on the former due to greater generalizability—only a small fraction of communities experience repeated damage—and higher statistical power.

Each stack d consists of communities in the treated states, which adopted the disclosure policy in year t^*, and communities in the control states, which adopted the policy in $\tilde{t} > t^*$.[17] I drop observations from the control states for $t >= \tilde{t}$ because they are no longer "not-yet-treated". I also include year × stack (ω_{td}) and community × stack (θ_{md}) fixed effects, to control for overall time trend and unobserved community characteristics. I use 20 years of observation for each state around the disclosure policy change year (i.e., 10 years before and after the policy change) to keep the sample composition unchanged.

Because the impact of natural disasters is not confined by administrative units, previous studies on cyclone damage function have used spatial-HAC standard errors (Hsiang 2010). Following this, I allow spatial correlation of up to 500 miles for inference (Newey and West 1987, Conley 1999), but I also show that state-level clustering produces similar results.[18]

5.2 Findings

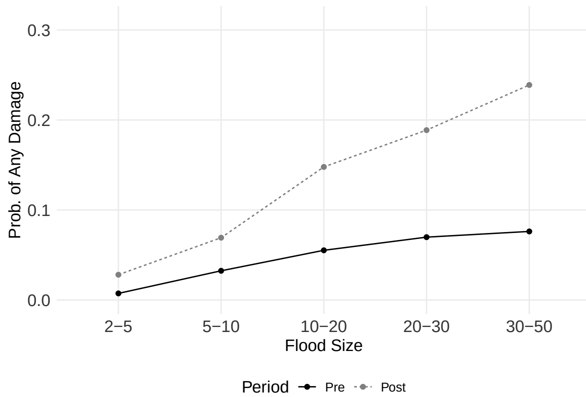
In Figure 5.1, I plot the damage functions for the (a) control—not-yet-disclosed—and (b) treatment—disclosed—groups using the estimated coefficients from equation (4).[19] For instance, $\hat{\beta}_1^k$ and $\hat{\beta}_1^k + \hat{\beta}_3^k$ for each k are used to plot the pre-treatment period damage functions for panel (a) and (b), respectively. Because the dependent variable in Figure 5.1 is the probability of any damage, the estimated coefficients indicate the additional probability of damage when the baseline flood (k=1–2) is replaced by a flood of size k.

Figure 5.1 allows visual inspection of the estimated damage function. To begin, I first focus on the slope of this function, which reveals a monotonically increasing relationship between flood size and the probability of any flood damage. Further, panels (c)–(f) show that high risk communities in panels (c)–(d) (an above-median fraction of the area covered by an SFHA) have much higher vertical

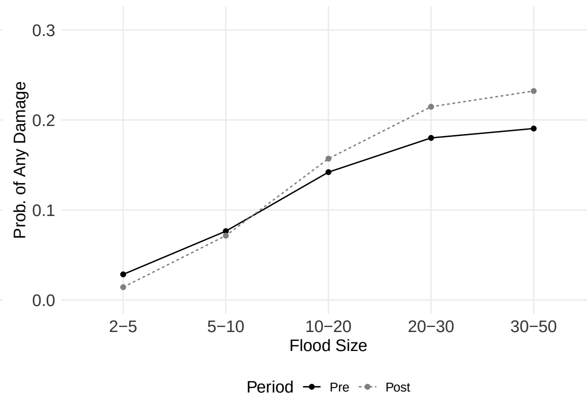
[17] Stack refers to data that is created for a specific treatment year (or a cohort year). A state can belong to both treatment or control groups depending on the stack. For instance, PA and CT, which changed their policy in 1996 are in the "treatment group" in a stack for $t^* = 1996$. The two states belong to the "control group" when $t^* < 1996$.

[18] Weights in this matrix are uniform up to that cutoff distance. When the variance-covariance matrix is not positive-semidefinite, I use eigendecomposition of the estimated variance matrix and convert any negative eigenvalue(s) to zero following Cameron et al. (2011).

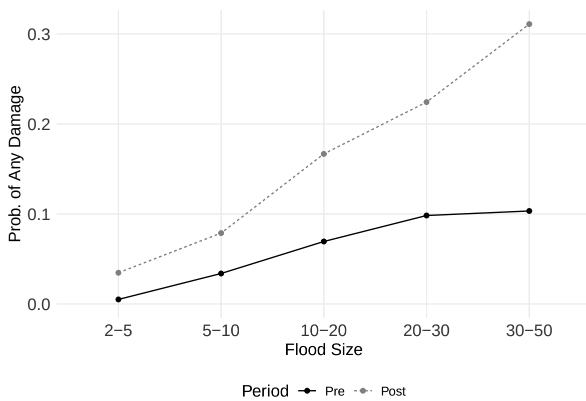
[19] Appendix Figure E.8 reproduces Figure 5.1 with a 95% confidence interval.



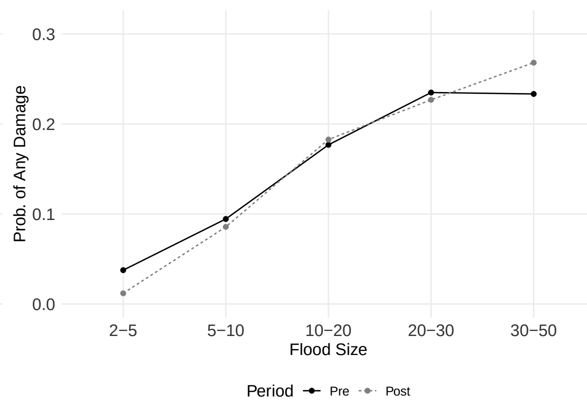
(a) Control Group (All Communities)



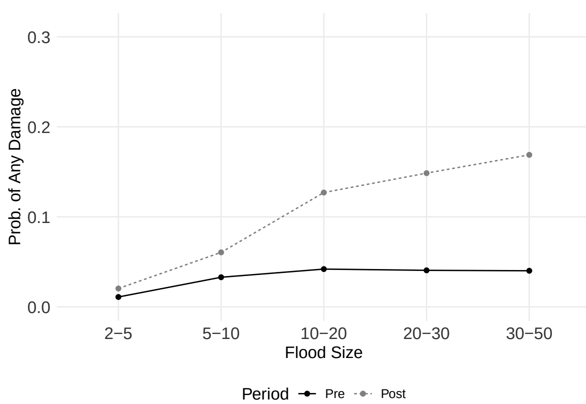
(b) Treatment Group (All Communities)



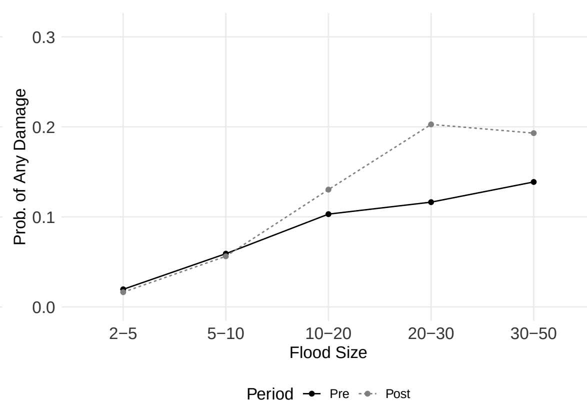
(c) Control Group (High Risk Communities)



(d) Treatment Group (High Risk Communities)



(e) Control Group (Low Risk Communities)



(f) Treatment Group (Low Risk Communities)

Figure 5.1: The Effect of Disclosure on the Damage Function. These plots illustrate estimated damage functions (dep.var: probability of any damage) from equation (4). Panels (a)–(b) are damage functions for all communities. Panels (c)–(d) and (e)–(f) illustrate the damage functions for high (above–median SFHA ratio) and low (below–median SFHA ratio) flood risk communities, respectively. Appendix Figure E.8 reproduces Figure 5.1 with 95% confidence intervals.

levels and steeper slopes in comparison to the low risk communities in panels (e)–(f), which further validates the estimated function.[20]

Table 5.1 highlights the impact of the disclosure requirement on flood damage. For brevity, I only report $\hat{\beta_4^k}$ from equation (4), but the full sets of coefficients are in Appendix Table E.3. In column (1), I report that the disclosure requirement reduces the probability of having any flood damage per housing unit by 4–14 percentage points for different values of k for the communities in the disclosed states relative to the ones in the not-yet-disclosed states.[21] The damage reduction effect can be verified visually as well: Figure 5.1 shows that in panel (a) (control), flood probability has substantially increased over time, whereas in panel (b) (treated), it remains nearly identical.

Using equation (5), I summarize the coefficients in Table 5.1 into probability-weighted average treatment effects. Note, because $Pr(K = k)$ is the likelihood of occurrence for flood size k each year and β_4^k is the change in probability of having damage from flood size k, equation (5) can be interpreted as the reduction in annualized damage probability due to the disclosure policy.[22]

$$\sum_k Pr(K = k) \times \beta_4^k \tag{5}$$

In Table 5.1 column (1), I report that the reduction in the annualized damage probability is 2.7 percentage points. When I compare this with the baseline of 7.1—average probability of having any damage conditional on exposure to a flood of size 2 or larger—the effect size is a 38 percent reduction. In columns (2) and (3), I show that the annualized damage probability is nearly three times larger for high-SFHA communities than for low-SFHA communities, which is consistent with the fact that the treatment intensity is higher for high-SFHA communities.

Column (4) reports the intensive margin effect, where the dependent variable is the log of damage per housing unit. Because the sample for this exercise is restricted to community-years with positive damage, the model is underpowered. Still, I find evidence that the disclosure policy reduces damage for communities with repetitive flood events for the costliest floods.

[20]To illustrate why the damage function is likely to be heterogeneous, consider two communities, A and B, with distinct risk profiles: A is entirely within the SFHA, while B lies outside it. During a 100-year flood, all properties in A (B) are expected to be underwater (unaffected) by the definition of SFHA, and thus damage should be significantly larger for community A.

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

[22]Since the flood size is defined by recurrence interval, the inverse of the size corresponds to $Pr(K = k)$. For instance, the probability of having a flood of size 30–50 in a given year is $\frac{1}{40}$.

