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In Harm's Way? The Effect of Disasters on the Magnitude and Location of Low-Income Housing Tax Credit Allocations

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ABSTRACT

This paper analyzes the effect of disasters on affordable housing construction. Exploiting the exogenous timing of disasters and 26 years of affordable housing data, we derive causal estimates of the effect of severe floods on county-level Low-Income Housing Tax Credit (LIHTC) allocations nationwide. We find that states respond to severe floods by increasing the number of LIHTC units per capita allocated to a flood-struck county by 57 percent in the year after the disaster, compared to other years. We argue that this increased allocation of LIHTC units is indicative of a process of institutional or policy conversion, in which states are repurposing the three-decade old housing tax credit program to meet contemporary disaster assistance and recovery needs. Given that the LIHTC program was not designed with disasters in mind, do the new units ameliorate or exacerbate renter's exposure to disaster risk? We find that these disasters are associated with a significant increase in LIHTC units per capita allocated outside of the 500-year floodplain in an affected county within the three years of a severe flood. The findings highlight the ways in which states and housing developers are using the LIHTC program to support disaster recovery by expanding subsidized rental options in disaster-struck counties, and ameliorating risk to low-income renters by locating those units outside of floodplains.

1. INTRODUCTION

Recent hurricanes, floods, and wildfires have highlighted the devastating effect of disasters on individuals and communities, as well as the importance of programs to meet survivors' housing needs in the short and the long term. Disasters disproportionately affect low-income renters, yet existing federal and state disaster assistance programs disproportionately benefit homeowners (Fothergill & Peek, 2004; Furman Center, 2017a, 2017b; GAO, 2009; Howell & Elliott, 2019; Lee & Van Zandt, 2019). From 2015 through 2017, disasters extensively damaged more than 500,000 units of rental housing and displaced 324,000 renters (Joint Center for Housing Studies, 2020). This extensive damage to and destruction of affordable rental housing raises two crucial policy questions. First, how, if at all, do federal, state, or local governments facilitate the rebuilding of affordable rental housing after disasters? Second, to what extent does rebuilding occur in disaster prone areas, such as floodplains, versus less hazardous areas?

Congress has given the Federal Emergency Management Agency (FEMA) the power to provide financial assistance for the first 18 months after a disaster so that affected households can temporarily rent undamaged units and so that homeowners can repair their homes. After 18 months, however, FEMA's authorization to provide housing aid generally ends. Further assistance depends on, first, whether Congress appropriates funding for Community Development Block Grant Disaster Recovery assistance and, second, if such funding is appropriated, how the state or territory decides to use those resources. Generally, much of the funding is used to support homeowners' repairs, leaving affected renters with few options and an increased likelihood of outmigration (Elliott, 2015; GAO, 2010).

The main federal program to support the construction of rental housing outside of the disaster context is the Low-Income Housing Tax Credit (LIHTC) program (McClure, 2008). Congress created the LIHTC provisions in the Tax Reform Act of 1986 in order to leverage federal tax credits for private investment in the construction of affordable housing. More than three million subsidized housing units have been placed in service through the LIHTC program since 1987, which totals roughly 9,000 units for every 1 million people in the United States today. Each year, the Department of the Treasury transfers approximately $9 billion worth of tax credits to states, territories, and some municipal housing agencies, each of which develops an allocation plan that outlines the criteria by which the state will distribute the credits among projects proposed by developers (Ellen, Horn, & Kuai, 2018).

To what extent do states and territories turn to the LIHTC program to address disaster recovery needs, in addition to the affordable housing production objectives it was originally designed to serve? In this paper, we assemble a panel dataset on LIHTC allocations, disasters, and the social and built environment for U.S. counties between 1990 and 2015. To characterize the effect of disasters on LIHTC unit allocations, we specify a distributive lag model. We exploit the exogenous timing of disasters to interpret our results causally.

Our results indicate that state policymakers use LIHTC as a tool to catalyze recovery after disasters. First, we establish the extent and timing of LIHTC unit allocations relative to severe flooding disasters. Specifically, we estimate the effect of severe floods in a county on allocations of LIHTC units in the following years. We find that, on average, severe floods lead to an additional 80 units allocated per million people in the year following a disaster compared to other years. This result is significant and substantial. The mean county is allocated 140 units per million people annually, so a severe flood disaster leads to a 57 percent increase in the number of LIHTC units allocated.

Next, we focus on where within flood-affected counties these LIHTC units are allocated relative to floodplains. Across all years, more units are allocated outside of floodplains than inside floodplains. Descriptively, we find that severe floods in a county drive fivefold more allocations outside of 500-year floodplains (on average 155 units) than inside 500-year floodplains (on average 32 units) in the three years after the disaster. After estimating a model that controls for housing and demographic characteristics, including the number of rental units already in the floodplain and the share of floodplain units that are rentals, we find that severe floods have a significant positive effect on the number of allocations outside of the floodplain for the following three years.

These insights into American disaster-housing policy contribute to two lines of scholarship. First, a central empirical question in policy analysis is how public programs support vulnerable groups affected by societal shocks (e.g. Bitler, Hoynes, & Kuka 2017; Klerman & Danielson 2011). The recessions, environmental disasters, and pandemic of the past two decades have disproportionately negatively impacted low- and moderate-income households, making the question of how social supports are provided after a crisis even more salient. By showing when, where, and the extent to which LIHTC unit allocations respond to disasters, we provide evidence on how a broader social safety net program responds to disaster-specific shocks.

Second, a central theoretical interest in institutions scholarship is how safety net institutions or policies change over time, especially in light of emerging needs and legislative inaction (Hacker, Pierson, & Thelen, 2015). Theorists in political science have identified processes of drift, through which static policies have different effects in changing contexts, and conversion, through which institutional actors adapt existing policies to serve originally unintended ends. Existing disaster housing assistance programs have failed to keep up with changing housing market and wage trends and currently contribute to widening wealth inequality between renters and homeowners after disasters (Howell & Elliott, 2019), an example, we argue, of policy drift. There is no evidence that Congress created the LIHTC program in 1986 with disaster housing needs in mind. The focus of Congress was instead on leveraging private investment to produce housing affordable to renters earning less than 60 percent of the area median income.[1] But over the past three decades, state and local governments have adapted the program to serve a crucial role in the disaster recovery process. This adaptation is an example, we suggest, of policy conversion. This conversion of a broad safety net program into a disaster recovery program raises the question of how and when other social programs focused on housing, food, or medical care are converted to serve dual purposes in both the poverty- and disaster-safety nets.

Section 2 reviews literature on disaster housing policy, the consequences of disasters for renters, and debates regarding subsidizing housing development in floodplains. Section 3 presents our panel dataset and specifies our model. Section 4 describes the results regarding the effects of disasters on the timing, location, and extent of LITHC allocations. Section 5 discusses the disaster- and housing-policy implications. Section 6 concludes.

2. BACKGROUND

[1] Congress established two primary ways to meet the income requirements: 1) a "20–50 test" in which "20 percent or more of the residential units in such project are both rent-restricted and occupied by individuals whose income is 50 percent or less of area median gross income"; and 2) a "40–60 test" in which "40 percent or more of the residential units in such project are both rent-restricted and occupied by individuals whose income is 60 percent or less of area median gross income" (26 U.S.C. § 42(g)(1)). As of 2017, however, the median household income of LIHTC tenants (for the 86% of households for whom income data were reported) was $17,943, just under 30 percent of the U.S. median household income of $61,372 in 2017 (U.S. Department of Housing and Urban Development Office of Policy Development and Research, 2019).

Climate related disasters, such as coastal and riverine flooding stemming from hurricanes, storms, and sea level rise, have increased in severity in the past three decades (Barthel & Neumayer, 2012; Kunkel et al., 2013; Smith & Katz, 2013). At the same time, the share of household budgets, especially low-income household budgets, going to pay for housing has been rising, and the homeownership rate has been declining (Joint Center for Housing Studies, 2019; Shuey, Leventhal, & Coley, 2016). These intersecting trends make understanding the relationship between disasters and affordable rental housing production increasingly important.

2.1 Implications of Disasters for Vulnerable Renters

Severe flooding disasters often have substantial effects on housing, and particularly housing occupied by lower income households. Recovery measured in terms of population, housing, or economic growth takes years, if not decades. The recovery from Hurricane Katrina is an extreme, but well-documented, example of the destruction of housing, the displacement of residents, and the transformation of much of the city's affordable housing stock. Before Katrina, the population of New Orleans was 452,000 residents. About one year after the storm, the population was 223,000 residents (Sastry, 2009). By 2016, New Orleans had grown by roughly 160,000 residents from its post-storm low, but many of those additional residents were not returnees but new movers into the city (Fussell, 2015). Hurricane Katrina destroyed nearly all of the homes in the primarily African-American neighborhood of the Lower Ninth Ward and the majority Vietnamese neighborhood of Village de l'Est in New Orleans East (Kamel, 2012). A decade later, housing repair and rebuilding remained unfinished in many low-income neighborhoods, including these two areas (Adams, Van Hattum, & English, 2009; Seidman, 2013). Part of the net out-migration of lower-income residents from New Orleans can be attributed to the damage to homes and the slow pace of housing recovery. The extent of damage is a crucial factor in individuals' decisions to relocate permanently (Myers, Slack, & Singelmann, 2008). Further, increases in the cost of housing in New Orleans after Katrina made returning impossible for many low-income renters (Vigdor, 2008).

A substantial literature focuses on the importance of housing in disaster recovery. Much work focuses on the temporary sheltering needs of survivors as well as differential access to shelter and to housing aid based on class and race or ethnicity (Bolin & Stanford, 1991; Brennan, Srini, Steil, Mazereeuw, & Ovalles, 2021; Nigg, Barnshaw, & Torres, 2006; Peacock, Van Zandt, Zhang, & Highfield, 2014). Relatively few studies, however, look simultaneously at the effects of disasters on housing across multiple years and localities. One study that does take a long-term view is Boustan, Kahn, Rhode, & Yanguas (2017), who estimate the effect of disasters on home values, population, and poverty. They find that over the past century, counties in the United States struck by severe disasters have experienced net out-migration, on average (Boustan et al., 2017). As populations decline after disasters, counties that experienced severe disasters also experience long-term declines in home values. At the same time, poverty rates in disaster-hit counties increase, on average (Boustan, Kahn, & Rhode, 2012; Boustan et al., 2017; Strobl, 2011). This increase in poverty may be explained by the out-migration of the non-poor, who have more resources to move; by the in-migration of the poor, attracted by lower housing costs; by a transition of the existing population into poverty because of economic dislocation caused by the disaster; or by some combination of all three processes (Boustan et al., 2017). Demographic shifts and local housing markets are intertwined as places recover from disasters. Building on this research on population shifts, here we investigate what effect disasters have on the creation of federally subsidized, state allocated, privately built housing. On the one hand, the findings regarding declining population size and falling home values might lead us to expect a decline in the construction of subsidized housing. On the other hand, increasing poverty rates combined with public efforts to catalyze economic recovery might lead us to expect an increase in the construction of subsidized housing. Because housing assistance from FEMA is temporary and there is no permanent federal program to spur post-disaster rental housing recovery except occasional Congressional allocations of Community Development Block Grant Disaster Recovery funds, state policies are central to recovery dynamics for low-income renters, as discussed below.

