The Economics of Climate Change Adaptation: Infrastructure, Migration, and the Unintended Consequences of Risk Mitigation

Dissertation

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

Kunxin Zhu,

Graduate Program in Agricultural, Environmental, and Development Economics

The Ohio State University

2025

Dissertation Committee:

Sathya Gopalakrishnan, Advisor

Martin D. Smith

Daniela A. Miteva

H. Allen Klaiber

Elena Irwin

Abstract

Climate change has intensified natural hazards, exposing both coastal and inland communities to mounting risk from hurricanes, floods, and rising sea levels. Effective policy responses require a deep understanding of the economic tradeoffs associated with natural hazard mitigation, adaptation, and recovery—particularly how households and communities respond to these events, and how those responses interact across space and time. This dissertation quantifies these interactions across three dimensions—risk reduction from natural capital investment, household mobility, and real-estate dynamics—and shows how they jointly shape community demographics and long-run vulnerability. The applications also span a wide range of risk settings—mangrove-buffered coastlines in a developing country (India), densely developed coastal counties in the United States, and inland flood-plains—and examine both demand-side (migration) and supply-side (renovation) responses to natural hazards. The findings inform policy design by providing new empirical strategies to assess both environmental protection and behavioral responses.

Chapter 2 examines the protective role of mangroves in mitigating cyclone damages in coastal India. Using exogenous variation in cyclone wind fields and high-resolution satellite night lights data, I find that areas with dense mangrove coverage

experience up to 40% smaller declines in night lights following a cyclone, relative to comparable areas without mangroves. I further show that the protective benefits of mangroves vary by local socioeconomic characteristics and exhibit spatial externalities across neighboring areas. These results offer robust, policy-relevant estimates of the ecosystem services that mangroves provide, with implications for coastal conservation and disaster risk reduction in low- and middle-income countries.

Chapter 3 examines how natural disasters shape migration patterns and income inequality across U.S. East Coast households. Using household-level data, I demonstrate an inverted-U relationship between income and migration: low-income households are constrained from moving, high-income households can afford in situ adaptation, and middle-income households are most likely to relocate. Results show that disasters significantly increase out-migration among middle-income households, with little effect on the poorest or richest. Simulations under future climate scenarios suggest that this selective migration will, over time, reduce the share of middle-income residents while concentrating both low-income and ultra-high-income households in hazard-prone coastal regions, thereby amplifying economic inequality in already highly stratified coastal areas.

Chapters 4 shifts focus to inland flooding in the United States. Using the 2008 Iowa flood as a case study, I estimate a regression discontinuity model and show that flood exposure reduces homeownership rates by 10 percentage points in the areas with flood risk information. The decline is driven primarily by incoming residents, who are significantly more likely to rent rather than buy homes in high-risk areas. These results suggest that natural hazards not only affect current residents but also shape future housing tenure decisions, reinforcing patterns of risk exposure across socioeconomic lines.

Chapter 5 examines supply-side responses in Miami-Dade County, Florida following Hurricane Irma. Merging flood extent maps with novel renovation and redevelopment data, I find that flooded parcels are significantly more likely to be renovated or redeveloped after the hurricane. I also find positive neighborhood spillover, which increases housing renovation and redevelopment in unflooded locations. While the results signal accelerated neighborhood recovery in the short-term, it also suggests potential for overcapitalization in coastal low lying areas that face repetitive natural hazard risks.

Overall, this dissertation provides new evidence on the spatial and behavioral dimensions of climate risk in different settings. It highlights the economic value of natural ecosystems in buffering extreme events and reveals how households and housing markets respond to both sudden shocks and gradual adaptation hazard-induced change. These findings offer practical tools for designing equitable, efficient, and forward-looking policies to manage climate risks in both coastal and inland regions.

To my parents, for their endless love and dedication.

Acknowledgments

I express my deepest gratitude to my advisor, Sathya Gopalakrishnan, for her continuous support and invaluable guidance throughout this project. I also thank my committee members—Martin Smith, Daniela Miteva, Allen Klaiber, and Elena Irwin—for their thoughtful feedback and encouragement. I am grateful to Brent Sohngen, Alex Hollingsworth, Liu Bin, Stefan Wrzaczek, Michael Freiberger, Yixuan Wang, Hyeseon Shin, Jongeun Park, Alex Ryan, and numerous seminar and conference participants for their insightful comments and discussions during various stages of this research, including Heartland Environmental and Resource Economics Workshop, Forest and People: From Skyview to Local Dynamics Workshop, Agricultural and Applied Economics Association Annual Meeting, Midwest Economics Association Annual Meeting, AERE Annual Meeting. All remaining errors are mine.

Vita

2018 .... Bachelor of Science, Physics, Nankai University

2020 .... Master of Environmental Management, Duke University

2020–present .... Graduate Associate, Agricultural, Environmental, and Development Economics, The Ohio State University

Fields of Study

Major Field: Environmental Economics, Applied Econometrics, Development Economics

Publications

Gopalakrishnan, S., Malik, K., and Zhu, K., Climate Change and Coupled Human and Natural Systems, Routledge Handbook of Climate Change and Society, 2nd Edition

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

The impacts of global climate change are among the most pressing issues facing society in the 21st century and present unprecedented challenges stemming from complex and interconnected systems. Rising global temperatures have increased the frequency and intensity of natural hazards such as hurricanes, floods, wildfires, droughts, and extreme heat events (IPCC, 2023). These changes contribute to more intense storm systems, accelerate sea-level rise, and shift weather patterns that exacerbate the severity and cost of natural disasters. In the United States, these effects are particularly pronounced, with a steady rise in billion-dollar weather and climate disasters (A. B. Smith, 2020). As these impacts are expected to worsen in the future (Oppenheimer et al., 2014), communities in high-risk regions—especially low-lying coastal areas—will face growing threats and escalating damages.

Coastal zones, which are home to 40% of the global population, continue to experience both the population growth (Maul & Duedall, 2019) and rising economic activity (Kocornik-Mina et al., 2020). The welfare consequences of increasing climate-induced natural hazard events largely depend on behavioral responses in disaster-prone areas. Communities adopt a range of adaptation strategies, including regional investments in protective infrastructure and natural capital, national disaster assistance programs, and individual actions such as private defensive expenditures (e.g., home elevation), relocation, or migration away from high-risk areas. Understanding how households and communities respond to natural hazards, and how those responses interact across space and time is critical for effective policy. This dissertation quantifies these interactions across three dimensions—risk reduction from natural capital investment, household mobility, and real estate dynamics—and shows how they jointly shape community demographics and long-run vulnerability.

1.1 Local Adaptation Investments: Community Infrastructure, Defensive Expenditures, and Relocation

Adaptation is essential for managing the growing risks posed by extreme weather events, rising sea levels, and other climate-related hazards. These strategies can be broadly categorized into three complementary approaches: community-level investments, private adaptation in place, and household relocation decisions. Community-level investments include investment in 'gray' and 'green' infrastructure. Investments in gray infrastructure or built capital include dams, levees, seawalls, beach nourishment and supporting institutions such as early warning systems and hazard assistance programs. Green infrastructure or investment in natural capital includes restoring wetlands, mangroves, and other ecosystems that absorb floodwaters, curb erosion, and blunt storm surge at lower long-run cost. Household in situ adaptation strategies, such as reinforcing or elevating structures, flood-proofing utilities, and purchasing hazard insurance, allow households to manage risk that public investment cannot eliminate. Finally, relocation or migration, though often a last resort, removes households entirely from high-risk zones (Hoffmann et al., 2022). Each of these approaches has distinct economic trade-offs, and their interactions shape both the efficiency and equity of climate hazard adaptation.

1.1.1 Community-Level Investments

Community-scale adaptation includes engineered ("gray") infrastructure, disaster assistance programs, and ecosystem-based ("green") investment. Built infrastructure, such as levees, seawalls, and beach nourishment, helps stabilize the shoreline by providing a physical barrier against erosion and storm surge. Hedonic studies show that protection benefits from levees (Fell & Kousky, 2015; Georgic & Klaiber, 2022), seawalls (Jin et al., 2015), and beach nourishment (Qiu & Gopalakrishnan, 2018) are capitalized into housing values, with price premiums typically between 5% and 20% (Beltrán et al., 2018; Dundas, 2017; Kelly & Molina, 2023; Kim, 2020). Yet amenity values from beach quality often dominate risk-reduction premiums, though hardened structures also generate negative spillovers. For example, seawalls may accelerate erosion on unprotected properties (Brucal & Lynham, 2021; Ells & Murray, 2012). By lowering risk perception, public investments in adaptation infrastructure also induce migration into hazard-prone areas (Husby et al., 2014), accelerate new development (Li et al., 2023), and reduce uptake of private insurance (Vinnakota & Ziff, 2024), and mask sea level rise vulnerability (McNamara et al., 2024).

Community-level adaptation also includes institutional investments such as federal hazard assistance programs and early warning systems. While they do not prevent hazards, such programs help mitigate damages by enhancing preparedness, response, and recovery (Basher, 2006). While early warning systems have been shown to significantly reduce fatalities, they can also raise economic damages by enabling greater capital accumulation in vulnerable coastal regions (Botzen et al., 2019; Coronese et al., 2019; Sadowski & Sutter, 2005). Disaster aid shows similar moral hazard effects (Lewis & Nickerson, 1989). Federal disaster assistance increases net in-migration to hazard-prone counties (Henkel et al., 2022) and reduces enrollment in the National Flood Insurance Program (Kousky et al., 2018), ultimately lowering aggregate output by as much as 20% through spatial misallocation of population across time.

In recent years, there has been increasing recognition of the role that natural ecosystems can play in mitigating the effects of climate-induced hazards. Wetlands, forests, mangroves, and other types of natural capital provide cost-effective buffers by absorbing excess rainfall and reducing the speed and volume of floodwaters (Taylor & Druckenmiller, 2022), stabilizing slopes to prevent landslides (Grilli et al., 2020; Notaro & Paletto, 2012), and by dissipating wind and wave energy (Hochard et al., 2019). Compared with traditional gray infrastructure, these investments in natural capital generate multiple co-benefits, including biodiversity conservation, carbon sequestration, and shoreline stability. Valuation studies of ecosystem services suggest high benefit-cost ratios (Dundas, 2017; Taylor & Druckenmiller, 2022), strengthening the economic case for integrating green solutions into community-level adaptation portfolios.

Together, these studies highlight a policy tension: community-level investments can simultaneously reduce direct hazard losses and incentivize behavior that increases future exposure to hazard risk. Efficient adaptation policy therefore requires accounting for both the protective benefits and the behavioral feedback they induce.

1.1.2 In Situ Household-Level Adaptation

Households that remain in hazard-exposed areas manage residual risk through two main channels: risk-transfer instruments (principally flood insurance) and property-level defensive expenditures. Empirical studies of the U.S. National Flood Insurance Program (NFIP) shows that enrolment is driven largely by lender-mandated purchases; voluntary take-up stays low even in high-risk zones because many residents underestimate their exposure (Bakkensen & Barrage, 2021; Kousky & Michel-Kerjan, 2017). While the overall uptake rate is low, subsidized premiums are viewed as an amenity, as places with lower NFIP premiums witness increase in incoming migrants and housing demand (Peralta & Scott, 2024). On the other hand, a significant share of NFIP claims occur outside of mandatory flood zones. This pattern is consistent with high-income households—who are better able to afford flood insurance and more likely to access flood risk information—choosing to voluntarily participate in the program (Bradt et al., 2021; Kousky & Michel-Kerjan, 2017). Realization of natural hazard shocks temporarily increases in risk perception and NFIP uptake, but the effect generally dissipates within a decade (Gallagher, 2014).

Households also adapt through direct mitigation investments, such as elevating properties, installing backflow flaps, or home upgrades to protect against wind damage. These ex-ante mitigation measures yield substantial benefits (Davlasheridze et al., 2017; Simmons & Sutter, 2007) and are capitalized into housing prices (Atreya et al., 2013; Dumm et al., 2011). Although the empirical literature on the decision-making process for private defensive investments remains thin, evidence from the United States, Germany, and Bangladesh confirms that households invest in private hazard mitigation (Andor et al., 2020; Mahmud & Barbier, 2016; Petrolia et al., 2015). Moreover, the option value of such investments is also reflected in property markets—for example, the eligibility to build private seawall in Oregon can result in a price premium exceeding 10% (Dundas & Lewis, 2020).

Investments in defensive measures and insurance enrollment demonstrate how household choices complement community-level actions, with important implications for both risk distribution and housing market outcomes.

1.1.3 Household Relocation and Managed Retreat

Migration is often framed as one of the direct forms of household adaptation to increasing natural hazard risk. However, while leaving the hazard zone may eliminate exposure, voluntary migration remains relatively rare due to the high costs of relocation—including disruptions to employment, social networks, and housing stability (Bohra-Mishra et al., 2014; Cattaneo et al., 2019; Dell et al., 2014). Consistent evidence of hazard-induced migration is seen in rural agricultural regions, where droughts and repeated extreme weather events undermine local livelihoods and reduce labor demand, leaving migration as a necessary last-resort strategy (Hoffmann, 2022; Hornbeck, 2012). By contrast, the effect of sudden-onset disasters like floods and hurricanes on migration are mixed and often temporary (Bohra-Mishra et al., 2014).

Recognizing the limits of adaptation in place, policy makers have turned attention to managed retreat – the strategic, often subsidized, relocation of people and assets away from high-risk areas (Siders et al., 2019). In practice, managed retreat often takes the form of voluntary buyouts and property acquisition programs, where relocation decisions are left to individual households (Hino et al., 2017). While such programs have been implemented in the aftermath of major disasters, uptake tends to be higher among lower-income residents in relatively wealthier jurisdictions, raising concerns about the equity and inclusiveness of locally driven retreat policies (Mach et al., 2019). Buyouts can also impose disamenity effects on surrounding neighbors, resulting in up to 20% decline in housing values (Hashida & Dundas, 2023). These findings underscore the importance of system thinking in climate adaptation, as migration and relocation decisions interact with broader housing market outcomes, community composition and local provision of public goods that shape both social welfare and future risk.

1.2 Adaptation and Resilience: Unintended Consequences of Localized Decisions

Household- and community-level adaptation strategies are shaped by local socio-economic conditions and, in turn, influence a community's vulnerability or resilience to future hazards. Short-term, localized disaster responses can become maladaptive in the longer term, increasing future exposure to hazard risk and cascading damages. For example, if homeowners relocate after a natural hazard event (Chapter 4), high-risk regions can shift toward renter communities, which are more vulnerable to future hazards due to lower investment in public amenities (Hausman et al., 2022). On the other hand, if people underestimate hazard risks and continue to convert natural protective features—such as wetlands and mangroves—into residential developments (Aronoff & Rafey, 2023) or farmland (Nasrin et al., 2023), such land-use changes are likely to increase both exposure and vulnerability to future hazards. Similarly, community-level investments in local adaptation, like beach re-nourishment, can accelerate economic development by stabilizing or increasing property values (Lazarus et al., 2018; Li et al., 2023; Qiu & Gopalakrishnan, 2018), and thereby reinforce incentives to maintain and continue to inhabit low-lying coastal regions.

Figure 1.1: Four hypotheses on natural hazard resilience in short-term (Adopted from S. Hsiang and Jina (2014))

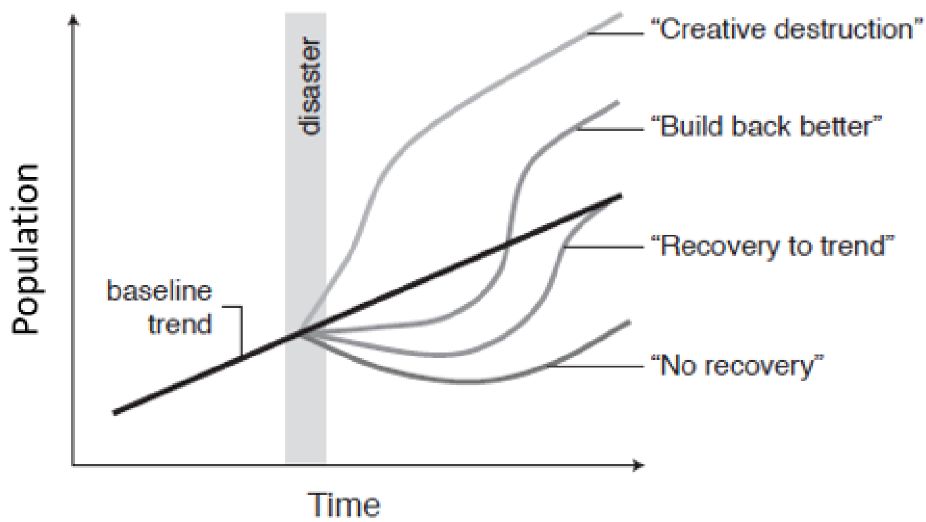


Figure 1.1. presents four classic hypotheses about short-term economic outcomes after a natural hazard, each highlighting different potential pathways for post-disaster adaptation (S. Hsiang & Jina, 2014). The two interesting pathways—"creative destruction" and "build back better"—highlight scenarios in which natural hazards can

ultimately foster net long-run economic growth through forced capital replacement, improved infrastructure, or strategic planning, reflecting local resilience and adaptability (Hornbeck & Keniston, 2017). However, resilience observed over the short term (months to years) may mask longer-term maladaptive trends (decades to centuries), especially in regions facing recurring stressors like low-lying coastal regions (Lazarus et al., 2018).