Table 5.1: Effect of Disclosure Requirement on Flood Damage

	Prob. of Any Damage Per Housing Unit			Log Damage Per Housing Unit
	(1)	(2)	(3)	(4)
Post × Disclosure (Size 2-5)	$-.035^{*}$	$-.055^{**}$	$-.013$	$-.134$
	(.020)	(.027)	(.011)	(.300)
Post × Disclosure (Size 5-10)	$-.042^{*}$	$-.054^{*}$	$-.031^{*}$	.164
	(.022)	(.029)	(.018)	(.243)
Post × Disclosure (Size 10-20)	$-.078^{**}$	$-.091^{*}$	$-.058^{**}$	.051
	(.037)	(.053)	(.023)	(.210)
Post × Disclosure (Size 20-30)	$-.084^{*}$	$-.134^{***}$	$-.022$	.467
	(.049)	(.044)	(.070)	(.554)
Post × Disclosure (Size 30-50)	$-.121^{*}$	$-.173^{**}$	$-.074$	$-.334^{**}$
	(.063)	(.079)	(.054)	(.133)
Annual Effect	-0.027**	-0.039**	-0.014	-0.003
	(0.013)	(0.017)	(0.01)	(0.109)
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	505383	242458	262925	22319

Note: The dependent variable in columns (1) to (3) is the probability of having any flood damage per housing unit. Column (1) is from the entire set of communities while in columns (2) and (3), I repeat (1) using the subsample of communities with different levels of risk exposure. Dependent variables in columns (4) is log transformed per housing unit damage. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix D.2 presents various results from robustness checks. Specifically, it includes an event study graph that illustrates no pre-trends and a sharp reduction in damage probability following the implementation of the disclosure requirement. Furthermore, using placebo states, I show that disclosure requirements without information on flood risk fail to reduce damage. Lastly, the results in Table 5.1 are robust to flood map updates or expansion of flood sizes to 100.

To explore the mechanism of damage reduction, first revisit Figure 5.1 (c) and (e). These figures collectively show that, in the absence of a disclosure policy, flood damage has significantly increased over time in high-risk communities compared to low-risk ones. In contrast, Figure 5.1 (d) reveals that high-risk communities in states with disclosure requirements did not experience such an increase in damage, presumably because the policy effectively prevented an increase in flood risk exposures by diverting in-migration, as discussed in Section 4.2. Such a damage reduction effect is much smaller in (f), which is plausible given that treatment intensity is lower for low-risk communities.

While the estimated impact of a simple disclosure policy is non-trivial, this number is likely to underestimate the true benefit because the analysis excludes rare but devastating floods. Besides, I abstract away from a potential gain due to a better matching in flood risk preferences between properties and homebuyers (Bakkensen and Ma 2020).

6 Conclusion

Floods are the costliest natural disaster in the US and are expected to become more frequent and severe in the future. Thus, curbing economic loss from these events is of first-order importance. In this paper, I study whether alleviating information frictions regarding flood risk in the housing market can be an effective way to foster adaptation. By exploiting plausibly exogenous variations created by the disclosure requirements, I find the disclosure requirement reduces the population and increases the vacancy rate in high-risk areas. With fewer people exposed to flood risk, the annualized probability of flood damage decreases by 2.7 percentage points (or 38 percent from the baseline). The findings of this paper show that the disclosure requirement can facilitate voluntary adaptation by helping homebuyers make more informed choices.

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A Appendix A: Flood History Data

A.1 Background and Procedure

Background. A key input to the flood damage function is flood size data. An ideal measure of flood size should satisfy the following four conditions. First, it should be a continuous measure that allows a non-linear relationship between flood size and damage (Burke et al. 2015, Hsiang 2016).

Second, it should be objective. For instance, the widely used EM-DAT measures flood size using economic cost or death tolls, which are directly correlated with outcome variables of interest (Felbermayr and Gröschl 2014). Another example of a potentially endogenous measure is the occurrence of the Presidential Disaster Declaration (PDD) floods, which depends on the discretion of the president and thus could reflect political interests (Reeves 2011).

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

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

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

Procedure. Following the USGS guideline (England Jr et al. 2019), I implemented the following steps using USGS/NOAA water levels data from 3,505 gauge stations distributed in the 26 ever-disclosed states in the contiguous US (Appendix Figure A.1).[23]

First, I construct a site-specific flood frequency distribution. For this, I retrieved annual peak flow records using the R package "dataRetrieval" and fit the Log-Pearson III distribution to estimate gauge-specific parameters (Cicco et al. 2018). Importantly, as I use annual peak discharge data to fit the distribution, the quantile of the distribution has an intuitive interpretation. For instance, if a certain water level is the 95th percentile of the distribution, it means that such an event would happen with a 5 percent probability in a given year. Equivalently, such an event is called a 20-year ($\frac{1}{0.05} = 20$) flood. I keep stations with at least 10 or more annual peak observations following the USGS guideline. Also, I use annual peak data until 1990 to fix flood thresholds and make flood size comparable across different years.

Second, I convert the daily water level into the recurrence interval using the fitted flood size distribution from the previous step. For this, I need an instantaneous flow, because flood exposure is determined by the maximum, rather than mean, water level. The problem is that 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. This is problematic because, with

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

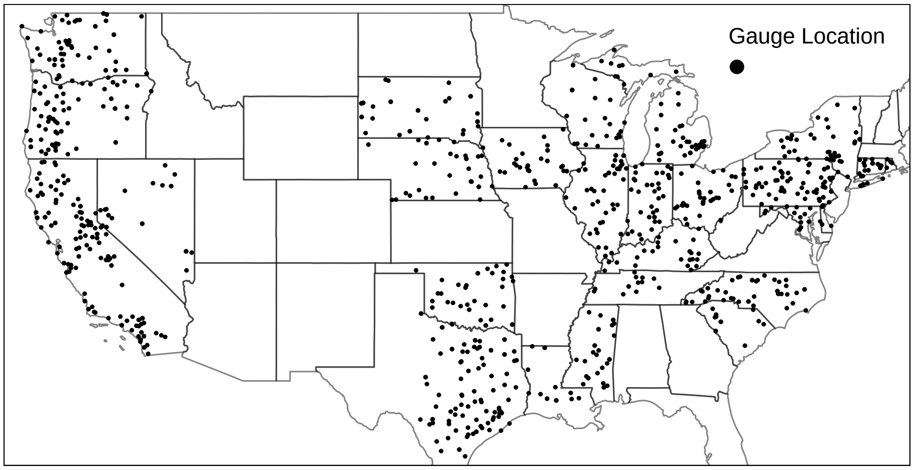


Figure A.1: The Distribution of a Sample of USGS/NOAA Gauges

Table A.1: Number of Stations with Non-Missing Water Levels Data 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

many missing observations, flood events will be significantly under-recorded. To overcome this problem, I estimate a projected instantaneous peak flow from the *mean* daily flow. Appendix Table A.1 illustrates the benefit of using mean daily flow in alleviating the missing data problem. For this, I report the number of water gauge stations in Iowa that have daily water level records for at least 80 percent of the days (i.e., 292 days or more) for a given year. It can be easily seen that there can be an order of magnitude difference in the number of stations that have mean versus maximum daily water records.

To estimate the daily maximum water level from the daily mean water level, I use the Fuller method in the following steps (Fuller 1913).[24] Step 1, I list up gauge stations that (1) are located in a given geographic units (state, HUC4, and HUC2) and (2) have both instantaneous peak flow (Q_{it}^{IPF}) and mean daily flow (Q_{it}^{MDF}) records.[25] Step 2, using these gauge stations, I estimate Fuller coefficients using equation (6) (Fuller 1913).[26] Step 3, using the estimated coefficients, I calculate the projected instantaneous peak flow and compare that with the actual instantaneous peak flow to pick the geographic unit (state, HUC2, HUC4) that minimizes the prediction error for each gauge. Step 4, using the chosen Fuller coefficients, I estimate instantaneous peak flow for gauges that only have daily mean flow records.

$$Q_{it}^{IPF} = Q_{it}^{MDF}(1 + \alpha A^{\beta}) \tag{6}$$

Now, by converting the estimated instantaneous peak flow to the quantile of the estimated Log-

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

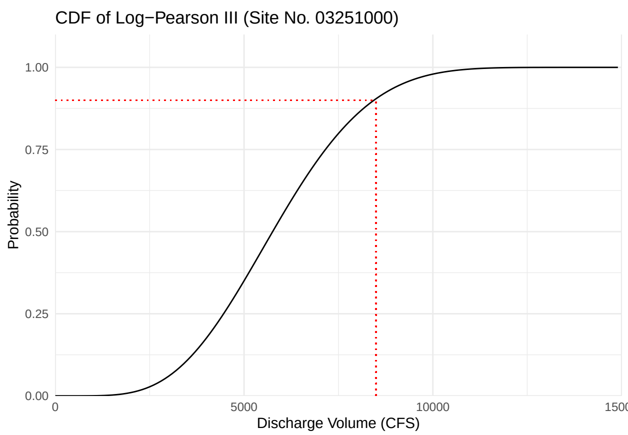
[25] A watershed is uniquely identified by a hydrologic unit code (HUC). There are six levels in the hierarchy, and HUC2 (regions) and HUC4 (sub-regions) are the two highest levels. There are a total of 18 and 202 HUC2s and HUC4s in the contiguous US (Maimone and Adams 2023).

[26] I manipulate equation (6) as $\frac{Q_{it}^{IPF}}{Q_{it}^{MDF}} - 1 = \alpha A^{\beta}$ and take log on both sides to estimate α and β.

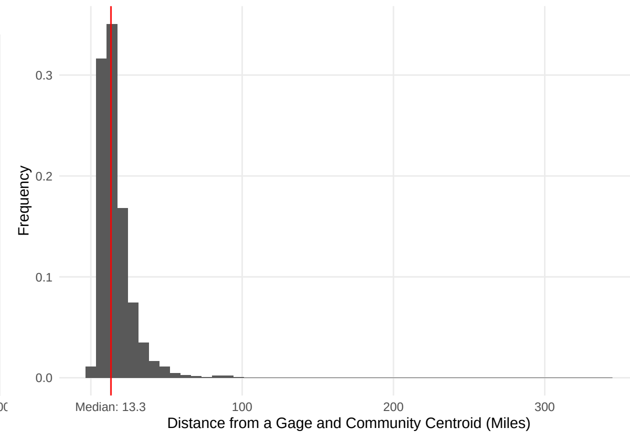
Pearson III CDF from step 1, I identify each day's flood size.

Third, I translate the quantiles into recurrence intervals and take the maximum recurrence interval for each year.[27]

Finally, to translate gauge-level flood events to community-level data, I match each community to its three nearest gauges, determined by the distance between the community's centroid and the gauge stations. I then calculate a community-level flood size using an inverse distance-weighted average of the flood sizes recorded at these gauges. Appendix Figure A.2 (b) presents the distribution of the average distance between gauges and community centroid. Over 90 percent of them are within 20 miles with a median distance of 13 miles.



(a) Flood Frequency Analysis



(b) Distance between Gauge and Community Centroids

Figure A.2: Flood Frequency Analysis and Gauge Matching. Panel (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 a daily discharge volume is 8,500 CFS, it corresponds to the 90th quantile or a 10-year flood. Panel (b) presents the distribution of the distance between a gauge and community centroid. Over 90% of them are within 20 miles with the median distance 13 miles.

