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

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2025-10-10

Abstract

Despite rising flood risk, US households continue to settle in high-risk locations. In response, disclosure policies are gaining traction. While the Tiebout mechanism predicts that households will "vote with their feet" when provided with such information, federally subsidized flood insurance may dampen this response. Exploiting two quasi-experimental variations in home seller disclosure requirements, I find that providing flood risk information significantly reduces population, housing prices, and housing supply in high-risk areas, with minimal impact on insurance take-up. These findings indicate that markets can facilitate climate adaptation when individuals can make more informed location choices.

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I am deeply grateful to Ryan Kellogg, Koichiro Ito, and Dan Black for their guidance and mentorship. I also benefited tremendously from numerous discussions with Tatyana Deryugina, Cory Koedel and Peter Mueser. I thank 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, US floods have caused $1 trillion in damage, and climate scientists expect them to worsen (Milly et al. 2002, NOAA 2020). Despite these warnings, many Americans continue to settle in flood-prone areas, thus 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 (Bakkensen and Barrage 2021, Wagner 2022).[1] Recently, flood risk disclosure policies, which provide property-level flood risk information to homebuyers, have gained traction to address this problem, but limited evidence exists on their effectiveness.[2]

Theoretically, disclosure policies are predicted to induce households to "vote with their feet" by altering perceptions of local amenities (Tiebout 1956, Banzhaf and Walsh 2008). Such population shifts can, in turn, reduce housing demand in less desirable areas, depress property values, and discourage future development in those locations. In the flood risk context, however, homebuyers have a powerful substitute—heavily subsidized federal flood insurance—that can significantly dampen the incentive to choose a safer location. This distortion makes homebuyer responses to a disclosure policy an empirical question. Crucially, the social benefit of the policy depends on the margin of response: whereas choosing a safer location reduces the probability of flooding in the first place, subsidized insurance mainly reduces homebuyers' financial exposure without necessarily addressing the physical risk (Ehrlich and Becker 1972).

This paper exploits quasi-experimental variation from a Home Seller Disclosure Requirement (hereafter, "the disclosure requirement") to test whether providing flood risk information can reduce physical exposure to the risk. For this, I estimate the impact of the disclosure requirement on changes in population and the National Flood Insurance Program (NFIP) take-up across flood risk zones. Furthermore, I examine its impact on housing prices and supply to test whether disclosure facilitates broader climate adaptation through market mechanism.

The disclosure requirement specifies that home sellers disclose known property defects to buyers through a standardized form (Lefcoe 2004). Regarding flood risk, the policy requires a buyer to be

[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). Australia recently considered implementing a mandatory seller disclosure of flood risk (Brown et al. 2023).

notified 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 limited awareness may result from the costs of acquiring and processing information (Kunreuther and Pauly 2004), the disclosure requirement could alleviate the problem by efficiently informing homebuyers about flood risks.

The disclosure requirement was introduced across 26 US states between 1992 and 2003. Variation in implementation timing arose from plausibly exogenous state-court rulings on the scope of realtor liability for incomplete disclosure (Roberts 2006). Coupled with differential disclosure effects for SFHA- versus non-SFHA areas, this staggered rollout facilitates a triple difference research design. I also leverage alternative 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). To further control for potentially confounding time-invariant differences at the SFHA border, I use the difference-in-discontinuity approach (Grembi et al. 2016). To leverage these variations, I compile comprehensive data that link official flood risk maps with US Census data, NFIP policy records, and transaction-level housing market data, at multiple geographic units, including communities and blocks.

The empirical analysis yields two main findings. Using a stacked event-study framework on annual population and NFIP policy counts data, I show that the disclosure requirement significantly reduces population in high-SFHA communities but has little impact on flood insurance take-up. Specifically, high- and low-SFHA communities show identical pre-policy population trends for a decade, but the relative population in high-SFHA communities falls by about 4% five years after implementation. Also, the impact of disclosure on population grows monotonically with treatment intensity (i.e., (%) community land within an SFHA). In contrast, I find that post-disclosure take-up rates in high-SFHA communities were no greater than in low-SFHA communities, and the effect size appears unrelated to treatment intensity. Furthermore, using property transaction data, I show that the disclosure requirement reduces housing prices in SFHA areas, consistent with numerous earlier findings on flood risk capitalization (Pope 2008, Bin and Landry 2013, Gibson and Mullins 2020, Hino and Burke 2021).

Given the limited evidence of an insurance response, I next examine location choices in greater depth, accounting for within-community impacts, as prior work suggests location adjustments to flood risk can be highly local (Elliott and Wang 2023, Fairweather et al. 2024). To do so, I exploit block-level decennial Census data and leverage the spatial discontinuity in flood risk information at SFHA boundaries. The results show that the disclosure widens the population differences at the border: comparing the pre- versus post-disclosure differences between SFHA and non-SFHA blocks (the difference-in-discontinuities estimate), the relative population in SFHA blocks has declined by 7% after the disclosure. This population effect is accompanied by an 8% reduction in housing units in SFHA blocks. I also document demographic changes, including a larger share of racial minority residents and renters in SFHA locations.

Collectively, these findings are consistent with the theoretical prediction that population shifts due to the disclosure reduce demand for SFHA properties, lower property values, which will in turn discourage development in risky areas. Voting with their feet rather than relying on flood insurance likely reflects the relative costs and benefits of the two strategies in this context. Choosing a safer location is often less costly for homebuyers who are already planning to move. Conversely, NFIP coverage offers limited protection, due to caps on payouts and exclusions for many indirect losses such as disruptions in daily life (Lee et al. 2024).

This paper contributes to three bodies of literature. First, it contributes to research on how housing markets respond to flood risk information (Pope 2008, Bin and Landry 2013, Bosker et al. 2019, Gibson and Mullins 2020, Hino and Burke 2021). Within this literature, my paper is most closely related to a concurrent study by Fairweather et al. (2024), which examine how flood information shapes homebuyers' risk-avoidance behavior.[3] Their large-scale experiment shows users are more likely to make offers on safer properties and that this behavior lowers prices of high-risk properties. I complement this by analyzing disclosure policies that apply across the broader housing market. More importantly, I provide direct evidence that information provision reduces aggregate exposure to flood risk—both human exposure, through population shifts, and capital exposure, through reductions in housing units. This distinction is critical because information may affect prices and who occupies high-risk areas without necessarily reducing the total stock of people and structures at risk, particularly when housing supply is inelastic.

Second, this paper extends previous studies on Tiebout sorting over environmental qualities

[3]Another close paper is Hino and Burke (2021), which use flood map updates as the source of information shock and test if the housing market efficiently prices flood risk. My paper extends Hino and Burke (2021) by assessing the quantity (population and housing units) margin.

(Greenstone and Gallagher 2008, Banzhaf and Walsh 2008, Hornbeck 2012, Bakkensen and Ma 2020, Chen et al. 2022). Unlike settings such as hazardous waste, air pollution, or dust storms, where relocation is the dominant response margin, flood risk operates in a fundamentally different institutional environment. That is, the availability of heavily subsidized NFIP means that earlier findings may not readily translate here. Moreover, while the literature has typically focused on the population effect, I also investigate the impact on housing stock, a key determinant of long-run exposure.

Finally, I add to the literature on the role of government in shaping household adaptation behaviors (Kousky et al. 2006, 2018, Gregory 2017, Baylis and Boomhower 2022, Peralta and Scott 2024). 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 encourage voluntary adaptation. By quantifying the impact of an informational regulation, I provide evidence on the effectiveness of "light-touch" regulatory tools in generating substantial aggregate adaptation.

2 Background

Background 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, as Figure 2.1 and Appendix Table C.1 show, between 1992 and 2003, 26 states (excluding DC) in the contiguous US adopted a disclosure requirement with an explicit question on flood risk while the remaining 22 states did not implement such a requirement until at least the late 2010s.