A classic example of such maladaptation is reflected in the "levees effect", where the construction of levees can induce additional economic development in flood prone area, potentially resulting in heightened damage from future flooding events (Kates et al., 2006; Kydland & Prescott, 1977; White, 1942). These dynamics are further complicated by positive feedback loops and the co-evolvement of human and natural systems where growing population justifies higher protection levels, which in turn attracts more settlement (Di Baldassarre et al., 2015). Over time, this dynamic can result in lock-in conditions, where hazard-prone regions become highly exposed yet difficult to abandon due to their accumulated infrastructure and social value (Grames et al., 2016).

Empirical evidence suggests that post-disaster assistance indeed can lead to such feedback loops, as investments in defensive infrastructure and post-hazard assistance can act as economic stimuli that attract more populations and economic activities to hazard-prone regions (Fu & Gregory, 2019; Henkel et al., 2022; Husby et al., 2014; Li et al., 2023). As these areas become increasingly populated by households with limited incentives for self-protection and insurance (Vinnakota & Ziff, 2024), the potential natural hazard risks might outweigh the agglomeration benefits from concentrations of population (Henkel et al., 2022; Hsiao, 2023).

Understanding feedbacks at different spatial and temporal scales is therefore crucial to evaluate the unintended consequences of different adaptation policies. Effective climate adaptation must go beyond immediate recovery metrics and instead focus on long-term resilience, accounting for system-wide interactions and potential lock-ins. Without an integrated systems perspective, it becomes difficult to assess which short-term trends after natural hazards can lead to long term resilience.

While some cities recover after disasters, and eventually return to or exceed pre-disaster growth trends following natural hazards (Kocornik-Mina et al., 2020), not all areas follow this path. In some cases, natural hazards result in permanent population losses and productivity declines, which at first glance may seem detrimental. Yet, such declines can also signal a rational retreat from high-risk areas, potentially leading to more sustainable regional development patterns. Net outmigration may, therefore, support long-term resilience by reducing exposure and reallocating resources to safer regions. The socially optimal, welfare-maximizing recovery path is therefore an empirical question that is likely to vary with local conditions and policy design.

1.3 Scope of this Dissertation

This dissertation investigates adaptation to natural hazards across three dimensions—risk reduction for natural capital investment, household location decisions, and real-estate market outcomes—and how those choices reshape community vulnerability over time. The overarching goal of this research is to examine behavioral responses to natural disasters and the implications for local vulnerability against future hazards. How does the impact of hazards vary across space and to what extent can investments in natural capital mitigate damages from natural hazards? How do natural hazards affect human mobility and the demographic composition of communities in regions with high risk? How do disaster-induced adaptation responses affect patterns of real estate development? Should disaster relief resources be utilized for reconstruction in risky disaster affected areas or organizing retreat to safer locations? To address these policy-relevant questions, I examine the impact of natural hazards on economic activity, human mobility, community composition, and real estate development in three settings – the effect of mangroves in coastal risk mitigation in India, hazard-induced migration in the U.S. East Coast, the impact of inland-flooding on community composition, and the effect of hazards on re-development patterns in coastal communities in the U.S.

First, I explore heterogeneity in the impact of coastal hazards and the benefits of protective natural capital in mitigating damages – specifically, the role of coastal trees (mangroves) as a bioshields against cyclones in India. While engineering approaches such as sea walls can protect the coastal areas, they can be costly and have negative impacts on the environment (Temmerman et al., 2013). Nature-based solutions have therefore gained recognition for being both economically viable, and as a sustainable climate adaptation strategy (Menéndez et al., 2020). Leveraging village-level cyclone damage data from India and an instrumental variables design to account for the endogenous distribution of mangroves, I estimate the hazard mitigation benefits of mangrove forest cover around a village. I show that the benefits depend on the extent (width) of mangrove cover and, in the average village, three miles of mangroves can mitigate all cyclone damage. However, the benefits are heterogeneous, with largest gains accruing to poorer, infrastructure deficient regions. This work provides evidence that natural capital investments are critical to support local economies in low- and middle-income countries.

Second, I examine household-level behavioral responses to natural hazard events through voluntary migration decisions and examine the impact of these responses on longer-term economic inequality in coastal regions. Using exogenous variation in hurricane-induced wind damage along the U.S. Atlantic and Gulf Coasts, I estimate the causal effect of natural hazard exposure on migration decisions across income groups. I show an inverted-U shaped relationship between income and migration: hurricane-affected regions experience higher outmigration among high-income households, while low-income residents are unable to move out and households in the top-1-percentile income group are more likely to adapt in situ, resulting in increased local income inequality. Simulations using synthetic hurricane data and historic migration networks suggest that repeated hurricane exposure can exacerbate economic inequality over time.

I then combine relocation decisions with tenure choice to examine how inland flooding affects community composition through changes in homeownership rates. Using a regression discontinuity design at the inundation boundaries of the 2008 Iowa Flood, I find that homeownership rates declined by up to 9% in flooded areas, with the major effects observed in regions where flood risk information was already available. Though this effect fades after four years, I also show, using staggered-difference-in-difference model, that localized effects can lead to county-level shifts in community composition. A decomposition analysis shows that the change is driven by the influx of renters into flood affected regions. Because renter-dominated jurisdictions and those with higher levels of inequality are typically more vulnerable to natural hazards, such shifts amplify future hazard exposure, indicating the presence of a potential positive feedback loop between natural hazard events and community vulnerability.

Finally, I examine neighborhood spillover effects from post-hurricane renovations in a high-risk, supply-constrained market. Using Hurricane Irma's 2017 landfall in Miami-Dade County as an exogenous shock I show that the storm accelerated renovations and redevelopment in flood-affected areas. Using Irma-induced renovation activity as an instrument, I estimate the effect of neighborhood renovations on the likelihood that an unaffected parcel undergoes renovation. The results also reveal positive neighborhood spillovers, with increased housing renovation and redevelopment in unflooded areas.

Together, this dissertation demonstrates that adaptation responses to natural hazards often interact at different spatial and temporal scales that ultimately determine recovery pathways and community outcomes. Well-designed ecosystem investments can lower direct damages, whereas household migration and tenure adjustments may unintentionally raise long-term vulnerability and inequality. These findings help to inform the policy debate on whether post-disaster resources should prioritize rebuilding in place or facilitate retreat to safer ground.

Chapter 2: Mangroves help mitigate cyclone damage in India

Climate change has increased the frequency and intensity of tropical cyclones, making coastal regions especially vulnerable to damages to life and property. Consistent with this global trend, there is an observed rise in intense (category 4 or higher) cyclones along the east coast of India (Bacmeister et al., 2018), where the frequency of cyclones has increased by around 50% since the beginning of the 21st century (Balaji et al., 2018; Deshpande et al., 2021). As coastal population continues to grow (Maul & Duedall, 2019), safeguarding coastal communities and infrastructure has become an urgent priority in India.

2.1 Mitigating natural hazard damage by community investment in natural capital

In the US, much of the literature emphasizes the dual amenity and protective value of natural capital. The existing evidence supports the notion that investment in natural capital such as wetlands and forests can provide protection to properties from flooding (Taylor & Druckenmiller, 2022), hurricanes (Sun & Carson, 2020) and sea level rise (Rezaie et al., 2020). In addition to their protective function, natural infrastructure projects like dunes and beach nourishment are valued for enhancing natural amenities, including increased beach width and scenic views (Dundas, 2017; Qiu & Gopalakrishnan, 2018). In contrast, conventional coastal engineering solutions, such as building seawalls and dikes, can exacerbate coastal erosion in nearby areas and harm natural landforms (Rangel-Buitrago et al., 2018), reducing overall amenity value (Brucal & Lynham, 2021; Dundas & Lewis, 2020).

In addition to their environmental drawbacks, these "hardened" structures are expensive to build and maintain, making them less viable in economically disadvantaged regions facing increasing hazard risk (Hinkel et al., 2014). Nature-based solutions have, therefore, gained greater attention for being an economically viable, environmentally friendly (Temmerman et al., 2013), and a sustainable climate adaptation strategy in the long term, particularly in developing countries such as India (Menéndez et al., 2020; Shah & Ramesh, 2022). Such solutions include investments in natural capital like mangroves – shrubs and trees that grow in brackish waters along coastlines and tidal rivers in tropical regions – to mitigate the impact of coastal hazards and to sequester and store carbon. After the catastrophic Asian tsunami in 2004, mangroves were recognized as "bioshields" due to observed differences in impact between regions with and without existing mangroves (Barbier et al., 2008; Danielsen et al., 2005). Mangroves can decrease wave action (Loder et al., 2009) and wind speed (DasGupta & Shaw, 2013), thereby mitigating the potential damage from cyclones and storms. Because they are effective investments in climate adaptation and mitigation, there is growing public interest in mangrove restoration projects in India: Mangrove regeneration programs are recognized as a key conservation pathway in several states, including Tamil Nadu (Sekhsaria, 2021), West Bengal, Odisha, and Gujarat (Dubey et al., 2019; Shah & Ramesh, 2022).

Though there is consistent policy emphasis on mangrove preservation and restoration projects in India (Shah & Ramesh, 2022), few studies have quantified the economic value of the ecosystem services reflected in hazard mitigation. Early empirical analysis shows that mangroves mitigate the impact of tropical cyclones by saving human lives or reducing fatality risk (Das & Vincent, 2009) but, the study is limited to one state (Odisha) and estimates ignore the impact on other economic activity. Other studies estimate mitigation effects from mangroves and wetlands at global scales (Hochard et al., 2019, 2021), but ignore heterogeneity across and within countries. Thus, existing estimates are likely not representative in India, especially considering the significant differences in cyclone frequencies, density of mangroves, and population distributions within India (Deshpande et al., 2021; Kandasamy, 2017). Spatially explicit evaluation of the benefits of mangroves in mitigating hazards is a key first step to inform better mangrove investment decisions in India.

2.2 Endogeneity of mangrove distribution

India hosts an extensive and diverse mangrove areas along the coastline spanning 12 states, including 4,992 sq. km of mangrove forests and surrounding mangrove wetlands. Over 42% of mangroves are located in the Sundarbans in the eastern Bay of Bengal delta region, and together with mangroves in Odisha, Andhra Pradesh, and Tamil Nadu, almost 57% of mangroves in India are on the east coast (Forest Survey of India, 2021). While Gujarat and the Andaman and Nicobar Islands also have large areas of mangroves, I do not include the west coast area because of different cyclone characteristics. I also exclude Andaman and Nicobar Islands because of their distinctive geographic location. Therefore, our study area is the eastern coastline (Figure 2.1), which is conducive for mangrove habitats because of the relatively flat shoreface in intertidal areas characterized by shallow brackish water bodies and a complex network of tidal creeks and canals (Selvam, 2003).

The current extent of mangroves is only a modest fraction of the historical mangrove habitat. During 1960s, India had a mangrove cover of about 6,000 sq. km, which reduced to 4,046 sq. km in 1987 (Kandasamy, 2017). Mangrove degradation and destruction was driven largely by increased population pressure including agriculture and increasing aquaculture production (Suresh & Sahu, 2015; Yamamoto, 2023), pollution from local industrial development (Agoramoorthy et al., 2008), urban development in coastal regions (e.g. Paradip port), along with ecological pressures (Giri et al., 2015). This trend began to reverse after mangrove habitats were classified as national parks or wildlife sanctuaries under the Indian Forest Conservation Act of 1980 and the Wildlife Protection Act of 1972. Moreover, during the same period, multiple community-based management initiatives were created to support the sustainable use of mangrove resources, which helps to maintain the mangrove habitats till now (DasGupta & Shaw, 2013).

The current distribution of mangrove forests is therefore shaped by the suitability for mangrove habitats, population growth and economic development, and the endogenous selection of areas for mangrove protection and community management. To address the endogeneity in the location of mangroves, I instrument for the current distribution of mangroves using the mangrove distribution in 1944. Following Das and Vincent (2009), I retrieve historical mangrove habitats based on digitized India and Pakistan maps at 1:250,000 scale for historical mangrove designation (Service, 1955). Although the map was published in 1955, it was derived from ground surveys conducted between 1929 and 1931 and aerial photographs from 1944 (Das & Vincent, 2009), which predates coastal development and mangrove degradation during the 1960s and following mangrove conservation efforts.

Using the instrumental variable approach, I quantify the cyclone mitigation benefits of mangroves by analyzing 27 cyclone events that affected the eastern coast of India between 2012 and 2019. I make three new contributions to the literature. First, I add to the literature on the benefits from natural capital by quantifying the storm protection mitigation by mangroves in India. Second, our work examines two types of heterogeneity in the economic impact of cyclones-wind speeds and socio-economic conditions on the ground. Finally, I examine spillover effects across villages with mangroves and surrounding villages without mangroves.

2.3 Wind damage model for exogeneous cyclone damage

Following S. Hsiang and Jina (2014) and Pelli et al. (2023), I develop a village-level cyclone damage index from interpolated local wind speed using the International Best Track Archive for Climate Stewardship dataset (Knapp et al., 2018). The dataset contains cyclone tracks and windspeed in 3-hour intervals. In this analysis, I restrict our sample to all cyclones with wind speed above 33 knots that affected India between 2012 and 2019. I start by interpolating each cyclone track into waypoints that represent cyclone eye location and corresponding wind speed in 30-minute intervals. Then, following Pelli et al. (2023), I compute the village-level local wind speed using the following wind field model:

$$w_{pv} = e_p \left(\frac{D_{pv}}{26.9978} \right) \; if \;\; D_{pv} \leq 26.9978 \tag{2.1}$$

$$w_{pv} = e_p \left(\frac{D_{pv}}{26.9978} \right)^{-0.5} \; if \;\; D_{pv} > 26.9978 \tag{2.2}$$

where w_{pv} is the local wind speed in village v because of waypoint p, e_p is the wind speed for each way point p and D_{pv} is the distance between way point and villages in miles. The formula suggests that the wind speed increase linearly to the maximum at the distance cutoff and then slowly decreases with higher distances. This pattern correspond to the idea that cyclones have relative calm inner ring and wind speed reach the maximum at certain radiuses (Deppermann, 1947).

I assume that physical damage is a quadratic term of difference between local wind speed and the 33 knots threshold. I choose 33 knots as the threshold instead of 50 knots (Emanuel 2011) because infrastructure and built environment in rural villages in India are vulnerable to minor cyclones, reflecting the vulnerabilities commonly observed developing country contexts[1]. As a result, I generate the normalized cyclone damage index C_{vt}

$$C_{vt} = \sum_{p \in T} \frac{(w_{pv} - 33)^2}{(113 - 33)^2} \; if \; w_{pv} > 0 \tag{2.3}$$

by summing all way points p within each year t. Specifically, I normalize the wind damage at the category-4 equivalent cyclone level. Thus, our cyclone damage index should be interpreted as the number of hours for category-4 equivalent cyclone damage.

2.4 Data

Using village-level boundaries from the Socioeconomic High-resolution Rural-Urban Geographic (SHRUG) data platform for India (Asher et al., 2021), I construct an annual panel dataset covering coastal villages from 2012 to 2019. I choose this time frame due to data availability and to limit any potential confounding economic effects of the COVID-19 pandemic after 2019. I define coastal villages as those within 15 kilometers from the shoreline. I exclude 115 island villages which are outside the shoreline since the effect of cyclones on island villages can be significantly different

[1]In robustness tests, I change the threshold to 33, 50, and 64 knots. I also use a cubed damage function, since the density of cyclone energy is the cubic term of local wind speed (S. M. Hsiang, 2010). Our results are robust to all different wind field models.

from villages along the contiguous coast. I also exclude all villages in West Bengal due to the Sundarbans National Park protected mangrove region in West Bengal[2].

I rely on the 2011 Indian census dataset to obtain the socio-economic characteristics of the rural villages (Office of the Registrar General and Census Commissioner, India, 2011). Because many data fields are missing for rural areas, particularly for villages that only have village directory data,[3] I restrict the sample to villages that have more than 30% male and drop villages with 0% children younger than 6 years of age[4]. Our final sample consists of 6,850 villages along the east coast of India (Table 2.1).