Appendix Figure A.2 (a) illustrates how to construct flood size from the daily water level using a site-specific flood frequency distribution. The black solid line is the fitted Log-Pearson III CDF from the USGS site 03251000. To fit the distribution, I use the annual peak flow data from 1947 to 1990 to calculate the mean, standard deviation, and skewness parameters. Now suppose that on a given date, the daily discharge volume is 8,500 CFS. As it corresponds to the 90th percentile of the CDF, it can be concluded that there was a 10-year flood on that day.

Note, because the USGS gauge stations rarely cover coastal areas, I add 45 additional NOAA sites to the gauge station data. Zervas (2013) documents GEV distribution parameters for all NOAA sites, so I adopt them and calculate gauge specific recurrence intervals. NOAA water level data are retrieved using the R package "Rnoaa" (Edmund et al. 2014).

Unified flash flood database. The Unified Flash Flood Database (Gourley et al. 2013) is a USGS-gauge record-based dataset constructed following a similar procedure described above. It is a comprehensive and objective measure of flood events that can present the overall trend of flood events for the contiguous US, which overcomes many limitations of the existing data. However, I have opted not to utilize this database due to its likely substantial underreporting of flood events. This under-

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

reporting arises because the database is constructed using instantaneous peak flows, which, as shown in Appendix Table A.1, have a significant number of missing observations (and missing data is regarded as "no flood").

A.2 Validation and Summary Statistics

To validate the flood history data, I check the number of average 2-year flood events over a 20-year period for the 8,194 communities from the 26 ever-disclosed states that are on the Q3 map. By definition, a 2-year flood happens 10 times in a 20-year period on average. Figure A.3 (a) shows that most communities had ten 2-year floods over the 20 years whereas the average number of 2-year floods is 11.1. While this is slightly higher than 10, it is plausible given that I stop updating annual peak flow beyond 1990 for consistency over time. Although this approach can be problematic as the period in consideration gets longer, it should not be a major problem for this paper as the sample period is 20 years.

Figure A.3 (b) shows the distribution of flood size (i.e., recurrence interval), where flood size is truncated at 100 for readability. As well documented in the literature, the histogram follows a log-normal distribution, and the frequency decreases as an inverse power function of the flood size (Jackson 2013).

In panel (c), I plot the number of unique flood events for each community-year, conditional on having an event with a flood size between 2 and 50. The histogram shows that 65 percent of the community-years have exactly one event. This alleviates a concern over measuring flood exposure as the maximum flood size for a given year. More importantly, when I limit attention to floods with size over 10 in panel (d), which incurs disproportionately large damage, 95 percent of the community-year pairs have only one such event.

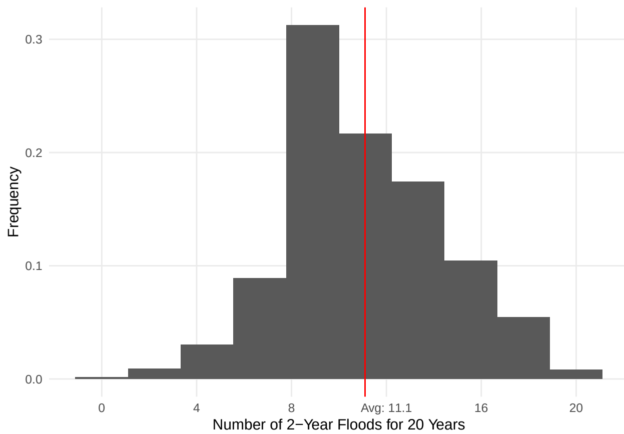
Table A.2: Comparing the Estimated Flood Size Thresholds with the NWS Threshold

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

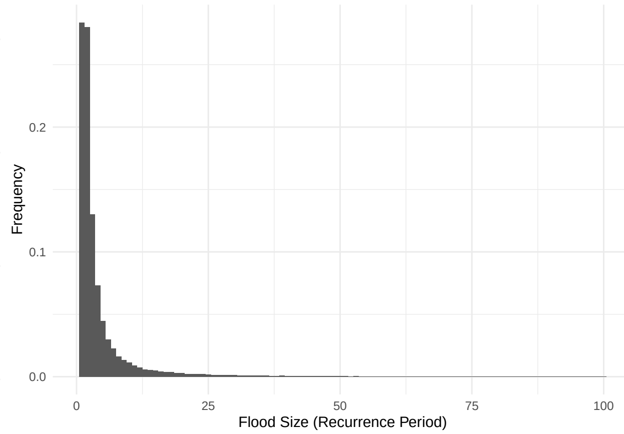
Note:
Note: The entries report the results from 12 separate regressions where each column represents four different dependent variables and each row represents three different regressors. Standard errors are clustered at the gauge level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

To better contextualize the recurrence interval based flood size, in Appendix Table A.2, I compare flood size with the gauge-specific NWS thresholds for minor, moderate, and major floods.[28] Specifically, I estimate equation (7) where Q_{ik} is the estimated flood threshold for site i for flood size k where $k \in \{2, 10, 50, 100\}$. NWS_{ij} is flood thresholds from the NWS for site i for flood severity j where $j \in$ {minor, moderate, major}.

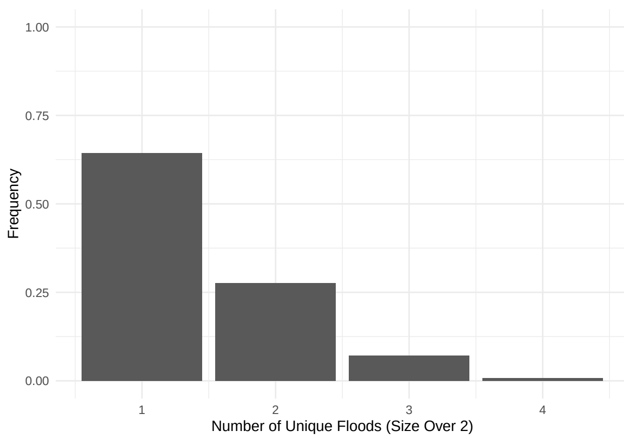
[28]NWS defines each flood category as the following (National Weather Service 2019). Minor: minimal or no property damage, but possibly some public threat (e.g., inundation of roads). Moderate: some inundation of structures and roads near a stream, evacuations of people, and/or transfer of property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



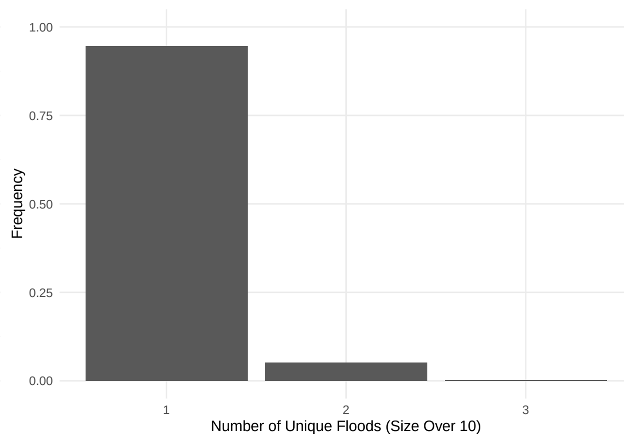
(a) Number of 10-Year Floods over 20 Years



(b) Flood Size



(c) N of Unique Floods (size between 2 and 50) by Community-year



(d) N of Unique Floods (size between 10 and 50) by Community-year

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

$$Q_{ik} = \beta NWS_{ij} + \epsilon_{ijk} \tag{7}$$

β is the coefficient of interest which illustrates how comparable the two thresholds are. Namely, the closer β is to 1, the more comparable the two thresholds are. For this analysis, I use 2,093 sites that have both recurrence interval-based flood size and the NWS flood thresholds. Appendix Table A.2 reports the estimated β for 12 separate regressions and provides useful insights. First, a minor flood from the NWS is comparable to a flood of size between 2 and 10. To see this, observe that when a minor threshold increases by 1 unit, a 2-year flood threshold increases by only 0.78 units. Conversely, when a minor threshold increases by 1 unit, a 10-year flood threshold increases by 1.29 units. Second, a 10-year flood threshold is tightly comparable to a moderate flood threshold ($\beta = 0.99$). Similarly, a 50-year flood closely matches a flood with a major impact ($\beta = 1.08$). Note, a 100-year flood threshold is 23 percent higher than a major flood threshold, which is plausible given that a 50-year flood threshold is comparable to the major category.

A.3 Using Flood Data in Damage Function

There are three points to discuss regarding flood size F^k in damage function specification. First, I use the annual maximum flood size as a proxy for flood exposure for a given community-year. While this means smaller floods in the same community and year are ignored, this is unlikely to be a practical concern because the majority of the community-years in the dataset had just one flood, especially for floods of size over 10 or larger, which cause disproportionately large damage (Appendix Figure A.3 (c) and (d)).

Second, I focus on flood sizes between 1 and 50 because larger floods are frequently accompanied by interrelated perils, which cause substantial measurement errors (Kron et al. 2012). Further, as shown in Appendix Figure A.3 (b), the frequency of flood events reduces exponentially as flood size increases, making it difficult to non-parametrically identify statistical relationships for very large floods. Appendix Table A.2 shows that the threshold for flood sizes 10 and 50 are closely matched to the threshold for "moderate" and "major" floods defined by the National Weather Service, indicating that the chosen flood sizes cover a wide enough band to capture floods of different severity. In Appendix Table D.9 however, I show that the conclusion in Table 5.1 is robust to the expansion of flood size to 100.

Third, the assumption behind binning is that the damage per housing unit is identical within each k. While flood sizes of 21 and 29, for example, are likely to have a different effect in reality, I choose bin sizes to strike a balance between flexibility and precision. I choose flood size bins {1-2, 2-5, 5-10, 10-20, 20-30, 30-50} and each bin represents 48%, 33%, 10%, 5%, 2.7%, and 1.3% of the total observations, respectively. Notably, this distribution aligns with the definition of flood sizes; for example, floods of size 2 or greater are expected to occur every two years. When expanding to size 100 (Appendix Table D.9), bins are adjusted to {1-2, 2-5, 5-10, 10-20, 20-40, 40-100} to maintain relative frequencies.

B Appendix B: Descriptive Statistics and Validation of Key Dependent Variables

Appendix Table B.1 shows summary statistics for the key independent variable: flood size; and dependent variables: population and flood damage per housing unit. Population figures are for the census blocks within the optimal bandwidth (more detail in Section 4). The other two values are for the NFIP communities in my sample.