Disclosure content. A statutory disclosure requirement mandates that home sellers fill out a stan-

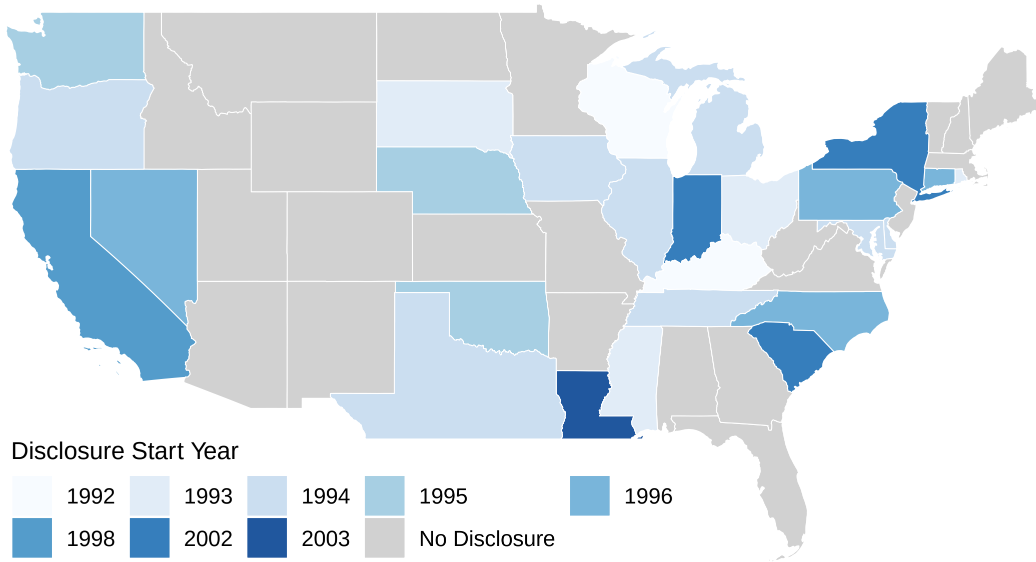


Figure 2.1: The Disclosure Requirement Implementation over Time

dardized form regarding known property conditions and typically deliver it before closing (Stern 2005). Importantly, the disclosure is not exclusively about flood risk; a typical form covers a wide range of property conditions, including structural issues and flood risks (Appendix Figure C.1).[4] The broad scope of these mandates suggests that the policy adoption decision is likely to be uncorrelated with underlying flood characteristics (e.g., flood risk levels, insurance take-up, damage, or local flood policies), and Appendix Figures C.2 corroborate this.

The exact language of disclosure on flood risk varies slightly from state to state, but some combination of the following three questions usually appears: Is the property in an SFHA? Does the property have a flood damage history? and Does the property have flood insurance?[5] Because properties on the SFHA are more susceptible to flooding, answers to these questions are highly correlated: flood insurance policy and claims data show that 71% (75%) 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.

[4]Since the disclosure delivers a bundle of information, discerning treatment mechanism can be challenging if there is a positive correlation between flood risk and other property defects. In Appendix Table C.2, I demonstrate that properties near SFHAs are notably newer compared to those farther away from SFHAs. As property defects typically emerge over time, this table suggests that the disclosure policy's impact likely stems from flood risk information rather than other property defects.

[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.

Flood Map and Special Flood Hazard Area (SFHA). Three facts about SFHA, an area designated by an official flood map for potential inundation by a 100-year flood, are worth highlighting. First, the SFHA boundary is determined by comparing water surface and ground elevations under a 100-year flood scenario (FEMA 2005). This gives rise to the spatial discontinuity design because the disclosure treats flood risk as binary, whereas actual flood risk varies more gradually across boundaries (Noonan et al. 2022). Second, in a typical community, SFHAs are narrow and irregular, closely following rivers and coastlines, and thus cover only a small fraction of the land area (median is 8% as Appendix Figure C.3 shows).[6] Third, SFHA areas change occasionally due to flood maps updates, although such instances were relatively infrequent prior to 2008 (see Appendix Figure B.1). Such a map update is a potentially confounding source of information shock (Gibson and Mullins 2020, Bakkensen and Ma 2020, Hino and Burke 2021, Weill 2023), and thus I test robustness to map updates in my empirical analysis.

Flood Insurance. The federal government has historically provided nearly all flood coverage in the US through the National Flood Insurance Program (NFIP).[7] Importantly, the program has heavily subsidized rates, distorting the true price of risk: GAO (1993) documents that over 40% of insured SFHA properties receive an average subsidy of 67%. The NFIP's premium subsidy and its coarse premium structure, which cannot reward those who alter their properties to reduce potential losses (Kousky 2019), have an important implication: voting by feet and NFIP purchases are likely to be substitutes in this context (Ehrlich and Becker 1972). This theoretical prediction is confirmed by Wagner (2022) and Peralta and Scott (2024).

3 Data

Data sources. To determine SFHA status of a given geographic unit, I use the Q3 map—the first generation of a digitized flood map—that reflects flood risk as of the mid-1990s (FEMA 1996). I spatially merge the Q3 flood maps with NFIP community and Census block maps. For communities, I calculate the share of land area within the SFHA, since their jurisdictions are often large and thus

[6] A community, as defined by the NFIP, is a local political entity (e.g., village, town, city) that is similar to, but not always aligned with, a US Census Place (Gallagher 2014).

[7] Given that private insurers account for only 3–4% of the market as of 2023 (Kousky et al. 2023), the NFIP is the de facto source of coverage.

encompass both SFHA and non-SFHA areas (Appendix Figure C.3). For blocks, which is the smallest Census geographic unit, I classify them as inside or outside the SFHA. To track changes in flood map over time, I draw on the Community Map History table from FEMA's Flood Insurance Study (FIS) reports.[8]

Annual data on population and flood insurance take-up at the NFIP community level over the 1982—2002 period come from Gallagher (2014). Flood insurance take-up is measured as the number of active flood insurance policies per capita, partly reflecting the lack of annual community-level data on the number of insurable structures (homes and businesses). Since NFIP communities closely align with Census Places, population figures in Gallagher (2014) are drawn from the Census Bureau's annual population estimates.

I complement the community-level population data with census-block-level Decennial Censuses, which track population counts, housing units, and demographic shares (renters, seniors, Hispanic origin). I account for changing block boundaries by calculating the weighted sum of count variables using interpolation weights from the NHGIS block-to-block crosswalk (Manson et al. 2022).

For housing prices, I use the Zillow Transaction and Assessment Database (ZTRAX), which documents transaction dates, sales prices, and housing characteristics such as type (e.g., single house, condominium, etc.), longitude and latitude, year built, and the number of bedrooms.[9] I spatially merge property locations with the Q3 map to determine the SFHA status of each property.

Finally, the primary data source for tracking 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). Appendix Table C.3 reports summary statistics.[10]

[8]Practically, I extract the information from the National Flood Hazard Layer (NFHL). Further details and validation of the NFHL map revision data are in Appendix B.

[9]The results and opinions are those of the author(s) and do not reflect the position of Zillow Group. In accordance with the ZTRAX Access Agreement, only regression outputs were retained. For recent applications of ZTRAX, see Bradt and Aldy (2025) and Liu et al. (2025).

[10]In Panel A, the maximum value of flood insurance take up (i.e., per capita insurance policy counts) is 5. This reflects summer destinations that have many structures but relatively few residents.

4 Do Homebuyers Vote by Feet or Buy Insurance Instead?

4.1 Empirical Framework

To assess whether homebuyers respond to the disclosure policy by choosing a safer location or by relying on insurance instead, I first analyze annual community-level data using the event-study specification in equation (1).

$$Y_{msztd} = \sum_{k=-10}^{4} \beta^k H_m D_{sd} \mathbf{1}(t - t_s^* = k) + \theta_{std} + \lambda_{zdt} + \psi_{szd} + \epsilon_{msztd} \tag{1}$$

Y_{msztd} denotes the log population or per capita flood insurance counts for community m in state s in flood risk status z, in year t, and stack d. H_m is a binary indicator for whether community m belongs to group z, where $z \in \{\text{high-SFHA}, \text{low-SFHA}\}$. $\mathbf{1}(t - t_s^* = k)$ is an event time indicator equal to 1 if year t is k years from the policy change year t_s^* in state s, for $k \in \{-10, -9, \cdots, 4\}$. D_{sd} is an indicator for whether state s belongs to the disclosure group in stack d. Other terms in a standard triple difference model are subsumed by fixed effects. The coefficient β^k captures the effect of the disclosure policy in high-risk communities, relative to low-risk communities, in disclosed states relative to not-yet-disclosed states, at event time k.

Equation (1) takes a stacked triple difference approach to overcome potential bias from conventional two-way fixed effect models under treatment heterogeneity (Cengiz et al. 2019, Goodman-Bacon 2021). Importantly, I use late adopting states as a control group in equation (1) because, as Appendix Table C.4 shows, (1) the 22 never-adopted states are different in baseline 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.[11] Moreover, consistent with these baseline differences, when I use never-adopting states as controls, the event-study estimates in Section 4.2 exhibit pronounced pre-trends. Thus, 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 $\tilde{t} > t^*$.[12] Each d covers a window of 10 years before and 5 years after t^* and sample com-

[11] 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.