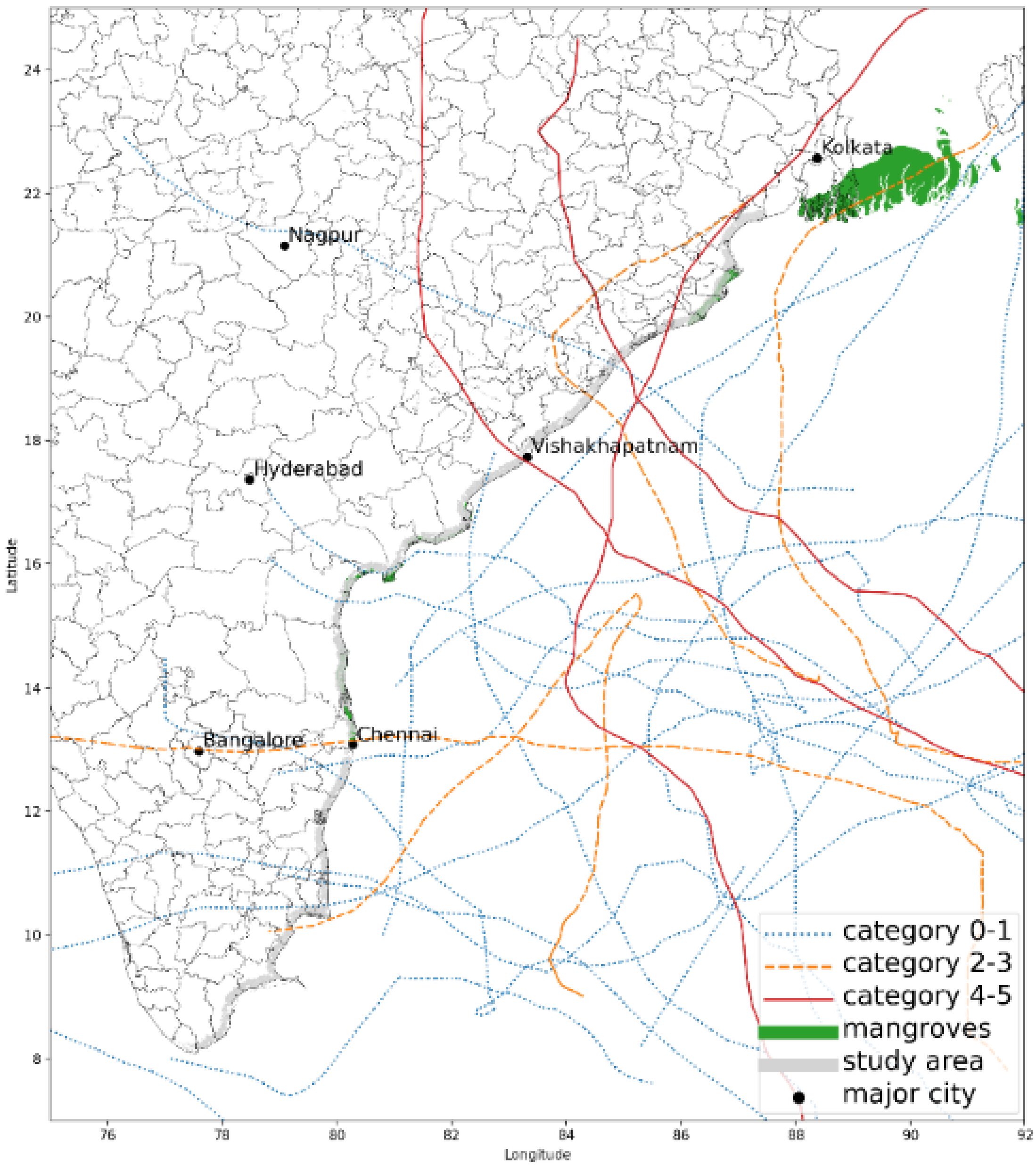
During the study period, 27 cyclones affected the eastern coast of India, including 5 major cyclones (categories 3 or higher). Among all cyclone events in our study periods, 16 cyclones affected areas with mangroves, which provides sufficient spatial variation to estimate the hazard mitigation effects of mangroves (Figure 2.1).

[2]Some villages in West Bengal are protected by over 15 km of mangroves, which are outliers compared to other states where 99% of villages are not protected by more than 3 km of mangroves. Including West Bengal does not alter the results.

[3]For example, some villages reported no male population or no individuals under the age of six.

[4]Results are qualitatively similar if I do not drop outliers.

Figure 2.1: Distribution of cyclone activities (given as lines), mangrove (in green), and east coast villages (in grey)



Note: In this paper, I focus only on rural area in India's East Coast, as indicated by grey area. In our preferred model, I drop villages within West Bengal because extensive mangrove areas within Sundarbans protected forest is not representative for other study areas. I consider only cyclone events that generate local wind speeds above 33-knots in the analysis.

Note: In this paper, I focus only on rural area in India's East Coast, as indicated by grey area. In our preferred model, I drop out villages within West Bengal since protection benefits from extensive mangrove areas within Sundarbans regions might not be representative for other study areas. I do not include cyclone events below category 0 since those cyclones could not generate local wind speed above 33-knot threshold

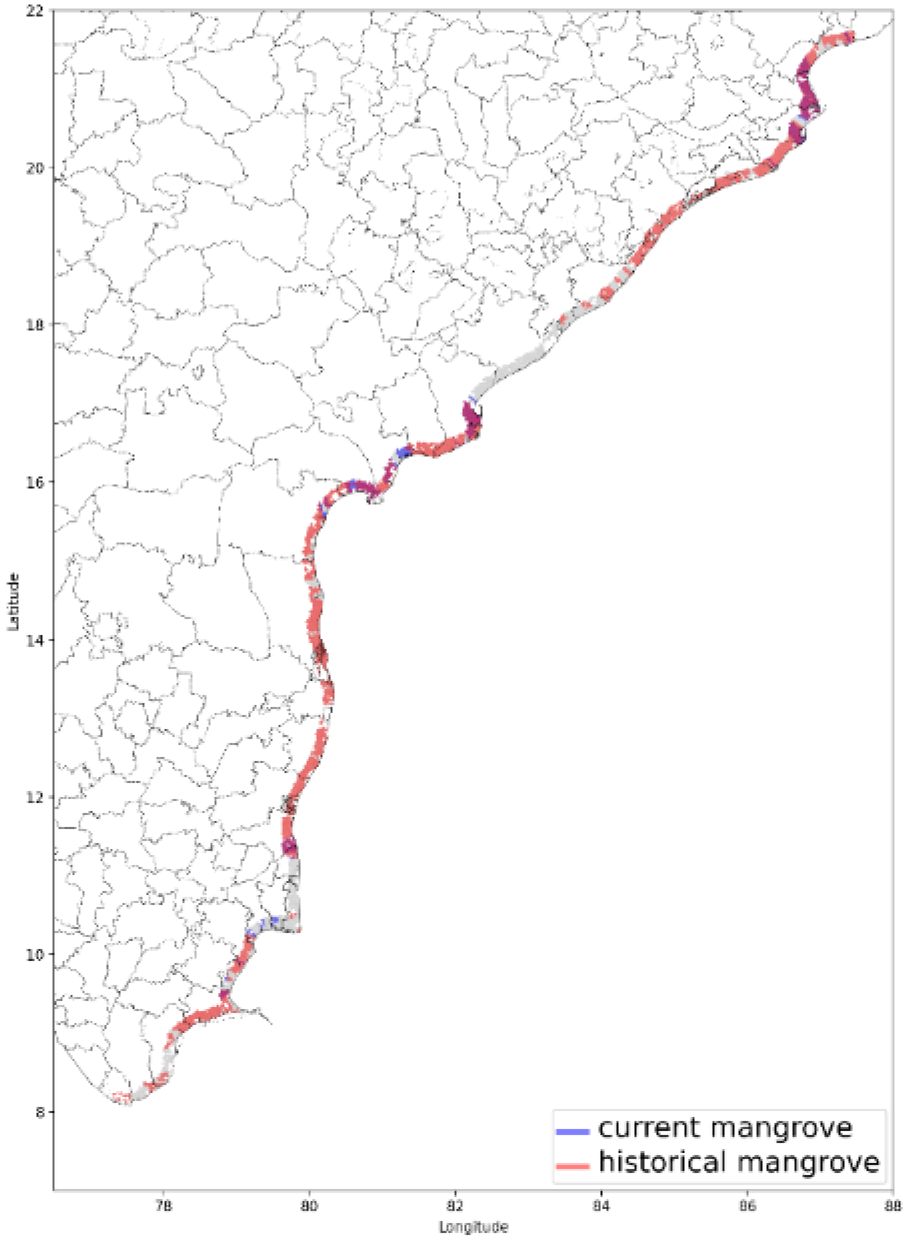
2.4.1 Mangrove

Mangroves have been recognized as a natural bioshield against storms, reducing wind speeds and storm surge due to their intricate root systems and dense canopy structures (Krauss & Osland, 2019; Rahuman et al., 2022). Empirical evidence shows that villages with mangroves experience less wind and wave damage compared to those without (Das & Crépin, 2013). For example, the first 100 meters of mangroves can reduce up to 66% of wave energy, equivalent to the difference between category 3 and category 5 cyclones (Liu et al., 2013; Spalding et al., 1997). However, mangroves can themselves also be affected by cyclones. A category-3 cyclone can induce extreme visible changes in mangrove forests, leading to broken stems and knocked-down trees. For cyclones with category 4 or higher, the dominant trees are often felled (Krauss & Osland, 2019). Therefore, to quantify the mitigation benefits, I use the width of mangroves from villages to the nearest boundary of the exclusive economic zone, measured in the year prior to the cyclone, to account for temporal variation, as mangrove cover can change due to cyclone impacts (Das & Vincent, 2009; Laso Bayas et al., 2011)

To capture the spatial and temporal distribution of mangroves on India east coast, I assemble annual active mangrove data at 30m resolution (Vancutsem et al., 2021), accounting for long-term loss, degradation, and regrowth. While our data capture both mangrove forests and shrubs, since around 85% of India's mangrove habitat exceeding 5 meters in height (Bunting et al., 2018), our result should be interpreted as the mitigation effects of mangrove forests on cyclone damage. To control for endogeneity, I construct instrumental variables based on historical mangrove extents. Specifically, I use the 1944 map of forests and wetland vegetation in intertidal regions, estuaries, and river deltas to define historical mangroves[5] (Service, 1955). I verify this classification, finding that the mangrove coverage in 1944 aligns closely with the mangrove forest areas identified in 1985 and 1996 (Bunting et al., 2018; ROY et al., 2016). The historical mangrove areas are positively correlated with the current mangroves (a Pearson correlation coefficient of 0.637 statistically significant at the 0.0001%). Exceptions include the Pulicat Lake and Chilika Lake regions, where most historical mangroves have disappeared since 1944 (Mishra SP, 2023). Overall, the historical mangrove areas serve as a credible proxy for the potential extent of current mangrove forest cover (Figure 2.2).

[5]Since the map does not distinguish forests and wetland vegetation in intertidal region, estuaries, and river deltas, I classify them all as mangroves.

Figure 2.2: Distribution of villages directly protected by mangrove in 2010 and in 1944



2.4.2 Night light intensity

I use nightlight intensity data from the Visible Infrared Imaging Radiometer Suite (VIIRS) as a proxy for village-level economic development (Elvidge et al., 2017). Nightlight intensity is reported at 15 arc second (~500 m) resolution at monthly level. The night light data are filtered to restrict background noise, solar and lunar contamination, cloud cover, and features unrelated to electric lightning such as fires and flares (Elvidge et al., 2017). Moreover, since VIIRS data are retrieved from a single satellite system after 2012, I avoid the consistency concern regarding the Defense Meteorological Satellite Program (DMSP) night light data retrieved from multiple satellites. Moreover, with finer spatial and temporal distribution, changes in night light data can detect damages and power outages caused by cyclones and flood events (Zhao et al., 2018).

Night lights data can serve as a good proxy for local electrification as well as development, especially in rural areas (Chanda & Kabiraj, 2020; Dugoua et al., 2018; Mirza et al., 2021; Singhal et al., 2020): Multiple studies indicate that night light data can capture cross sectional distribution of economic activity at subnational levels under the assumption that light is a normal good (Donaldson & Storeygard, 2016; Sutton et al., 2007). In the Indian context, empirical studies find consistent evidence of high correlation between night light intensity and local GDP, population density, and rural electricity in a time series analysis (Asher et al., 2021). However, because nightlight data are correlated with multiple economic indicators (e.g. population, employment, consumption, electricity usage), it is hard to isolate specific measures of economic impact (Asher et al., 2021). As a result, following the literature (del Valle et al., 2020; Henderson et al., 2012; Kocornik-Mina et al., 2020), I interpret our result as the impact on local economic activity. This interpretation is further supported by the fact that both population and electrification tend to change gradually over time. As a result, sudden changes in night light intensity are more likely to reflect short-run or marginal shifts in economic output rather than long-term structural change.

In this study, I derive annually varying night light intensity using night light data from December. In the eastern coast of India, cyclone events typically occur between May and November, resulting in heterogeneous impacts on year-end night light intensity. However, because the occurrence of cyclones is randomly distributed within a cyclone season and across space, variation in the cyclone timing does not bias our estimation (See appendix A for detailed discussion). To address concerns about the quality of the data, I first restrict our sample to rural areas. This is to limit concerns that nightlight data might not be consistent across urban and rural areas. To test whether nightlight is a reliable measure of economic activity, I calculate the correlation between nightlight data and the state-level agricultural sector contribution to the gross domestic product (GDP): I find 93.6% correlation with elasticity of 0.837, suggesting high correlation between nightlights in rural area and rural GDP. Following (Kocornik-Mina et al., 2020), I interpret differences in nightlight as differences in local economic activity.

2.4.3 Other data

I further supplement the village-level panel dataset with geological and socio-economic characteristics (Table 2.1). Specifically, I include the average number of hours of electricity available per day to capture baseline electrification in the village. I also include a wide array of socio-economic characteristics that could affect vulnerability to natural disasters such as cyclones and flooding (Bhattacharjee & Behera, 2018).

While there are differences between villages located in historical mangrove areas and those that are not (Table 2.1), exposure to cyclones varies between these areas. Therefore, our identification assumption is that historical mangrove distribution affects current cyclone damage only through the distribution of current mangrove forests, after controlling for bathymetric conditions (e.g., slope of the shoreface to continental shelf). Further, when comparing villages historically protected by mangroves, I find that areas with mangrove degradation since the 1960s tend to have higher night light intensity, higher population density, and a higher proportion of agricultural workers. This indicates a positive correlation between mangrove degradation and economic growth.

Table 2.1: Summary statistics

Variable	Villages with mangroves	SD	Villages without mangroves	SD	Difference
Log nightlight	1.557	1.260	1.932	1.290	-0.375***
Cyclone index	0.552	1.207	0.567	1.126	-0.015
Mangrove width (km)	0.282	1.053	0.007	0.051	0.276***
Population density (1000s/sq km)	0.509	0.839	0.416	0.534	0.094***
Distance to nearest town (log km)	2.098	0.792	1.850	0.736	0.248***
Percentage male	0.503	0.022	0.499	0.021	0.004***
Percentage younger than 6	0.111	0.026	0.109	0.023	0.003***
Percentage scheduled caste	0.250	0.244	0.225	0.234	0.025***
Percentage ag worker	0.197	0.128	0.222	0.139	-0.025***
Monthly precipitation (mm)	113.900	22.100	102.400	22.570	11.540***
Distance to shoreline (km)	8.627	3.955	7.698	4.144	0.929***
Baseline electricity hours (2011)	9.031	7.888	12.490	6.517	-3.460***
Dist. to shelf/20m-depth bathymetry (km)	1.369	1.346	1.048	1.056	0.320***
Log area (sq. m)	14.440	1.152	14.850	1.099	-0.407***
Elevation (m)	11.970	14.280	17.630	21.710	-5.656***
Percentage landowner	0.418	0.278	0.304	0.232	0.114***
Pct. with monthly income > 10k INR	0.053	0.074	0.046	0.078	0.007***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2.5 Estimation using Instrumental variables approach

2.5.1 Estimating the cyclone damage

First, I estimate the impact of cyclones on night light intensity at the village level using a pooled OLS model:

$$lnNL_{vt} = \alpha + \beta C_{vt} + \gamma X_{vt} + \delta_{sd} + \eta_t + \epsilon_{vt} \tag{2.4}$$

where $\ln NL_{vt}$ is the natural log of the average nightlight intensity in village v in year t. The right-hand side covariates include the cyclone damage index (C_{vt}) constructed based on local wind speed. X_{vt} includes average precipitation level in each village v and year t, and village-level baseline socio-economic indicators from 2011 census including percentage male population, percentage population younger than age six, share of agricultural workers and hours of electricity available per day. I include subdistrict-level (indicated by δ_{sd}) spatial fixed effects to control for time invariant unobservables and year fixed effects, η_t, to control for year-specific conditions that affect the study area uniformly. Thus, our identification assumption is that timing of cyclone events is random conditional on subdistrict fixed effects. In our preferred model, I cluster the standard errors at village level (Abadie & Spiess, 2022).

2.5.2 Spillover effects

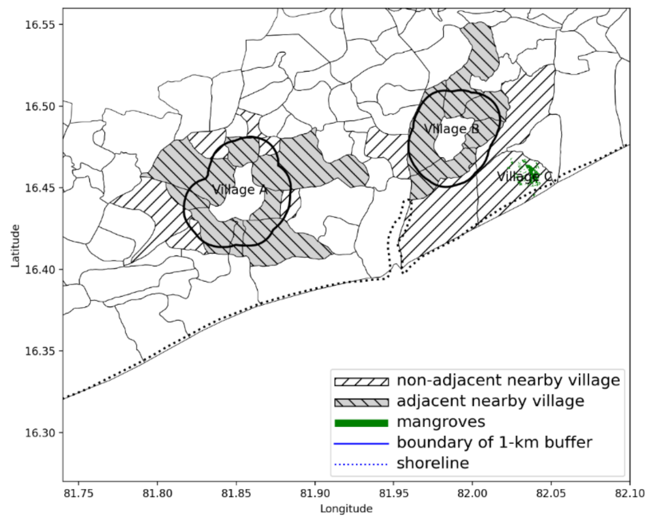
In addition to the direct hazard mitigation benefits in villages with wide mangrove cover, surrounding villages are likely to experience spillover effects. On one hand, villages not immediately adjacent to mangrove forest may also experience reduced cyclone impact and, thus, smaller impact on economic activity. Conversely, households impacted by cyclones may migrate to nearby areas less affected by the natural hazard (Osama, 2023). Consequently, villages adjacent to the ones directly protected by mangroves might witness a decrease in nightlight intensity, reflecting a reduction in economic activity and population as people relocate to villages sheltered by mangroves. For these reasons, the overall net spillover effect of mangroves cannot be signed a priori and is an empirical question.