Table B.1: Summary Statistics for Key Variables

Variables	Min.	Q25	Median	Mean	Q75	Max.	N
Census Block Population	0	0	13	37.5	44	9,888	2,723,580
Flood Damage Per Housing Unit	0	0	0	5.78	0	23,991	505,383
N of 2-Year Floods (For 20 Years)	0	9	11	11.1	13	20	8,194

A notable aspect of the data is the high prevalence of zeros among the dependent variables. For instance, 27 percent of observations for the block population and 95 percent of the observations of community-level flood damage per housing unit are zero. In addition, these variables also exhibit substantial skewness (long and thin right tails), as the difference between median and mean values suggests. To account for this, I follow Chen and Roth (2022) and estimate extensive and intensive margin effects separately for each dependent variable. This approach resonates with a hurdle or two-part model, which is used extensively in modeling health expenditures that are characterized by a similar distribution (Mullahy and Norton 2022). The last row of Appendix Table B.1 indicates that an average community experiences 11 2-year flood events over a 20-year period. This is close to the expected value of 10.

Appendix Table B.1 shows that key dependent variables in this paper have a prevalence of zeros. These statistics are consistent with findings from external sources. For block population, Bureau of the Census (1994) reports that a substantial number of blocks have zero population, with state-level proportions ranging from 14 percent (RI) to 65 percent (WY), and a median value of 31 percent (WA). In my sample, the numbers are slightly different at 17 percent for RI and 26 percent for WA (WY is a non-disclosure state). A minor discrepancy is not surprising given that blocks not included in the digitized flood map are excluded from the analysis.

For flood damage, no prior studies have cataloged the fraction of community-years with zero flood damage. However, a back-of-the-envelop calculation suggests that this statistic is in line with existing studies. For that, I take the average probability (1.45 percent) of filing a claim per policy over 1980–2012 from Kousky and Michel-Kerjan (2015) and multiply it by the number of flood insurance policies by the community in my sample. The result reveals that 17 percent of communities are predicted to have more than one claim in a given year (i.e., 83 percent of community-year observations are predicted to have zero claims). Note, while 83 percent is substantially lower than 95 percent as discussed in Section 3, this is a direct consequence of sample restriction: as I discuss in detail in Section 5.1, I remove floods with size 50 or above from my analysis for various economic and statistical reasons. When I undertake the same calculation without imposing these sample restrictions, I find that 86 percent of community-year observations have zero claims, a figure consistent with the 83 percent calculated based on Kousky and Michel-Kerjan (2015).

C Appendix C: Disclosure and Flood Insurance Take Up

To evaluate the impact of the disclosure requirement on flood insurance take up, I collect the number of flood insurance policies at the National Flood Insurance Program (NFIP) community level for 1978–2008.[29] As a typical community contains both SFHA and non-SFHA areas (Appendix Figure E.4 and E.5), the distance to the nearest SFHA border is not defined. Thus, I estimate a triple difference model in equation (8). Here, Y_{mstd} denotes outcome variables on NFIP for community m in state s in year t in stack d. H_{md} is an indicator variable equal to one if a community has an above-median fraction of the area covered by an SFHA, which proxies for the treatment intensity. I_{std} is a post disclosure indicator and D_{std} is a treatment group indicator. α_1 captures the disclosure effect.[30]

$$log(Y_{mstd}) = \alpha_0 H_{std} I_{std} + \alpha_1 H_{md} D_{std} I_{std} + \omega_{std} + \psi_{md} + \epsilon_{mstd} \tag{8}$$

Similar to Section 5.1, I use the stacked approach to estimate the policy impact using clean controls (Cengiz et al. 2019, Brot-Goldberg et al. 2020). To construct the data stack, I first keep each state's flood insurance data for seven years before and after the policy change to prevent composition changes.[31] Then I follow similar steps as described in Section 5.1. Equation (8) also include ω_{std}, the state × time × stack fixed effect to account for year-specific state level shocks and a community × stack fixed effect ψ_{md}, which captures unobserved community characteristics. Including these fixed effects ensures that the comparisons are made within each stack.

Table C.1: Effect of Discosure Requirement on Flood Insurance Take-Up

	Prob. of Any Insurance		Log Insurance Per Housing Unit	
	(1)	(2)	(3)	(4)
High SFHA × Disclosure × Post	.003	.003	−.024	−.023
	(.007)	(.008)	(.030)	(.030)
Avg D.V.	0.823	0.819		
State × Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Sample	All	No Map Update	All	No Map Update
Num. obs.	400919	390382	329863	319639

Note: This table is produced from equation (8) using community-level NFIP data. In columns (2) and (4), communities with flood map updates are excluded. Standard errors are clustered at the state level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In Appendix Table C.1 column (1), I show the disclosure policy increases the probability of having at least one flood insurance policy in high-risk communities relative to low-risk communities by 0.003 (or 0.4 percent from the baseline of 0.82). Column (3) indicates the intensive margin effect of the disclosure policy on the number of insurance policies per housing unit is also small at –2 percent. Further, columns (2) and (4), I show that removing communities that have experienced map updates during the sample period produces similar results as columns (1) and (3). Given the estimated coefficients, flood insurance does not seem to be the primary margin homebuyers respond to the disclosure policy.

[29] I thank Justin Gallagher for graciously sharing these data.

[30] Other terms in a standard triple difference model are subsumed by fixed effects.

[31] The data from 1978–2008 are sufficient to cover a 15-year window for policy changes in all states except Louisiana,

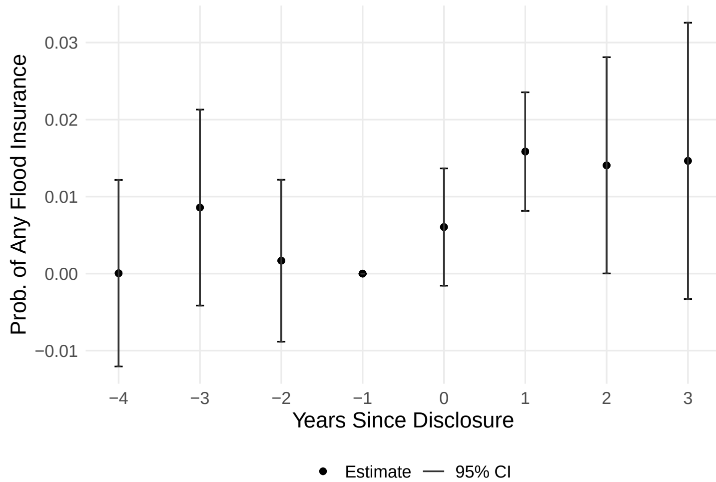


Figure C.1: The Effect of Disclosure on the Probability of Having Any Flood Insurance. This figure depicts the impact of disclosure on the probability of having any flood insurance policy at the community level using an event study version of equation (8). The error bar represents the 95% confidence interval.

In Appendix Figure C.1, I plot the differential impact of disclosure policy on the probability of having flood insurance for high-risk communities in event time using an event study version of equation (8). The estimated coefficients show no pre-trend and a small increase in the probability of flood insurance take up after the policy change. A simple average of estimated coefficients in the pre vs. post treatment event time suggests that the magnitude of policy effect is 0.007, which is larger than column (1) in Table C.1 yet still small.

which implemented its policy in 2003, leaving just six post-policy years for analysis.

D Appendix D: Robustness Checks

D.1 Robustness Checks for Population Changes

Two potential concerns regarding the validity of the results in Section 4.2 merit attention. First, the disclosure requirement may have a spillover effect (Donaldson 2015). For instance, homebuyers who would have chosen properties on SFHAs may instead choose nearby properties in non-SFHAs after the disclosure policy, which may violate the stable unit treatment value assumption (SUTVA).

Second, while my difference-in-discontinuity design controls for time-invariant confounders, concurrent policy changes are still a threat to identification. Although, as discussed in Section 2, compliance with the flood insurance mandate was far from perfect, especially during the sample period of this study, one might worry that there have been changes in the enforcement of the flood insurance purchase requirement over time. Additionally, updates to flood maps could have served as a competing source of informational shock (Gibson and Mullins 2020, Bakkensen and Ma 2020, Weill 2021, Hino and Burke 2021).

Per the first issue, it is important to note that the area covered by the SFHA is relatively small in a typical jurisdiction, which makes it unlikely that non-SFHA areas will be seriously "contaminated" by the disclosure requirement (Busso et al. 2013, Alves et al. 2024). For instance, as shown in Appendix Figure E.5, the median community has only 7.8% of its land area in SFHA. Similarly, only 15% of blocks in the difference-in-discontinuity analysis sample (corresponds to Table 4.1 column (1)) are in the SFHA. Further, as of 1990 (before any disclosure policy), the average population of high risk blocks is 13, which is substantially smaller than 35, the average population in non-SFHA blocks.

Consistent with this, the results are similar when I reproduce Table 4.1 after removing blocks that are located in communities with a high fraction (50% or more) of SFHA areas, which are potentially more susceptible to a treatment spillover. Appendix Table D.1 shows that the estimates are essentially identical to Table 4.1, which suggests that spillover effects are likely small even in the worst case scenario.

Table D.1: Effect of Discosure Requirement on Net Population Flow (w/o Blocks in High Risk Communities)

	Log Population	Prob. of Any Population	Vacancy Rate
	(1)	(2)	(3)
SFHA × Post	$-.070^{**}$	$-.012^{***}$	$.015^{***}$
	(.032)	(.003)	(.003)
Avg D.V.		0.675	0.095
Bandwidth	301	138	262
Num. obs.	1829292	1400151	1620985

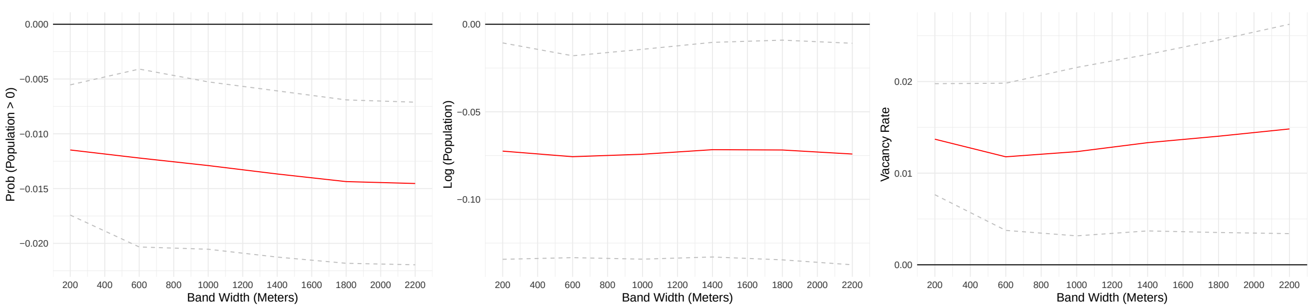
Note: Columns (1)–(3) are estimated based on equation (1) using the decennial census block-level data in 1990, 2000, 2010, and 2020. Blocks in communities with over 50% of land areas in SFHA are excluded. Standard errors are clustered at the state level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Despite the results in Appendix Table D.1, one might believe that spillover effects can be large, especially at the local level. To investigate this possibility, I repeat my analysis using a doughnut difference-in-discontinuity approach that excludes blocks very close to the border (Kline and Moretti 2014). The idea is that if there is endogenous sorting near the border, the treatment effect may change when those observations are excluded (Cattaneo and Titiunik 2022). In Appendix Table D.2, I show that the estimates are similar even if I remove blocks that are within 20 or 40 meters from the border.