[12] Stack refers to data that is created for a specific treatment year (or a cohort year). A state can belong to both

position during this period remains stable. I drop observations from the control states for $t >= \tilde{t}$ because they are no longer "not-yet-treated".[13]

Also, because disclosure intensity is defined as the fraction of land area within the SFHA, it is inherently a continuous measure. Recent work shows that difference-in-differences with a continuous treatment can be biased when treatment effects vary with intensity (Callaway et al. 2024). To address this problem, I "binarize" the treatment intensity variable: that is, I set $H_m = 0$ for communities with SFHA share less than 1% and $H_m = 1$ for those with SFHA share above 70% (roughly the bottom 10% vs. top 3% of the distribution), dropping all intermediate cases. I also report sensitivity to the choice by changing the high-SFHA cutoff to 50% and 30%.

Finally, because equation (1) includes state-year-stack (θ_{std}) and high SFHA-year-stack (λ_{zdt}) fixed effects, the specification controls for any concurrent policies or shocks that: (1) affect all communities within a state equally or (2) affect high-SFHA communities uniformly across states—such as federal-level flood policies. Further, state-high SFHA-stack (ψ_{szd}) fixed effects control for time-invariant characteristics that distinguish SFHA from non-SFHA areas within each state.

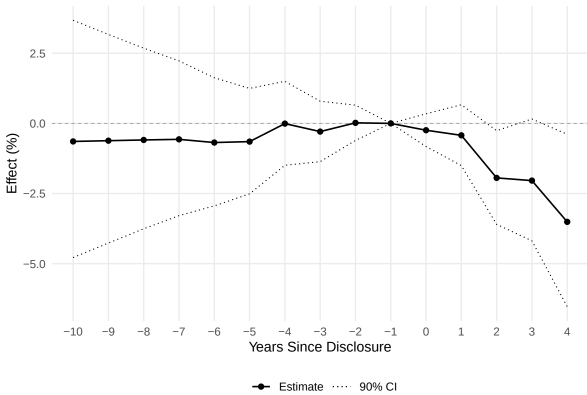
4.2 Findings

Figure 4.1 (a) reports $\hat{\beta}^k$ from equation (1), where the dependent variable is the log of population. Here, $H_m = 1$ for communities with more than 70% SFHA area. Over the ten years preceding the disclosure policy, population trends in high-SFHA communities closely tracked those in low-SFHA communities (less than 1% SFHA area). In the first two years following the policy's implementation (event times 0 and 1), I find little evidence of population change in high-SFHA communities. This likely reflects short-run housing supply inelasticity, with effects absorbed by prices rather than population. Starting in year 3, however, these communities begin to experience population declines, with the effect reaching nearly 4% five years after implementation.

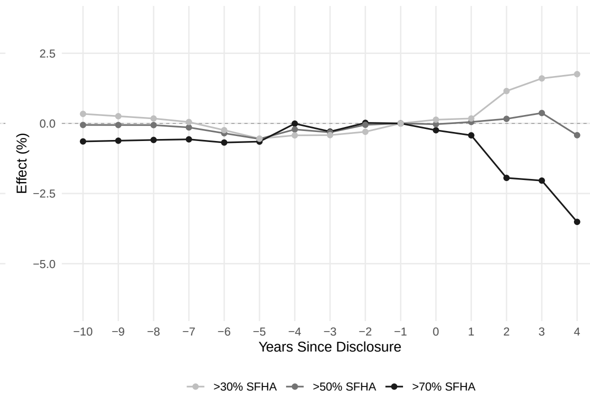
Panel (b) shows how results change when high-SFHA communities are instead defined as those with SFHA shares above 50% or 30% (rather than 70%), each compared to communities with less than 1% SFHA area. The figure overlays the estimates from Panel (a) with those from alternative

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 $t^* < 1996$.

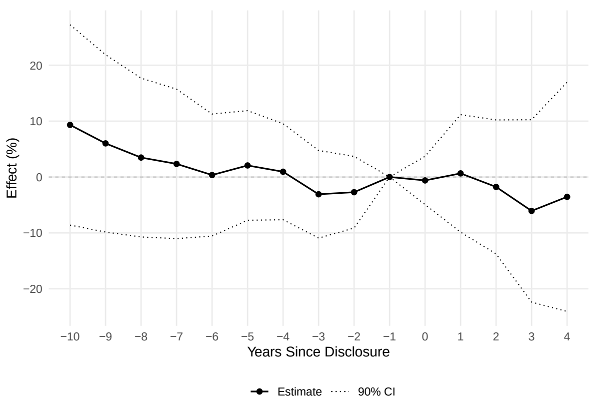
[13] Because the policy adoption is complete by 2003, the 2003 cohort has no control units available for its post-treatment period, and the 2002 cohort only has one post-treatment year with a corresponding not-yet-treated control (the 2003 cohort). Accordingly, I include the 2002 and 2003 cohorts only as control units.



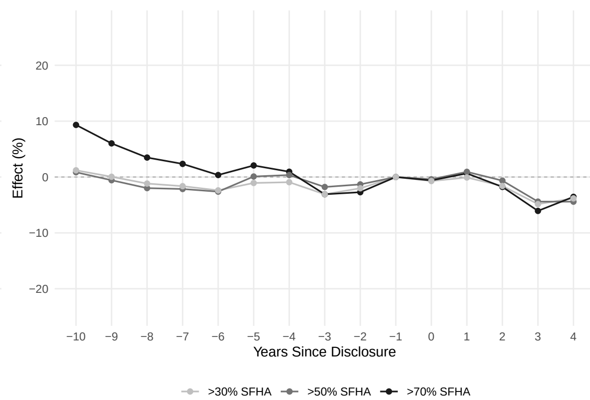
(a) Population: Event Study Estimates



(b) Population: Alternative High-Risk Definitions



(c) Flood Insurance: Event Study Estimates



(d) Flood Insurance: Alternative High-Risk Definitions

Figure 4.1: The Effect of Disclosure on Community Level Population and Flood Insurance Take Up. Panel (a) reports the estimated effects of the disclosure policy on community population (β^k from equation (1)), defining high-SFHA communities ($H_m = 1$) as those with more than 70% of their area in the SFHA. Panel (b) shows results for alternative thresholds for $H_m = 1$. Panels (c) and (d) present the corresponding analyses for per capita flood insurance counts, paralleling the specifications in Panels (a) and (b), respectively. Dotted lines represent the 90% confidence interval.

thresholds. The coefficients display a clear monotonic attenuation: as the threshold is lowered, the estimated population decline becomes smaller and, in some cases, even turns slightly positive—though statistically insignificant (Appendix Figure C.4 (a) and (b)). This monotonic relationship between treatment intensity and its effect size provides reassurance that the disclosure policy triggers the Tiebout sorting. Importantly, because the policy informs prospective buyers rather than existing homeowners, these effects are most plausibly driven by diverted in-migration, rather than active out-migration.

A Tiebout model predicts that population reductions in the SFHA area following the disclosure will coincide with declines in the prices of SFHA properties (Banzhaf and Walsh 2008). Indeed, numerous prior studies have shown that flood risk information from disclosure policies (Pope 2008), salient flood events (Bin and Landry 2013, Gibson and Mullins 2020), and flood map updates (Hino and Burke 2021) capitalizes into property values, typically leading to price reductions of around 5%. To corroborate this well-documented capitalization effect in this setting, in Appendix A, I use property-level data and estimate an event study model that parallels equation (1). Appendix Figure A.1 shows that the disclosure requirement reduces prices of properties in SFHA areas by about 4-7% in the post period, with no evidence of pre-trends.

In Panels (c) and (d), I test whether homebuyers respond to the disclosure policy by purchasing flood insurance using the same models as Panels (a) and (b). Panel (c) provides little evidence of increased NFIP take-up (i.e., per capita policy counts): that is, all post-disclosure coefficients are near zero or negative.[14] Further, in contrast to Panel (b), where effect sizes were proportional to the treatment intensity, in Panel (d), the post-disclosure point estimates are essentially identical across all three thresholds. This lack of dose-response relationship reinforces the conclusion that the disclosure requirement has little impact on flood insurance take-up.