To test the spillover effects of mangroves in mitigating cyclone damage, I exclude villages that are directly protected by mangroves in the study period and examine whether villages not directly protected by mangroves, but adjacent to protected ones, are less impacted by cyclones. Specifically, I model the extent of nearby mangrove protection by the maximum mangrove width within 1-km radius from a village that is not immediately adjacent to a village with mangroves. As shown in Figure 2.3, the mangrove width near *Village b* is equal to the maximum mangrove width among all the white-shaded villages, which equals to the mangrove width protecting *Village c*.

$$\text{Ln}NL_{vt} = \alpha + \beta_0\ C_{vt} + \beta_1 C_{vt} S_v + \beta_2 C_{vt} NM_{vt-1} + \beta_3 C_{vt} Bathy_v + \beta_4 NM_{vt-1} + \gamma X_{vt} + \delta_{sd} + \eta_t + \epsilon_{vt} \tag{2.5}$$

where NM_{vt-1} is nearby mangrove width for village v in year $t-1$. I use the same set of covariates in X_{vt} as in the main specification. Because I do not observe variation in mangrove width in locations that do not have mangrove cover, I am not able to instrument for mangrove width in this specification.

Figure 2.3: Illustration for nearby mangrove width calculation



Note: The thick dotted line indicates the shoreline. The thick black buffer lines indicate the 1 km buffer around *Village a* and *Village b*, which are both unprotected by mangroves. Within the buffer, the white areas are non-adjacent nearby villages while the grey areas are adjacent nearby villages. For the spillover model, I test whether cyclones have different impacts on villages near mangrove protected areas (treatment group, *Village b*) compared to villages not near a mangrove protected area (control group, *Village a*). Villages directly protected by mangroves (e.g. *Village c*) are excluded in the analysis.

2.5.3 Quantifying the direct benefits from mangroves

I then quantify the direct benefits from mangrove using a shift-share instrument based on historical mangrove coverage for current mangrove width.

$$\ln NL_{vt} = \alpha + \beta_0\ C_{vt} + \beta_1 C_{vt} S_v + \beta_2 C_{vt} \widetilde{M_{vt-1}} + \beta_3 C_{vt} Bathy_v + \beta_4 \widetilde{M_{vt-1}} + \gamma X_{vt} + \delta_{sd} + \eta_t + \epsilon_{vt} \tag{2.6}$$

where S_v is the distance to shoreline from village v, $Bathy_v$ is average distance from shoreline to the 20m-depth bathymetry contour line, and M_{vt-1} represents mangrove width in village $\boldsymbol{v}$ in the previous year (t-1). I use a one-year lagged measure of mangrove width to minimize bias from contemporaneous damage to mangrove cover from a cyclone that confounds the hazard mitigation impact of mangroves. Specifically, $C_{vt}\widetilde{M_{vt-1}}$ and $\widetilde{M_{vt-1}}$ are jointly determined in the instrumental variables regression.

I measure the extent of mangrove protection by the width of current mangrove cover between the edge of each village and the nearest boundary of the exclusive economic zone. To control for the endogenous mangrove distribution, I use the historical mangrove width in 1944 as an instrument in a shift-share framework (Borusyak et al., 2022). Specifically, I combine annual variation in the total extent of mangrove cover (the "shift") with historical mangrove distribution at the village-level in 1944 (the "share"). The resulting shift-share instrument, reflecting the ratio of variability in mangrove cover relative to its historic share, strongly predicts current mangrove width, while not correlated with mangrove degradation patterns after 1960s and mangrove preservation pattern during 1980s. Thus, the identifying variation is the exogenous variation in historical mangrove width within each subdistrict as well as overall variability in mangrove width across the study period. I use this shift-share instrumental variable to jointly instrument the mangrove width and the interaction between the mangrove width and cyclone index by interacting the instrument with the cyclone index. As a robustness test, I use matching methods to identify mangrove mitigation benefits with similar village characteristics (Appendix A).

I also include an interaction between the distance to the shoreline and the cyclone index as storm surge and wind will have lower damage in inland regions, regardless of the presence of mangroves. Moreover, I use local bathymetric information to assess the intensive margin of mangrove presence. I use distance from the shoreline to the 20-meter bathymetry depth to capture the slope of the shoreface nearest to each village. Since mangroves grow in shallow regions, they are likely to be present where the slope of the shoreface is flatter. On the other hand, cyclones tend to cause larger damage in places with flatter shoreface slopes because of larger storm surge and wider flooding regions.

To mitigate bias from spillover effects, I exclude all villages that are adjacent to villages directly protected by mangroves and villages that are within one kilometer from areas with mangroves based on our spillover effects model results. Similar to the previous specification, I cluster standard errors at village-level and include subdistrict and year fixed effects.

2.6 Results

Table 2.2 shows the local economic impacts of cyclones. Villages on India's east coast darken in the year that cyclones hit,*ceteris paribus*. Specifically, I find that exposure to one additional hour of a standard category-4 cyclone decreases rural economic activity in the average village by 3.24% in a year (Table 2, Column 1). Consistent with our assumptions, proximity to the coastline and to the nearest town, higher baseline electricity coverage, and higher population density increase village-level night light intensity, *ceteris paribus.* Moreover, the interaction between the percentage of agricultural workers and monthly precipitation levels is positive, suggesting that night light captures economic activity in the agricultural sector in our study region.

I then examine whether mangroves help mitigate the impacts of cyclones. Consistent with our expectations, the coefficients of the interaction between the cyclone damage index and distance to the shoreline are positive and statistically significant (Columns 2 to 5), suggesting that cyclone damage decreases in villages located further inland. The coefficient for mangrove width in the IV model is approximately five times larger than the one in OLS model, indicating a substantial bias in the OLS estimates due to endogeneity (Columns 2, 3). The difference suggests that the current mangrove distribution is endogenous and unobserved factors leading to lower mangrove width may also contribute to lower economic damage from cyclones. Thus, given the supporting evidence that economic development driven mangrove degradation might be a source of endogeneity along the Indian east coast, I adopt the IV model (Column 3) as our preferred specification. Specifically, I find a 34.2% decrease in cyclone damages in locations that have 1-kilometer wider mangrove[6] (Column 3).

[6]The average damage from one additional hour of a standard category-4 cyclone is calculated by subtracting the average damage mitigation from distance to shoreline (8.37×0.00249) and the average mangrove mitigation (0.217×0.0211) from the average cyclone damage (0.0385), and then adding the increased damage due to bathymetry conditions (1.27×0.0383), resulting in a total of 6.17%. Thus, one kilometer of mangrove can lead to a decrease in cyclone damage by $0.0211/0.0617 = 34.2\%$.

To test the robustness of our results, I change the endogenous variable from a continuous variable (mangrove width) to an indicator variable for the presence of the mangroves wider than 100-meters in the village (Column 4). Consistent with previous findings (Hutchison et al., 2014), I find that the first 100 meters of mangroves can significantly decrease damage from cyclones. The coefficient for mangrove mitigation benefit (0.0675) is higher than the aggregate cyclone damage (0.0617), suggesting that villages protected by at least 100 meters of mangroves experience minimal damage from cyclone events. Since natural hazard mitigation benefits from mangroves might have decreasing returns to scale, as the first 100 meters can mitigate most of the damage (Spalding et al., 1997), I anticipate that incremental mangrove width yields lower marginal benefits in places with larger mangrove coverage. When I include West Bengal in our sample, I find that mangrove mitigation benefit reduces by half in villages with wider mangrove coverage (Column 5).

Table 2.2: Natural hazard mitigation benefits from mangroves

	(1) OLS log nightlight	(2) OLS log nightlight	(3) IV log nightlight	(4) IV log nightlight	(5) IV log nightlight
Cyclone index	-0.032***	-0.038***	-0.039***	-0.036***	-0.009
	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
Lag Mangrove width	-0.035***	-0.037***	-0.069***		-0.025***
	(0.010)	(0.010)	(0.018)		(0.002)
Population density	0.186***	0.186***	0.186***	0.188***	0.127***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.009)
Dist. to nearest town	-0.335***	-0.335***	-0.334***	-0.339***	-0.341***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.011)
Percentage male	0.044	0.038	0.027	0.060	0.108
	(0.366)	(0.366)	(0.366)	(0.364)	(0.335)
Younger than 6	-0.574*	-0.582*	-0.572*	-0.458	-0.201
	(0.336)	(0.336)	(0.336)	(0.336)	(0.261)
Scheduled caste	0.011	0.010	0.009	0.007	-0.001
	(0.036)	(0.036)	(0.036)	(0.036)	(0.028)
Ag worker	-2.311***	-2.287***	-2.272***	-2.338***	-2.103***
	(0.329)	(0.330)	(0.330)	(0.327)	(0.303)
Monthly precipitation	-0.002***	-0.002***	-0.002***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Monthly precipitation X Ag worker	0.011***	0.011***	0.011***	0.012***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Distance to shoreline	-0.019***	-0.020***	-0.020***	-0.020***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hours of electricity	0.012***	0.012***	0.012***	0.012***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dist. to continental shelf (km)	-0.060**	-0.054**	-0.065**	-0.061**	0.005
	(0.024)	(0.024)	(0.026)	(0.025)	(0.016)
Log area	0.632***	0.632***	0.632***	0.634***	0.631***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Distance to shoreline X Cyclone index		0.002***	0.002***	0.002***	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Lag Mangrove width X Cyclone index		0.004*	0.021***		0.011***
		(0.002)	(0.007)		(0.001)
Distance to continental shelf X Cyclone index		-0.035***	-0.038***	-0.044***	-0.043***
		(0.002)	(0.002)	(0.003)	(0.002)
Lag Mangrove above 100m X Cyclone index				0.068***	
				(0.022)	
Lag Mangrove above 100m				-0.382***	
				(0.103)	
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Sd fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	51320	51320	51320	51320	68488
Kleibergen-Paap rk Wald F statistic			149.500	224.400	703.700
Adjusted R-squared	0.709	0.710	0.709	0.711	0.675

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
In column (5), I include villages within West Bengal in the sample.

To examine the spillover effect of mangrove protection benefits, I consider how villages not directly protected by mangroves are indirectly affected by proximity to mangrove-protected villages. I restrict the sample to villages not directly protected by mangroves and test whether the mangrove protection benefits from nearby villages can impact night light change after cyclones. I find that the cyclone-induced decrease in nightlights is 7% larger in villages located within 1 kilometer from a mangrove protected area. The indirect effect of mangrove protection suggests that, after a cyclone, economic activity decreases in villages near a mangrove-protected village, indicating that negative spillover effects can outweigh the positive effects in rural India (Table 2.3, Column 1-2). The negative spillover effects dissipate for villages more than 2 kilometers away from mangrove-protected villages. Therefore, in our main specification, I drop all control villages that are within 1 km from mangrove directly protected regions.

Table 2.3: Spillover effects of mangroves in cyclone mitigation

	(1) log nightlight 1 km	(2) log nightlight 1 km not adjacent	(3) log nightlight 2 km	(4) log nightlight 2 km not adjacent
Cyclone index	-0.043***	-0.043***	-0.037***	-0.043***
	(0.007)	(0.007)	(0.006)	(0.007)
Distance to shoreline X Cyclone index	0.003***	0.003***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to continental shelf X Cyclone index	-0.039***	-0.038***	-0.037***	-0.039***
	(0.002)	(0.002)	(0.002)	(0.002)
Cyclone index X Nearby mangrove width	-0.070**	-0.078**	-0.002	-0.001
	(0.035)	(0.035)	(0.015)	(0.015)
Nearby mangrove width	-0.276**	-0.520**	-0.064	-0.062
	(0.129)	(0.211)	(0.049)	(0.048)
Year fixed effect	Yes	Yes	Yes	Yes
Sd fixed effect	Yes	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes
Observations	43440	40752	43440	43272
Adjusted R-squared	0.702	0.707	0.702	0.701

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
I further drop 336 villages and 21 villages in column (2) and column (4) respectively since some villages do not have non-adjacent villages within the range.

Differences in adaptive capacity and the ability of households to invest in private defensive expenditures to mitigate cyclone damage also affects the extent of damage from cyclones and thus the potential benefits from mangroves in mitigating cyclone risk. To examine heterogeneity in cyclone damage and identify regions that receive larger relative benefits from mangrove conservation and restoration, I further investigate the effect of socioeconomic conditions that limit or enhance adaptive capacity. I continue to follow our preferred specification and exclude the West Bengal region in the analysis.

In general, I find that cyclones cause lower damage in wealthier villages, indicated by various measures: For example, villages with a higher percentage of scheduled caste[7] population face 1.4% higher damage (Table 2.3, Column 1), and those with a higher percentage of landowners face 0.9% lower damages (Column 2). Though the effect is not statistically significant, I find that the damage is lower in villages with a larger percentage of high-income households (Column 3). Whereas the cyclone mitigation effect of mangrove width is similar across all models, heterogeneity in the severity of damage suggests possible substitution between investment in mangroves (natural capital) and private defensive expenditures (man-made capital) for mitigating the impact of cyclones. Moreover, my results are consistent with the prior literature (Hochard et al., 2021) that mangrove have lower benefits in low-lying villages around the coast, which are more vulnerable to the storm surge (Column 4).

[7]Scheduled caste populations are much more likely to be socio-economically disadvantaged pradhanUnevenBurdenMultidimensional2022.

Table 2.4: Heterogeneous effects of mangrove benefits

	(1) log nightlight	(2) log nightlight	(3) log nightlight	(4) log nightlight
Cyclone index	-0.034***	-0.059***	-0.041***	-0.046***
	(0.006)	(0.007)	(0.007)	(0.006)
Lag mangrove width X Cyclone index	0.018***	0.012*	0.018**	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)
Distance to shoreline X Cyclone index	0.003***	0.002***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to continental shelf X Cyclone index	-0.037***	-0.039***	-0.038***	-0.036***
	(0.002)	(0.002)	(0.002)	(0.002)
Interaction X Cyclone index	-0.047***	0.053***	0.032	0.000**
	(0.012)	(0.009)	(0.047)	(0.000)
Interaction	Percentage scheduled caste	Landowner share	Percentage ¿ 10k Rs	Elevation
Year fixed effect	Yes	Yes	Yes	Yes
Sd fixed effect	Yes	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes
Observations	51320	50232	50232	51288
Kleibergen-Paap rk Wald F statistic	150.000	143.600	144.900	147.300
Adjusted R-squared	0.709	0.722	0.710	0.709

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
In column (1) and (2), 136 villages are dropped because of missing values in the 2011 Socio-Economic and Caste Census.
In column (3), 4 villages are excluded due to missing elevation data as they are too small.

To examine the robustness of the preferred wind field model in predicting cyclone induced damage along Indian east coast, I estimate our main specification in Table 2.2, Column (3) with alternative wind field models. I also adopt alternative night light indicator. Specifically, I use aggregated annual night light intensity as the dependent variables instead of December nightlight measurements. The results are qualitatively similar

2.7 Discussion

Understanding the value of natural capital, such as mangroves, in mitigating cyclone risk is critical to inform investment policies for climate adaptation. As policy makers continue to grapple with long term natural capital investments to respond to the global climate crisis, our work adds to the small but growing literature on the value of ecosystem services that mangroves provide in protecting lives (Das & Vincent, 2009) and livelihoods in communities affected by increasing natural hazards like cyclones. I study the effect of 27 cyclones between 2012 and 2019 that affected rural coastal villages in India and find that the presence of mangroves can reduce the negative impact of cyclones on economic activity, measured by changes in nightlight intensity at the village level; 2.9 km of mangrove protection between the village and the shoreline effectively mitigates all the damage risk. However, I also note that such benefits might be overestimated because of potential negative spillover effects from nearby villages that do not have mangrove protection.

I also examine heterogeneity in the impact of cyclones across rural villages and highlight inequalities in the exposure to climate risk. Our results suggest that investment in adaptive infrastructure in villages with wealthy households can serve as substitutes for public investment in nature-based solutions in rural settings. Wealthier villages can invest in defensive infrastructure to mitigate natural hazard damage. Thus, the incremental benefits of mangrove protection can disproportionately benefit low-income and under-resourced populations. Because mangroves are more likely to be degraded in less wealthy regions for short-term gains in agriculture and fishery sectors (Suresh & Sahu, 2015), policymakers need to be cautious about long-term trade-offs in land use change decisions and the justice implications of increased exposure to natural hazards.

Chapter 3: Disaster-Induced Migration and Rising Inequality in the United States

Migration represents a direct form of adaptation, particularly in coastal and low-lying regions, where households choose to relocate to reduce their exposure to increasing natural hazard risk. Yet, empirical evidence indicates that such voluntary migration as an adaptation strategy remains limited because of high economic and social costs, especially associated with the disruption of labor markets and support networks (Bohra-Mishra et al., 2014; Cattaneo et al., 2019; Dell et al., 2014). While some opt to relocate, wealthier households with greater financial resources often choose to stay and invest in protective measures or benefit from disaster assistance programs. The dynamic heterogeneous household responses across income groups complicates the relationship between natural hazard exposure, demographic shift due to migration, and community resilience.