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

	Log Population	Prob. of Any Population	Vacancy Rate	Log Population	Prob. of Any Population	Vacancy Rate
	(1)	(2)	(3)	(4)	(5)	(6)
SFHA × Post	$-.079^{**}$	$-.012^{**}$	$.013^{***}$	$-.080^{**}$	$-.007$	$.014^{**}$
	(.031)	(.004)	(.004)	(.033)	(.005)	(.006)
Avg D.V. (Within BW)		0.692	0.093		0.704	0.092
Doughnut Size	20	20	20	40	40	40
Num. obs.	1763552	1227096	1549019	1607388	984066	1394047

Note: This table is produced from equation (1) after excluding observations closest to the SFHA border. In columns (1)–(3), doughnut sizes are 20 meters and in columns (4)–(6) doughnut sizes are 40 meters. Standard errors are clustered at the state level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

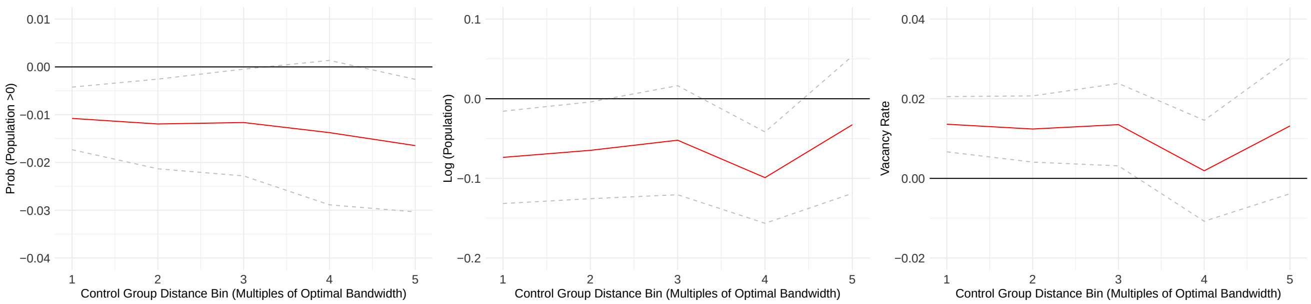


(a) Prob. of Any Population (b) Log Population (c) Vacancy Rate

Figure D.1: The Effect of the Disclosure Requirement on Population and Vacancy Rate for Different Bandwidths. These figures plot $\hat{\delta_6}$ from equation (1) for a range of bandwidths. The level of observation is census block, which is the smallest census geographical unit. Standard errors are clustered at the state level.

Consistent with Appendix Table D.2, Appendix Figure D.1 shows that the policy effect does not diminish even if I expand the bandwidth. Further, in Appendix Figure D.2, I repeat my analysis using progressively farther away control blocks while holding treated blocks fixed (to those within the optimal bandwidth). In particular, I estimate equation (1) using control blocks that are within the distance of $(r-1) \times$ *optimal bandwidth* and $r \times$ *optimal bandwidth* for $r \in \{1, 2, 3, 4, 5\}$. Again, Appendix Figure D.2 shows that disclosure policy reduces population and increases vacancy rate. Taking these results together, potential spillover effects do not seem to be a major threat to identification.

To address potential concerns over concurrent policy changes, I conduct three robustness checks. First, I use the five placebo states that have implemented disclosure policies without a question about flood risk. If my findings are driven by concurrent policy changes rather than the disclosure of flood risk, I would expect to find similar results in the placebo states. In Appendix Table D.3, I repeat Table 4.1 for placebo states and find no evidence of a reduction in population or an increase in the vacancy rate in the placebo states. Note, as there are only five placebo states, I use wild bootstrap for inference and report p.values in parentheses.



(a) Prob. of Any Population (b) Log Population (c) Vacancy Rate

Figure D.2: The Effect of the Disclosure Requirement on Population and Vacancy Rate by Control Group Distance Bin. These figures plot $\hat{\delta}_6$ from equation (1) for control groups of varying distance. The horizontal axis indicates the distance bin of control group in multiples of variable specific optimal bandwidth (i.e., distance bin r on x-axis indicates that control group blocks are within $(r - 1)$ and r times optimal bandwidth). The level of observation is census block, which is the smallest census geographical unit. Standard errors are clustered at the state level.

Table D.3: Effect of Discosure Requirement on Household Responses (Placebo States)

	Log Population	Prob. of Any Population	Vacancy Rate
	(1)	(2)	(3)
SFHA × Post	.040	−.001	.000
	(.601)	(.899)	(.987)
Avg D.V. (Within BW)		0.659	0.089
Bandwidth	459	452	324
Num. obs.	169094	253533	130398

Note: This table is produced from equation (1). Columns (1)–(3) are estimated using the decennial census block-level data in 1990, 2000, 2010, and 2020. Bootstrapped p.values are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Second, I allow time-varying discontinuity at the SFHA border to more directly control for confounding policy changes. For this, I estimate equation (9).

$$\begin{aligned} Y_{bst} = \delta_0 + \delta_1 X_{bs} + \delta_2 D_{bs} + \delta_3 X_{bs} D_{bs} + \sum_{t=\{2000,2010,2020\}} G_t[\delta_0^t + \delta_1^t X_{bs} + \delta_2^t D_{bs} + \delta_3^t X_{bs} D_{bs}] + \\ T_{st}[\delta_4 + \delta_5 X_{bs} + \delta_6 D_{bs} + \delta_7 X_{bs} D_{bs}] + \epsilon_{bst} \end{aligned} \tag{9}$$

Here G_t is an indicator that takes 1 if the time period is in $t = \{2000, 2010, 2020\}$. Importantly, $G_t * \delta_2^t$ allows period-specific discontinuities (1990 is omitted as baseline), which again more directly controls for potentially confounding policy changes. The rest of the notations follow equation (1) and the coefficient of interest is δ_6 as before.

Table D.4: Effect of Discosure on Population and Vacancy Rate (Time Varying Discontinuity)

	Log Population		Prob. of Any Population		Vacancy Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
SFHA × Post	−.314	.589	.123	.337	.026	−.036
	(.013)	(.458)	(.001)	(.047)	(.250)	(.375)
Group	Treated	Placebo	Treated	Placebo	Treated	Placebo
Avg D.V.			0.675	0.659	0.095	0.089
Bandwidth	301	459	138	452	262	324
Num. obs.	1900591	167160	1331286	225007	1685653	128772

Note: This table is produced from equation (9). Columns (1)-(2) show the impact on log of population for treated and placebo states while columns (3)-(4) show the impact on the probability of having any population and columns (5)-(6) on the vacancy rate. P.values, which are calculated using clustered standard error for columns (1), (3), and (5) and bootstrapping for columns (2), (4), and (6), are reported in parentheses.

Appendix Table D.4 shows that the impact of disclosure policy on the log of population in column (1) and vacancy rate in column (5) are much larger than the preferred specification in Table 4.1, although the effect on vacancy rate is statistically insignificant (p.values are reported in parentheses). One exception is in column (3), which shows that the policy has a positive impact on the probability of having any population. However, when compared with the impact on placebo states in column (4), the net effect still seems to be negative.

Table D.5: Effect of Discosure on Net Population Flow (Exc. Blocks with Map Revision)

	Log Population	Prob. of Any Population	Vacancy Rate
	(1)	(2)	(3)
SFHA × Post	$-.072^{**}$	$-.011^{***}$	$.014^{***}$
	(.031)	(.003)	(.004)
Avg D.V.		0.67	0.098
Bandwidth	301	138	262
Num. obs.	1680266	1312266	1493043

Note: Estimates are based on equation (1) after removing geographic units that have experienced flood map update. Standard errors are clustered at the state level. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Third, in Appendix Table D.5, I reproduce Table 4.1 after removing geographic units that have experienced flood map updates over the sample period and find that the results barely change.

D.2 Robustness Checks for Damage Reduction

I test the robustness of my findings in Section 5.2 by conducting a placebo test using the five states that had implemented disclosure policies without a question on the flood risk.

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

	Prob. of Any Damage		
	(1)	(2)	(3)
Post × Disclosure (Size 2-30)	$-.015^{***}$	$-.035^{**}$	.001
	(.005)	(.015)	(.008)
Post × Disclosure (Size 30-50)	$.223^{***}$	$.246^{***}$	$.185^{***}$
	(.053)	(.083)	(.049)
Sample	All	High SFHA	Low SFHA
Year × Stack FE	X	X	X
Community × Stack FE	X	X	X
Num. obs.	31246	14984	16262

Note: This table repeats Table 5.1 using the placebo states. The dependent variables in columns (1) to (3) are the probability of having any flood damage per housing unit. Column (1) is based on the entire set of communities while in columns (2) and (3), I repeat (1) using the subsample of communities with an above median SFHA ratio and below median SFHA ratio. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference for columns (1)–(3). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In Appendix Table D.6, I estimate a version of equation (4) with coarser flood bins.[32] In columns (1) to (3), the coefficients for large floods are *positive*. Such an increase in damage in the absence of flood risk disclosure is consistent with Figures 5.1 (a), (c), and (e), which show flood damage increases over time for not-yet-disclosed states.

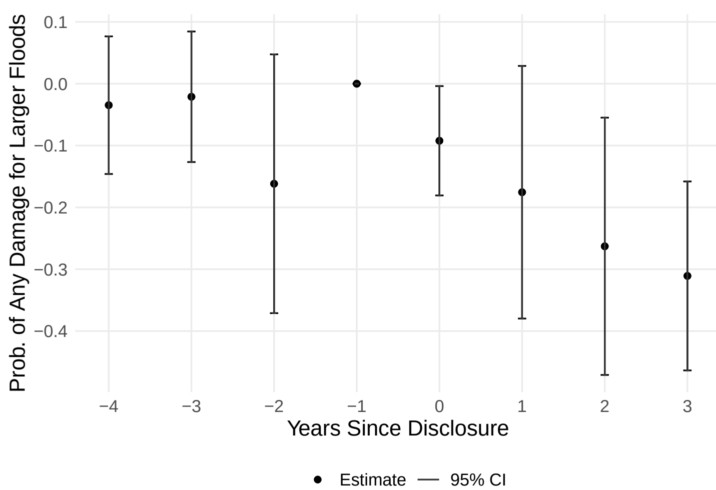


Figure D.3: The Effect of Disclosure on the Damage in Event Time. This figure depicts $\hat{\beta_{4,t}^{30-50}}$ for flood size of 30-50 in event time t where the dependent variable is probability of having any damage. The error bar represents the 95% confidence interval.