Together, the results in Figure 4.1 suggest that choosing a safer location, rather than purchasing insurance, is a prevalent homebuyer response. This is consistent with recent experimental evidence from Fairweather et al. (2024), showing that homebuyers make offers to safer properties upon receiving flood risk information. The prevalence of voting by feet may reflect relative benefits and costs of the two strategies in this setting: choosing a safer location is often less costly for homebuyers, as they plan to move regardless and typically consider more than 10 properties before closing (Zumpano et al. 2003). Moreover, the NFIP coverage may provide limited benefits, as it caps asset losses at $250,000 and excludes compensation for numerous economic costs (e.g., loss of income or use value) beyond asset losses (Lee et al. 2024).

In Appendix Figure C.4 (c), I present an event study plot that include all 22 never-adopted states as a control group. In contrast to Figure 4.1 (a), Appendix Figure C.4 (c) has a noticeable pre-trend, which implies that the never-adopted states are unlikely to satisfy the parallel trend assumption. This is also consistent with differences in baseline characteristics between ever vs. never-adopted

[14]Note, to express the results in percentage terms, I divide the estimated coefficient by the mean flood insurance take-up rate of high-SFHA communities (0.23). I do not log-transform the outcome because over 20% of control communities (with SFHA area below 1%) have zero insurance policies, which would result in substantial loss of observations if logs were used.

states as discussed in Section 4.1. In Appendix Figure C.4 (d), I show that the result is robust to the exclusion of communities that had experienced flood map updates during the sample period.

5 Decennial Census Evidence on Population, Housing Units, and Demographic Shifts

Given the limited evidence of an insurance response, this section turns to block-level Decennial Census data to examine Tiebout mechanism in greater detail. The analyses have three aims: (1) to revisit disclosure effects on population, accounting for intra-community shifts; (2) to document changes in demographic composition; and (3) to investigate broader consequences of population shifts (i.e., housing supply effects).

5.1 Empirical Framework

For the decennial census data analysis, I use an alternative source of identification from equation (1).[15] I exploit the discontinuity in flood risk information at the SFHA boundary and employ a difference-in-discontinuity approach following Grembi et al. (2016). This strategy compares blocks just inside and just outside the boundary in both the pre- and post-disclosure periods, taking the difference between these two contrasts to isolate the policy's effect.[16] The design is particularly valuable because it accounts for time-invariant cross-sectional differences between SFHA and non-SFHA areas, such as building code regulations in the SFHA area (Ostriker and Russo 2023).

$$\begin{aligned} Y_{bst} =& \delta_0 + \delta_1 X_{bs} + \delta_2 D_{bs} + \delta_3 X_{bs} * D_{bs} + \\ & T_{st}[\delta_4 + \delta_5 X_{bs} + \delta_6 D_{bs} + \delta_7 X_{bs} * D_{bs}] + \epsilon_{bst} \end{aligned} \tag{2}$$

In equation (2), Y_{bst} represents population and housing outcomes 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-

[15] Applying equation (1) to decennial census data is impractical. Small-area data was restricted to urban areas until 1990, so using earlier censuses would lose substantial portions of the sample. Given the 1992–2003 policy timing, this gap leaves only the 1990 census as a usable pre-treatment year, making estimation with equation (1) essentially impossible.

[16] While Noonan et al. (2022) shows that (true) flood risk changes continuously at the border in Texas, true risk may change more abruptly in other states within my sample. However, because flood risk, which is largely a function of land contour, is likely to remain stable at least in a relatively short term, such differences will also be controlled by the difference-in-discontinuity approach.

SFHA area), which is approximated by taking the difference of (1) the distance between block centroids and the closest SFHA border and (2) a block diameter. $D_{bs} = 1$ if $X_{bs} > 0$ is a high risk group (i.e., SFHA) indicator variable, and $T_{st} = 1$ if $t > t_s^*$ is a post disclosure-period indicator variable. δ_6 captures the impact of the disclosure policy for blocks located in close proximity to the border, under the assumption that there are no other important time-varying differences at the discontinuity.

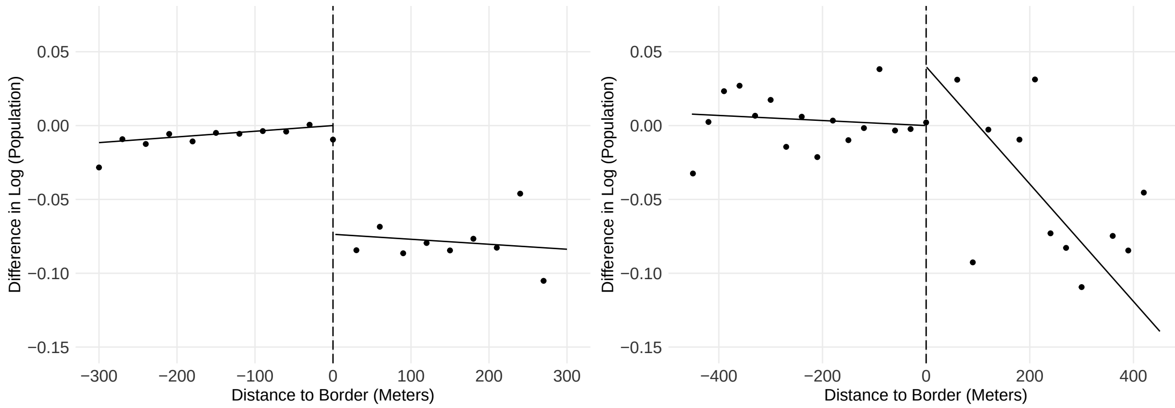
To estimate δ_6, I first estimate the optimal bandwidth for each outcome variable. Then, I estimate equation (2) using blocks within the optimal bandwidth (Calonico et al. 2014, Cattaneo et al. 2019).[17] For states that implemented disclosure policies between 1990-1999 (2000-2009), the 1990 (2000) decennial census is used to estimate δ_0 to δ_3 whereas 2000 and 2010 (2010 and 2020) decennial censuses are used to estimate δ_4 to δ_7. I exclude 17% of blocks that contain SFHA borders from the analysis, because the distance between a block boundary and the nearest SFHA boundary is not defined for them. As in Section 4, standard errors in this section are clustered at the state level.

5.2 Findings

Figure 5.1 (a) illustrates the impact of disclosure policy on the log population. The horizontal axis is the distance between a block border and the closest SFHA border, and SFHA blocks are presented on the right-hand side of the dotted vertical line. The vertical axis is the difference in log population between pre and post treatment periods. The solid lines are the regression fit and points reflect the difference in log population for each distance bin. δ_2 from equation (2) is normalized to 0 to enhance readability.

Panel (a) indicates a 7% drop 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 has minimal impact on the estimates. This estimate is notably larger than the 4% reduction observed at the community level in the event-study analysis (Figure 4.1 (a)). This is likely because the 4% result underestimates the population effect, as it cannot capture intra-community location responses. Indeed, earlier studies show that location responses to flood risk are often highly local (Elliott and Wang 2023, Fairweather et al. 2024).

[17] 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.



(a) Change in Spatial RD Estimates (Disclosed States) (b) Change in Spatial RD Estimates (Placebo States)

Figure 5.1: The Effect of Disclosure on Population. Panel (a) illustrates difference-in-discontinuity estimates for the disclosed states. The dependent variable is the change in log of population after the disclosure. The running variable is the distance between a census block and the nearest SFHA border. The discontinuity at the threshold (dashed vertical line) represents δ_6 in equation (2). Panel (b) repeats Panel (a) for the placebo states

While the magnitude (7%) is a local average treatment effect at the SFHA boundary, most SFHA blocks are close to the boundary. Appendix Figure C.5 shows that, among all SFHA blocks located in the 26 ever-disclosed states, the median (75th percentile) distance to the nearest boundary is only 166 meters (578 meters), indicating that SFHA blocks rarely extend deep into the floodplain. Appendix Figure C.6-C.8 reinforces this point by overlaying block boundaries with SFHA zones for three example communities with varying level of SFHA shares (8%, 25%, and 70%). The 8% case reflects the median community in ever-disclosed states. The maps show that when SFHA shares are modest, as in most communities, the floodplain is a relatively narrow strip and nearly all SFHA blocks lie close to the boundary.[18] The histogram and maps, taken together, indicate that the boundary analysis reflects a typical SFHA block rather than a marginal fringe.