3.1 Voluntary migration as an adaptation strategy

Systematic evidence of climate-induced migration is most consistent in rural, agriculture-dependent developing economies where drought and rainfall variability directly affect livelihoods (Hoffmann et al., 2022; Hornbeck, 2012). In these contexts, migration is often a last-resort response, used only after in-situ coping mechanisms—such as crop switching, irrigation, and seasonal labor—are exhausted. Empirical studies across sub-Saharan Africa, South Asia, and Latin America show that droughts lead to increases in temporary and long-term migration (Hoffmann et al., 2022; Mueller et al., 2014; Oliveira & Pereda, 2020). However, migration flows are selective and partial, involving younger household members or seasonal migrants. Financial and social barriers often prevent the poorest households from relocating, creating a "climate trap" that reinforces vulnerability (Black et al., 2011; Cattaneo & Peri, 2016).

Unlike slow-onset stressors like drought, evidence on the effect of sudden-onset natural disasters—such as floods, hurricanes, and wildfires—on long-term out-migration is mixed (Berlemann & Steinhardt, 2017; Cattaneo et al., 2019). The U.S. Current Population Survey data show that between 2000 and 2020, only 0.4% of U.S. households reported natural disasters as their primary reason for moving. In most cases, natural hazard risks and events are considered alongside other factors—such as employment opportunities, family circumstances, or housing affordability—when making relocation decisions. Empirical studies find mixed evidence – some find substantial temporary displacement after severe natural disasters (Boustan et al., 2020), while others suggest quick population recovery and even net in-migration due to disaster assistance and reconstruction efforts (Henkel et al., 2022; Husby et al., 2014). The literature reflects heterogenous responses across disaster type and geography – tornadoes tend to increase net out-migration (Boustan et al., 2012) while recent county-level analysis suggests that hurricanes, floodings, and severe storms contribute sustained decrease in population (Ton et al., 2024). These findings challenge the narrative that natural disasters universally push populations away from high-risk areas and highlight the need to examine theoretical foundations and trade-offs between natural hazard risk and other attributes, like the labor market, housing costs, and social networks, in hazard-induced migration research (Partridge et al., 2017).

Recent structural models examine some of these trade-offs. A random utility model of location choice shows that households with children display a significant marginal willingness to avoid hurricane risk (Fan & Bakkensen, 2021). Sorting models that embed flood insurance prices reveal heterogeneous preferences across income and racial groups, suggesting that low-income households and minority populations are more likely to sort into high-risk areas (Bakkensen & Ma, 2020). Dynamic spatial equilibrium models with endogenous household relocation further suggest significant welfare gains from hazard-driven migration, provided that labor and housing markets accommodate the inflow (Desmet et al., 2021).

3.2 Community composition change through relocation decisions

Migration is not just a private adaptation strategy; household-level decisions also have broader implications for community composition and local demographic trends. Natural hazards impact communities in two primary ways: directly, through physical destruction and asset loss, and indirectly, through shifts in population and housing tenure resulting from disaster-induced relocation and sorting (Botzen et al., 2019; Cattaneo et al., 2019; Pleninger, 2022). These indirect effects are particularly important because they can reshape the long-term social and economic landscape of hazard-prone areas.

Two seemingly contradictory demographic trends have emerged in hazard-prone regions. On the one hand, these areas tend to exhibit higher poverty rates than the national average, especially when frequently exposed to hurricanes, floods, or wildfires (Boustan et al., 2020; Schultz & Elliott, 2013). On the other hand, these same regions are often home to a disproportionately high share of socially advantaged populations, including wealthier and white households (Elliott & Pais, 2010; Howell & Elliott, 2019), even after controlling for amenity-based sorting into regions with high disaster risk (Raker, 2020). Housing market dynamics help reconcile this paradox. Post-disaster price discounts attract high-income homebuyers, who often have a higher willingness to pay for coastal amenities, accelerating gentrification as lower-income residents are priced out (Bin & Landry, 2013; Graff Zivin et al., 2023; McNamara et al., 2024).

The net effect of migration flows on inequality remains ambiguous. Some studies find that hazards narrow wealth gaps by eroding high-valued properties (Kulanthaivelu, 2023), whereas others show widening disparities when recovery aid flows disproportionately to wealthier owners (Begley et al., 2018; Billings et al., 2022; Howell & Elliott, 2019). This trend is particularly concerning because regions with greater income inequality tend to suffer higher mortality and economic losses during disasters, implying a positive feedback loop where inequality amplifies disaster vulnerability, and disasters, in turn, exacerbate inequality (Lindersson et al., 2023).

Housing tenure decisions add another layer in shaping community composition. Unlike income, which can fluctuate due to economic shocks, homeownership status rarely changes without relocation. Therefore, shifts in the renter–owner balance signal deeper transformations in neighborhood quality, stability and investment capacity (Hausman et al., 2022). Within a stable location, transitions between renting and owning are rare, except for potential policy interventions (Keeler et al., 2022). Despite its importance, relatively few economic studies examine how natural hazards affect homeownership. One notable exception is a nationwide study that finds that households moving into areas impacted by severe disasters are more likely to rent than buy (Sheldon & Zhan, 2019). This pattern can increase local exposure as renters generally have fewer resources and less control over structural mitigation investments. If post-disaster migration leads to declining homeownership rates and a growing renter population in high-risk areas, these regions may face compounding vulnerability over time.

Understanding the interaction between migration, community composition, and disaster-related changes is therefore critical for designing effective recovery policies that do not inadvertently amplify inequality or future hazard exposure. The next two chapters of this dissertation address these questions directly. In chapter 3, I first investigate the indirect effects of natural hazards on economic inequality, focusing on how heterogeneous post hazard migration responses contribute to changes in community composition. In chapter 4, I explore the effects of inland flooding events on homeownership rates through inflows and outflows of homeowners and renters.

3.3 Conceptual Framework

Our conceptual model extends early work by Ehrlich and Becker (1972), where households maximize their utility by deciding whether to adapt in place or migrate out of high-risk regions. Following their terminology, I assume that in situ adaptation is a self-protection strategy. This means that adaptation reduces the probability that a nearby disaster causes damage but leaves the actual revealed damage unchanged if the household is hit by a disaster event. I can write the expected utility of household choosing to invest in in situ adaptation as

$$EU^I = (1 - p\,(p_0, I, Y))\,U\,(Y - I) + p\,(p_0, I, Y)\,U\,(Y - D - I) \tag{3.1}$$

where Y is the household income, D is the damage from a natural disaster event, p_0 is the probability of experiencing damage without adaptation effort and $p(p_0, I, Y)$ is the probability of experiencing natural disaster damage for a household with income Y that invests I in in situ adaptation. The utility function $U(\bullet)$ is a standard concave utility function such that $U'(c) = +\infty$, implying that households cannot consume below a minimum threshold c.

I assume that in situ adaptation and migration are mutually exclusive strategies. As an alternative to mitigation, households could invest in migration with a cost m to migrate to another location with a new probability, p_1 of experiencing damage from a natural disaster. Hence, the expected utility of a household after migration is

$$EU^m = (1 - p_1) U (Y - m) + p_1 U (Y - D - m) \tag{3.2}$$

I assume that $p(p_0, 0, Y) = p_0$, $p_I < 0$, $p_{II} > 0$, and $p_{IY} < 0$. Intuitively, for any income level, a household that does not invest in in situ adaptation will face the same probability of damage p_0. The probability of damage from a natural disaster decreases with investment I, and the household faces diminishing marginal returns on investment. Furthermore, the probability of experiencing damage from natural disasters is lower for households with higher income as the capacity to mitigate risk increases with income.

Maximizing expected utility for the case of in situ adaptation yields the first order condition

$$-(1-p)\,U'(Y-I) - pU'(Y-D-I) + p_I\left(U(Y-D-I) - U(Y-I)\right) = 0 \quad (3.3)$$

and the second order condition [8]

$$\begin{aligned} A = (1-p)U''(Y-I) + pU''(Y-D-I) &\quad + 2p_I\left(U'(Y-I) - U'(Y-D-I)\right) \\ + p_{II}\left(U(Y-D-I) - U(Y-I)\right) < 0 & \end{aligned} \quad (3.4)$$

Proposition 1. There exists $\overline{Y}$ such that for all $Y \geq \overline{Y}$, $EU^I(I^*) \geq EU^m$ where I^* maximizes EU^I.

For given Y, because $p(p_0, I, Y)$ is monotonically decreasing in I, there is a unique $\tilde{I}(Y)$ such that $p\left(p_0, \tilde{I}(Y), \mathrm{Y}\right) = p_1$.

Since $p_Y < 0$ for all $I > 0$ [9], I have $\frac{d\,\tilde{I}}{d\,Y} < 0$. Therefore, with higher income, a household will invest fewer absolute resources ($\tilde{I}$) to mitigate in place and reach the same natural disaster protection as migration. For sufficiently large $Y \geq \overline{Y}$ such that $\tilde{I}\left(\overline{Y}\right) \leq Y$, households will not migrate in response to natural disaster risk. Therefore, in-place mitigation is the optimal choice for a high-income household.

Proposition 2. There exists $(p_0, p_1, \hat{m}, \hat{Y})$, such that $EU^m > EU$. For the same $(p_0, p_1, \hat{m})$, there exists $\underline{Y}$ such that for all $Y < \underline{Y}$, $EU^m < EU$.

[8] Note that $p_{II} > 0$ and a concave utility function are not sufficient conditions for the second-order condition to hold. An internal solution might not exist in our setting. To simplify the argument, I assume that the second derivative $EU^I_{II} < 0$ for all suitable I.

[9] Since $p(p_0, 0, Y) = p_0$, $p_I < 0$, and $p_{IY} < 0$, I have $p_Y < 0$ for all $I > 0$.

Holding p_0, p_1, and m constant, I can define the expected utility gain from migration as

$$\Delta EU\left(Y\right) = EU^M - EU = \left(1-p_1\right)U\left(Y-m\right) + p_1 U\left(Y-D-m\right) - p_0 U\left(Y\right) - p_0 U\left(Y-D\right) \tag{3.5}$$

I can find $\lim_{Y\to D+c} \Delta EU\left(Y\right) < 0$ and $\lim_{Y\to +\infty} \Delta EU(Y) > 0$ for any (p_1, p_0, m) pair. Since $\Delta EU\left(Y\right)$ is a continuous function, there exists $\hat{Y} = \min\{Y^*\}$ such that $\Delta EU\left(p_1, p_0, m, Y^*\right) = 0$.

As a result, I can find $\hat{m} \in (0,\ m)$ so that $\Delta EU\left(p_0, p_1, \hat{m}, \hat{Y}\right) > 0$. Then, for this updated $(p_0, p_1, \hat{m})$ pair, I can again find $\underline{Y} = \min\{Y^*\}$ such that $\Delta EU\left(p_1, p_0, \hat{m}, Y^*\right) = 0$. Note that since ΔEU is a continuous function, $EU^m < EU$ for all $Y < \underline{Y}$. Intuitively, this suggests that if households only choose between migration or not, low-income households will not be able to migrate because of their budget constraints. The remaining question is whether $EU^m > EU^I(I^*)$ for middle income households.

Proposition 3. For some income $Y \in (\hat{Y}, \tilde{Y}\ )$, a household's optimal solution is migration if $\frac{\partial EU}{\partial\ I}|_{I=0} < 0$.

Since $EU^I_{II} < 0$[10],if $\frac{\partial EU}{\partial\ I}|_{I=0} < 0$, the optimal investment level is $I^* = 0$ for EU^I. Moreover, since $EU^m > EU$ for the $(p_0, p_1, \hat{m}, \hat{Y})$ pair, there exists $\tilde{Y} > \hat{Y}$, such that $EU^m > EU$ for all $Y \in (\hat{Y}, \tilde{Y}\ )$. Thus, if in situ adaptation is not efficient for middle-income households, the optimal strategy for middle-income households to decrease natural disaster risk is migration.

[10]Note that $p_{II} > 0$ and a concave utility function are not sufficient for $EU^I_{II} < 0$. I need to assume $EU^I_{II} < 0$ for Proposition 3 to hold.

Overall, the theoretical model incorporating a binary choice between in situ adaptation and migration suggests an inverted-U shape relationship between household income and the likelihood of migration after a natural disaster. Low-income households will neither migrate nor invest in in situ adaptation because of budget constraints, while high-income households with resources to adapt in-place are more likely to invest in defensive infrastructure and less likely to migrate. As a result, middle-income households have the strongest incentive to migrate in response to natural disasters. Because the threshold income level (between middle and high income) at which migration probability declines is implicitly defined in the theoretical model, identifying migration responses across income categories remains an empirical question. In the empirical analysis below, I divide the sample into four income categories, separating out top-1-percentile income groups from the broader high-income group to examine non-linearity in the relationship.

3.4 Data

I assemble a dataset that links household-level information on income and migration, county-level natural hazards data, and socioeconomic characteristics for all counties along the U.S. Atlantic and Gulf coasts from 2015 through 2020. The primary source of household-level information is Data Axle, a commercial dataset that compiles household-level records from a variety of sources, including public filings, utility connections, credit data, and other proprietary databases. The dataset captures a broad cross-section of U.S. households and includes key attributes such as estimated income, detailed residential location, and homeownership status. Data Axle is a repeated cross-sectional dataset, documenting households at the address level over time. While it is not a true panel, approximately 80% of households can be matched across consecutive years, allowing for limited tracking of household migration and tenure transitions. Moreover, the total number of households recorded in the dataset is relatively stable over time, and the population estimates for each county align closely with official statistics from the U.S. Census and American Community Survey (Appendix C). This suggests that the dataset is randomly sampled and broadly representative of the underlying population across time. These features make Data Axle a valuable resource for studying spatial mobility and housing behavior in response to environmental shocks such as hurricanes and floods.

Household migration and income: I utilize the Data Axle U.S. Historical Residential Database (Axle, 2021) to analyze household migration decisions across the United States between 2015 and 2020. Data Axle compiles longitudinal household-level information—including residential address, household age, presence of children, income, and ownership status—from real estate data, voter registration lists, and more than 20 types of publicly available secondary sources, with additional verification and enhancements through proprietary algorithms.

Specifically, I derive migration decisions based on changes in household addresses across metropolitan regions. I focus on long-term migration by examining moves across metropolitan borders, which are more likely to involve changes in the labor market and reflect permanent relocation, as opposed to short-distance moves that may indicate temporary displacement. I also examine moves across counties, noting that a move within the same county or to an adjacent county is arguably not a long-term migration at all because people can remain within the same labor market.

To ensure accuracy, address records are verified with credit card billing statements within a two-year timeframe. If mail has not been collected in the past 90 days, Data Axle classifies the address as vacant. As a result, if a household migrates in 2015, it is unlikely to be identified as a migrator in the 2016–2017 period, since the household would no longer be collecting mail at its original address. That address would be flagged as vacant and removed from subsequent samples. While a small share of addresses—approximately 3% of households with property values below 5,000—are located in trailer parks, most of these households remain at the same location for over five years, suggesting that the inclusion of trailer park residents does not meaningfully bias the results. Importantly, the main findings remain robust even when all trailer park households are excluded from the analysis (Appendix B).

A key advantage of the Data Axle dataset is that it provides household income profiles derived using proprietary algorithms that combine information on wage, home equity, and invested assets to represent all forms of earnings each household could obtain. By matching the names and addresses from a consumer dataset with a large national survey of consumers from MRI-Simmons, Data Axle predicts the income of households based on individual, household, and lifestyle characteristics.

Households in the top-1-percentile-income group are, on average, married couples, living in single-family houses in large metropolitan areas, and more likely to work in professional, legal, or managerial occupations, and have a higher likelihood of being golfers. In contrast, households in the bottom 50th income percentile are 50% less likely to be married, 30% less likely to have children, and live in homes valued $1,000,000 less. The generated income data are calibrated with national surveys, such as ACS, to ensure alignment with regional and subpopulation characteristics across the United States. Further, to test for external validity, I compare sample attributes with the 2020 census, affirming the reliability of the sample for studying migration and income patterns (Appendix C).

Natural hazard data: Similar to Chapter 2, I use exogeneous hurricane wind damage data based on an extrapolated wind field model. I calculate the wind damage index (WDI) using cubic scaling and a minimum threshold of 50 knots to adjust for hurricane damage significant enough to impact properties in the US (Figure 3.1). Like in Chapter 2, I use alternative wind damage functions and find similar results.