2.2 Post-Disaster Housing Policy

The federal disaster safety net is under increasing strain. Much of the existing disaster relief and recovery infrastructure is three to five decades old, dating to the 1966 Disaster Relief Act and its subsequent amendments or to the 1988 Robert T. Stafford Disaster Relief and Emergency Assistance Act (Stafford Act).[2] The major hurricanes of the past 15 years, such as Hurricanes Katrina, Sandy, Harvey, Irma, Maria, and others, have highlighted the need to continually reevaluate and improve disaster recovery programs. The Stafford Act authorizes the Federal Emergency Management Agency (FEMA) to provide financial assistance of up to $35,000 to affected households to repair owner-occupied private residences or to rent alternate housing for up to 18 months.[3] The Stafford Act also authorizes FEMA to provide direct assistance in the form of temporary housing units, acquired by the federal government through purchase or lease, and provided for up to 18 months directly to households who would be unable

[2] Disaster Relief Act of 1966, P.L. 89-769 (Nov. 6, 1966); Disaster Relief Act of 1974, P.L. 93-288 (May 22, 1974); Robert T. Stafford Disaster Relief and Emergency Assistance Act, P.L. 100-707 (Nov. 23, 1988); see also Sandy Recovery Improvement Act of 2013 (SRIA, Division B of P.L. 113-2) and the Post-Katrina Emergency Management Reform Act of 2006 (PKEMRA, P.L. 109-295).

[3] 42 U.S.C. §§ 5174(c)(1) (A), 5174(c)(2-3).

to make use of the financial assistance.[4] There is no established program that addresses the need for permanent rental housing after disasters.

Congress has occasionally supported new approaches to disaster recovery, such as the 2006 one-time authorization of the Alternative Housing Pilot Program and the resulting "Katrina Cottages" and HUD's experimentation with the Rebuild by Design and subsequent National Disaster Resilience Competition after Hurricane Sandy.[5] The recent Disaster Recovery Reform Act of 2018 also breaks new ground in directing a share of Community Development Block Grant Disaster Recovery allocations for disaster mitigation and, in some circumstances, allowing states to administer direct temporary housing assistance.[6]

The closest existing program to a long-term housing recovery program is the periodic Congressional appropriation of Community Development Block Grant Disaster Recovery funds, which affected states can use in flexible ways to fund rebuilding and recovery. If funds are appropriated by Congress, which is uncertain after any given disaster, each state then subsequently designs its own recovery program in compliance with Department of Housing and Urban Development (HUD) guidelines. A Government Accountability Office (2010) study found that, overall, federal disaster assistance primarily benefited homeowners as compared to renters. When the estimated number of assisted units after Hurricane Katrina were compared to the estimated number of damaged units, 62 percent of damaged homeowner units but only 18

[4] 42 U.S.C. § 5174(c)(1)(B)(i)).
[5] Emergency Supplemental Appropriations Act, 2006, P.L. 109-234 (June 15, 2006); Disaster Relief Appropriations Act, 2013, P.L. 113-2 (Jan. 29, 2013).
[6] Disaster Recovery Reform Act of 2018 (DRRA), P.L. 115-254 (Oct. 5, 2018). Section 1234 of the DRRA allows the President to set aside funding for pre-disaster mitigation from the Disaster Relief Fund (DRF) at an amount equal to 6 percent of the estimated aggregate amount of the grants to be made pursuant to the principal Stafford Act authorizations. Sections 1211, 1212, and 1213 of the DRRA also makes it possible for states to administer direct temporary housing assistance, separate the cap on the maximum amount of financial assistance for housing assistance from that for other needs assistance and remove rental assistance from that cap, and expands the eligible areas for FEMA's multifamily lease and repair program while also removing the requirement that the value of the improvements or repairs not exceed the value of the lease agreement.

percent of damaged rental units were assisted (GAO, 2010). Congress has twice approved special LIHTC allocations to facilitate long-term housing recovery after disasters, through the Gulf Opportunity Zone (GO-Zone) Act of 2005 and the Heartland Disaster Tax Relief Act of 2008.[7] The Government Accountability Office study found that "the GO-Zone LIHTC program addressed only a small part of the repair and replacement needs of rental properties" (GAO, 2010, p. 44), but we control in our regression models for counties and years in which the GO-Zone legislation was in effect.

Perhaps in part because there is not an existing program to address permanent housing needs after disasters, states have identified housing as a national area for improvement in every annual National Preparedness Report since the inception of these preparedness reports in 2012. State and local preparedness levels for housing recovery actually appear to be getting worse instead of better (FEMA, 2017, pp. 13, 88). As the 2019 Report emphasized, "States and territories frequently reported being furthest from their goals for establishing long-term housing [and] relocating individuals affected by disasters" compared to other areas of disaster preparedness and "more than half of urban areas reported that they are far from their goals to relocate affected individuals and establish long-term housing" (FEMA, 2019, p. 11). Especially given the central role that housing plays in efficient and equitable recovery, a focus on improving hazard mitigation and disaster recovery processes for low-income renters is essential.

2.3 The Low-Income Housing Tax Credit Program

Without an existing federal program focused on catalyzing the repair and rebuilding of rental housing after disasters, it may be instructive to examine the principal federal program to support affordable housing construction in general. Congress created the LIHTC program in

[7] Gulf Opportunity Zone Act of 2005, P.L. 109-135 (Dec. 22, 2005); Heartland Disaster Tax Relief Act of 2008, P.L. 110-343 (Oct. 3, 2008).

1986 to leverage federal tax credits for private investment in the construction of housing targeted at renters with incomes below 60 percent of the median income in their metropolitan area. The U.S. Treasury distributes LIHTC credits to every state and territory roughly in proportion to its population. State, territorial, or municipal housing finance agencies then award the tax credits to affordable housing developers through a competitive application process. The LIHTC program allows private real estate developers to receive federal income tax credits for constructing or renovating rental properties for households with average incomes below 60 percent of the area median and operating the housing development under the Internal Revenue Service's LIHTC guidelines for a certain compliance period, originally 15 years and now 30 years (Freedman & McGavock, 2015; Lens & Reina, 2016). These real estate developers partner with investors who provide equity for the housing development and, in exchange, receive the tax credit annually over 10 years. The partnership with equity investors through the tax credit program reduces the debt and debt service costs, allowing the buildings to operate with rents targeted at households averaging between 50 and 60 percent of the Area Median Income.

Federal law requires the LIHTC allocation plans created by housing finance agencies to give preference to projects that serve the lowest income tenants, for the longest period of time, in low-income census tracts in which the project contributes to a concerted community revitalization plan.[8] Allocation plans must include selection criteria regarding project location, local housing needs, and capacity to house individuals with special needs, among others.[9] The federal statute authorizing LIHTC does not, however, include any requirements related to disaster mitigation, preparedness, response, or recovery.

[8] 26 U.S.C. § 42(m)(1)(B)(ii).
[9] 26 U.S.C. § 42(m)(1)(C).

In practice, the Internal Revenue Service has recognized that LIHTC may be a useful tool for disaster recovery and sometimes temporarily suspends some of the statutory LIHTC requirements for affected buildings after federal disaster declarations.[10] The Internal Revenue Service also sometimes temporarily suspends certain income limitations for individuals displaced by a major disaster, allowing owners of LIHTC buildings to rent units to disaster displaced households even if their income does not fit within the LIHTC requirements. Nevertheless, there are no federal statutes, rules, or permanent guidance regarding the use of LIHTC allocations for disaster recovery. Formal state adoption of disaster recovery provisions in their LIHTC allocation plans has been piecemeal at best, with fewer than half of states and territories including any provisions related to disaster preparedness or disaster recovery in their plans (Mehta, Brennan, & Steil, 2020; Shamsuddin & Leib, 2021).

It is important to note that Congress designed the LIHTC program to serve households with incomes between 50 and 60 percent of the area median income, households falling within what Congress has defined as the low-income and very low-income thresholds.[11] The LIHTC program, therefore, does not meet the housing needs of the lowest income renters or provide units directly targeted to those renters with incomes below 30 percent of the area median income, where affordability shortages are the most severe. In practice, however, residents of LIHTC units often have substantially lower incomes than the maximum thresholds that Congress has set (O'Regan & Horn, 2013). The median household income of LIHTC tenants (for the 86% of

[10] See for instance, IRS Rev. Proc. 2007-54; IRS Rev. Proc. 2014-49; IRS Rev. Proc. 2014-50; IR-2017-165.

[11] Congress has defined low-income households as those with incomes below 80 percent of the area median income, very low-income households as those with incomes below 50 percent of the area median income, and extremely low-income households as those with incomes below 30 percent of the area median income, all adjusted for household size. See 42 U.S.C. § 1437a(b)(2). The statutes governing the LIHTC program require only that at least 20 percent of the units in a LIHTC development are occupied by households with incomes at or below 50 percent of the area median income or, alternatively, that at least 40 percent of the units are occupied by households with incomes at or below 60 percent of the area median income. See 26 U.S.C. § 42(g)(1).

households for whom income data were reported) in 2017 was $17,943 (U.S. Department of Housing and Urban Development Office of Policy Development and Research, 2019). In 2017, 43 percent of households residing in LIHTC units had incomes at or below 30 percent of the area median, 62 percent at or below 40 percent of the area median, and 77 percent at or below 50 percent of the area median (U.S. Department of Housing and Urban Development Office of Policy Development and Research, 2019). The reach of the LIHTC program to these households was enabled by the combination of multiple subsidies. At least 40 percent of LIHTC residents received some additional monthly rental assistance, most commonly tenant-based Housing Choice Vouchers or project-based rental assistance (U.S. Department of Housing and Urban Development Office of Policy Development and Research, 2019). Unlike public housing or the Housing Choice Voucher program, rents in the LIHTC program are set for the unit and are not limited to 30 percent of tenant income. Thus, rent may exceed 30 percent of a tenant's income, and more than one third of LIHTC households in 2017 paid more than 30 percent of their income to rent (U.S. Department of Housing and Urban Development Office of Policy Development and Research, 2019). In short, the LIHTC program is the largest federal program subsidizing the construction of rental units targeted to households with low-incomes and it financed the construction or renovation of more than 3 million housing units in its first three decades of existence, but it is not directly targeted at the lowest income households where affordability needs are greatest and it is not nearly large enough to meet the continuing need for affordable housing on its own.

2.4 Affordable Housing, Floodplains, and the Tension between Relocating and Rebuilding

The National Environmental Policy Act, enacted in 1970, requires federal agencies to assess the environmental impact of their proposed actions.[12] The Act sets out a process through which agencies prepare public assessments of the environmental impact of, and alternatives to, federal actions that significantly affect the environment.[13] The Department of the Treasury and the Internal Revenue Service maintain that because tax credit programs including LIHTC are essentially processing of tax returns, LIHTC projects are not federal actions subject to the National Environmental Policy Act. Many LIHTC developments also receive funding from HUD, however, which triggers HUD's environmental review procedures created to comply with the National Environmental Policy Act and Executive Order 11988 on Floodplain Management.[14] Projects subject to HUD's regulations must identify alternatives to locating in the 100-year floodplain, estimate the impacts of the proposed development, identify steps to minimize harm and preserve natural values, reevaluate the project in light of the alternatives, issue findings and a public explanation, and then, if approval is received, implement the development in compliance with minimization plans and flood insurance requirements.

As powerful as federal environmental regulations in shaping siting and developer behavior are concerns from investors and lenders regarding environmental conditions and the risks of loss. Building in floodplains can be economically appealing in the short term because land may be less expensive inside the floodplain than outside of it, as well as flat and easy to manage during construction (Hammett, Worzala, & Springer, 2018). Investors and lenders will often set out conditions regarding building elevation or other risk mitigation elements before approving a project in a 100- or 500-year floodplain. In short, while federal regulations together with lender

[12] Pub. L. 91-190 (January 1, 1970), codified at 42 U.S.C. §§ 4321-4347.
[13] See 42 U.S.C. §§ 4321 et. seq.
[14] See 24 C.F.R. §§ 58 et. seq., setting out Environmental Review Procedures for Entities Assuming HUD Environmental Responsibilities.

and investor expectations are likely to require most LIHTC developments in floodplains to be more resilient to flooding than they might otherwise have been, they are unlikely to prevent LIHTC construction in the floodplain.