[32]For statistical power, I group flood events into baseline ($k = 1 - 2$), small ($k = 2 - 30$) and large ($k = 30 - 50$).

Another robustness check comes from an event study plot in Appendix Figure D.3, which illustrates the marginal effects of disclosure policy on the probability of flood damage for larger ($k = 30 - 50$) floods. Similar to Appendix Table D.6, I use coarser flood bins to increase power. I also impose an endpoint restriction at -5 and 4. The estimated coefficients show no pre-trend and sharp and persistent reduction in the probability of flood damage after the policy change. Simple average of estimated coefficients in the pre vs. post treatment event time suggests that the magnitude of policy effect is $-.12$. This on par with the average policy effect ($-.12$) of flood category $k = 30 - 50$ in column (1) in Table 5.1.

Table D.7: Effect of Disclosure on Flood Damage (Exc. Communities with Map Revision)

	Prob. of Any Damage Per Housing Unit			Log Damage Per Housing Unit
	(1)	(2)	(3)	(4)
Post × Disclosure (Size 2-5)	$-.033^{*}$	$-.052^{*}$	$-.012$	.061
	(.020)	(.027)	(.010)	(.194)
Post × Disclosure (Size 5-10)	$-.044^{*}$	$-.055^{*}$	$-.034$	.232
	(.025)	(.032)	(.022)	(.252)
Post × Disclosure (Size 10-20)	$-.068^{*}$	$-.082$	$-.047^{**}$	.110
	(.036)	(.056)	(.019)	(.200)
Post × Disclosure (Size 20-30)	$-.078$	$-.127^{***}$	$-.015$	.260
	(.051)	(.046)	(.071)	(.571)
Post × Disclosure (Size 30-50)	$-.126^{*}$	$-.166^{**}$	$-.088$	$-.375^{***}$
	(.071)	(.076)	(.072)	(.129)
Annual Effect	-0.026*	-0.037**	-0.014	0.057
	(0.014)	(0.017)	(0.01)	(0.087)
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	487704	233225	254479	20842

Note: This table repeats Table 5.1 after removing communities that have experienced map updates during the sample period. Spatial-HAC standard errors that allow spatial correlation of up to 500 miles are estimated for inference. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix Table D.7 shows that excluding communities with map revision produces essentially the same results.
Appendix Table D.8 shows that clustering standard errors at the state level reaches similar conclusion as Table 5.1 especially for the annualized effects.
Finally, Appendix Table D.9 shows that expanding flood size from 50 to 100 causes minimal changes to the annualized effect.

Table D.8: Effect of Disclosure Requirement on Flood Damage (State Level Clustering)

	Prob. of Any Damage Per Housing Unit			Log Damage Per Housing Unit
	(1)	(2)	(3)	(4)
Post × Disclosure (Size 2-5)	−.035	−.055*	−.013	−.134
	(.021)	(.031)	(.010)	(.399)
Post × Disclosure (Size 5-10)	−.042**	−.054*	−.031*	.164
	(.020)	(.028)	(.016)	(.284)
Post × Disclosure (Size 10-20)	−.078*	−.091	−.058*	.051
	(.042)	(.064)	(.029)	(.268)
Post × Disclosure (Size 20-30)	−.084	−.134*	−.022	.467
	(.058)	(.073)	(.067)	(.585)
Post × Disclosure (Size 30-50)	−.121*	−.173*	−.074	−.334
	(.071)	(.094)	(.056)	(.335)
Annual Effect	-0.027**	-0.039*	-0.014	-0.003
	(0.013)	(0.019)	(0.009)	(0.147)
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	505383	242458	262925	22319

Note: This table repeats Table 5.1 with state level clustering. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table D.9: Effect of Disclosure Requirement on Flood Damage (Flood Size 2-100)

	Prob. of Any Damage Per Housing Unit			Log Damage Per Housing Unit
	(1)	(2)	(3)	(4)
Post × Disclosure (Size 2-5)	−.036*	−.057*	−.013	−.124
	(.021)	(.031)	(.010)	(.406)
Post × Disclosure (Size 5-10)	−.044**	−.055*	−.033**	.175
	(.019)	(.028)	(.015)	(.280)
Post × Disclosure (Size 10-20)	−.082*	−.097	−.062**	.104
	(.042)	(.063)	(.030)	(.276)
Post × Disclosure (Size 20-40)	−.095	−.140*	−.041	.220
	(.064)	(.072)	(.071)	(.499)
Post × Disclosure (Size 40-100)	−.145***	−.121	−.174***	−.516
	(.051)	(.081)	(.054)	(.337)
Annual Effect	-0.027**	-0.036**	-0.016**	-0.005
	(0.012)	(0.016)	(0.008)	(0.104)
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	505383	242458	262925	23238

Note: This table repeats Table 5.1 with alternative flood bins. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E Appendix E: Additional Tables and Figures

Table E.1: Building Age by SFHA Status

	N of Houses (< 5Yrs)	N of Houses (> 40Yrs)	(%) Houses (< 5Yrs)	(%) Houses (> 40Yrs)
	(1)	(2)	(3)	(4)
Tract with SFHA	119.507***	−254.004***	.057***	−.192***
	(13.437)	(29.864)	(.007)	(.034)
Num. obs.	32391	32391	31490	31490

Note: This table compares the proportion of older and newer housing stocks in census tracts with and without SFHAs using the 1990 decennial census data. Standard errors are clustered at the state level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Back to 2.

Table E.2: State Characteristics in 1990

Variables	Ever/Early Mean	Ever/Early SE	Never/Late Mean	Never/Late SE	Difference Mean	Difference P.Value
Panel A: Ever vs. Never States						
Population (millions)	6.57	1.31	3.43	0.651	3.143	0.048
Median Age	33.04	0.204	32.82	0.409	0.22	0.616
(%) White	0.827	0.019	0.879	0.018	-0.053	0.051
(%) BA	0.121	0.005	0.129	0.006	-0.007	0.324
Unemployment Rate	0.06	0.003	0.061	0.002	-0.001	0.773
GDP (billions)	152	34.38	74	14.95	78	0.057
N Housing Units (millions)	2.66	0.506	1.47	0.291	1.187	0.059
(%) Vacancy	0.095	0.005	0.132	0.008	-0.037	0
Democratic Party Vote Share	0.455	0.01	0.425	0.012	0.03	0.06
Average Flood Damage per Housing Unit	3.86	1.99	0.964	0.497	2.891	0.199
Flood Size	6.34	0.805	3.58	0.713	2.76	0.015
(%) in SFHA	0.16	0.012	0.132	0.013	0.028	0.117
Panel B: Early vs. Late States						
Population (millions)	5.53	1.29	7.8	2.42	-2.274	0.397
Median Age	33.07	0.286	33	0.302	0.071	0.865
(%) White	0.842	0.026	0.808	0.027	0.034	0.374
(%) BA	0.119	0.006	0.124	0.008	-0.005	0.592
Unemployment Rate	0.061	0.004	0.06	0.004	0.001	0.89
GDP (billions)	119	29.72	191	66	-72	0.306
N Housing Units (millions)	2.25	0.527	3.12	0.917	-0.87	0.402
(%) Vacancy	0.095	0.007	0.096	0.007	-0.001	0.908
Democratic Party Vote Share	0.47	0.013	0.438	0.014	0.031	0.118
Average Flood Damage per Housing Unit	3.81	2	3.9	3.75	-0.09	0.983
Flood Size	6.17	1.01	6.55	1.34	-0.388	0.816
(%) in SFHA	0.157	0.01	0.163	0.023	-0.006	0.788

Note:
This table compares key characteristics of ever-disclosed vs. never-disclosed (Panel A) and early-disclosed vs. late-disclosed (Panel B) states. All variables are as of 1990 except for the Democratic party vote share variable, which comes from 1988 presidential election. The last two columns show mean differences and p-values.

Back to 2.

Table E.3: Effect of Disclosure Requirement on Flood Damage

	Prob. of Any Damage Per Housing Unit			Log Damage Per Housing Unit
	(1)	(2)	(3)	(4)
Flood Size 2-5	.007	.005	.011	.144
	(.008)	(.010)	(.007)	(.175)
Flood Size 5-10	.032***	.034***	.033***	.416***
	(.009)	(.010)	(.011)	(.069)
Flood Size 10-20	.055***	.069***	.042***	1.124***
	(.012)	(.016)	(.010)	(.100)
Flood Size 20-30	.070***	.098***	.041***	2.025***
	(.019)	(.027)	(.010)	(.286)
Flood Size 30-50	.076***	.103***	.040	1.574***
	(.030)	(.034)	(.027)	(.358)
Disclosure × Size 2-5	.021**	.033*	.009*	−.030
	(.010)	(.017)	(.005)	(.177)
Disclosure × Size 5-10	.044***	.061***	.026***	−.087
	(.009)	(.016)	(.007)	(.149)
Disclosure × Size 10-20	.087***	.107***	.061***	−.038
	(.011)	(.019)	(.011)	(.080)
Disclosure × Size 20-30	.110***	.137***	.076***	−.295**
	(.014)	(.026)	(.011)	(.137)
Disclosure × Size 30-50	.114***	.130***	.099***	.031
	(.026)	(.030)	(.030)	(.176)
Post × Size 2-5	.021*	.030**	.009	.577***
	(.011)	(.013)	(.009)	(.210)
Post × Size 5-10	.037***	.045***	.028*	.607***
	(.013)	(.015)	(.015)	(.157)
Post × Size 10-20	.093***	.097***	.085***	.306***
	(.019)	(.018)	(.022)	(.088)
Post × Size 20-30	.119***	.126***	.108**	−.174
	(.040)	(.042)	(.053)	(.294)
Post × Size 30-50	.163***	.208***	.129**	.850***
	(.051)	(.054)	(.053)	(.194)
Post × Disclosure × Size 2-5	−.035*	−.055**	−.013	−.134
	(.020)	(.027)	(.011)	(.300)
Post × Disclosure × Size 5-10	−.042*	−.054*	−.031*	.164
	(.022)	(.029)	(.018)	(.243)
Post × Disclosure × Size 10-20	−.078**	−.091*	−.058**	.051
	(.037)	(.053)	(.023)	(.210)
Post × Disclosure × Size 20-30	−.084*	−.134***	−.022	.467
	(.049)	(.044)	(.070)	(.554)
Post × Disclosure × Size 30-50	−.121*	−.173**	−.074	−.334**
	(.063)	(.079)	(.054)	(.133)
Sample	All	High SFHA	Low SFHA	Damage > 0
Year × Stack FE	X	X	X	X
Community × Stack FE	X	X	X	X
Num. obs.	505383	242458	262925	22319

Note: This table shows the full sets of coefficients for Table 5.1. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Back to 5.2.