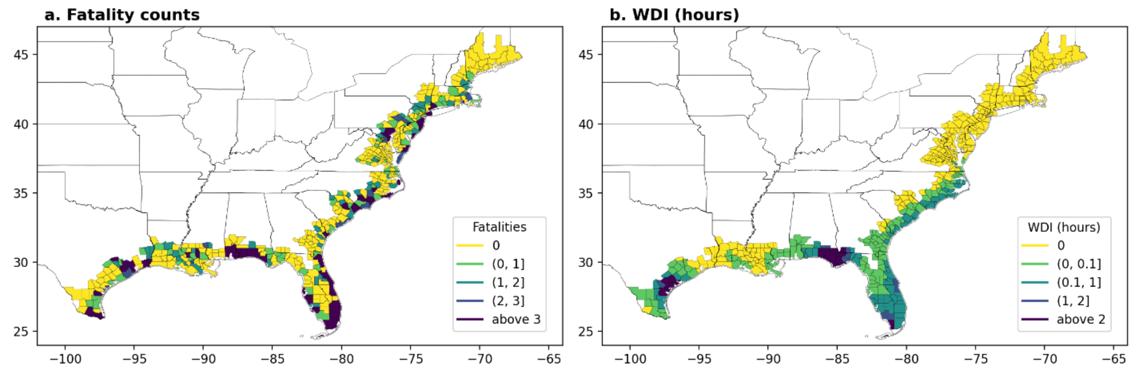
$$Damage_{ct} = \sum_{p \in T} \frac{(w_{pv} - 50)^3}{(113 - 50)^3} \; if \; w_{pv} > 0 \tag{3.6}$$

Hurricane-induced wind damage in county c at time t is calculated as a cubic function of the difference between local windspeed attributable to waypoint p on the hurricane track and the 50 knots threshold recommended by Emanuel (2011).

In addition to the continuous wind damage index (WDI), I also use the Spatial Hazard Events and Losses Database for the United States (SHELDUS) database to capture data on a range of natural disaster events (CEMHS, 2022). This database provides county-level information on 18 different types of extreme weather events from 1989 to the present. The data include event type, date and time, the number of direct fatalities and injuries, and the associated property and crop damage in 2017 USD. For events that affect multiple counties, the SHELDUS attributes damage equally to each affected county, which results in observations of 0.5 fatality.

During 2014-2019 the wind index is driven by Hurricanes Matthew, Harvey, Irma, and Laura, all of which struck the Carolinas, Florida, Louisiana, or Texas. No major hurricanes affected the northern Atlantic coast during this study period, therefore the results for New York and New Jersey should be interpreted cautiously. Figure 3.1 shows the distribution of county-level hazard induced fatalities (panel a) and hours of exposure to category-4 equivalent hurricane damage (panel b) between 2014-2019.

Figure 3.1: County-level exposure: Hours of category-4 equivalent hurricane damage 2014-2019



Note: US state and county outlines were obtained from the US Census Bureau. The coastal county definition was adopted from NOAA.

Socioeconomic Controls: County-level demographic variables include unemployment rates and homeownership rates obtained from the Bureau of Labor Statistics and the Data Axle sample. Population density is calculated by dividing county population by land area, obtained from the U.S. Census Population Estimates Program. Household attributes – age of head of household, number of children, and length of residence – are obtained from the American Community Survey.

The final dataset that I construct includes a repeated cross-sectional sample of 10,580,590 homeowners in metropolitan regions within 429 coastal counties along the U.S. Atlantic and Gulf Coast from 2015 to 2020 (Table 3.1). Specifically, I rely on the 2015 Core-Based Statistical Area (CBSA) delineation to define metropolitan regions and delineate labor market migration patterns. I exclude non-working-age households and renters, as they may have different migration strategies. In the sample, 95,573 homeowners (1%) migrated across metropolitan regions. While the migration rate is low compared to other data sources [11], this is primarily due to the cautiousness in our definition of movers and the exclusion of renters.

Table 3.1: Summary statistics

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Individual attributes					
Migration across metro (0/1)	10,580,590	0.007	0.084	0	1
Head of household age	10,580,590	47.228	8.495	27	57
Household income ($1000)	10,580,590	107.529	88.783	5	500
Property value ($1000)	10,580,590	319.240	327.703	5	9,999
Household with children (0/1)	10,580,590	0.512	0.500	0	1
Length of residence (years)	10,580,590	14.346	8.689	3	61
County attributes					
WDI (50 knots)	10,580,590	0.020	0.185	0	6.318
Hurricane event (50 knots)	10,580,590	0.220	0.414	0	1
Unemployment rate	10,580,590	0.518	0.021	0.019	0.162
Population density	10,580,590	2,904.260	7,182.911	44.570	71,694.820
Homeownership rate	10,580,590	0.782	0.126	0.157	0.997

Note: Property value is measured in thousands of dollars. A value of 5 indicates property value is below $5,000. Property value and household income are top-coded, and head of household age is reported in 5-year intervals.

[11] The across-metropolitan-region migration rate in Data Axle is approximately one-third of that in IRS data and one-eighth of that in ACS data. This discrepancy likely reflects differences in how migration is measured, as well as potential overestimation of long-term migration in both IRS and ACS sources. IRS address changes may reflect PO Boxes, preparer addresses rather than permanent moves. ACS respondents may interpret migration broadly, including temporary stays or secondary homes, which do not necessarily indicate sustained migration across labor markets.

3.5 Methods

3.5.1 Empirical Specification

I investigate the impact of hurricanes on homeowners' outmigration decisions using a linear probability model with county level fixed effects. These relationships are identified by focusing on year-to-year variations in hurricane exposure that do not follow the time trend at the state-level. I use a linear probability model instead of logit and rare event logit models (Allison, 2012) to reduce the incidental parameter bias with extensive fixed effects (Angrist & Pischke, 2009).

I categorize homeowners into four income groups: low-income (0–50th percentile, \$0–\$90,000), middle-income (50–90th percentile, \$90,000–\$269,000), high-income (90–99th percentile, \$269,000–\$500,000), and the top 1% (above \$500,000) (See Appendix B for alternative definitions). The probability of migration across metropolitan area P_{it} is predicted for these income groups using the following model:

$$\mathrm{P_{it}} = \sum_{p} (\beta_p Income_{pit} + \gamma_p Income_{pit} Damage_{ct-1}) + \delta_1 HC_{it} + \delta_2 CC_{ct} + r_i + C_c + g_{st} + \xi_{ict} \tag{3.7}$$

where i, s, c, t, and p index household, state, county, year, and percentile bin respectively. $Damage_{ct-1}$ is the county level natural hazard damage index in the previous year. I use natural hazard data from the previous year, as migration across labor markets may take time. Specifically, hurricanes in the U.S. typically occur in September and October, leaving households limited time—approximately 3 to 4 months—to respond within the current year. To ensure that all homeowners in our sample have been exposed to natural hazards before migration, I exclude those who have not lived at their current address for at least two years. $Income_{pit}$ are the dummy variables indicating whether household i belongs to a specific percentile group p, HC_{it} is the household characteristics, and CC_{ct} is the time varying county characteristics including unemployment rate, homeownership rate, and population density, r_i is an indicator for race, C_c is county fixed effects that capture time invarying county characteristics such as local natural disaster intensity, State by year fixed effects g_{st} capture state specific time trend and ξ_{iscb} is the error term. I cluster the standard errors at county level. The main identification assumption is that the distribution of households across income bins remains similar over the study period, which is reasonable given low average migration rates over the 6-year study period. To test the robustness of our results to different natural hazard indicators, I estimate the model using county-level fatality rate and per capita damage to measure natural hazard damage instead of wind damage index based on hurricane exposure, which is the primary specification (Appendix C).

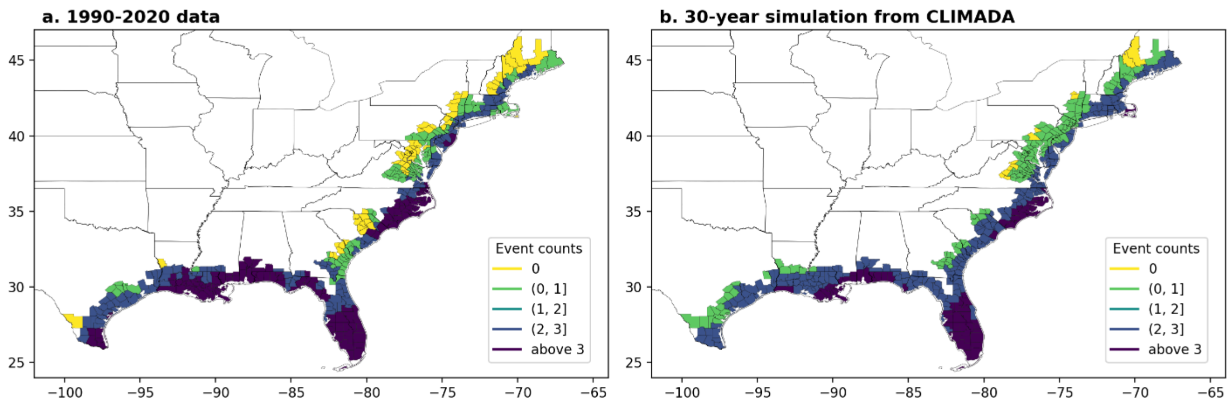
3.5.2 Projected Population Change through Disaster-Induced Migration under Future Climate Scenarios

To assess the long-run effects of hurricanes on population distribution and economic inequality, I simulate migration responses of homeowners across income strata under future climate scenarios (RCP 2.6, RCP 4.5, and RCP 8.5) from 2020 to 2050 using the estimation results and baseline migration network. Note that simulation results only represent the indirect impacts of hurricanes on economic inequality through migration decisions and do not account for the direct effects of hurricanes on economic performance because I assume that household income does not change across years. Therefore, these results present a lower bound for the effect of hurricanes on population and income distribution.

Synthetic hurricane tracks: Historical records alone are too short and spatially sparse to sample the full range of future hurricane exposure. Consistent documentation of hurricanes in the International Best Track dataset (Knapp et al., 2018) has only been available since the 1980s, and many coastal locations lack recorded events in observational datasets. Synthetic hurricane tracks offer a valuable tool for generating a large and representative sample of potential storm events under various climate scenarios. By simulating a wide range of hurricane paths, intensities, and landfall locations, they enable researchers to assess the potential impacts of hurricanes on future migration patterns across diverse geographic contexts (Bertinelli et al., 2016; C.-Y. Lee et al., 2018).

I generate synthetic hurricane tracks using the CLIMADA platform, which generates storm paths via a directed random walk model (Aznar-Siguan & Bresch, 2019). Specifically, the hurricane tracks are resampling of synthetic hurricane tracks generated based on hurricanes between 1980 and 2020 from the International Best Track Archive for Climate Stewardship (IBTrACS) dataset. For each historical hurricane event, CLIMADA generates an ensemble of 10 synthetic tracks by applying directional and spatial perturbations to replicate the randomness and variability of actual storm paths. Wind speed decay after landfall is modeled using a statistically calibrated exponential function. For synthetic events in different scenarios, hurricane frequency and intensity are adjusted for each RCP scenario using linearly interpolated climate parameters. The validity of the synthetic tracks is confirmed by comparing simulated hurricanes against observed IBTrACS data. The simulated back-cast for 1990-2020 consistently reproduces hurricane exposure, landfall counts and spatial wind-field footprint (Figures 3.2), supporting the use of the synthetic tracks for forward projections. The resulting exposure map shows the familiar Gulf Coast hotspot—especially Florida and Louisiana—followed by the Carolinas; the Mid-Atlantic and Northeast remain less frequently struck but still far more exposed than their inland neighbors. I further tried alternative simulation methods and find similar results (Appendix D).

Figure 3.2: Total number of hurricane exposures with local maximum sustainable wind speed above 50 knots for each county based on observed and synthetic cyclone data



Note: (a) represents mean annual maximum sustained wind speed derived from IBTrACS landfall records for 1990–2020 (b) presents the median of 100 synthetic realizations generated with CLIMADA using the same historical climate parameters (i.e., no future climate adjustment). State and coastal county boundaries are from the U.S. Census Bureau and coastal-county definition adopted from NOAA.

Hazard induced migration: Baseline migration flow of households come from Data Axle microdata for 2006–2014. The baseline migration network defines a matrix with the annual probability that a households in each county c and each income strata i moves across metropolitan areas within a county or to a different county. Because this period includes years when natural hazard events occurred, the baseline migration rate also captures historic responses to those events, potentially overestimating the outmigration rate, particularly for middle- and high-income group.

The simulation of annual population flow captures both the local effects of hurricanes on population relocation decisions and changes in population inflows due to hurricanes in other counties. This is particularly important if households from natural hazard-prone regions tend to relocate to other similarly vulnerable areas. Specifically, I assume that climate-induced hurricanes influence migration decisions but do not alter destination choices once households decide to migrate across metropolitan regions (Hauer et al., 2020). This assumption is consistent with prior findings suggesting that migration decisions triggered by environmental factors are often reactive and constrained by existing socioeconomic networks. However, it is important to recognize that previous trends are not always indicative of future outcomes. Socioeconomic shifts, population growth, local growth ordinances, adaptive behavior, and the rate of climate change itself could all reshape future migration systems in ways that are not fully captured by historical patterns. While I model the destinations of potential migrants following hurricane exposure, I do not explicitly incorporate how other climatic stressors or evolving social dynamics might influence future migration flows.

In my simulations, households in each county c and each income strata i have baseline migration rate $p_c i$. If a coastal metropolitan area (MSA) county is exposed to a hurricane with maximum local sustainable windspeed above 50 knots, the migration rate in the county is updated by

$$\hat{p_{ci}} = p_{ci} + e_i \tag{3.8}$$

where e_i is the empirically estimated effect of a hurricane with above 50 knot local sustainable wind speed on migration probability. For inland counties and counties outside MSAs, e_i equals 0, resulting in no change. Thus, the simulated hurricane events only affect migration decisions of households in MSAs along the east coast, whereas the baseline migration network determines population flow in unaffected areas. If the outmigration rate increases in a hurricane-affected county, fewer households will stay in the original MSA, resulting in income strata specific decrease in population.

Conditional on choosing to relocate, a household selects the migration destination d based on the historical migration network m_{cd} [12]. This applies to moves within the same metropolitan area and across metropolitan areas. Thus, a hurricane event changes how many households move out of the affected region but not where they go—an assumption supported by evidence that disasters trigger the migration decision yet rarely alter preferred labor-market destinations and the effect of current public adaptation investments (Hauer, 2017).

Migration flows into coastal counties remain constant over time, with each county d receiving in-migrant flows by income strata based on baseline data, because I assume that inland households do not alter their migration patterns in response

[12] $m_c d$ represents the probability to migrate to destination county d if a homeowner in county c decides to migrate.

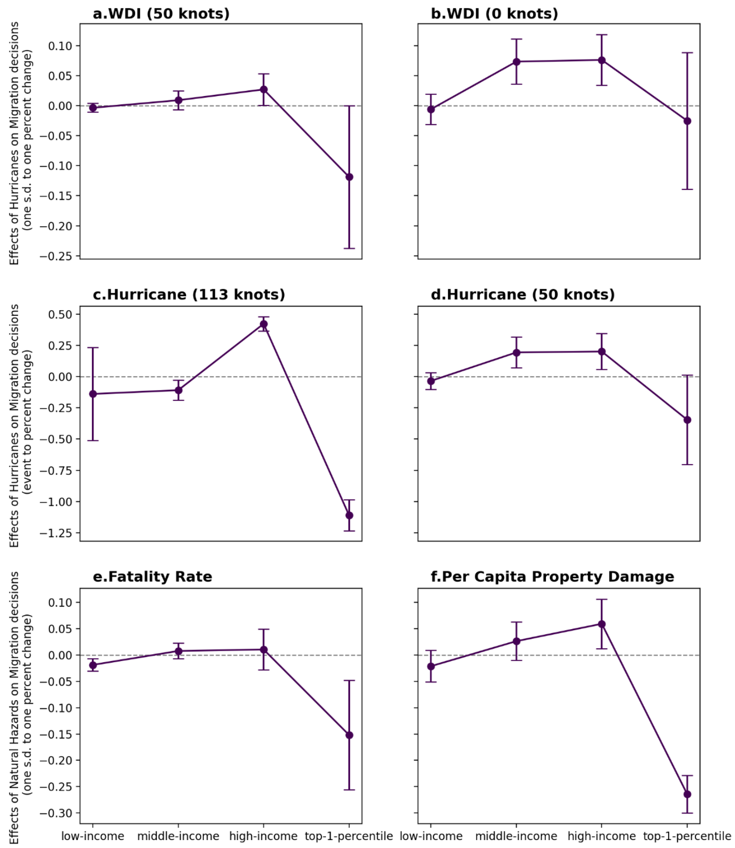
to coastal natural hazards. Since roughly 31% of the households moving into to coastal counties come from inland regions, simulated migration flows capture both the out migration from hazard hit counties and the continued inward migration from unaffected areas. By aggregating the updated origin–destination flows annually, I derive county- and income-specific population paths through 2050 under each climate scenario.

3.6 Empirical results

To quantify how natural hazards influence homeowner migration, I estimate the linear probability model (equation 3.7) using three damage exposure measures: a continuous wind-damage index that reflects hours of exposure to a category-4 equivalent hurricane, county-level fatality rate, and per capital property damage that captures other disasters.