As discussed above with regard to the implications of disasters for low-income renters, low-cost and subsidized housing is frequently located in floodplains in part because of a history of both race and class discrimination that relegated subsidized housing to more risky locations (Rothstein, 2017). The economics of land values also mean that as risks increase, values generally decline, and units affordable to low-income households therefore often have higher disaster risks. This local history and context thus substantially shape the development and rebuilding of affordable housing in neighborhoods with high levels of disaster risk, in addition to regulatory concerns (Phillips, Stukes, & Jenkins, 2012).

One response of individuals living in disaster-prone areas amid a changing climate is to "retreat" or relocate after repeated flood damage (Koslov 2016; Siders 2019). Several federal programs fund state efforts to purchase properties in the floodplain from voluntary sellers and support their relocation, primarily FEMA's Hazard Mitigation Grant Program and HUD's Community Development Block Grants. For instance, in 2012, after Superstorm Sandy, homeowners on Staten Island organized their own "buyout groups" in eight different neighborhoods. With support from Hazard Mitigation Grant Program funding and Community Development Block Grant funding, both the State of New York and New York City bought and demolished damaged homes, returning the wetlands to the coastline (Koslov, 2016). These programs focus on encouraging homeowners to move away from risk, not renters. While renters in properties in the floodplain that are acquired and demolished with funding from these federal programs may get some support to pay for moving costs and temporarily cover increases in rent pursuant to the Uniform Relocation Assistance and Real Property Acquisition Act of 1970, any assistance is temporary and will not cover higher rent costs in new housing over the long term.[15]

Sometimes communities seek to relocate as a whole, rather than in a piecemeal fashion. The experience of the Biloxi-Chitimacha-Choctaw tribe is one example. The Indian Removal Act of 1830 forced the Biloxi-Chitimacha-Choctaw tribe to move off the mainland of Louisiana and on to the remote Isle de Jean Charles, situated between two bayous, nearly two centuries ago. The Isle de Jean Charles has lost 90 percent of its land mass since 1955, subjecting residents to extreme, repeated flooding. The Department of Housing and Urban Development granted $48 million in 2016 to the state of Louisiana to help the Biloxi-Chitimacha-Choctaw members on Isle de Jean Charles in Louisiana relocate, although subsequent frustration from many tribe members with the state's approach and changes to the tribe's plan have complicated the effort (Davenport & Robertson, 2016).

Another reaction many have to living in disaster-prone areas is to continue to invest in their neighborhood and, after disasters, to rebuild. Whether in New Orleans or the Ile de Jean Charles, Staten Island or Houston, the attachment to place and to community and the desire to remain and to rebuild can be strong, and socially significant. Efforts to advance climate adaptation can make rebuilding more difficult, however, especially for low-income communities. The success of such efforts in low-income communities are in part mediated by who from communities are involved in recovery work (Williams & Jacobs, 2021). In a manner similar to the way that redlining by lenders forced people of color and lower-income residents into flood-prone areas over decades, "bluelining" by lenders and public agencies today can limit private and public funding available to maintain lower-income units in flood prone-areas, both before and after disasters.

[15] P.L. 91-646 (January 2, 1971), codified at 42 U.S.C. §§ 4601 et. seq.

Decisionmaking is particularly fraught in places that people of color have transformed into thriving, socially and culturally meaningful communities, havens against social disasters. For instance, Princeville, North Carolina was originally known as Freedom Hill because it was founded by freed slaves. Located along the south side of the Tar River in North Carolina, Princeville has experienced at least seven major floods since 1800. In 1999, the town was largely submerged for the better part of two weeks by flooding from Hurricanes Floyd and Dennis. After the sustained devastation of this flooding, residents considered government financial assistance to acquire their homes and relocate, but many preferred to rebuild (Phillips et al., 2012). As one resident explained: "'Wait a second, I don't want to move. This is my home, this home has history – not only my history, but also a community history''(Phillips et al., 2012).

This tension between retreating and rebuilding is one that is salient after almost all disasters, on both the individual and collective level. Throughout the popular and scholarly discussion of the need for managed retreat and the tensions between relocating or rebuilding, the focus is almost always on homeowners. Yet renters face the same challenging decisions about whether to relocate or to remain in a community, usually with fewer resources and less public support. The rental units that the LIHTC program provides can be a crucial resource for low-income renters as they try to rebuild their lives after disasters, but little is known about where these homes are built after disasters and how states and developers weigh tensions between building LIHTC units inside or outside of floodplains in disaster-hit counties.

2.5 Institutional Change

This background understanding of the context of post-disaster housing assistance and affordable housing policy raises the question of what happens when policymakers fail to change policies to meet the demands of changing contexts. Scholarship on institutions generally has noted that institutions are not fixed, but evolve over time (Hacker et al., 2015). The question, then, is "what kinds of institutional changes propelled by what kinds of social processes are most likely under what kinds of political configurations" (Hacker et al., 2015, p. 180). One common process of institutional change is *drift*, when institutions or policies are bound in place even as the setting in which they operate changes, thus limiting or changing the policy's effect. Another common process of institutional change is *conversion* in which actors are able to repurpose and apply existing institutions or policies toward a new and originally unintended aim. The focus on institutional drift and conversion highlights the role of administrative agencies and their staff in powerfully, but often somewhat opaquely, shaping policy outcomes over time beyond the common public focus on voters or legislators, whose effects are more visible in the overt political reforms that create or expressly change institutions or policies at a given moment. The attention to the power of these institutional actors also helps explain the common observation in industrialized states of relative stability in formal institutions yet often marked changes in political outcomes (Hacker et al., 2015).

3. DATA AND METHODS

3.1 Data

To explore these questions, we merge disaster, LIHTC allocation, and demographic and housing covariate datasets by county-year, using the shared subset of the counties and years. We create a panel dataset for 1990 through 2015 of 2,371 counties. These counties meet two criteria. First, they have floodplains, so are exposed to a higher likelihood of experiencing flooding disasters. All but 133 of the counties with floodplains experienced a flood disaster at one point in the panel, and 458 counties experienced a severe flood disaster. And second, these counties are not extremely rural and sparsely populated, specifically they are not in the top 10% least dense counties in the United States. Given that LIHTC is a financing program for multi-family housing, some degree of population density is almost a prerequisite for a county to have the potential for LIHTC units to be proposed by a private developer and awarded by a state, local, or territorial housing finance agency. After initially selecting the 2,450 counties with a floodplain, we remove an additional 79 extremely rural counties, leaving 2,371 counties total.

The dependent variable in the analysis is the LIHTC units allocated in a county in a given year, drawn from the Department of Housing and Urban Development LIHTC Database of all LIHTC projects in American states and territories. For the 32,452 projects included in the panel, the dataset includes the number of housing units, allocation year, 2010 census tract, and longitude and latitude of the project. We focus the analysis on the competitive 9 percent tax credit (70% subsidy) allocations that are for new construction projects. [16]

The independent variables related to disasters are gathered from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) compiled by scholars at Arizona State University. For each county and year and Presidentially Declared Disaster in the continental United States, the dataset includes detailed information about the value of estimated damage caused by the disaster. The primary independent variable of interest is whether there is a severe flood disaster in a county in a year and that flag lagged for one through six years. We define severe flood disasters as the 670 county-years in the panel with presidential disaster declarations with a value of property damage in the top 5 percent of all such disasters between 1984 and

[16] Data available at https://lihtc.huduser.gov/. Project types in addition to new construction are acquisitions, and credit types in addition to nine percent credits are four percent credits. The full dataset runs from 1987 through 2019. Observations missing data for any necessary geographic or timing variables make up 13 percent of the dataset and are removed to get the final set of 32,452 projects allocated in the counties and years in the panel. We categorize unassigned project types as new and unassigned credit types as nine percent. Unadjusted for population, the distribution is skewed, with roughly 1 percent of counties comprising 23 percent of the total number of units nationwide. But examined per capita, 1 percent counties have just 6 percent of the total number of units per capita nationwide.

2019, the most recent, complete year in the data. This time frame allows us to define a six-year lag on disaster damage in 1990, and a six-year lead in 2013, the most recent year possible. Here, we include in flooding disasters riverine and coastal floods, storms and hurricanes, all of which can lead to significant water damage to buildings. One in five counties experience a severe flooding disaster at least at one point in the 26 years studied.[17]

Drawing from U.S. Census Bureau and Bureau of Labor Statistics data, we construct a panel of demographic and housing covariates. For population and economic measures, we use yearly reports from the Census Bureau and Bureau of Labor Statistics, respectively.[18] From these reports, we build annual variables for population density and share of the population that is unemployed. Brown University's Diversities and Disparities Project provides measures of demographic and housing market characteristics for each 2010 census tract in the United States in 1990, 2000, and 2010 from the decennial census (Logan, Xu, & Stults, 2014). [19] We directly access the American Community Survey for these characteristics for 2015. We bind the Diversities and Disparities Project data to the American Community Survey data and linearly

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[17] Data available at https://cemhs.asu.edu/sheldus. The full dataset runs from 1965 through 2019. Observations have no missing data, though, because it is assembled through a National Weather Service local office reporting process, missingness may exist if a local office does not report an event. We work with Presidential Declared disasters. It is important to note that because the declaration process includes multiple factors and is not immune from political pressure, there are some relatively large disasters that do not receive federal declarations and there are some relatively minor events that do receive federal declarations (Salkowe & Chakraborty, 2009; Schmidtlein, Finch, & Cutter, 2008). The federal regulations at 44 C.F.R. § 206.48 set out the factors considered when evaluating a Governor's request for a major disaster declaration.

[18] Census Bureau data for 1990-2000 population available at https://www2.census.gov/programs-surveys/popest/datasets/1990-2000/counties/asrh/, for 2000-2010 available at https://www2.census.gov/programs-surveys/popest/datasets/2000-2010/intercensal/county/, and for 2010-2020 available at https://www2.census.gov/programs-surveys/popest/datasets/2010-2020/counties/totals/. Bureau of Labor Statistics data for 1990-2010 unemployment is available at: https://www.bls.gov/lau/ .

[19] Brown University data available at https://s4.ad.brown.edu/projects/diversity/Researcher/LTBDDload/DataList.aspx The full dataset includes 1980, 1990, 2000, and 2010. The advantage of this Brown Dataset is it is standardized to 2010 tracts and counties for a range of variables, several not available at other sources, including the Census Bureau. Where medians (instead of counts) were reported, we used the average of the medians across the tracts in a county. Census Bureau's data profiles for the 2017 American Community Survey centered on 2015 is available at: https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2017/ The dataset includes a superset of what the Brown data makes available, all also based on 2010 tracts and counties.

interpolate these data between 1990, 2000, 2010, and 2015.[20] From these data we construct variables representing percent of people who are in poverty, percent of the population identifying as non-Hispanic white, and share with a four-year college degree or higher. We also construct variables describing housing characteristics, including the percent of units that are owner-occupied, vacant, and in multi-family buildings, as well as median rent and home value.