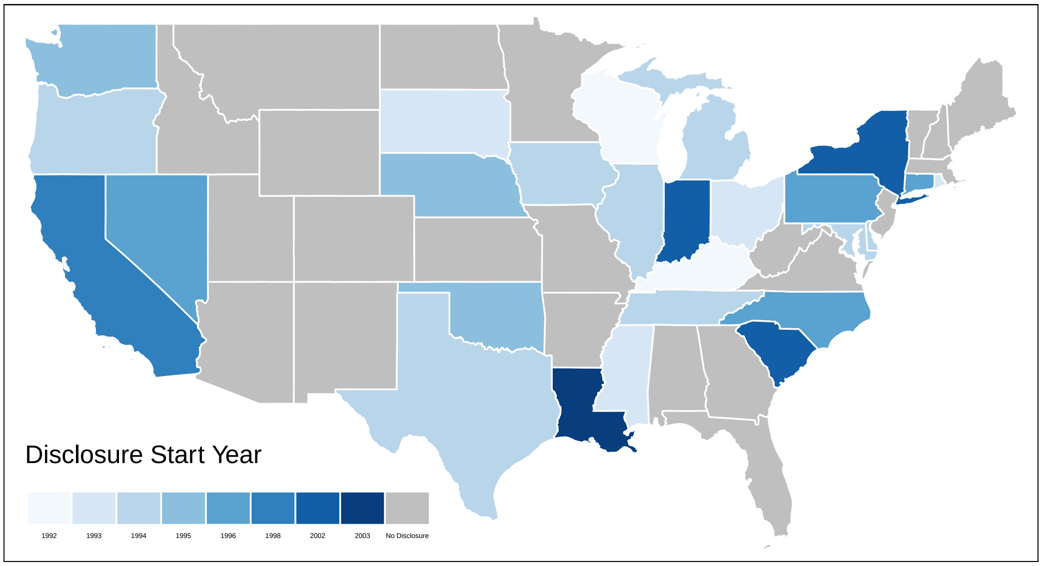
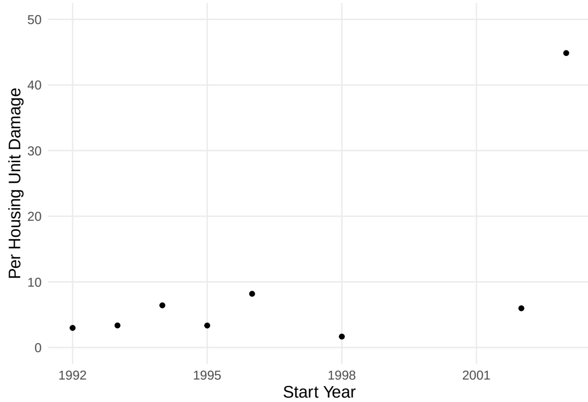
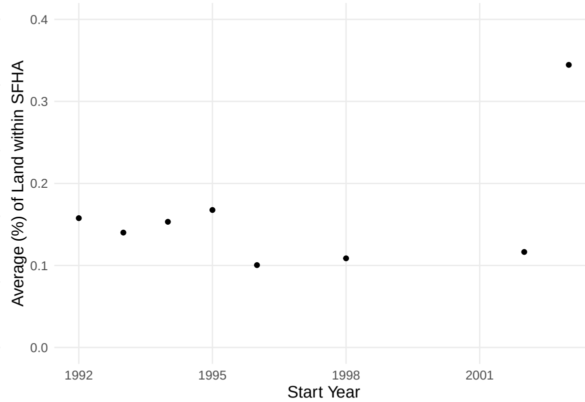


Figure E.1: The Disclosure Requirement Implementation over Time

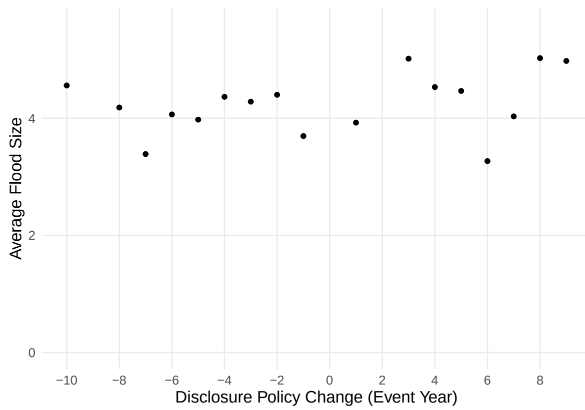
Back to 2.



(a) Timing and Flood Damage



(b) Timing and (%) of Land in SFHA



(c) Timing (in Event) and Flood Size

Figure E.2: Correlation Between Disclosure Timing and Flood Profiles. These figures plot the disclosure policy timing against (a) past flood damage and (b) ex-ante flood risk profile. Panel (c) plots the average flood size in event time. Values on the y-axis is pooled across all states with the same treatment or event year.

Back to 2.

ILLINOIS REALTORS

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

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

Property Address: ____________________

City, State & Zip Code: ____________________

Seller's Name: ____________________

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

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

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

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

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

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

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

 Page 1 of 4

Figure E.3: Example of the Home Seller Disclosure Form (IL)

Back to 2.

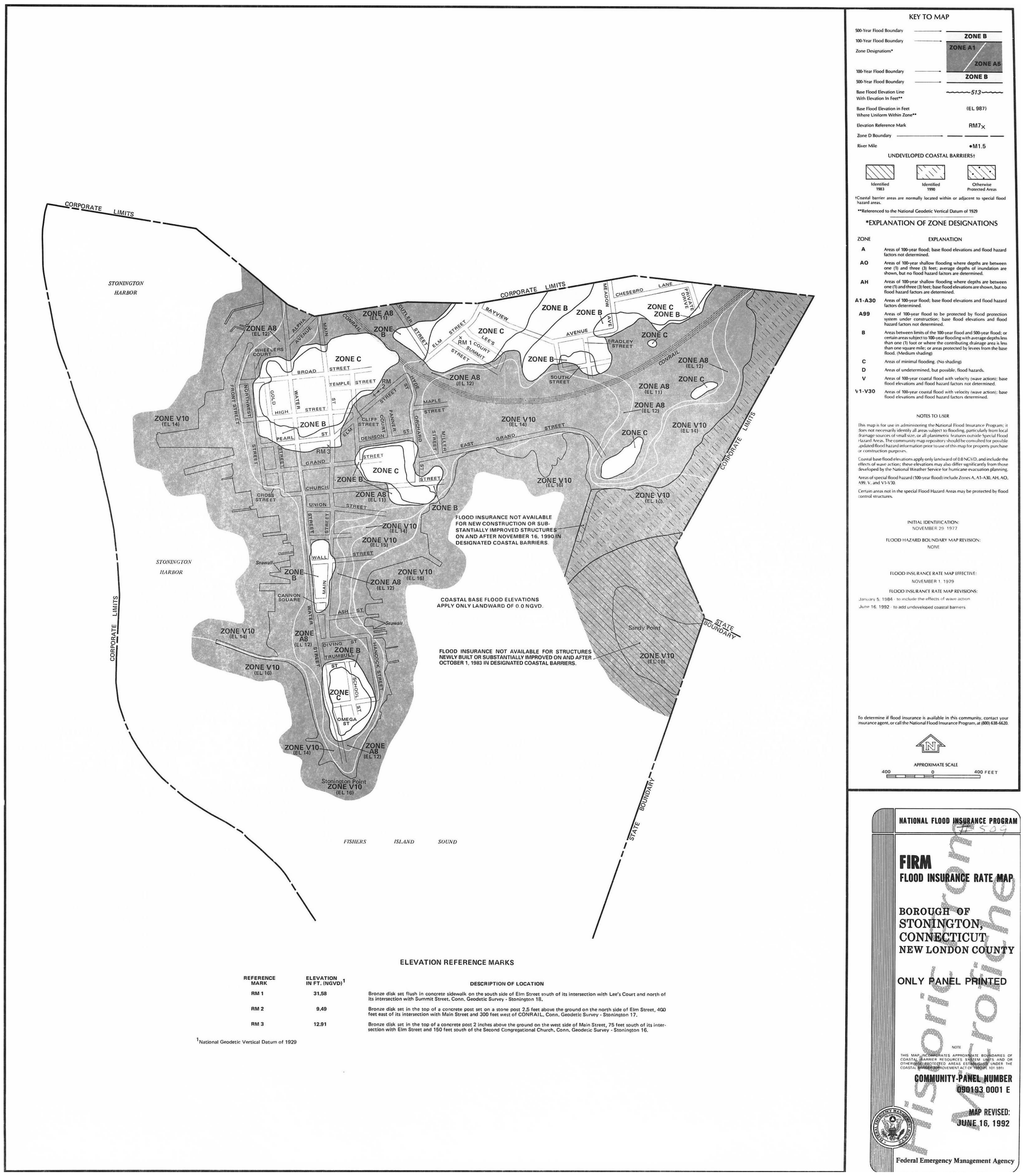


Figure E.4: Sample Flood Insurance Rate Map (Borough of Stonington, CT)

Back to 2.