Figure 3.3 presents the marginal effect of a one–standard deviation increase in wind damage on the probability that an owner household leaves its metropolitan area, reflecting an inverted-U shape relationship between household income and likelihood to migrate. Natural disasters have a negative but statistically insignificant effect on the out-migration probability for homeowners in the bottom 0-50th percentile (low-income) and 99-100th percentile (the top-1-percentile) income distribution. However, there is a positive and statistically significant effect on homeowners from 90-99th percentile (high-income) income distribution. Furthermore, I find a statistically significant difference in the marginal effect for low-income homeowners and high-income homeowners at the 10% significance level and between high-income homeowners and the top-1-percentile homeowners at the 5% statistical significance level. The results are consistent with the hypothesis that low-income households with limited financial and economic resources might not have the capacity to migrate out after a natural disaster. As income increases, high-income households, who have greater economic resources, likely view migration as the optimal adaptation strategy. However, households in the top-1-percentile-income distribution, with greater access to resources, can invest in costly in-situ adaptation to reduce the damage from natural disasters and therefore are less likely to migrate out.

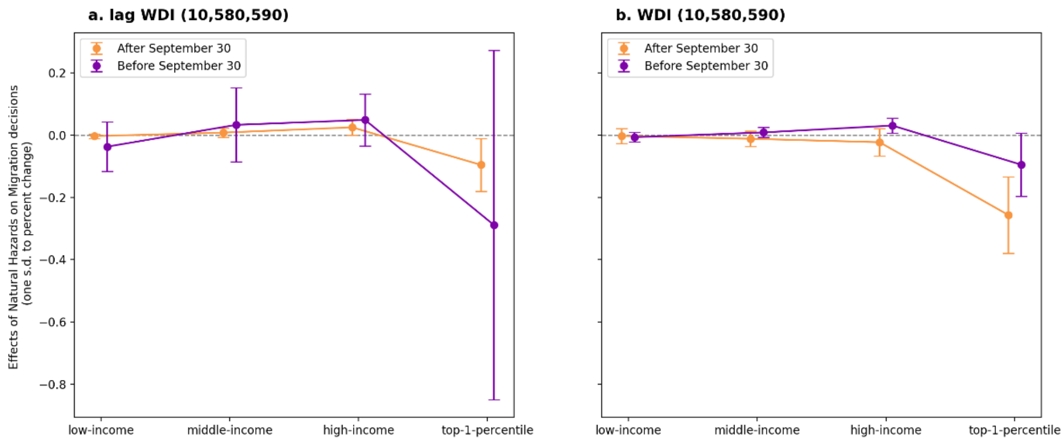
Figure 3.3: Marginal effect of natural disasters on migration probability



Note: Natural hazard damage indicators are normalized by standard deviation in a., b., e., and f. Thus, the interpretation of the effect of WDI on high-income households (0.021 in a.) is that one standard deviation change in WDI can lead to 0.02% increase in migration across metropolitan regions, which is one quarter of standard deviation for outmigration rate (Table 3.1).

I further examine whether the timing of storms affects the estimated impact by analyzing whether extreme precipitation events that occur later in the calendar year lead to lower observed effects on migration. Because most Atlantic hurricanes occur after 30 September, current-year moves may be under-recorded. Splitting the wind index by storm timing shows no detectable effect for late-season events in the current year, but a significant lagged effect in the following year (Figure 3.4). The lack of statistically significance for hurricane events after September 30 suggests that migration decisions involve some lag. In the one-year lag model, estimates for hurricanes occurring after September 30 are statistically significant, while the effect of earlier hurricanes have larger confidence intervals, though results are qualitatively consistent relationship across income groups. Overall, the results justify the use of a one-year lag as the preferred specification and indicate that hazard salience decays after a year.

Figure 3.4: Heterogeneous effects of hurricane damage across different treatment timing



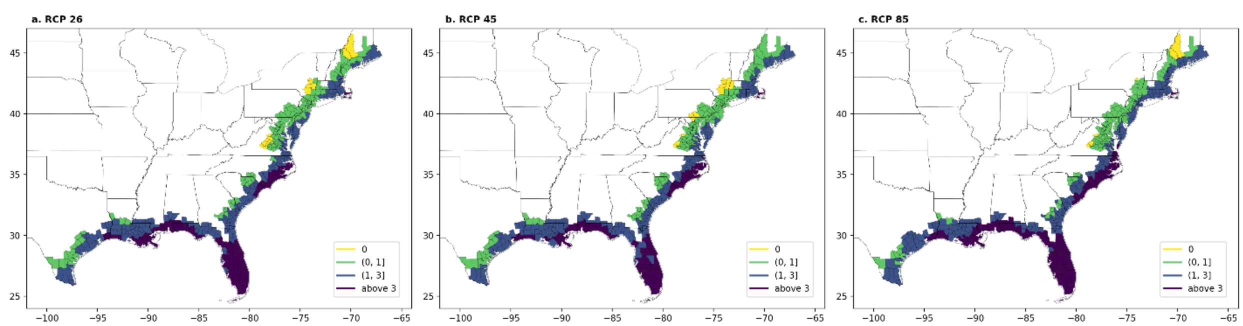
Note: As in our preferred model, the sample only includes households who stay in the same county for over 2 years. The wind damage index is normalized by standard deviation.

Results using other damage indicators – fatality rates and per-capita property loss – reflecting all natural hazards replicate the same curvature (Figure 3.3), confirming that the finding is not specific to hurricane winds. Though the coefficients are small, the marginal effects can be economically significant given that the migration indicators are conservative, and capture only one-third of the migration decisions compared to other data sources (Appendix C).

3.7 Simulation results

Although hurricane exposure increases substantially under more severe climate scenarios, I find that the overall spatial distribution remains largely unchanged (Figure 3.5). Exposure is most intense along the Gulf Coast, with Florida and Louisiana emerging as the most affected states. North Carolina and South Carolina also exhibit elevated future exposure levels. Although the northern Atlantic Coast is comparatively less exposed, coastal counties in this region still face substantially greater exposure than their inland counterparts.

Figure 3.5: Median number of total hurricane event exposures with local maximum sustainable wind speed above 50 knots for each county from 2020 to 2050 for 100 simulations in different scenarios

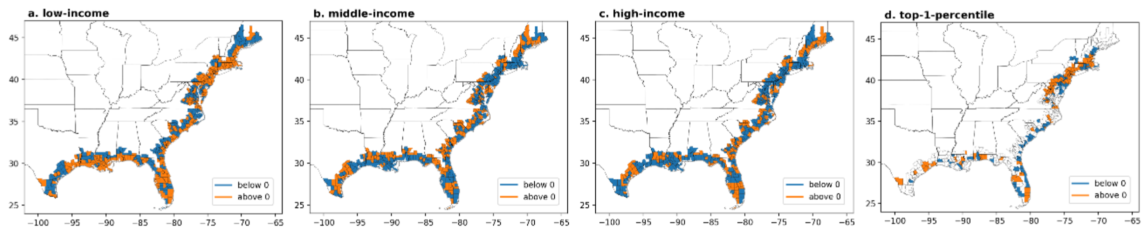


Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

Figure 3.6 and Figure 3.7 present simulation results comparing the projected 2050 population distribution with hazard-induced migration to the distribution without hazard-induced migration. Thus, the results can be interpreted as the effect of natural hazards on population distribution and resulting in change in Gini coefficients at the state, county, and metropolitan areas (See Appendix D for other comparisons and additional simulation results). Simulations based on the baseline migration matrix and estimated income-specific hurricane-induced migration indicate a clear sorting by 2050: heightened hurricane exposure is associated with a decline in the population of middle- and high-income households across most coastal counties and increase in both low-income and top-1-percentile households. I present results for RCP 8.5 in the main text, as patterns under RCP 2.6 and RCP 4.5 are qualitatively consistent. Focusing on high-income households (Figure 3.6c.), the majority of coastal counties experience net out-migration, with the exception of Florida's western coast. These areas attract inflows of hurricane-displaced households from Gulf Coast counties that face even greater future exposure. In contrast, most inland counties, including those in northern Atlantic states such as New York, New Jersey, Maryland, and Virginia, also experience declines in households—likely due to limited in-migration from hurricane-prone coastal regions.

When comparing across income strata, I find a strong correlation between declines in high-income and middle-income households, coupled with concurrent increases in both low-income and top-1-percentile households. Inconsistencies in this pattern are primarily observed in counties where direct hurricane losses offset the indirect effect through migration.

Figure 3.6: Predicted population change in each income groups for climate scenarios RCP 8.5.

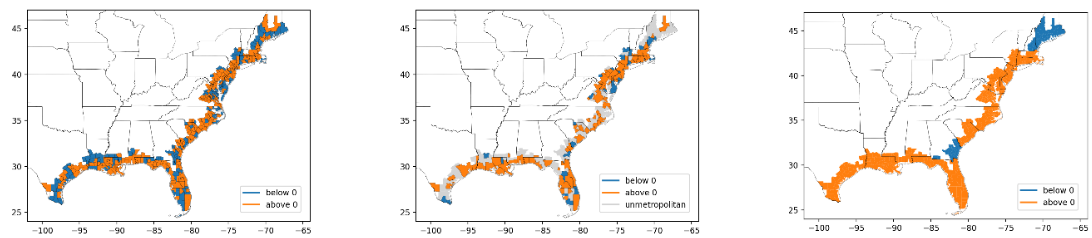


Note: I restrict the top-1-percentile map (d.) to metropolitan counties with above 100 top-1-percentile income households to ensure valid comparisons. State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

These population shifts result in rising income inequality, as reflected by increases in county-level gini coefficients. Gini coefficients rise sharply in coastal counties in Florida, Louisiana, North Carolina, South Carolina, and in the hurricane corridor of Texas. Counties along the northern Atlantic coast also exhibit increasing inequality, driven by limited in-migration of middle- and high-income households (Figure 3.7.a). At broader scales, I observe a general upward trend in Gini coefficients at both the metropolitan (Figure 3.7.b) and state (Figure 3.7.c) levels, indicating that hurricanes will exacerbate regional income disparities even if household earnings themselves remain unchanged. Importantly, these hurricane-driven changes occur on top of a broader upward trend in inequality (Figure C.3), meaning that storms further exacerbate preexisting disparities in coastal regions.

Figure 3.7: Predicted Gini coefficient changes at the county, metropolitan region, and state levels for climate scenario RCP 8.5.

a. County b. Metro c. State



Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

3.8 Discussion and Conclusions

This chapter examines the effect of natural hazards (focusing on hurricanes) on outmigration decisions of homeowners along the US Atlantic and Gulf Coasts. While much of the existing literature focuses on short-term displacement and evacuation responses to natural hazards (Deryugina et al., 2018; Groen & Polivka, 2008) our study emphasizes the marginal effects of hurricanes on migration across labor markets and explores long-run implications for the coastal income distribution. Our approach leverages both synthetic hurricane tracks and baseline migration networks to examine the extent to which hurricane exposure alters population distribution patterns, net of outflow and inflow of hurricane induced migrants.

I find substantial heterogeneity in migration responses across income groups and demonstrate an inverted-U relationship between income and the likelihood of relocating. Low-income households with limited financial resources are significantly less likely to relocate in response to rising climate risk, increasing their exposure to future disasters. This finding aligns with prior empirical and modeling studies of climate gentrification, wherein higher-income households sort into less vulnerable areas, effectively trapping lower-income households in high-risk zones (Keenan et al., 2018). Wealthy communities at the high end of the income spectrum (top 1 percentile) are more likely to secure shoreline stabilization resources—such as beach nourishment—allowing them to adapt in-situ and retain access to coastal amenities, further widening adaptation disparities (McNamara et al., 2015). Since both adaptive infrastructure and beach width are capitalized into property values (Qiu & Gopalakrishnan, 2018), these processes may reinforce socioeconomic stratification.

Simulated population flows under future climate scenarios shows how even modest differences in mobility can compound over time. Under RCP 8.5 most coastal counties lose middle- and high-income owners while gaining both the poorest and the very richest, a pattern that widens county-, metro-, and state-level Gini coefficients by 2050.

These findings underscore the critical need for targeted climate adaptation policies, including subsidized relocation assistance and property buyout programs designed to support low-income households with limited adaptive capacity. As climate change accelerates, migration patterns reflected in our empirical results can reinforce existing socioeconomic inequalities in hazard-prone regions by driving population sorting and altering community demographics. Even modest shifts in migration behavior can cumulatively exacerbate inequality over time, highlighting the need for adaptation strategies that explicitly account for environmental justice and the distributional consequences of climate risk.

Chapter 4: Inland Floods, Migration, and the Impact on Community Compositions

Climate-induced natural disasters threaten U.S. communities far beyond the coasts. Between 1980 and 2021, inland floods accounted for nearly one-quarter (23%) of all billion-dollar weather events (A. B. Smith, 2020). Their socioeconomic toll rivals that of hurricanes: Hurricane Helen alone, which made landfall in Florida but had impact extending to North Carolina, caused damages estimated at nearly $80 billion and over 200 fatalities in 2024. Whether such shocks ultimately magnify or mitigate vulnerability depends on how households in these floodplains respond. Despite increasing risk, both population (Mård et al., 2018) and economic activity (Kocornik-Mina et al., 2020) continue to rise in flood-prone regions, suggesting that adaptation through flood-resilient infrastructure, flood insurance uptake (Gallagher, 2014), and migration will be critical.

In this chapter, I link tenure choice (ownership vs renting decisions) with relocation decisions to examine how floods restructure local community demographics.

Understanding these joint decisions in flood-prone neighborhoods can help inform disaster preparedness policies, voluntary buyout programs, and post-disaster rebuilding strategies. Changes in homeownership can affect household wealth, local financial well-being (Goodman & Mayer, 2018), investment in neighborhood quality (Hausman et al., 2022), and economic inequality. If low-income households or disadvantaged communities – already disproportionately exposed to hazards losses (Adler, 2015; Gillis Peacock et al., 2012; IPCC, 2022) – are unable to maintain homeownership, flood events can exacerbate existing inequalities, as documented in coastal communities in Chapter 3. I begin with an in-depth study of the 2008 Cedar Rapids flood – one of the most devastating in Iowa's modern history – to examine the factors that drive migration and tenure choice, and then extend the analysis to a county-level study of a nationwide panel of inland flood events.

4.1 Conceptual Framework

Flood events can influence homeownership through several theoretical channels. Housing is both a consumption good and a capital investment: the use value derives from the housing services it provides, while the investment value reflects the property's resale potential (Henderson & Ioannides, 1983; Ioannides & Rosenthal, 1994). When flood risk undermines the reliability of that investment value, risk-averse households may be more likely to rent rather than own. This behavioral response aligns with findings that homeownership rates are lower in neighborhoods characterized by high volatility in housing prices (Rosen et al., 1984), unstable amenity flows (Hilber, 2005), and broader political or macroeconomic uncertainty (Turner, 2003).

Another key determinant is the relative cost of owning versus renting, captured by the price-to-rent ratio (Coulson, 2002; Davis et al., 2008; Eilbott & Binkowski, 1985; Raya & Garcia, 2012). Floods often reduce housing sale prices, particularly in directly affected areas (Atreya et al., 2013; Bin & Polasky, 2004; Gibson & Mullins, 2020), while simultaneously increasing demand for rental housing—driven in part by temporarily displaced homeowners—thereby pushing rents upward (Brennan et al., 2022; Gillis Peacock et al., 2012). This dynamic tends to lower the price-to-rent ratio, which, conditional on household income, may make homeownership more attractive.

However, these price incentives may be offset by broader vulnerability dynamics in the rental market. Renters are often more economically fragile and disproportionately impacted by post-disaster instability. Following a flood, renters face heightened risk of eviction due to income disruption or rent hikes, even as rental units become scarcer due to damage or demand from displaced households (Brennan et al., 2022; Gillis Peacock et al., 2012). Thus, natural hazards can exacerbate housing insecurity among the most vulnerable, potentially reinforcing patterns of displacement and inequality.

Because these channels operate in opposite directions, the net effect of flooding on homeownership is ultimately an empirical question. Theoretical mechanisms suggest that tenure outcomes hinge on whether perceived and actual flood risk outweigh economic incentives to buy. To examine this, I first conduct a detailed case study of the 2008 flood in Cedar Rapids, Iowa. I then extend the analysis to a nationwide panel of inland flood events using a staggered difference-in-differences approach to estimate the long-term effect of flooding on county-level homeownership rates.

4.2 The 2008 Cedar Rapids Flood in Iowa

Iowa's history of flooding is long, with major events recorded in 1927, 1961, and 1993. Since the 1980s the state has recorded a string of low-probability, high-intensity flood events (¡ 1% annual probability)—1993, 2008, 2011, and 2019—reflecting a broader Midwest trend toward more frequent and severe inland flooding (Mallakpour & Villarini, 2017; Zhang & Villarini, 2021). Climate projections suggest that these trends will intensify with continued climate change (Mallakpour & Villarini, 2017; Slater & Villarini, 2016), underscoring the need for robust adaptation and flood mitigation strategies (Cusick, 2021; M. Smith, 2019).

The June 2008 flood stands out as Iowa's costliest modern flood. In Cedar Rapids, the state's second-largest city, heavy rainfall pushed the Cedar River to a record 31.1 feet, which was more than 11 feet above the previous high (Buchmiller & Eash, 2010). The impact inundated around 10 square miles, 1100 city blocks, and more than 7000 buildings, including much of the downtown area and key public infrastructure (City of Cedar Rapids, 2023). The floodwaters extended beyond the 500-year floodplain, inundating approximately 10 square miles, including 1,100 city blocks and over 7,000 buildings. Key public infrastructure, including the downtown core, was significantly affected. Affecting seven states across the Midwest, the floods resulted in 24 fatalities and billions in economic and agricultural damage. Damage in Cedar Rapids alone exceeded $5.4 billion and displaced more than 10,000 residents (FEMA, 2009). The socioeconomic impacts were unevenly distributed. Affordable rentals and marginal owner-occupied homes, concentrated in low-lying areas, experienced disproportionately greater losses relative to owner-occupied single-family homes (Adler, 2015; City of Cedar Rapids, 2023; Tate et al., 2016), mirroring patterns observed in coastal regions (Gillis Peacock et al., 2012; Washington et al., 2006).