Using FEMA floodplain maps from 2019, we identify, using the geographic information system (GIS) software ArcGIS, the share of each county that is located in a 100- or 500-year floodplain. We identify the locations of each specific LIHTC project developed since 1987 and identify whether or not that LIHTC project is located in a block group with its centroid in the floodplain. Finally, we estimate the shares of each county's housing units and population living in block groups in the floodplain.[21]

The unit of analysis is the county-year. Many studies of LIHTC developments use the project, tract-, or city-level to explore different aspects of the program, such as neighborhood economic or demographic characteristics, effects on home values, and other dimensions of the LIHTC program (Baum-Snow & Marion, 2009; Dawkins, 2013; Deng, 2011; Ellen et al., 2018; Ellen, Horn, & O'Regan, 2016; Freedman & McGavock, 2015; Gould Ellen & Voicu, 2006; Woo, Joh, & Van Zandt, 2016). Studies of federal disaster programs, however, often focus on the county-level (Berke, Kartez, & Wenger, 1993; Bolin & Stanford, 1991; Horney, Dwyer, Aminto, Berke, & Smith, 2017; Simo & Bies, 2007; Yoon, Youngs, & Abe, 2012). The county level is an

[20] We fill in missing values for each county using the values from the subsequent Census or Survey year. We use values from subsequent censuses to populate missing values in the preceding one. We recognize that linear interpolation relies on the assumption that the measures change in a linear fashion between decades, which is not always true. But in the absence of annual data over the whole time period, we believe reliance on the common strategy of linear interpolation is the most appropriate approach.

[21] Data available at https://www.fema.gov/flood-maps and made available on ArcGIS. To measure the share of the county in the floodplain we identify the centroid of each block group. If the centroid is in the floodplain, we categorize the block group as in the floodplain.

appropriate scale at which to study disasters because Major Disaster Declarations and the federal programs that come with them are determined at the county-level, and, even in the absence of federal assistance, county governments play crucial roles in disaster response and recovery. Furthermore, federal and state disaster recovery programs often work at the county level, and state and local governments, in particular, have an interest in retaining residents, making it plausible that a disaster in a county would be met with LIHTC unit allocations in the same county.

In **Appendix Table A1.1**, we present descriptive statistics by county, describing the total number of allocated LIHTC units and flood disasters from 1990 to 2015 as well as demographic and housing market measures at 1990 and again at 2015. We sort the table into quartiles by the total number of LIHTC units allocated to counties between 1990 and 2015. Demographic and housing measures vary substantively with the total number of LIHTC units in ways consistent with existing research, for instance, on the relationship between LIHTC project locations and economic and demographic characteristics (Dawkins, 2013; Ellen et al., 2018; Freedman & McGavock, 2015).

3.2 Methods

We identify the effect of severe flood disasters on LIHTC unit allocations using these panel data. The timing of disasters is exogenous to state or county level characteristics, allowing for causal estimation of the effects of disasters on LIHTC allocations.

We estimate a linear panel regression model across the 2,371 counties and 24 years, from 1990 to 2013, to estimate the effect of flood disasters on LIHTC unit allocations, in counties with any floodplain and that are not extremely rural. We are limited to 1990 to 2013, instead of 2015, for the regression analysis because six-year leads on severe floods cannot be defined starting in 2014.

We specify a distributive lag model, to test whether a severe flood disaster in one year has an effect on LIHTC unit allocations per million people in subsequent years. A distributive lag model interpretably captures two scenarios in the data. First, when one county experiences one or more severe floods in a year, the flag for that county-year indicates there is (at least) one disaster in that year. There is a severe flood in 657 county-years in the regression panel. Second, when one county has multiple recent years in which there was a severe flood, the lags of flags from preceding years indicate a previous disaster. Of the 2,400 county-years in which there was *at least* one severe flood in the past three years, 160 of those had two or more recent severe floods, each of which is captured in the model with its respective lagged flag. Thus, in the somewhat rare case that a county has a severe flood, and in a previous year has had another one, and possibly even another one in an earlier year, and so on, this set of flood exposures would be captured among the seven flags for the present and previous years.

We isolate the effects of severe floods on LIHTC unit allocations by including demographic and housing market measures as pre-treatment controls and specifying county-level fixed effects to control for time-invariant unobserved differences between counties. Our pre-treatment controls vary with time to avoid an estimate biased by change in the counties over the 24 years. We use time-level fixed effects to control for unobservable differences between years. To account for serial correlation within each county across years, we cluster robust standard errors at the county level.[22]

The model is described in equation (1):

$$\mathrm{Y}_{\mathrm{it}} = \beta_0\, \mathrm{D}_{\mathrm{i,t}} + \beta_1\, \mathrm{D}_{i,t-1} + \ldots + \beta_6\, \mathrm{D}_{i,t-6} + \mathbf{C}_{it} + \mathrm{G}_{\mathrm{it}} + {}_{+}\, \beta_0\, \mathrm{D}_{\mathrm{i,t}} + \beta_7\, \mathrm{D}_{i,t+1} + \ldots + \beta_8\, \mathrm{D}_{i,t+6} + c_i + y_t, + e_{it}$$

Y_{it} is the number of allocated LIHTC units per capita in county *i* and time *t*. $D_{i,t}$, $D_{i,t-1}$, etc. are the severe flood disasters in county *i* and time *t, t-1,* etc. $\boldsymbol{C}_{it}$ are a collection of time-varying demographic and housing market characteristics. G_{it} is a flag for counties and years for which the GO-Zone Legislation, the special LIHTC allocations to facilitate long-term housing recovery, was in effect. As part of our baseline specification we include placebo leads for severe flood disasters, $D_{i,t+1}$, $D_{i,t+2}$, etc. County and year fixed effects are c_i and y_t, respectively. The error term is e_{it}.

4. RESULTS

4.1 Descriptive Analysis

In **Table 1**, we present a descriptive analysis of the panel, tabulating counties with and without severe flood damage against those with LIHTC units inside and outside of the 500-year floodplain. We observe that 458 counties experienced severe flooding disasters at some point over the 26 years. Of those counties, 206 counties had some LIHTC units in a floodplain, while 252 counties did not.

[22] To the extent that disasters may catalyze the creation of LIHTC units in neighboring counties without a disaster declaration, that would only suggest that our findings are a conservative estimate of the impact of disasters on allocated LIHTC units.

Table 1: Count of Counties by Severe Flood Damage and LIHTC Units in Floodplain

		LIHTC Units	
		None in Floodplain	Any in Floodplain
Flooding Disaster	No Severe Flood	1,496	417
	Any Severe Flood	252	206

In **Table 2**, we divide all of the counties in the dataset into quartiles by the value of the total flood disaster damage over the 26 years in the study. As expected, counties with higher damage estimates are more highly populated than those with lower damage estimates. Counties with higher damage estimates also have higher home values, higher rents, more multifamily housing, more LIHTC units overall than counties with lower damage estimates, but across both sets of counties there are comparable numbers of LIHTC units per million people. Renters in counties with higher damage estimates are also more likely to live in the 500-year floodplain than renters in counties with lower damage estimates. Similarly, counties with higher damage estimates have a higher share of LIHTC units located in the 500-year floodplain than counties with lower damage estimates. The likelihood that a renter in a LIHTC unit will be located in a floodplain is comparable to the likelihood for a renter overall.

Table 2: Quartiles of Counties by Total Flood Damage 1990-2015

	0-25% (Mean)		25-50% (Mean)		50-75% (Mean)		75-100% (Mean)	
Count counties	593		593		593		592	
Years	**1990-2015**		**1990-2015**		**1990-2015**		**1990-2015**	
Sum flood damage ($1000s) ('90-'15)	251		2,948		14,612		658,340	
Count floods ('90-'15)	2		4		5		6	
Count severe floods ('90-'15)	0		0		0		1	
LIHTC units allocated ('90-'15) per million people ('15)	3,247		3,424		3,263		3,290	
LIHTC units allocated in floodplain ('90-'15) per million people ('15)	211		156		204		438	
Share land in floodplain ('15)	12		14		15		17	
Share LIHTC units in floodplain of all LIHTC units ('15)	3		4		5		9	
Years	**1990**	**2015**	**1990**	**2015**	**1990**	**2015**	**1990**	**2015**
Pop. (million)	55,871	73,578	48,228	63,834	75,061	94,984	209,908	271,342
Pop. (million) per square mile	296	347	142	184	286	345	398	475
Share pop. non-Hispanic white	83	75	86	79	88	80	80	71
Share units owner-occupied	72	71	73	72	73	71	71	69
Share pop. unemployed	6	6	7	6	6	6	6	6
Share pop. in poverty	17	17	17	17	15	16	16	16
Share pop. B.A. or higher	13	13	12	13	13	14	16	15
Share multi-family housing	12	7	11	7	13	8	17	10
Median rent	230	722	224	708	250	752	300	844
Median home value	52,866	139,680	51,138	129,556	57,325	145,375	73,365	173,520
Share units renter-occupied in floodplain of all units	2	2	2	2	2	2	4	4
Share units in floodplain of renter-occupied units	7	7	8	7	9	8	13	12
Share pop. in floodplain of all pop	7	6	7	6	8	7	12	11
Share in floodplain of non-Hispanic white pop.	7	6	7	7	8	8	12	11
Share in floodplain of non-Hispanic black pop.	6	6	7	7	8	8	12	11
Share in floodplain of Hispanic pop.	7	6	7	7	8	8	12	12
Share LIHTC units of renter-occupied units	-	3	-	3	-	3	-	3
Share LIHTC units of renter-occupied units in floodplain	-	4	-	2	-	3	-	3

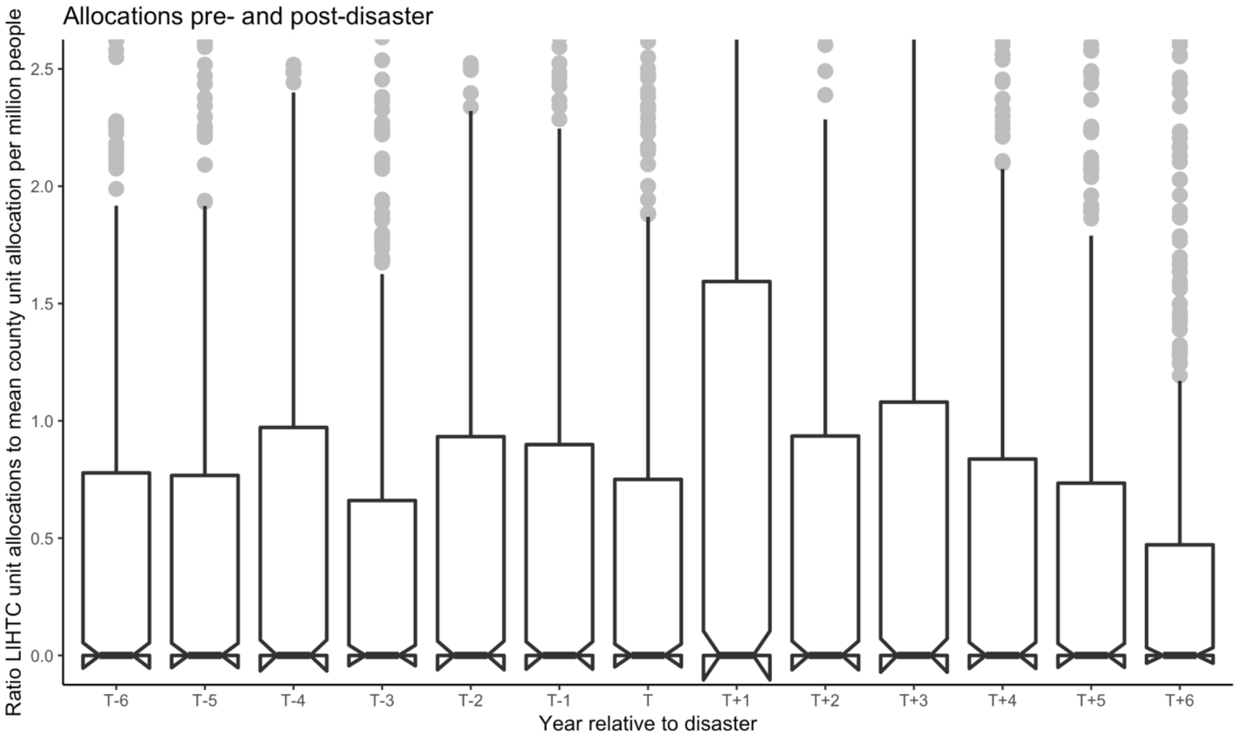
In **Table 3**, we focus again only on counties with at least some land in the floodplain and, within that group, now only on the 458 counties that experienced a severe flooding disaster over the 26-year study period. We divide the county-year LIHTC allocations into those years within the three years following a disaster and those years distant from a severe flood disaster. We present the count of LIHTC units allocated in the three years after a severe flooding disaster compared to the other years. First, we note that roughly one out of every four units is allocated in a county-year within three years after a severe flooding disaster, even though those county-years are only one out of every five county-years in the sample. On average states allocated 136 LIHTC units per million residents in a county-year distant from a severe flooding disaster (either before or more than three years after), but 187 units across each of the three years following a severe flooding disaster. In other words, the average annual allocation across the three years after a severe flooding disaster was 38 percent higher each year than in other years. Looking at the allocations by location relative to the 500-year floodplain, we see that even though allocations within the floodplain after a severe flooding disaster do seem to increase more dramatically (a greater percentage increase) than allocations outside of the floodplain after a severe flooding disaster, in absolute numbers, allocations within the floodplain are dwarfed by the much larger number of allocations outside of the floodplain both before and after disasters.