Table 5.1 presents additional results. Column (1) corresponds to Figure 5.1 (a). Column (2) reports 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).[19] In column (3), I show that the number of housing units in SFHA blocks changes by -8% after the disclosure requirement. Similarly, column (4) documents that the disclosure reduces the probability

[18] In these three communities, the mean (maximum) distances from SFHA blocks to the boundary are 18 (35), 204 (554), and 1,462 (6,524) meters, respectively.

[19] Note that the number of observations in column (1) is *greater* than in column (2), despite its sample restrictions (i.e., focusing on non-zero population blocks), because the estimated optimal bandwidth is larger for column (1). More generally, the estimated optimal bandwidths in Table 5.1 are specific to the outcome variables.

Table 5.1: The Effect of Discosure on Block Population and Housing Units

	Log Population	Prob. of Any Population	Log N Housing	Prob. of Any Housing	Renter Occupancy Rate	Hispanic Occupancy Rate	Senior Occupancy Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SFHA × Post	$-.074^{**}$	$-.011^{***}$	$-.081^{***}$	$-.017^{***}$	$.007^{**}$	$.008^{**}$	$-.005$
	(.030)	(.003)	(.019)	(.003)	(.003)	(.003)	(.004)
Avg D.V.		0.675		0.668	0.28	0.079	0.218
Bandwidth	301	138	243	133	564	380	798
Num. obs.	1915717	1483356	1600325	1438647	2952205	2243413	3650471

Note: Columns (1)–(7) are estimated based on equation (2) using the decennial census block-level data. Standard errors are clustered at the state level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

of having any housing unit in an SFHA block by 0.02 relative to a non-SFHA block (or 2.5 percent of the baseline value of 0.67). This dynamic is consistent with the Tiebout model discussed earlier: information provision redirects market demand away from risky locations, which suppresses housing prices and housing supplies.

In columns (5)-(7), I examine how demographic composition changes after the disclosure policy and find that the fraction of the renters and minority population, in particular, those of Hispanic origin, increases by about 0.7 and 0.8 percentage points, respectively. This pattern aligns with Bakkensen and Ma (2020), who find that households with fewer resources tend to sort into riskier areas after a flood risk information shock. The share of senior residents (age 65 and above) also falls by about 0.5 percentage points, although the estimate is statistically insignificant. A reduction in older residents is plausible given their lower physical capacity to cope with flooding events.

Two potential concerns regarding the block-level analyses merit attention. First, during the sample period, which is over 20 years, other factors may have evolved differentially between SFHA and non-SFHA areas (time-varying confounders). However, it is reassuring that Figure 5.1 (a) is consistent with Figure 4.1 (a), which, for instance, controls for federal level flood policy changes. Further evidence comes from Figure 5.1 (b), which replicates Figure 5.1 (a) for five placebo states that adopted disclosure rules unrelated to flood risk. I find no evidence of population decline in these placebo states; if anything, point estimates are slightly positive. This supports the view that the main results are not driven by other time-varying shocks. Moreover, Appendix Table C.5 column (1) shows that results are nearly unchanged when excluding blocks subject to flood map updates during the sample period, which could be a potential time-varying confounder.

Second, the disclosure requirement may have a spillover effect into non-SFHA areas. To address this concern, I estimate equation (2) using a doughnut difference-in-discontinuity approach that excludes blocks very close to the border (Kline and Moretti 2014). If endogenous sorting near the border is pervasive, the treatment effect may change when those observations are excluded (Cattaneo and Titiunik 2022). Appendix Table C.5 columns (3) and (4) show that the estimates remain nearly identical even if I remove blocks within 20 to 40 meters from the border. Likewise, the policy effect persists when I expand the bandwidth or restrict the control group to progressively more distant blocks (Appendix Figure C.9 Panels (a) and (b)).[20] These results suggest that any spillover effects are likely modest at most.

6 Conclusion

Floods are the costliest US natural disaster and are expected to worsen. Yet many Americans continue to settle in high-risk areas, partly due to information frictions. Despite growing attention to flood risk disclosure policies, evidence remains limited on whether such measures can induce homebuyers to vote with their feet, especially in the presence of heavily subsidized NFIP.

By exploiting plausibly exogenous variations created by a Home Seller Disclosure Requirement, I find that providing flood risk information to homebuyers reduces the population residing in high-risk areas by 4–7%, with little corresponding change in flood insurance take-up. Consistent with theoretical predictions of the Tiebout model (Tiebout 1956, Banzhaf and Walsh 2008), I also show that population shifts coincide with lower housing prices and housing supply in high-SFHA areas. Given that average annual flood losses for a typical SFHA property are three times greater than those for a non-SFHA property (Gourevitch et al. 2023), and that the compliance costs for this policy are likely moderate at most,[21] the policy likely generates substantial welfare gains. These findings indicate that disclosure policies can facilitate market-driven climate adaptation.

[20] In Panel (a), the standard errors remain relatively stable as the bandwidth increases. This is likely due to clustering: because increasing the bandwidth does not increase the number of clusters (states), the additional observations do not meaningfully reduce standard errors. In contrast, when standard errors are not clustered, they decline monotonically with bandwidth. In Panel (b), I estimate equation (2) using control blocks that are within the distance of $(r-1) \times$ *optimal bandwidth* and $r \times$ *optimal bandwidth* for $r \in \{1, 2, 3, 4, 5\}$.

[21] Moore and Smolen (2000) documents that home sellers spend less than 40 minutes to fill out the disclosure form.

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A Appendix A: Disclosure Requirement and Housing Price

Numerous prior studies have documented that flood risk information capitalizes into housing prices. To test whether similar patterns emerge in my setting, I use ZTRAX data to estimate equation (3), a stacked triple-difference event study that parallels equation (1). Here I compare SFHA and non-SFHA properties before and after disclosure, using not-yet-treated states as the clean control.[22]

$$log(Price_{ijmstd}) = \sum_{k=-3}^{4} \beta^k H_{id} D_{sd} \mathbf{1}(t - t_s^* = k) + \theta_{mjhld} + \mu_{jtd} + \lambda_{mtd} + \epsilon_{ijmstd} \tag{3}$$

$Price_{ijmstd}$ is the housing price for a property i with SFHA status j in community m in state s at time t in stack d. $H_{id} = 1$ is a dummy variable that takes 1 when a property i in stack d belongs to the SFHA area. $D_{sd} = 1$ is a dummy variable that takes 1 when state s in stack d belongs to a treated group. $\mathbf{1}(t - t_s^* = k)$ is an event time indicator equal to 1 if year t is k years from the policy change year t_s^* in state s, for $k \in \{-3, -2, \cdots, 4\}$. Note, because ZTRAX data becomes increasingly sparse before 1990, so I keep the pre-period to –3.

I also include a complete set of two-way fixed effects μ_{jtd}: SFHA-year-stack fixed effects, λ_{mtd}: community-year-stack fixed effects, and θ_{mjhld}: community-SFHA-Building Age-Number of Beds-Stack fixed effects to estimate β^k. Further, these fixed effects are interacted with the stack d, to ensure that comparisons are made within each stack. For building age h, I group construction years into 10-year bins (e.g., 2000-2009, 1990-1999, etc.) and for the number of bedrooms l, I group them into 1–3, 4–6, 7–10, and 10 or more bedrooms bins.

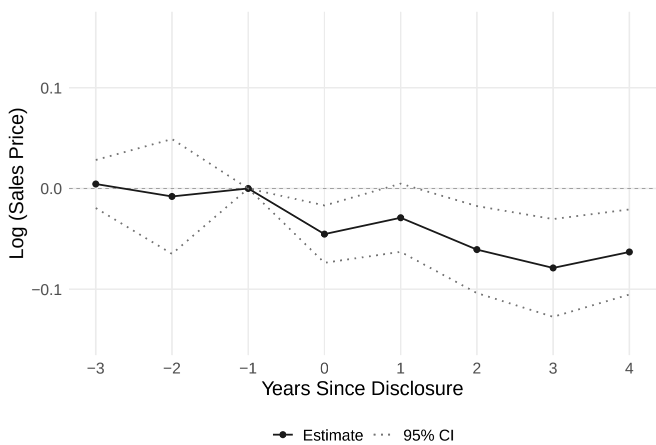

Figure A.1: The Effect of the Disclosure Requirement on Housing Price. These figures plot the coefficients of interaction terms between the SFHA status and disclosure policy dummies in event time. The dependent variable is the log of housing price. Standard errors are clustered on state.