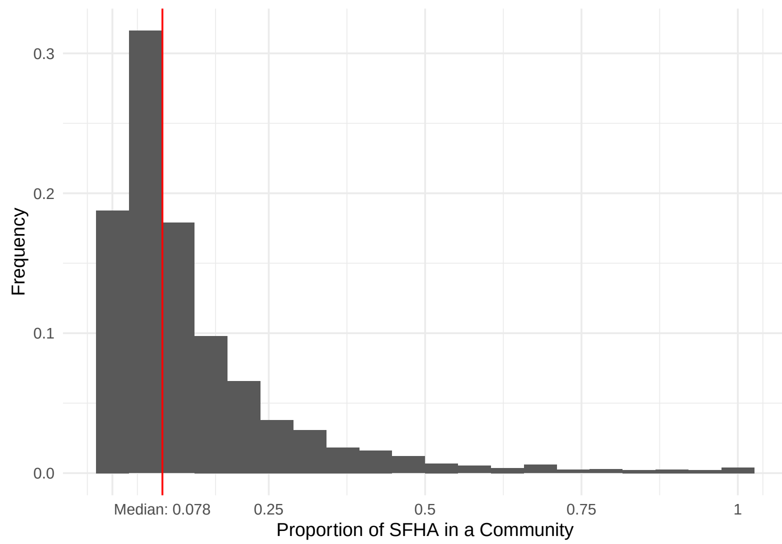
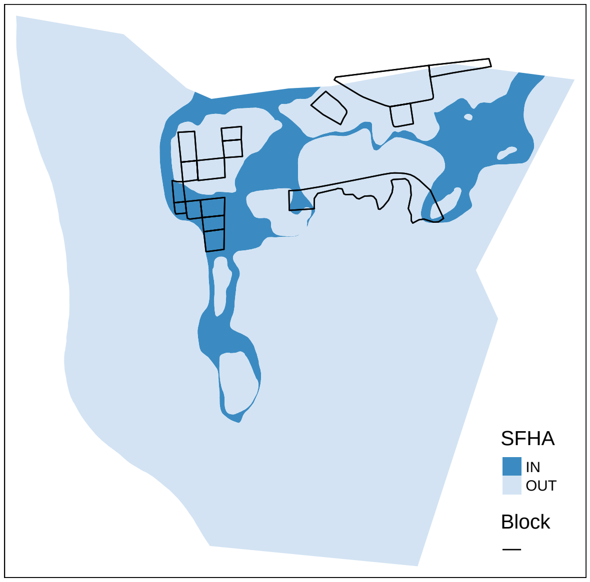
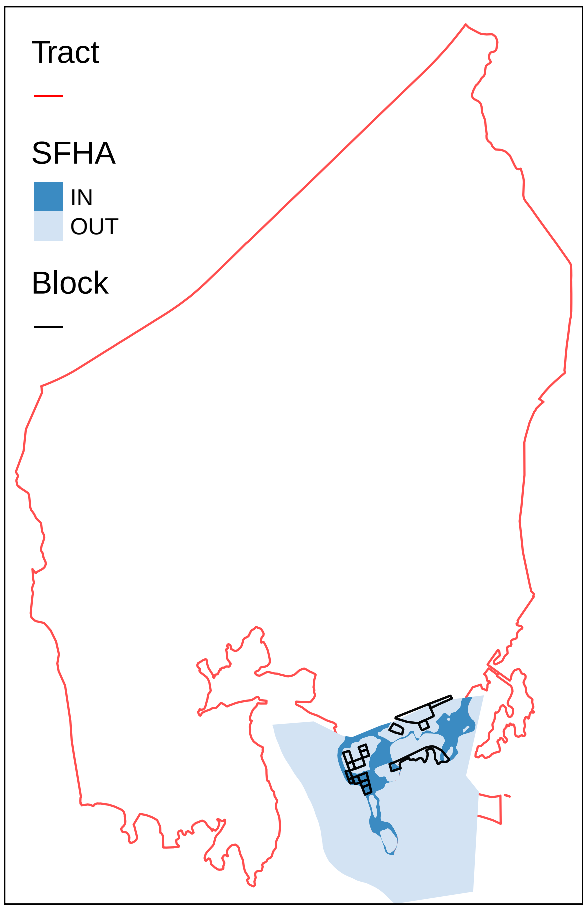


Figure E.5: Histogram of the Proportion of the SFHA at the Community Level. The plot shows the distribution of the SFHA ratio for the 8,194 communities that are on the Q3 map (first generation of digitized flood map) and in the 26 ever-disclosed states.

Back to 3.



(a) Block



(b) Tract

Figure E.6: Census Geographies and the SFHA Status (Borough of Stonington, CT)

Back to 4.1.

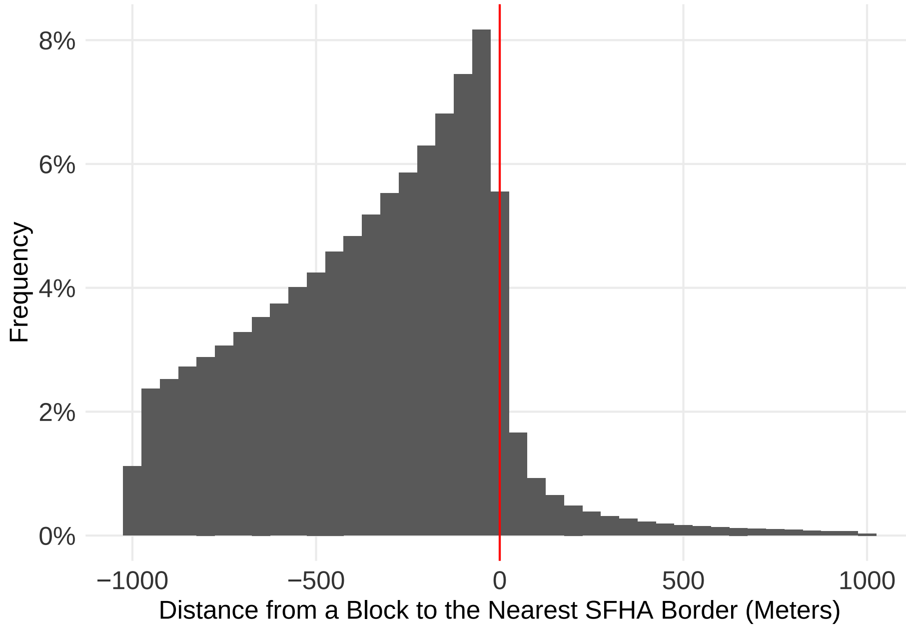
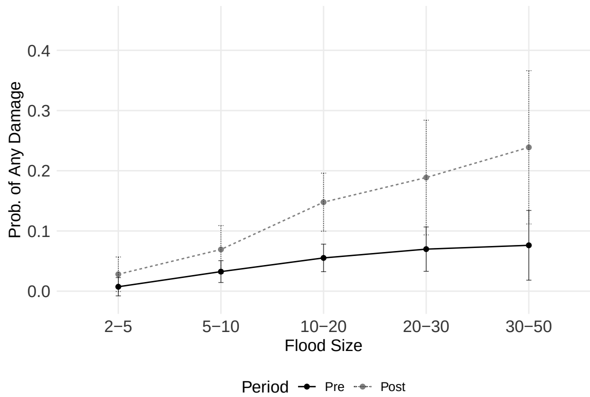
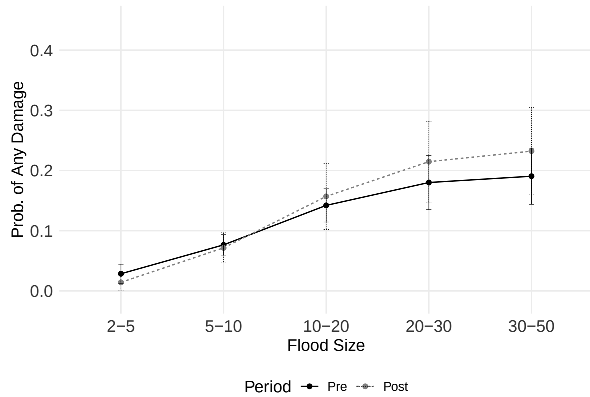


Figure E.7: Histogram of Running Variable (Distance to the SFHA Border)

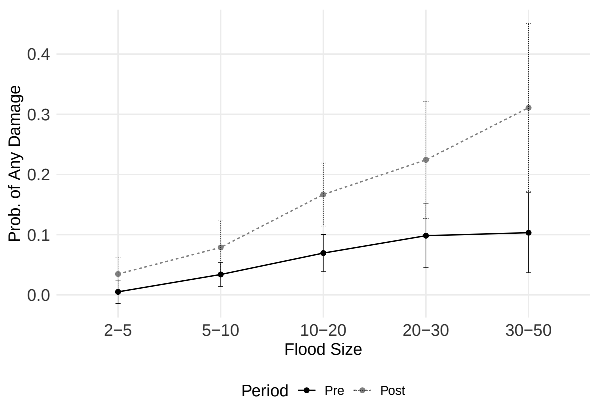
Back to 4.1.



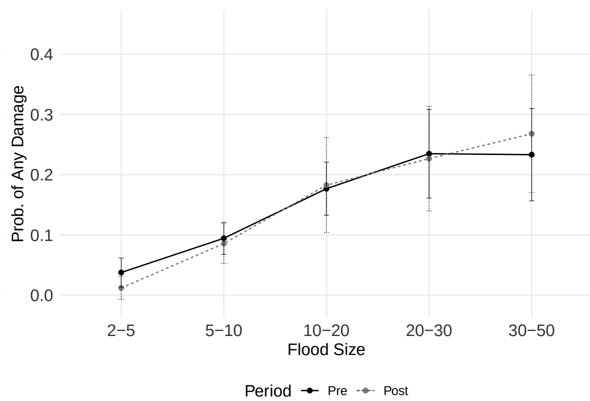
(a) Control Group (All Communities)



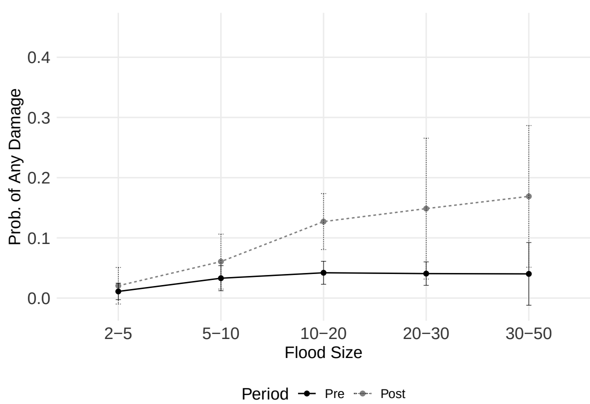
(b) Treatment Group (All Communities)



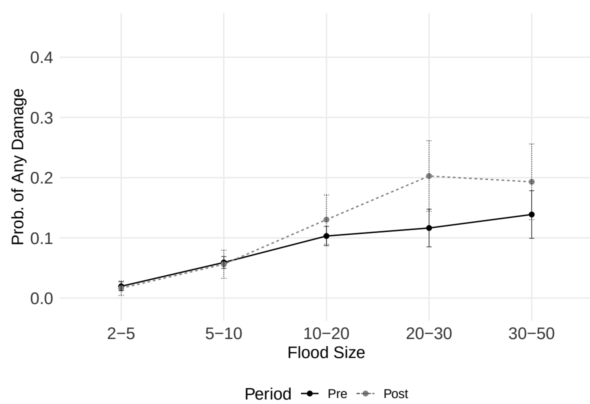
(c) Control Group (High Risk Communities)



(d) Treatment Group (High Risk Communities)



(e) Control Group (Low Risk Communities)



(f) Treatment Group (Low Risk Communities)

Figure E.8: The Effect of Disclosure on the Damage Function with 95% Confidence Intervals. These plots reproduce Figure 5.1 with corresponding confidence intervals.

Back to 5.2.