Table 3: LIHTC Unit Allocations Given Recent Disasters

	No recent severe flood disaster	Recent severe flood disaster	Ratio recent to no recent
Count county-years	9,434	2,474	0.26
Count LIHTC units allocated	323,523	111,293	0.34
Count LIHTC units allocated not in 500-yr floodplain	290,692	94,603	0.33
Count LIHTC units allocated in 500-yr floodplain	32,831	16,690	0.51
Average LIHTC units per million people allocated	136	187	1.38
Average LIHTC units per million people not in 500-yr floodplain allocated	118	155	1.31
Average LIHTC units per million people in 500-yr floodplain allocated	17	32	1.8

This pattern is represented visually year-by-year before and after a disaster in **Figure 1**, showing the ratio of LIHTC unit allocations per capita for each year before and after a disaster relative to the mean LIHTC unit allocations per capita across all years in a county. In other words, in terms of percents, the graph shows in each year before and after a disaster the share of LIHTC unit allocations in year relative to the mean for the county. The upper hinge represents the upper quartile and the upper whisker indicates 1.5x the inter-quartile range. An additional figure showing the share of a state's units that a county absorbs is represented in **Appendix Figure A1.1** and illustrates similar results.

Figure 1: LIHTC Unit Allocations Pre- and Post-Severe Flooding Disaster



We focus on the competitive nine-percent tax credit allocations for new construction in this study, but to explore the possibility that other types of allocations are used more after disasters we parse the data by credit type (four percent and nine percent), project type (new construction and acquisition) and whether the project is paired with CDBG funding. We do not observe substantial differences pre- and post-disaster in allocations for four percent credits, LIHTC acquisitions, or projects paired with CDBG funding (noting projects identified as paired with CDBG funding are only a small, if growing in recent years, share of the whole sample).

4.2 Causal Analysis

To estimate the effect of a severe flood disaster on LIHTC allocation, we formulate a linear panel regression model and specify a distributive lag. In Table 5, we find in Model 1.1 that a severe flooding disaster is positively associated with larger LIHTC allocations per million people in the first three years following the disaster, and in particular in the first year. Adding controls, Model 2.1 produces a parallel result. This finding suggests that states and localities use the LIHTC program in part as a disaster recovery program to facilitate the construction of affordable housing in disaster hit counties. Results in years four through six are not significant, but negative.

Table 4: Estimate of Effect of Flood Disasters on LIHTC Unit Allocations

	Model 1.1			Model 2.1		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Dependent	Units per million people			Units per million people		
Severe flood (t = 0)	10.98	(17.27)		10.54	(17.3)	
Severe flood (lag, t = -1)	83.53	(22.3)	***	80.25	(22.24)	***
Severe flood (lead, t = 1)	-9.5	(15.65)		-11.99	(15.75)	
Severe flood (lag, t = -2)	57.76	(23.3)	*	55.84	(23.22)	*
Severe flood (lead, t = 2)	-4.84	(18.16)		-7.58	(18.24)	
Severe flood (lag, t = -3)	57.36	(22.82)	*	55.7	(22.7)	*
Severe flood (lead, t = 3)	-10.56	(18.77)		-10.73	(18.69)	
Severe flood (lag, t = -4)	-2.28	(15.66)		-4.57	(15.79)	
Severe flood (lead, t = 4)	0.57	(16.93)		0.82	(16.91)	
Severe flood (lag, t = -5)	-10.84	(15.8)		-10.35	(15.95)	
Severe flood (lead, t = 5)	1.09	(17.31)		2.05	(17.24)	
Severe flood (lag, t = -6)	-13.53	(15.7)		-10.37	(15.71)	
Severe flood (lead, t = 6)	-7.89	(16.72)		-8.5	(16.74)	
Share pop. non-Hispanic white				2.46	(1.52)	
Share units owner-occupied				0.17	(2.35)	
Median rent				121.58	(99.46)	
Pop. (millions) per square mile				-0.01	(0.02)	
Share pop. unemployed				-12.59	(2.08)	***
GO-Zone Act in Effect				10.67	(11.29)	
Errors: HC1	County			County		
Effects: Fixed	Year, county			Year, county		
Complete observations	56,904			56,860		
DF	54,497			54,445		
Notes	-			44 records with incomplete covariates		

R2	0.0005	0.0017
F statistic	1.97	4.78
Significance: 0.001 ***; 0.01 **; 0.05 *; 0.1 .		
Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.		

The preceding results indicate that LIHTC allocations increase significantly in the three years following severe flooding disasters, leading to more than 80 additional units per county in the year after the disaster, compared to other years, and more than 190 units per county in the three years after the disaster combined, compared to other years. When the average number of LIHTC units allocated per county across the whole sample is 140, these additional units represent a large increase. These estimates take into account the GO-Zone Act being in effect in some county-years.

The coefficients in years four through six after a disaster are all negative, even though they are not significant. These negative coefficients in years four through six raise the possibility that there is a form of inter-temporal substitution taking place such that resources are directed to counties that experienced a severe flooding disaster in the immediate three years following the flooding disaster, but then directed away from those counties in the following years to compensate for the additional share of state resources allocated in the immediate aftermath. The magnitude of the coefficients here, however, suggest a net gain of 177 units to those counties even after taking into account the magnitude of the non-significant negative coefficients in years four through six after the disaster. Even if there were some marginal long-term diminution of the significant increase in allocations after severe flooding disasters through inter-temporal substitution, the direction of resources towards disaster-hit counties in the years following and the use of LIHTC as a disaster recovery tool is itself meaningful.

These overall findings regarding the use of the LIHTC program for disaster recovery raise the question of the extent to which these post-disaster LIHTC allocations to flood-hit counties are for projects that are in the 500-year flood plain and whether these allocations will mitigate or exacerbate future disaster exposure for low-income tenants.

The results in Model 1.1. in Table 5 indicate that a severe flooding disaster has no effect on LIHTC allocations *inside* of the 500-year floodplain after the disaster, while the results in Model 1.2 reveal that a severe flooding disaster in a county is associated with a substantial and highly significant increase in LIHTC allocations per million people outside of the 500-year floodplain in that county in each of the first three years after the disaster.

In Models 2.1 and 2.2, after including controls as well as taking into account the distribution of all units in that county relative to the floodplain, the share of rental units of all units in the floodplain, and the count of rental units in the floodplain, the results remain largely unchanged. With these controls added in Model 2.1, severe flooding disasters continue to have no effect on allocations within the floodplain after the disaster. The results in Model 2.2 indicate that even after adding these controls, severe floods lead to a significant increase in LIHTC allocations outside of the 500-year floodplain in the first year after a disaster, and a somewhat less significant association with increased allocations in the second and third year after the disaster. In terms of magnitude, severe floods lead to an increase of 63 units per million people outside of the 500-year floodplain in the year after the disaster, compared to an average annual county allocation of 129 units per million people outside of the floodplain across all years—a 49 percent increase in units allocated on average. Again, these estimates take into account the GO-Zone Act being in effect for some county-years.

Table 5: Estimate of Effect of Flood Disasters on LIHTC Unit Allocations Relative to Floodplain

	Model 1.1			Model 1.2			Model 2.1			Model 2.2		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Dependent:	Units in floodplain per million people			Units out of floodplain per million people			Units in floodplain per million people			Units out of floodplain per million people		
Severe flood (t = 0)	-6.69	(6.55)		17.68	(15.57)		-6.75	(6.63)		18.05	(15.54)	
Severe flood (lag, t = -1)	19.07	(12.64)		64.46	(17.17)	***	17.88	(12.61)		62.71	(17.2)	***
Severe flood (lead, t = 1)	-0.7	(9.15)		-8.8	(12.84)		-0.37	(9.22)		-10.39	(12.89)	
Severe flood (lag, t = -2)	10	(12.94)		47.76	(18.54)	**	8.49	(12.62)		47.31	(18.69)	*
Severe flood (lead, t = 2)	0.59	(10.02)		-5.43	(15.13)		1.04	(10)		-7.25	(15.21)	
Severe flood (lag, t = -3)	7.25	(8.88)		50.11	(19.39)	**	6.27	(8.76)		49.37	(19.37)	*
Severe flood (lead, t = 3)	-9.79	(7.51)		-0.77	(16.15)		-9.3	(7.41)		-0.74	(16.13)	
Severe flood (lag, t = -4)	-3.1	(6.8)		0.82	(14.24)		-4.31	(7.19)		-0.74	(14.32)	
Severe flood (lead, t = 4)	-4.2	(9.32)		4.77	(13.52)		-3.75	(9.21)		4.96	(13.54)	
Severe flood (lag, t = -5)	-1.72	(8.84)		-9.12	(13.05)		-2.71	(8.93)		-7.96	(13.18)	
Severe flood (lead, t = 5)	1.94	(8.89)		-0.85	(14.82)		2.54	(8.82)		-0.12	(14.79)	
Severe flood (lag, t = -6)	0.56	(6.98)		-14.09	(13.95)		0.23	(7.13)		-11.14	(13.93)	
Severe flood (lead, t = 6)	1.18	(8.71)		-9.08	(12.79)		1.79	(8.57)		-9.65	(12.87)	
Share pop. non-Hispanic white							0.7	(0.78)		1.6	(1.35)	
Share units owner-occupied							-0.12	(0.86)		0.64	(2.03)	
Median rent							92.8	(81.8)		21.01	(53.91)	
Pop. (millions) per square mile							-0.01	(0.01)		0.01	(0.02)	
Share pop. unemployed							-0.68	(1.17)		-11.57	(1.73)	***
Share units in floodplain of all units							-10.41	(5.65)	.	-6.69	(5.75)	
Share units renter-occupied of all units in floodplain							0.24	(0.24)		1.19	(1.3)	
Renter-occupied units in floodplain							0.00	(0. 00)		0.00	(0. 00)	
GO-Zone Act in Effect							8.37	(4.9)	.	3.4	(9.9)	
Errors	HC1: County			HC1: County			HC1: County			HC1: County		
Effects	Fixed: Year, county			Fixed: Year, county			Fixed: Year, county			Fixed: Year, county		
Complete Observations	56,906			56,906			56,860			56,860		
DF	54,497			54,497			54,445			54,445		

Notes			44 records with incomplete covariates	44 records with incomplete covariates
R2	0.0001	0.0003	0.0013	0.0016
F statistic	0.75	1.63	3.24	4.06
Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .				
Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.				