Figure A.1 presents an estimated policy effect over event time. $\hat{\beta}_k$ in the pre-disclosure periods are close to zero, supporting the parallel trends assumption. Beginning in the first year after the policy change, the prices of affected properties decline by approximately 4%. This effect persists and continues to grow through five years following implementation. This magnitude aligns with prior findings, which document housing price reductions of around 5% in response to flood risk information.

[22] I apply the following sample restrictions: I drop observations without location coordinates (longitude and latitude), restrict the sample to single-family houses (as the disclosure applies primarily to one-to-four dwelling units), and restrict the transaction price to be between \$10,000 and \$100,000,000 in nominal dollars.

B Appendix B: Map Updates Data Validation

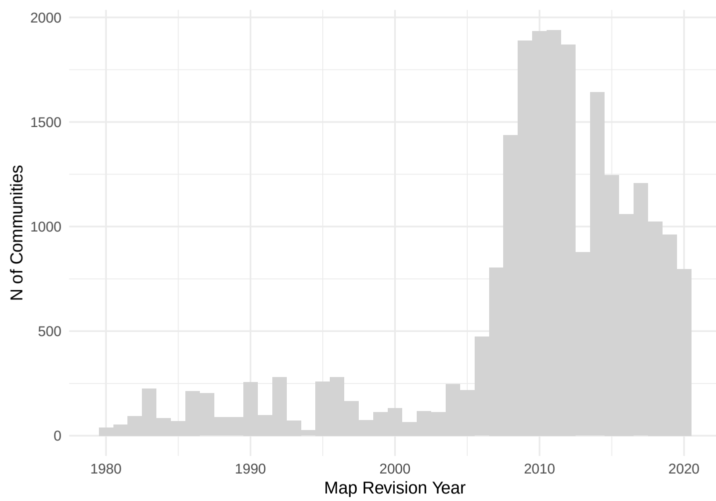

Figure B.1: The Number of Communities with Flood Map Revisions by Year. This figure illustrates the number of communities with flood map revision from 1980 to 2020 using Community Map History from the Flood Insurance Study (FIS) reports.

The Community Map History table serves as a credible source for tracking map revisions; for example, flood map panel notes, "For community map revision history, refer to the Community Map History table located in the FIS report for this jurisdiction."

According to the Community Map History, 10.8% of communities in my community-level sample revised their flood maps during the sample period—covering 10 years before and 5 years after each state's disclosure policy change. In comparison, in my block-level sample, 48.2% of communities revised their flood maps during the sample period, defined as 1990–2010 for states treated before 2000 and 2000–2020 for states treated after 2000.

Such a stark difference is explained by Appendix Figure B.1, which plots the distribution of flood map revision years from the FIS reports. The figure shows a sharp increase in revisions beginning in 2008. In the community-level sample, states implemented the policy in the 1990s (latest cohort year 1998) largely avoid this surge. In contrast, the block-level sample's windows overlap with the post-2008 spike, making them much more exposed to the surge in map updates.

It is also worth noting that FEMA's Compendium of Map Updates (Hino and Burke 2021), which is an alternative source of map updates, seems to document any changes made in a given year. For example, in 2009, communities 371038, 42027C, 21189C, and 17083C are all listed in the compendium as having map updates, but the corresponding FIS reports indicate that these maps were created for the first time. Since my goal is to account for potential changes in flood zones delineated in the Q3 flood map, I focus exclusively on map revisions. The Community Map History data from the FIS reports is therefore more appropriate for this purpose.

C Appendix C: Additional Tables and Figures

Table C.1: Disclosure Policy Adoption by Year

Policy Change Year	Disclosed	Disclosed (w/o Flood)
1992	KY, WI	
1993	MS, OH, RI, SD	
1994	DE, IA, IL, MD, MI, OR, TN, TX	ID, NH
1995	NE, OK, WA	KS
1996	CT, NC, NV, PA	
1998	CA	
1999		ME
2002	IN, NY, SC	
2003	LA	MN

Note:
This table presents the list of states that adopted a disclosure policy by year. The last column includes states that implemented a disclosure policy without a question on flood risk.

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Table C.2: Building Age by the SFHA Status

	N of Houses (< 5Yrs)	N of Houses (> 40Yrs)	(%) Houses (< 5Yrs)	(%) Houses (> 40Yrs)
	(1)	(2)	(3)	(4)
SFHA > 0	119.507***	−254.004***	.057***	−.192***
	(13.437)	(29.864)	(.007)	(.034)
Constant	73.182***	661.449***	.041***	.471***
	(24.349)	(54.139)	(.010)	(.053)
Num. obs.	32391	32391	31490	31490

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

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Table C.3: Summary Statistics

Variables	Min	Q25	Median	Mean	Q75	Max	N
Panel A: Community Level Variables							
Population	34	1,000	3,799	17,983	18,863	537,150	27,113
Flood Insurance Take Up	0	0	0.001	0.053	0.007	5.08	27,113
(%) In SFHA	0	0	0	0.189	0.009	1	27,113
Panel B: Block Level Variables							
Population	1	11	28	53.3	61	9,888	1,915,717
Housing Units	1	5	12	21.9	24	3,014	1,600,325
(%) Senior (65+)	0	0.056	0.182	0.218	0.333	1	3,650,471
(%) Hispanic Origin	0	0	0	0.079	0.065	1	2,243,413
(%) Owner Occupied	0	0.545	0.833	0.72	1	1	2,952,205
In SFHA	0	0	0	0.073	0	1	1,915,717

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Table C.4: State Characteristics in 1990 by Disclosure Status

	Ever/Early		Never/Late		Difference	
Variables	Mean	SE	Mean	SE	Mean	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
Flood Insurance Per Capita	0.036	0.014	0.019	0.007	0.017	0.306
Flood Damage (thousands)	48.64	23.66	24.45	6.41	24	0.375
(%) in SFHA	0.156	0.011	0.128	0.013	0.028	0.105
Panel B: Early (Before 1994) vs. Late (After 1994) 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
Flood Insurance Per Capita	0.037	0.024	0.034	0.013	0.003	0.912
Flood Damage (thousands)	62	43.02	33.53	12.86	28	0.565
(%) in SFHA	0.153	0.01	0.16	0.022	-0.008	0.75

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 4.1.

Table C.5: The Effect of Discosure on Net Block Population Flow (Robustness Checks)

	Log Population		
	(1)	(2)	(3)
SFHA × Post	$-.079^{**}$	$-.079^{**}$	$-.080^{**}$
	(.029)	(.031)	(.033)
Model	No Map Revisions	Donut: 20	Donut: 40
Bandwidth	301	301	301
Num. obs.	710342	1763552	1607388

Note: Columns (1)-(3) replicate the baseline result (Table 5.1, Column (1)). Column (1) excludes blocks that experienced flood map updates during the sample period. Columns (2) and (3) exclude blocks within 20 and 40 meters, respectively, of the SFHA border. Standard errors are clustered at the state level.

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

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

Property Address: ______________________________

City, State & Zip Code: ______________________________

Seller's Name: ______________________________

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

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

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

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

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

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

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

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

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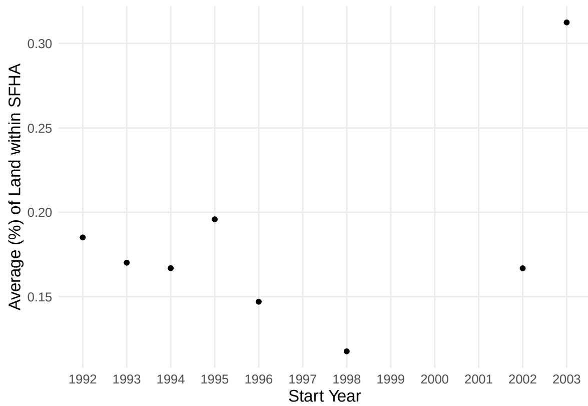
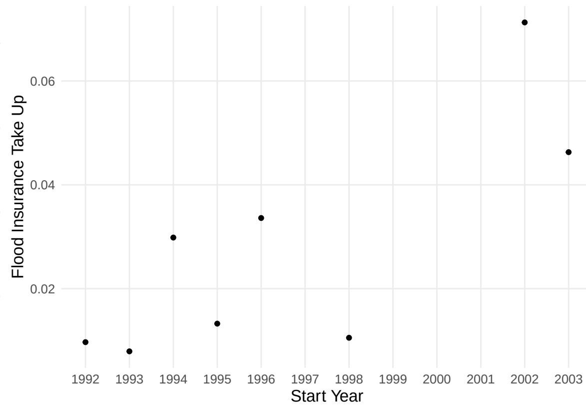
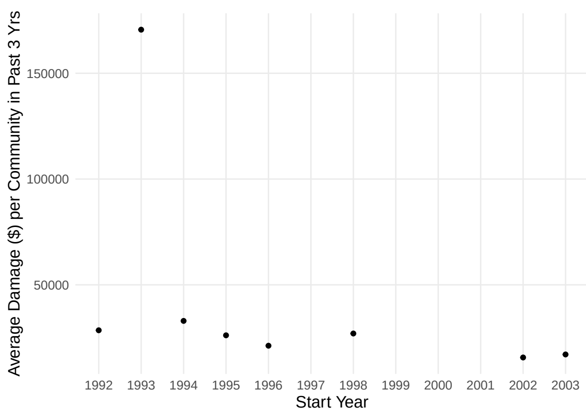