In sum, we find that severe flooding disasters lead to an increase in LIHTC unit allocations overall in the first three years after a disaster, and specifically that significantly more LIHTC units are allocated outside of the 500-year floodplain.

4.3 Sensitivity

To evaluate the robustness of these models, we conduct several additional tests, presented in the appendix. We evaluate the stability of results using alternative measures of the independent and dependent variables and alternative constructions of the model presented above.

First, we focus on evaluating changes to the dependent variable. We transform it with an inverse hyperbolic sin transformation, a helpful transformation for variables with some extreme values and also many zero values (Bellemare & Wichman, 2020). This alternative dependent variable produces results that are parallel to those presented. These results are presented in Tables A2.1 and A3.1.

Second, we focus on evaluating changes to the main independent variables of interest. Instead of measuring severity relative to all other disasters in the United States we measure it relative to all other disasters in the state. This alternative measure of disasters has significant and positive effects on the number of units allocated, in parallel with the results presented. This result is presented in Tables A2.2 and A3.2.

Third, we validate our specification. We specify a time-trend at the state level and separately a time-trend at the county level to account for any time-variant but unobserved confounders, which would undermine our model specification strategy. It does not produce results substantively different from ours. Next, we run the lags out to year *t-7* and *t-8.* The result remains qualitatively parallel. These results are available in Tables A2.3 and A3.3.

One additional check is to limit the dataset to counties with any flood damage recorded in the panel and to test the model on counties with only moderate numbers of LIHTC units by selecting only counties with between zero and 5,000 units, in the event the allocation process is different in those counties. These steps produce a dataset with 25 percent fewer counties and 30 percent fewer units. This check also produces results parallel to our initial ones. These results are available in Tables A2.4 and A3.4

5. DISCUSSION AND CONCLUSION

The findings here suggest that in the absence of a federal disaster housing program that creates permanent housing for renters, states turn to the LIHTC program to catalyze rental housing production after disasters. We find that the year after a severe flooding disaster is associated with a 57 percent increase in disaster-hit county LIHTC allocations relative to other years. For the average county, this means that a severe flood is associated with the production of more than 80 additional LIHTC units per million people in the year that follows, 63 of which are outside of the 500-year floodplain.

In the context of federal disaster assistance, the central housing programs have remained essentially the same since 1988. The Stafford Act favors temporary financial assistance over direct housing assistance and generally prohibits FEMA from providing permanent housing. The increasing frequency of flooding disasters that significantly affect housing, the disproportionate vulnerability of renters, and the increasing cost of rental housing relative to wages over the past three decades all mean that even as the programs have remained the same, the context has changed. Renters, and especially low-income renters, struggle to find and to afford nearby comparable housing after disasters (Brennan et al., 2021) and, the more aid that an area receives from FEMA, the wider wealth inequality between renters and homeowners increases after disasters (Howell & Elliott, 2019). Here we see policy drift at the federal level, where the federal disaster housing policy remains the same, even as the contexts of disasters and housing change, and the statute ends up disproportionately helping homeowners and leaving renters behind (GAO 2010).

The results here suggest that this policy drift at the federal level has been met with policy conversion at the state level. The LIHTC program was created in the Tax Reform Act of 1986 to encourage private investment in housing targeted at households with low incomes. It has come to serve as a fundamental part of the social safety net for millions of low-income households seeking a home in which they can afford to live. The results indicate that, after disasters, states convert the program to serve a new and originally unintended aim: disaster recovery. With the existing statutory framework for temporary disaster housing assistance failing to meet renters' long-term needs, states have turned to the LIHTC program to supplement funding for the construction of multi-family rental housing after disaster and to catalyze disaster recovery. Although the increased allocations after severe flooding disasters represent a relatively large percentage increase over the average level of county allocations in non-disaster years (57%), the actual number of additional units (80) is exceedingly modest in the context of affordable housing need, especially after severe disasters.

A limitation of converting existing policies to meet new objectives is that, when programs are used to serve needs that do not reflect their original legislative purposes, they may not allow agencies to equitably and efficiently meet those new objectives. One central tension in disaster policy, and safety net policies more broadly, is the degree to which the policy not only addresses current vulnerability or harm but also functions to reduce future vulnerability. This tension is central to any disaster-housing program and is especially acute in the context of affordable housing after disasters. After a flooding disaster, land in potential flood hazard areas is likely to be sold at a discount, enabling the creation of more affordable units or more deeply subsidized units, even as it places those subsidized renters at greater risk. To what extent has states' conversion of the LIHTC program to a disaster recovery tool ameliorated or exacerbated disaster risk for subsidized renters? Another central tension in disaster recovery policy is the extent to which aid should focus on recovery in place, recognizing the importance of fragile social networks and of the cultural and historical significance associated with specific places, or whether it should focus on encouraging migration to less hazard prone locations.

The regression analyses indicate that states and developers respond to severe flooding disasters by allocating new LIHTC units outside of the 500-year floodplain in the three years after a disaster. On average, a severe flooding disaster catalyzes the allocation of an additional 63 units outside of the floodplain in the year after a disaster. These severe flooding disasters have no statistically significant effect on the construction of units within the floodplain. These results indicate that the LIHTC program is being used to rebuild options for low-income renters in some proportion to the number and share of renters in the floodplain while, most significantly, also being used to expand options for renters in the same county but outside of the floodplain.

Together, these findings suggest that states are using LIHTC to catalyze recovery and potentially doing so in a nuanced way, placing an emphasis on increasing the units allocated to disaster-hit counties and also increasing the number of units within that county allocated outside the floodplain, in order to reduce the flooding hazards that future subsidized renters face, while not completely rejecting projects that will replace damaged units in floodplains to the extent that is where a large portion of renters already live. The fact that states and affordable housing developers are largely making these difficult decisions on a state-by-state and project-by-project basis highlights the need for more explicit conversations about the role that the LIHTC program plays in disaster recovery. These findings are particularly interesting given the lack of explicit disaster recovery provisions in most LIHTC allocation plans (Mehta et al., 2020) and the rarity of changes to plans after severe disasters (Shamsuddin & Leib, 2021). Mehta et al. (2020) find that only 24 states and territories include some explicit provisions for disaster preparedness or recovery in their allocation plans, and of those only 11 include any mention of disaster recovery. This contrast between formal provisions in LIHTC allocation plans and the findings here suggest that housing finance agencies do respond with increased allocations despite not having included disaster recovery in their allocation criteria at the outset. Future research should explore the extent to which these patterns vary across states and the factors that contribute to that variation.

The results also suggest there may be a role for federal guidance that can help states and developers weigh more clearly the competing goals of catalyzing disaster recovery, meeting the housing needs of low-income renters in the neighborhoods where they already live, and providing new options to renters in locations that will better protect them from future environmental harms. The existing drift of relatively static disaster-housing policies combined with substantial shifts in disaster-housing needs and renters' housing cost burdens has disproportionately harmed renters (Howell & Elliott, 2019). While state conversion of the existing federally funded and state managed LIHTC program to meet rental housing needs after disasters has helped fill this policy gap, federal policy could do more. For instance, adjusting federal LIHTC allocations automatically to meet disaster housing needs would allow states to act even more quickly to allocate more units for subsidized permanent rental housing after disasters. Future research could qualitatively and quantitatively explore state variation in LIHTC locations relative to the floodplain and look specifically at how states balance competing disaster recovery priorities in the context of housing. Further, the LIHTC program addresses only a fraction of the housing needs after many severe disasters and is not targeted at the lowest-income renters where affordability needs are highest, highlighting the need for additional research on disaster relevant dimensions of public housing and the Housing Choice Voucher program, as well as other innovative state and local approaches.

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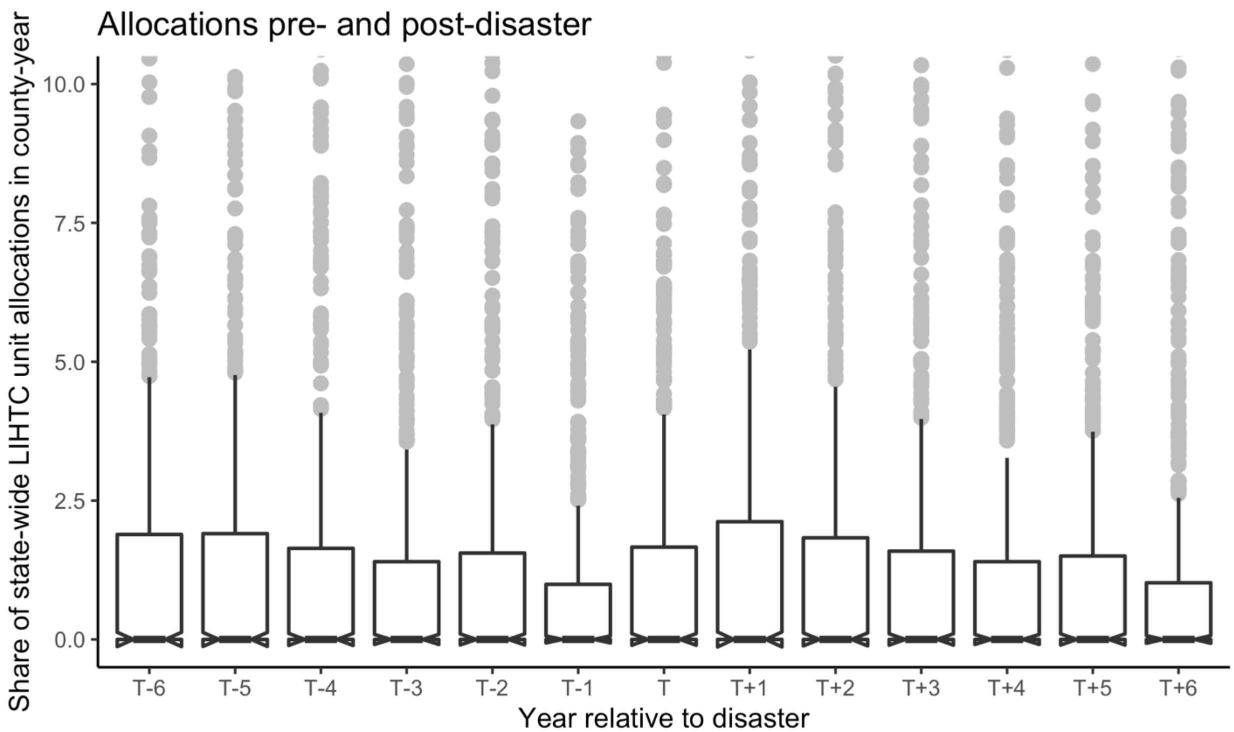
Appendix 1 – Additional Descriptives