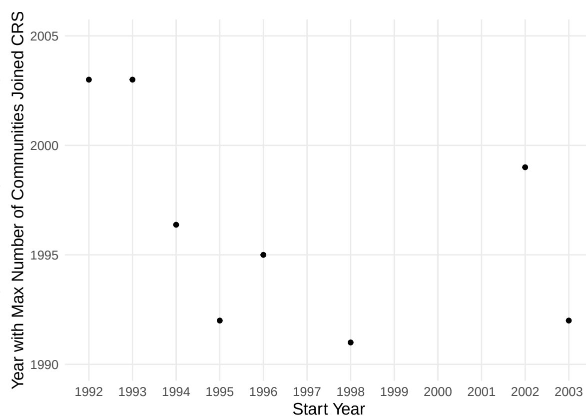
(a) Timing and (%) of Land in SFHA



(b) Timing and Flood Insurance Take Up



(c) Timing and Flood Damage



(d) Timing and Participation to the CRS Program

Figure C.2: Correlation Between Disclosure Timing and Flood Profiles. These figures plot the disclosure policy timing against (a) share of SFHA area, (b) flood insurance take up in the past three years, (c) flood damage in the past three years, and (d) flood policy (timing of participation to the Community Ratings System). Values on the y-axis is pooled across all states with the same treatment year. Data sources for Panels (a) and (b) are described in Section efsec:data. For (c) and (d), I use FEMA's official individual claims records (https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims-v2) and FEMA's NFIP community status book data (https://www.fema.gov/openfema-data-page/nfip-community-status-book-v1), respectively.

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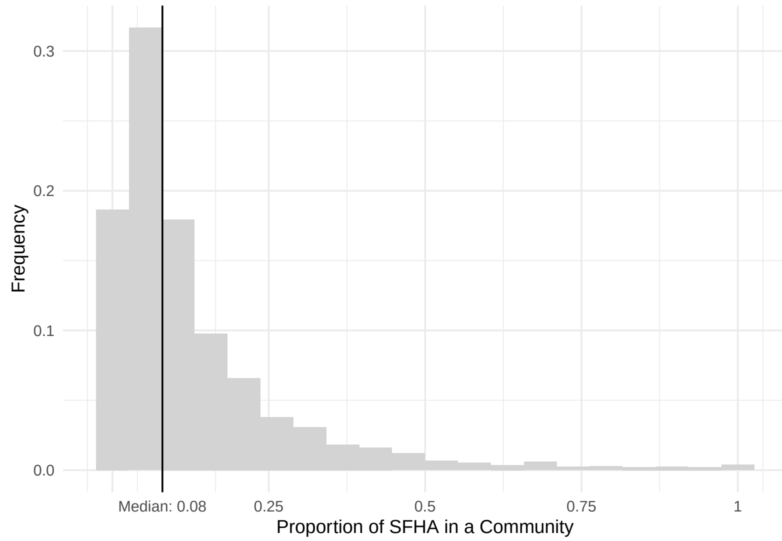

Figure C.3: Histogram of the Proportion of the SFHA at the Community Level. The plot shows the distribution of the SFHA ratio for the 8,175 communities that are on the Q3 map (first generation of digitized flood map) and in the 26 ever-disclosed states.

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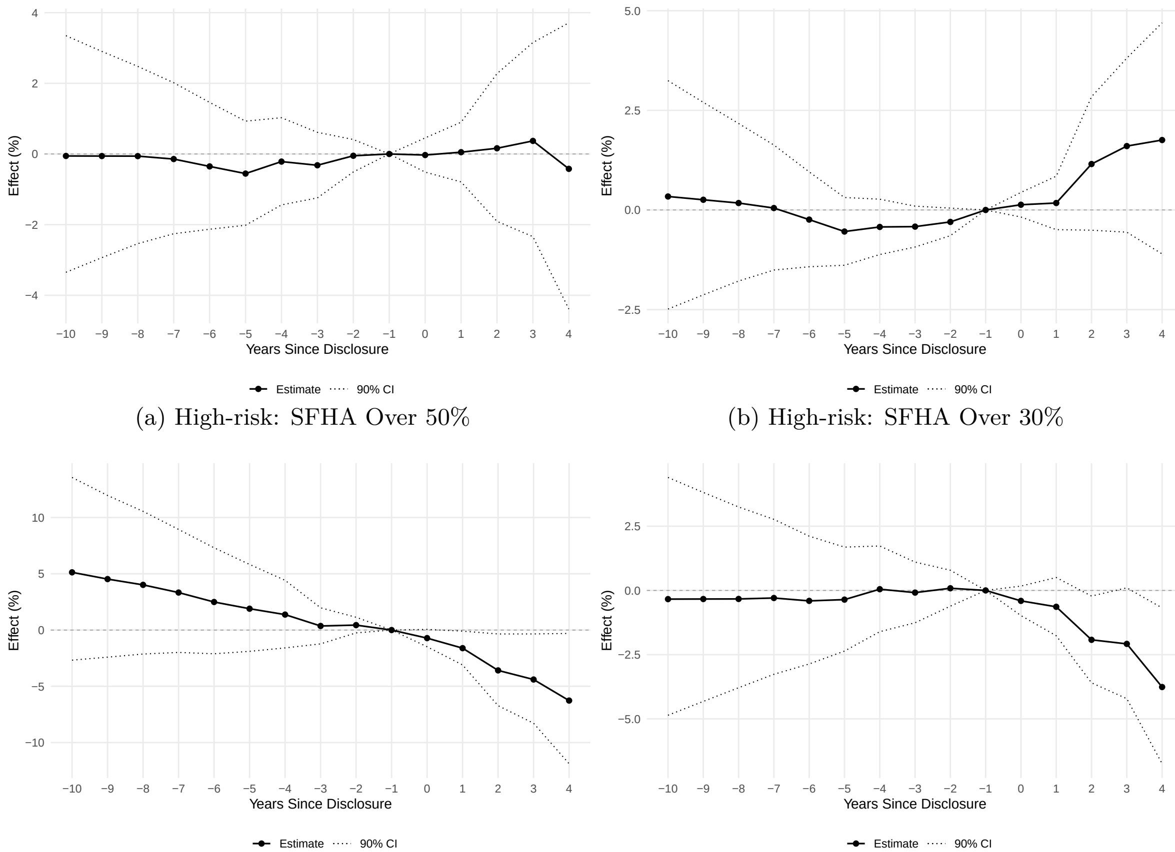

(a) High-risk: SFHA Over 50%

(b) High-risk: SFHA Over 30%

(c) Inc. Never-Adopted S,tates

(d) Exc. Map Updates

Figure C.4: The Effect of Disclosure Policy on Community Population. Panel (a) shows estimates of the disclosure policy's impact on community population (β^k from equation 1), where high-SFHA communities ($H_m = 1$) are those with more than 50% of their area in an SFHA. Panel (b) redefines high-SFHA communities as those with more than 30% in an SFHA. Panel (c) uses a 70% cutoff and also includes never-adopted states. Panel (d) replicates the main result after excluding communities with flood map updates during the sample period.