Table A1.1-- Quantiles of Counties by Total LIHTC Unit Allocations 1990-2015

	0-25% (Mean)		25-50% (Mean)		50-75% (Mean)		75-100% (Mean)	
Count counties	593		593		593		592	
Years	**1990-2015**		**1990-2015**		**1990-2015**		**1990-2015**	
LIHTC units allocated ('90-'15) per million people ('15)	111		1,811		3,647		7,663	
Sum flood damage ($1000s) ('90-'15)	49,695		101,917		302,575		221,226	
Count floods ('90-'15)	4		4		4		4	
Count severe floods ('90-'15)	0		0		0		0	
Share land in floodplain ('15)	16		14		13		15	
Share LIHTC units in floodplain of all LIHTC units ('15)	1		6		6		7	
Years	**1990**	**2015**	**1990**	**2015**	**1990**	**2015**	**1990**	**2015**
Pop. (million)	37,411	43,531	146,592	188,900	127,034	166,321	77,807	104,705
Pop. (million) per square mile	162	195	302	366	404	489	254	301
Share pop. non-Hispanic white	87	82	87	79	84	75	79	70
Share units owner-occupied	76	74	73	72	71	69	70	67
Share pop. unemployed	7	6	6	5	6	6	6	6
Share pop. in poverty	19	17	15	15	15	16	17	18
Share pop. B.A. or higher	11	12	15	15	15	15	14	14
Share multi-family housing	12	7	11	7	13	8	17	10
Median rent	208	685	279	802	273	789	244	749
Median home value	48,792	125,611	67,272	165,488	63,658	157,849	54,943	139,125
Share units renter-occupied in floodplain of all units	2	2	2	2	2	2	3	3
Share units in floodplain of renter-occupied units	9	9	9	9	8	8	10	9
Share pop. in floodplain of all pop	8	8	8	8	8	7	9	9
Share in floodplain of non-Hispanic white pop.	8	8	8	8	8	7	9	9
Share in floodplain of non-Hispanic black pop.	8	8	9	8	7	7	9	8
Share in floodplain of Hispanic pop.	8	8	9	8	8	7	9	9
Share LIHTC units of renter-occupied units	-	0	-	2	-	3	-	7
Share LIHTC units of renter-occupied units in floodplain	-	0	-	2	-	4	-	5

Figure A1.1 –LIHTC Unit Allocations Pre- and Post-Severe Flooding Disaster
The upper hinge represents the upper quartile and the upper whisker indicates 1.5x the inter-quartile range.



Appendix 2 – Sensitivity for Table 5

Table A2.1 – Alternative Dependent Variable

Model 1 uses an inverse hyperbolic sin transformation to adjust the dependent variable for the few counties that have a substantial share of the LIHTC units, nationally.

	Model 1		
	Estimate	Std. Error	-
Dependent	Log-transformed units		
Severe flood (t = 0)	0.10	(0.08)	
Severe flood (lag, t = -1)	0.45	(0.08)	***
Severe flood (lead, t = 1)	0.08	(0.08)	
Severe flood (lag, t = -2)	0.17	(0.09)	.
Severe flood (lead, t = 2)	0.03	(0.08)	
Severe flood (lag, t = -3)	0.32	(0.09)	***
Severe flood (lead, t = 3)	-0.02	(0.07)	
Severe flood (lag, t = -4)	0.17	(0.08)	*
Severe flood (lead, t = 4)	0.07	(0.08)	
Severe flood (lag, t = -5)	0.10	(0.07)	
Severe flood (lead, t = 5)	0.11	(0.08)	
Severe flood (lag, t = -6)	-0.06	(0.07)	
Severe flood (lead, t = 6)	0.13	(0.08)	.
Share pop. non-Hispanic white	-0.01	(0.00)	
Share units owner-occupied	0.00	(0.01)	
Median rent	0.55	(0.21)	**
Pop. (millions) per square mile	0.00	(0.00)	***
Share pop. unemployed	-0.03	(0.00)	***
GO-Zone Act in Effect	-0.08	(0.03)	**
Errors	HC1		
Effects	FE		
DF	54,445		
R2	0.003		

Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1. Following Bellemare & Wichman (2020), the percentage change (p) in the outcome from a discrete change in a dichotomous severe flood lag or lead with coefficient (b) is approximated by $p/100 \approx \exp(b)-1$. The magnitude of the percent change is consistent with the models in which the dependent variable is not log-transformed.

Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .

Table A2.2 – Alternative Independent Variable

Model 1 use a measure of severe floods relative to just other floods in the state.

	Model 1		
	Estimate	Std. Error	-
Dependent	Units per million people		
Severe flood (t = 0)	-0.98	(17.04)	
Severe flood (lag, t = -1)	89.15	(24.24)	***
Severe flood (lead, t = 1)	-14.4	(15.14)	
Severe flood (lag, t = -2)	51.52	(24.25)	*
Severe flood (lead, t = 2)	-8.09	(17.9)	
Severe flood (lag, t = -3)	24.73	(22.03)	
Severe flood (lead, t = 3)	-16.44	(18.66)	
Severe flood (lag, t = -4)	-27.57	(15.85)	.
Severe flood (lead, t = 4)	-6.15	(16.55)	
Severe flood (lag, t = -5)	-4.91	(17.4)	
Severe flood (lead, t = 5)	-4.26	(17)	
Severe flood (lag, t = -6)	-16.15	(17.41)	
Severe flood (lead, t = 6)	-14.71	(16.64)	
Share pop. non-Hispanic white	2.39	(1.53)	
Share units owner-occupied	0.32	(2.36)	
Median rent	124.41	(99.13)	
Pop. (millions) per square mile	-0.01	(0.02)	
Share pop. unemployed	-12.63	(2.08)	***
GO-Zone Act in Effect	11.51	(11.27)	
Errors	HC1		
Effects	FE		
DF	54,445		
R2	0.001		
Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.			
Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .			

Table A2.3 – Additional Controls
Model 1 includes state time trend.
Model 2 includes county time trend
Model 3 includes lags at t = -7 and t = -8.

	Model 1			Model 2			Model 3		
	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Dependent	Units per million people			Units per million people			Units per million people		
Severe flood (t = 0)	-1.02	(17.48)		-2.26	19.38		12.27	(17.3)	
Severe flood (lag, t = -1)	63.47	(21.63)	**	62.84	24.2	**	81.8	(22.6)	***
Severe flood (lead, t = 1)	-19.41	(15.76)		-20.19	18.23		-9.98	(15.91)	
Severe flood (lag, t = -2)	36.71	(22.56)	.	34.83	25.01		57.59	(23.78)	*
Severe flood (lead, t = 2)	-13.85	(18.24)		-13.14	20.33		-5.77	(18.23)	
Severe flood (lag, t = -3)	44.3	(22.26)	.	39.61	23.93	.	57.59	(23.05)	*
Severe flood (lead, t = 3)	-17.47	(18.72)		-17.98	20.3		-9.13	(18.77)	
Severe flood (lag, t = -4)	-17.75	(16.26)		-27.2	18.58		-4.11	(15.54)	
Severe flood (lead, t = 4)	0.05	(17.08)		-2.07	19.49		2.01	(17.01)	
Severe flood (lag, t = -5)	-24.08	(16.13)		-33.5	18.19	.	-10.24	(16.37)	
Severe flood (lead, t = 5)	3.69	(17.03)		0.11	19.46		3.28	(17.32)	
Severe flood (lag, t = -6)	-24.61	(15.75)		-32.85	17.21	.	-8.53	(15.82)	
Severe flood (lead, t = 6)	-4.32	(16.87)		-6.62	18.48		-6.92	(16.9)	
Severe flood (lag, t = -7)				-2.26	19.38		13.08	(16.98)	
Severe flood (lag, t = -8)				62.84	24.2		15.48	(20.16)	
Share pop. non-Hispanic white	2.92	(1.67)	*	13.02	10.66		2.48	(1.52)	
Share units owner-occupied	-0.46	(2.53)		-2.99	4.95		0.19	(2.35)	
Median rent	116.08	(118.8)		437.13	329.61		120.38	(99.69)	
Pop. (millions) per square mile	-0.03	(0.02)		-0.01	0.04		-0.01	(0.02)	
Share pop. unemployed	-11.29	(2.32)	***	-12.6	2.91	***	-12.59	(2.08)	***
GO-Zone Act in Effect	47.63	(13.95)	***	49.77	14.11	***	10.68	(11.23)	
State Time Trend	X								
County Time Trend				X					

Errors	HC1	HC1	HC1
Effects	FE	FE	FE
DF	59,137	52,077	54,443
R2	0.006	0.050	0.001

Notes: This table reports a distributive lag model with county and year fixed effects.
Robust standard errors are clustered at the county-level with HC1.

Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1
.

Table A2.4 – Limited Dataset

Model 1 limited to counties with floodplains and any flood damage and LIHTC units in the panel.

	Model 1		
	Estimate	Std. Error	
Dependent	Units per million people		
Severe flood (t = 0)	9.32	(20.45)	
Severe flood (lag, t = -1)	97.92	(26.47)	***
Severe flood (lead, t = 1)	-13.11	(18.7)	
Severe flood (lag, t = -2)	65.02	(27.78)	*
Severe flood (lead, t = 2)	-11.04	(21.72)	
Severe flood (lag, t = -3)	71.38	(27.24)	**
Severe flood (lead, t = 3)	-14.69	(22.25)	
Severe flood (lag, t = -4)	-5.87	(18.93)	
Severe flood (lead, t = 4)	-3.67	(19.95)	
Severe flood (lag, t = -5)	-13.54	(19.4)	
Severe flood (lead, t = 5)	-4.45	(20.17)	
Severe flood (lag, t = -6)	-16.65	(18.94)	
Severe flood (lead, t = 6)	-17.34	(19.29)	
Share pop. non-Hispanic white	2.28	(1.94)	
Share units owner-occupied	-0.11	(3.34)	
Median rent	212.1	(144.32)	
Pop. (millions) per square mile	-0.04	(0.04)	
Share pop. unemployed	-16.53	(2.9)	***
GO-Zone Act in Effect	14.62	(14.42)	
Errors	HC1		
Effects	FE		
DF	40,484		
R2	0.002		
Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.			
Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .			

Appendix 3 – Sensitivity for Table 6

Table A3.1 – Alternative Dependent Variable

Model 1 uses an inverse hyperbolic sin transformation to adjust the dependent variable for the few counties that have a substantial share of the LIHTC units, nationally.

	Model 1					
	Estimate	Std. Error		Estimate	Std. Error	
Dependent	Log-transformed units in floodplain			Log-transformed units not in floodplain		
Severe flood (t = 0)	0.02	(0.05)		0.11	(0.08)	
Severe flood (lag, t = -1)	0.12	(0.05)	*	0.40	(0.08)	***
Severe flood (lead, t = 1)	-0.02	(0.04)		0.12	(0.08)	
Severe flood (lag, t = -2)	0.08	(0.05)		0.16	(0.09)	.
Severe flood (lead, t = 2)	0.01	(0.04)		0.02	(0.08)	
Severe flood (lag, t = -3)	0.09	(0.05)	*	0.29	(0.09)	***
Severe flood (lead, t = 3)	-0.05	(0.03)		0	(0.07)	
Severe flood (lag, t = -4)	0.03	(0.04)		0.17	(0.08)	*
Severe flood (lead, t = 4)	0.02	(0.04)		0.04	(0.08)	
Severe flood (lag, t = -5)	0.01	(0.04)		0.09	(0.07)	
Severe flood (lead, t = 5)	0.02	(0.04)		0.09	(0.08)	
Severe flood (lag, t = -6)	0.03	(0.04)		-0.09	(0.07)	
Severe flood (lead, t = 6)	0.06	(0.04)		0.11	(0.07)	
Share pop. non-Hispanic white	0.00	(0.00)		-0.01	(0.00)	
Share units owner-occupied	0.00	(0.00)		0.01	(0.01)	
Median rent	0.23	(0.09)	*	0.48	(0.2)	*
Pop. (millions) per square mile	0.00	(0.00)		0.00	(0.00)	***
Share pop. unemployed	0.00	(0.00)		-0.02	(0.00)	***
Share units in floodplain of all units	-0.01	(0.01)		0.02	(0.01)	.
Share renter occupied units in floodplain of all units in floodplain	0.00	(0.00)		0.01	(0.00)	*

Count units renter occupied in floodplain	0.00	(0.00)		0.00	(0.00)	
GO-Zone Act in Effect	0.03	(0.01)	*	-0.09	(0.03)	**
Errors	HC1			HC1		
Effects	FE			FE		
DF	54,442			54,442		
R2	0.002			0.004		

Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1. Following Bellemare & Wichman (2020), the percentage change (p) in the outcome from a discrete change in a dichotomous severe flood lag or lead with coefficient (b) is approximated by $p/100 \approx \exp(b)-1$. The magnitude of the percent change is consistent with the models in which the dependent variable is not log-transformed.

Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .

Table A3.2 – Alternative Independent Variable

Model 1 use a measure of severe floods relative to just other floods in the state.

	Model 1					
	Estimate	Std. Error		Estimate	Std. Error	
Dependent	Units per million people in floodplain			Units per million people not in floodplain		
Severe flood (t = 0)	-10	(5.56)	.	9.16	(15.88)	
Severe flood (lag, t = -1)	17.32	(12.16)		71.68	(19.94)	***
Severe flood (lead, t = 1)	-0.26	(8.78)		-13.01	(12.69)	
Severe flood (lag, t = -2)	16.77	(13.39)		34.25	(19.52)	.
Severe flood (lead, t = 2)	2.32	(9.7)		-9.11	(14.94)	
Severe flood (lag, t = -3)	12.12	(8.89)		11.83	(17.9)	
Severe flood (lead, t = 3)	-10.37	(7.19)		-5.42	(16.13)	
Severe flood (lag, t = -4)	-0.47	(6.94)		-28.2	(14.47)	.
Severe flood (lead, t = 4)	-4.13	(8.71)		-1.71	(13.37)	
Severe flood (lag, t = -5)	-8.34	(5.61)		1.96	(15.99)	
Severe flood (lead, t = 5)	2.03	(8.52)		-6	(14.56)	
Severe flood (lag, t = -6)	-3.39	(5.5)		-14.3	(16.78)	
Severe flood (lead, t = 6)	1.43	(8.24)		-15.58	(12.81)	
Share pop. non-Hispanic white	0.70	(0.79)		1.54	(1.35)	
Share units owner-occupied	-0.11	(0.87)		0.75	(2.03)	
Median rent	92.97	(81.43)		23.45	(53.9)	
Pop. (millions) per square mile	-0.01	(0.01)		0.01	(0.02)	
Share pop. unemployed	-0.67	(1.17)		-11.62	(1.73)	***
Share units in floodplain of all units	-10.41	(5.65)	.	-6.75	(5.75)	
Share renter occupied units in floodplain of all units in floodplain	0.23	(0.24)		1.14	(1.3)	

Count units renter occupied in floodplain	0.00	(0.00)		0. 00	(0. 00)
GO-Zone Act in Effect	8.19	(4.94)	.	4.4	(9.86)
Errors	HC1			HC1	
Effects	FE			FE	
DF	54,442			54,442	
R2	0.001			0.002	

Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.

Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .

Table A3.3 – Additional Controls

Model 1 includes state time trend.

Model 2 includes county time trend.

	Model 1						Model 2					
	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Dependent	Units per million people in floodplain			Units per million people not in floodplain			Units per million people in floodplain			Units per million people not in floodplain		
Severe flood (t = 0)	-7.71	(6.81)		7.17	(15.67)		-9.69	9.37		7.81	16.92	
Severe flood (lag, t = -1)	16.9	(12.23)		46.84	(16.8)	**	14.55	14.47		48.88	18.58	**
Severe flood (lead, t = 1)	-1.24	(9.37)		-17.42	(12.83)		-3.07	11.33		-16.9	14.48	
Severe flood (lag, t = -2)	7.60	(12.09)		29.22	(18.39)		5.09	14.32		30.46	20.07	
Severe flood (lead, t = 2)	0.17	(10.13)		-13.27	(15.14)		-1.15	12.24		-11.96	16.69	
Severe flood (lag, t = -3)	5.70	(8.46)		38.68	(19.19)	*	1.77	10.29		38.6	20.61	.
Severe flood (lead, t = 3)	-10.34	(7.56)		-6.98	(16.07)		-12.87	9.43		-5.24	17.28	
Severe flood (lag, t = -4)	-5.04	(7.53)		-12.9	(14.49)		-9.69	9.21		-16.51	16.2	
Severe flood (lead, t = 4)	-4.16	(9.64)		4.07	(13.6)		-6.98	12.49		4.31	14.92	
Severe flood (lag, t = -5)	-3.28	(9.01)		-20.97	(13.35)		-7.17	10.3		-25.29	15.23	.
Severe flood (lead, t = 5)	2.46	(8.88)		1.06	(14.55)		-0.67	11.3		0.23	16.13	
Severe flood (lag, t = -6)	-0.46	(7.29)		-24.41	(13.95)	.	-3.13	8.47		-28.81	15.18	.
Severe flood (lead, t = 6)	2.16	(8.92)		-6.48	(12.89)		0.11	10.51		-7.17	14.31	
Share pop. non-Hispanic white	0.44	(0.76)		2.36	(1.52)		7.01	6.33		6.25	8.57	
Share units owner-occupied	0.02	(0.85)		-0.26	(2.22)		0.08	0.9		-2.22	4.93	
Median rent	118.54	(100.16)		-6.53	(58.45)		350.84	309.84		93.09	122.55	
Pop. (millions) per square mile	-0.01	(0.01)		-0.01	(0.02)		-0.01	0.01		0	0.04	
Share pop. unemployed	-0.87	(1.42)		-10.28	(1.85)	***	-0.91	1.73		-11.62	2.34	***
Share units in floodplain of all units	-10.65	(5.52)	.	-3.45	(5.47)		-8.55	8.90		-1.50	14.84	
Share renter occupied units in floodplain of all units in floodplain	0.25	(0.23)		0.89	(1.27)		-0.17	0.31		2.70	2.22	
Count units renter occupied in floodplain	0.00	(0.00)		0.00	(0.00)		-0.00	0.00		-0.00	0.00	
GO-Zone Act in Effect	8.08	(6.29)		39.85	(12.07)	***	9.96	6.06		40.12	12.34	**

State time trend	X	X	X	X
Errors	HC1	HC1	HC1	HC1
Effects	FE	FE	FE	FE
DF	59,134	59,134	52,074	52,074
R2	0.001	0.007	0.03	0.05

Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.

Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .

Table A3.3 (continued) – Additional Controls

Model 3 includes lags at t = -7 and t = -8.

	Model 3					
	Estimate	Std. Error		Estimate	Std. Error	
Dependent	Units per million people in floodplain			Units per million people not in floodplain		
Severe flood (t = 0)	-6.87	(6.64)		19.76	(15.54)	
Severe flood (lag, t = -1)	17.33	(12.86)		64.71	(17.45)	***
Severe flood (lead, t = 1)	-0.86	(9.15)		-8.04	(13.11)	
Severe flood (lag, t = -2)	8.23	(13.11)		49.2	(19.00)	**
Severe flood (lead, t = 2)	0.56	(10.01)		-5.1	(15.19)	
Severe flood (lag, t = -3)	5.79	(9.06)		51.6	(19.64)	**
Severe flood (lead, t = 3)	-9.74	(7.55)		1.18	(16.2)	
Severe flood (lag, t = -4)	-3.11	(6.8)		-1.54	(14.24)	
Severe flood (lead, t = 4)	-4.28	(9.33)		6.6	(13.58)	
Severe flood (lag, t = -5)	-3.96	(9.36)		-6.56	(13.34)	
Severe flood (lead, t = 5)	2.44	(8.97)		1.12	(14.81)	
Severe flood (lag, t = -6)	-0.07	(7.05)		-9.12	(14.12)	
Severe flood (lead, t = 6)	1.57	(8.65)		-7.98	(13.03)	
Severe flood (lead, t = -7)	-12.45	(4.75)	**	24.8	(16.11)	
Severe flood (lead, t = -8)	6.48	(11.12)		7.62	(16.05)	
Share pop. non-Hispanic white	0.7	(0.78)		1.63	(1.35)	
Share units owner-occupied	-0.12	(0.86)		0.65	(2.03)	
Median rent	92.87	(81.99)		19.9	(53.91)	
Pop. (millions) per square mile	-0.01	(0.01)		0.01	(0.02)	
Share pop. unemployed	-0.68	(1.17)		-11.57	(1.73)	***
Share units in floodplain of all units	-10.41	(5.63)	.	-6.63	(5.75)	
Share renter occupied units in floodplain of all units in floodplain	0.24	(0.24)		1.19	(1.3)	
Count units renter occupied in floodplain	0.00	(0.00)		0.00	(0.00)	
GO-Zone Act in Effect	8.16	(4.82)	.	3.62	(9.89)	
State time trend	X			X		
Errors	HC1			HC1		

Effects	FE	FE
DF	54,440	54,440
R2	0.001	0.002

Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.

Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .

Table A3.4 – Limited Dataset

Model 1 limited to counties with floodplains and any flood damage and LIHTC units in the panel.

	Model 1				
	Estimate	Std. Error	Estimate	Std. Error	
Dependent	Units per million people in floodplain		Units per million people not in floodplain		
Severe flood (t = 0)	-9.15	(8.01)	19.42	(18.32)	
Severe flood (lag, t = -1)	20.49	(15.16)	77.97	(20.32)	***
Severe flood (lead, t = 1)	-0.95	(11.03)	-10.84	(15.26)	
Severe flood (lag, t = -2)	9.14	(15.3)	56.08	(22.19)	*
Severe flood (lead, t = 2)	0.96	(11.97)	-10.58	(18.07)	
Severe flood (lag, t = -3)	7.12	(10.68)	64.64	(23.17)	**
Severe flood (lead, t = 3)	-11.16	(9.01)	-2.76	(19.14)	
Severe flood (lag, t = -4)	-5.04	(8.83)	-0.91	(17.13)	
Severe flood (lead, t = 4)	-4.95	(11.05)	1.93	(15.83)	
Severe flood (lag, t = -5)	-2.58	(10.99)	-10.94	(15.91)	
Severe flood (lead, t = 5)	2.87	(10.47)	-6.78	(17.2)	
Severe flood (lag, t = -6)	0.06	(8.78)	-17	(16.7)	
Severe flood (lead, t = 6)	0.8	(10.14)	-17.21	(14.68)	
Share pop. non-Hispanic white	1.35	(0.97)	0.59	(1.73)	
Share units owner-occupied	-0.23	(1.25)	0.88	(2.81)	
Median rent	145.91	(122.13)	58.61	(76.36)	
Pop. (millions) per square mile	-0.02	(0.02)	-0.01	(0.03)	
Share pop. unemployed	-0.9	(1.68)	-15.4	(2.38)	***
Share units in floodplain of all units	-10.66	(7.25)	-7.42	(7.24)	
Share renter occupied units in floodplain of all units in floodplain	0.3	(0.31)	2.29	(1.8)	
Count units renter occupied in floodplain	0	(0)	0	(0)	
GO-Zone Act in Effect	11	(6.28)	5.39	(12.69)	
Errors	HC1		HC1		
Effects	FE		FE		
DF	40,481		40,481		
R2	0.002		0.002		

Notes: This table reports a distributive lag model with county and year fixed effects. Robust standard errors are clustered at the county-level with HC1.

Significance: 0.001 ****; 0.01 **; 0.05 *; 0.1 .