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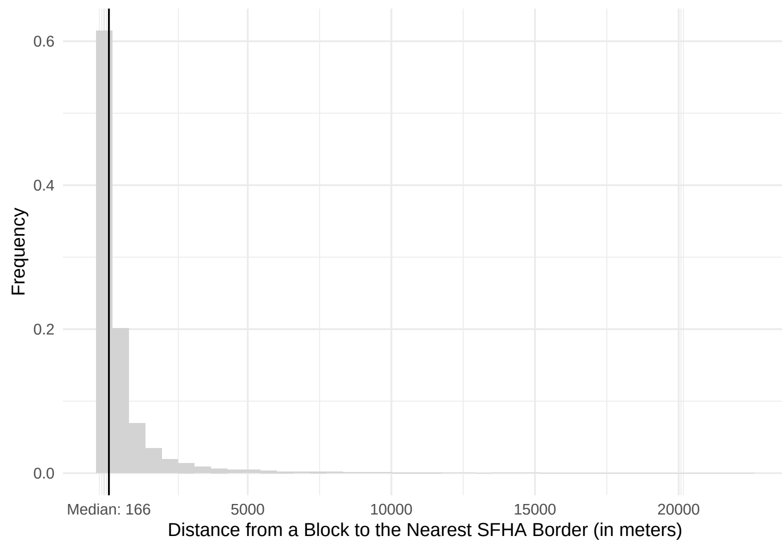

Figure C.5: Distance from SFHA blocks to the nearest SFHA border. The plot shows the distribution of the distances from SFHA blocks to the nearest SFHA border.

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Figure C.6: Census Blocks and the SFHA Zones for Village of Delhi, NY (8% SFHA)

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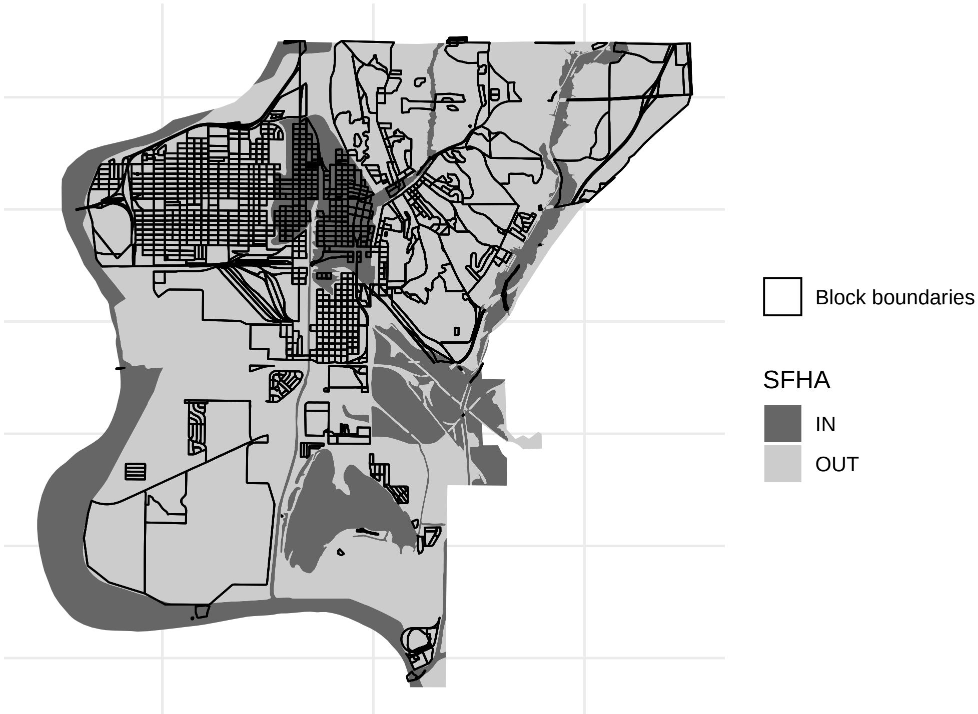

Figure C.7: Census Blocks and the SFHA Zones for Council Bluffs, IA (25% SFHA)

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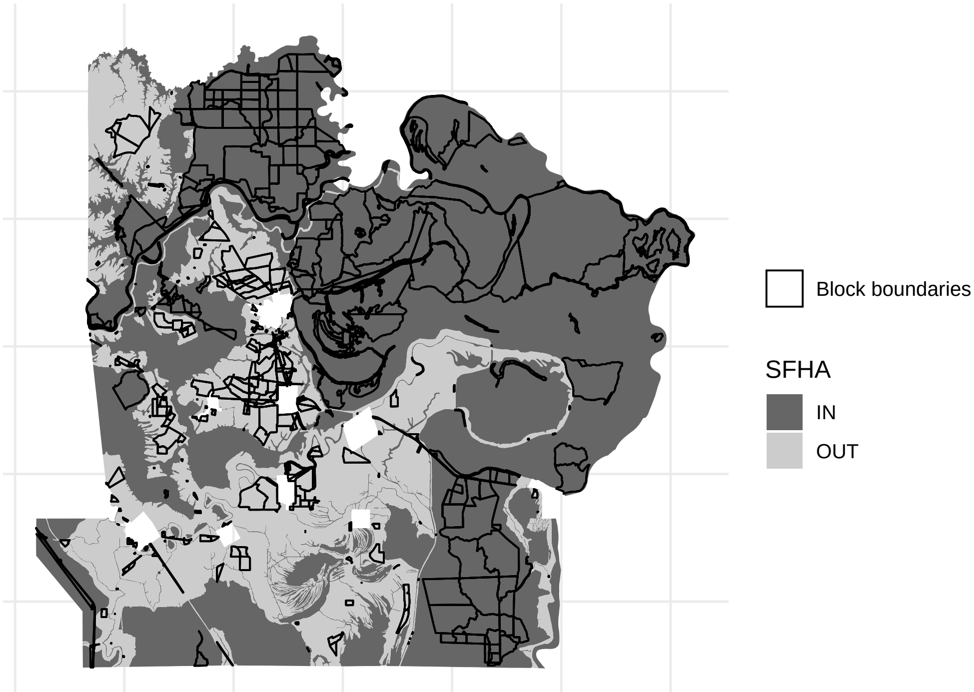

Figure C.8: Census Blocks and the SFHA Zones for Avoyelles Parish, LA (70% SFHA)

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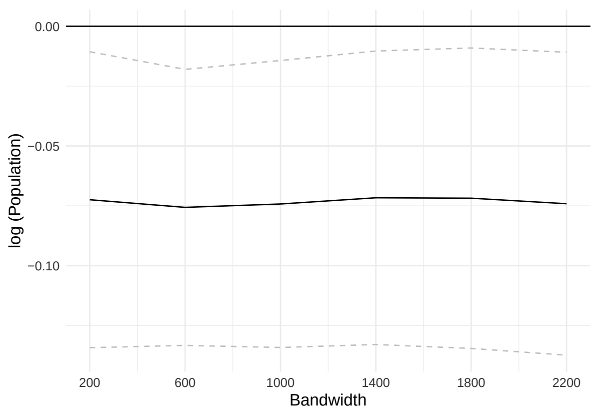
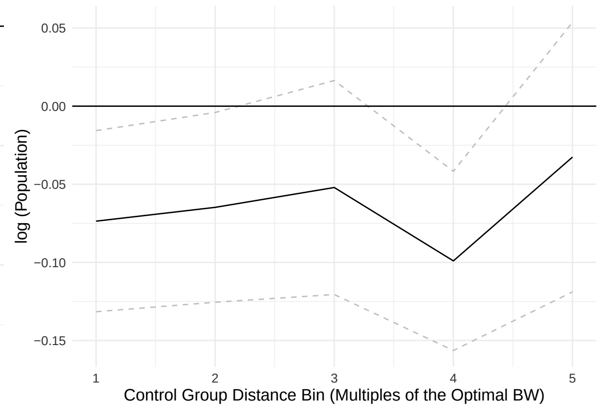


(a) Effect by Bandwidth Size



(b) Effect by Varying Control Units

Figure C.9: The Effect of the Disclosure Requirement on Population by Bandwidths and Control Group Distance Bin. Panel (a) plots $\hat{\delta}_6$ from equation (2) with log of population as an outcome variable for a range of bandwidths. Panel (b) plots $\hat{\delta}_6$ from equation (2) for control groups of varying distance. The horizontal axis of Panel (b) shows the control group's distance in multiples of the optimal bandwidth (for the log population outcome). Specifically, a distance bin labeled r includes control blocks located between $r - 1$ and r times the optimal bandwidth distance from the SFHA border. In all panels, the level of observation is census block, which is the smallest census geographical unit. Standard errors are clustered at the state level.

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