In response, the city launched an ambitious buy-out and flood-protection program. Between 2008 and 2015, Cedar Rapids acquired 1,356 properties in the flood zone (R. Smith, 2014), cleared land to build a new 7.5-mile-long flood control system, and paired these investments with neighborhood revitalization programs in the protected areas (Tate et al., 2016). The flood control system is estimated to cost over $750 million, which is substantion fiscal burden for mid-sized city (Cusick, 2021), There were no other major flood events in Cedar Rapids during our study period (until 2013), providing a clean setting for identifying flood impacts on migration of homeownership patterns.

4.3 Data

I assemble a household-level panel (2006-2013) from Data Axle's comprehensive residential database, which aggregates information from a variety of sources, including property deeds, mortgage records, tax assessor data, utility information, and credit-bureau address updates. After geocoding and data cleaning, the Cedar Rapids sample contains 446,043 total observations, representing approximately 27% of the city's population when benchmarked against the 2010 Census.. The primary variable of interest, homeownership status, is inferred from deed transfers and mortgage records, identifying approximately 52% of the Iowa sample as homeowners. To classify whether remaining households as renters or owners, Data Axle imputes the probability of ownership using household characteristics and proprietary demographic models, assigning each household a 1-8 "homeowner score." I then define households with a scores above 6 as owners and those with a score of 6 or below as renters. The classification aligns closely with census data for Cedar Rapids with a correlation coefficient of 0.81 with tract-level homeownership rate in the 2010 Decennial Census. The methodology is robust to different classification thresholds.

Each record has a household identifier. A move is coded when the mailing address (verified by credit-card billing data) changes between years; the destination tract and county are recorded, enabling analysis of within-metro, within-state, and out-of-state moves. A parcel is treated as flooded if its centroid intersects the inundation polygon (Fung et al., 2021). To control for prior flood information, I digitized the FIRM map in Linn county prior to 2008 to control for baseline information before flood event happened (FEMA, 1982). Census tract characteristics (median income, race/ethnicity composition, demographic composition) come from the ACS five-year file (Table 4.1).

Table 4.1: Summary statistics for Cedar Rapid case study

Variable	Count	Mean	SD	Min	Max
Panel A. Overall Sample					
Homeownership	40,705	0.820	0.384	0	1
Head of hh age	40,705	51.56	15.10	22	77
Child	40,705	0.199	0.399	0	1
Income ($1000)	40,705	76.54	67.36	5	500
Price to rent ratio	40,705	239.05	66.82	109.62	468.20
Median Income ($1000)	40,705	64.23	20.63	18.71	110.00
Vacancy Rate	40,705	0.0653	0.0487	0.0074	0.2737
Household Size	40,705	2.43	0.25	1.72	2.95
Panel B. Sample with Migration Data					
Homeownership	32,920	0.889	0.314	0	1
Head of hh age	32,920	53.05	14.63	22	77
Child	32,920	0.222	0.416	0	1
Income ($1000)	32,920	83.35	69.69	5	500
Price to rent ratio	32,920	247.47	73.61	113.82	468.20
Median Income ($1000)	32,920	62.28	20.51	18.71	110.00
Vacancy Rate	32,920	0.0646	0.0531	0.0074	0.2737
Household Size	32,920	2.41	0.25	1.72	2.95
Panel C. Incoming Residents Sample					
Homeownership	1,017	0.602	0.490	0	1
Head of hh age	1,017	44.37	14.12	22	77
Child	1,017	0.235	0.424	0	1
Income ($1000)	1,017	83.01	73.33	5	500

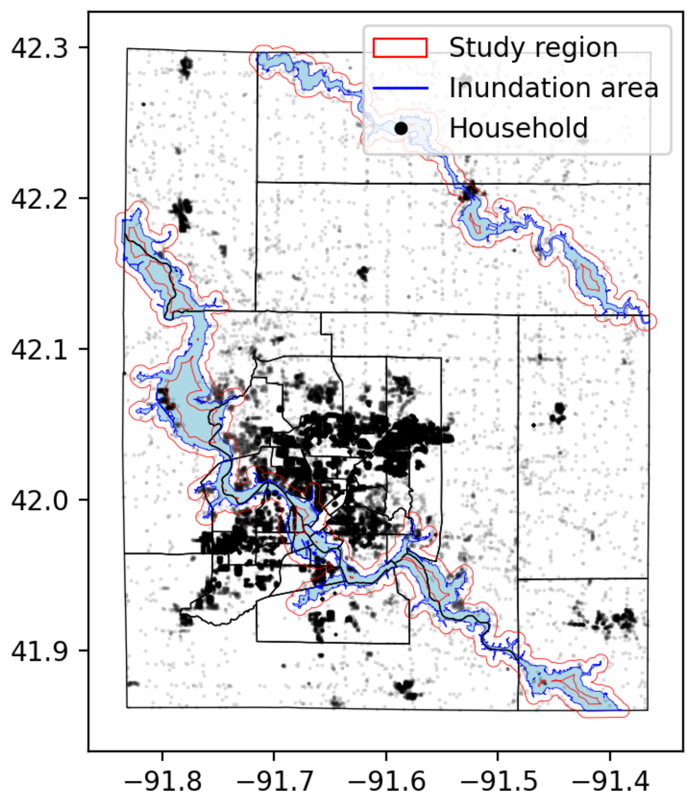
Note: In panel C, I do not include census tract level covariates since most of incoming residents move to same region.

The final panel merges household-by-year observations on migration and tenure outcomes, demographic proxies, parcel flood exposure in 2008, and time-varying neighborhood controls at the census tract-level. Data attrition is modest (≈ 3 % annually) and not systematically related to flood status after controlling for observable traits.

4.4 Empirical Strategies

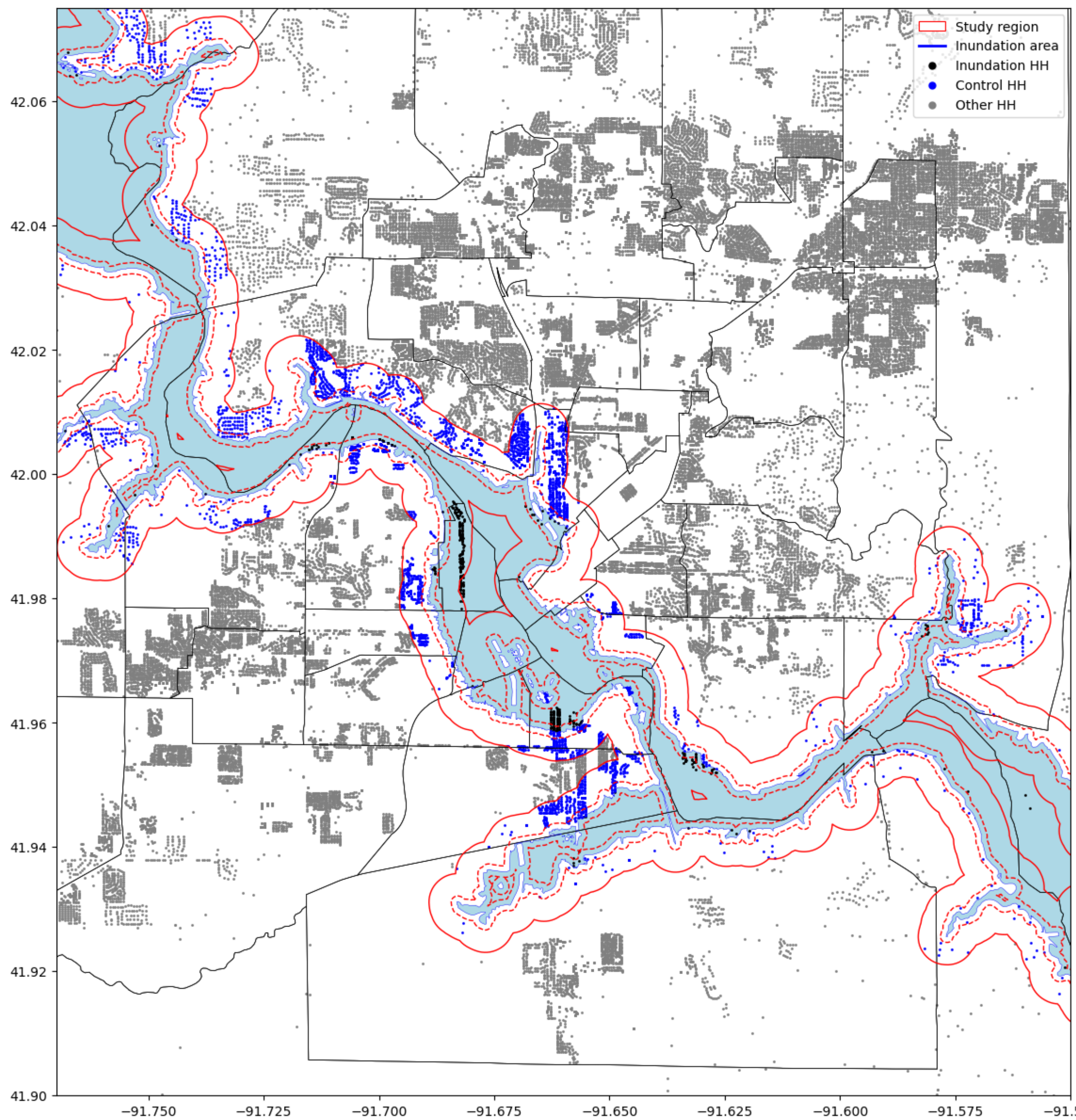
I identify the short-term effect of flooding on homeownership, exploiting the sharp spatial discontinuity created when floodwaters extended beyond the 100-year FEMA Flood Insurance Rate Map (FIRM) boundary (Figure 4.1). Prior to 2008, properties at the boundary of the inundation area are comparable; they received comparable flood-risk information, the same building codes, and displayed similar structural and neighborhood characteristics. Therefore, after controlling for the 100-year FEMA Special Flood Hazard Area (SFHA) boundary, any post-event difference in home tenure (owners vs renters) and migration decisions within and outside the inundation boundary can be attributed to the 2008 flood exposure. In the primary specification, I specify a regression-discontinuity (RD) design by restricting the sample households located within 500 meters of the inundation boundary (Red regions in Figure 4.1 and Figure 4.2). The detailed spatial distribution of households around the inundation boundary further supports the validity of this RD design. As shown in Figure 4.2, both inundated and control areas are densely populated and geographically interspersed along the boundary, in urban and rural neighborhoods. This dense and continuous distribution ensures that households on either side of the cutoff are locally comparable in terms of observable and unobservable characteristics, such as income, housing stock, and neighborhood amenities. To further validate our result, I also estimate equation (4.1) within 100m (Appendix E), which yield similar results.

Figure 4.1: Treatment area and household distribution around Cedar Rapids, Iowa



*Note:*2000 census tract boundaries were obtained from the U.S. Census Bureau and limited to Linn County, Iowa.

Figure 4.2: Detailed population distributions in Cedar Rapids



*Note:*2000 census tract boundaries were obtained from the U.S. Census Bureau and limited to Linn County, Iowa.

The empirical specification is as follows:

$$Owner_{hy} = \sum_i \Big(\beta_i \, SFHA_i \, Inundation_{hy} + \beta_{i,0910} \, SFHA_i \, Inundation_{hy} \, 0910_y$$
$$+ \beta_{i,1113} \, SFHA_i \, Inundation_{hy} \, 1113_y\Big) + \gamma X_{hy} + SFHA_i + \mu_{hy} + \theta_y + \epsilon_{hy} \tag{4.1}$$

where $Owner_{hy}$ represents homeownership status for household h in year y. $SFHA_i$ and $Inundation_{hy}$ represent whether households reside in Special Flood Hazard Area (SFHA) and whether households reside in the inundation area respectively. 0910_y is an indicator for households observed in short term immediately after the flood (2009-2010) and 1113_y is an indicators for the medium term (2011-2013) after the 2008 flood. X_{hy} is the vector of time-variant household-level characteristics, including age of the head of household and whether households have children. $\mu_h y$ and θ_y are the zip code fixed effects and year fixed effects respectively. The coefficients $\beta_{i,0910}$ and $\beta_{i,1113}$ indicate the short- and medium-term effects of the flood on homeownership. I cluster the standard errors at the zip code level to control for correlation in the error terms across different information groups. The analysis is based on household-level data rather than parcel-level observations. Although I do not include household fixed effects due to the unbalanced nature of the Data Axle panel, the identification remains valid under the assumption that household characteristics are randomly observed during the study periods. As long as the Data Axle database documents households randomly over time, the results based on the sampled renter population can still capture the true causal effect. To account for time-invariant unobservables, I include ZIP code fixed effects, which help control for differences in local amenities and neighborhood characteristics.

To decompose the different channels that affect change in homeownership rates, I study tenure outcomes for households moving into the study region (Sheldon & Zhan, 2019) in the year after the flood by:

$$\begin{aligned} Owner_{hy} &= \beta\, Inundation_{hy} + \beta_{09}\, Inundation_{hy}\, 09_y \\ &\quad + \beta_{1013}\, Inundation_{hy}\, 1013_y + \gamma X_{hy} + SFHA_i + \mu_{hy} + \theta_y + \epsilon_{hy} \qquad (4.2) \end{aligned}$$

where all variables are defined as in equation 4.1, except $Owner_{hy}$ indicates the tenure decision choice after households migrate into the study area. Since there were limited observations of households migrating into the study region from 2007 to 2013, I do not estimate the heterogeneous effect of flooding across different information groups. The standard errors are clustered at the FIRM level, as households within the same FIRM zone are likely to face correlated flood risk and share common information about flood exposure.

Another channel for change in homeownership rate after the flood is the difference in outmigration decisions across owners and renters. To estimate the effect of the 2008 flood on migration decisions across homeowners and renters in the study region, I use the equation:

$$\begin{aligned} Migrate_{hy} &= \beta_0 + \beta_1\, Inundation_{hy} + \beta_2\, Owner_{hy} + \beta_3\, Inundation_{hy} \cdot Owner_{hy} \\ &\quad + \beta_4\, Inundation_{hy} \cdot 08_y + \beta_5\, Owner_{hy} \cdot 08_y + \beta_6\, Inundation_{hy} \cdot Owner_{hy} \cdot 08_y \\ &\quad + \gamma X_{hy} + SFHA_i + \mu_{hy} + \theta_y + \epsilon_{hy} \qquad (4.3) \end{aligned}$$

where all variables are defined as in equation 4.1, but the dependent variable $Migrate_{hy}$ represents household h decision to migrate out in year y, which means that household addresses are different between year y and year $y+1$. β_6 explains the difference in the effects of flooding on homeowners and renters who migrated between 2008 and 2009. I only estimate the effect of the flood on outmigration between 2008 and 2009 because I am interested in the effect of short-term evacuation on aggregate homeownership rates. The 2008 flood was a major event that forced households to decide whether to rebuild or relocate. With continued assistance and buyout programs, homeowners may have been more likely to move due to financial incentives, while renters—facing fewer attachment or financial constraints—could relocate more easily. Standard errors are clustered at the census tract x FIRM level to capture spatial dependence in both exposure and housing-market conditions.

4.5 Results for Household-Level Models

I examine how migration into and out of inundated areas contribute to the overall change in homeownership rates in Linn County that experienced the 2008 flood and find that homeownership rates drop in the inundated area, but the effect is heterogenous within and outside flood zones. First, I confirm that parcels just inside and just outside the 2008 inundation boundary followed parallel trends in the three pre-flood years, supporting the assumption that properties are randomly distributed across the inundation line (Figure 4.3). In Column 1, I estimate the baseline model with RD design and FIRM fixed effects. In Column 2 and 3, I include zipcode fixed effects and household level covarites, which does not change our main results. In Column 4, I switch from zipcode level fixed effects to city level fixed effects, as households in the same administrative boundary tends to have similar time invariant characteristics. Consistently, homeownership rates decrease inside the 100-year Special Flood Hazard Area (SFHA), with no significant short-run effect outside the 100-year flood zone. In the preferred model, within two years of the flood event, inundated parcels inside the SFHA experience a 12.2-percentage-point fall in the home-ownership share ($p < 0.01$), with no significant short-run effect outside the 100-year flood zone (Table 4.1, Colum 3). Homeownership rates continue drop for all regions in the medium term but the drop is faster in regions inside the SFHA: by 2013 the gap between flooded-SFHA and flooded-non-SFHA parcels widens to 7.4 percentage points (Table 4.1, Column 3). In unflooded parcels within 500 m of the boundary, tenure shares remain essentially flat, indicating that spillover effects are limited.

These results suggest that severe inland flood events can lower homeownership rates at a micro scale, especially in regions already classified as high-risk. The tenure shift occurs through two channels—owners leaving and renters arriving—with the net effect of increasing the concentration of rental housing in the most hazard-exposed neighbourhoods. Such compositional change is consistent with broader evidence that tenure structure adjusts slowly but persists following extreme events.

Figure 4.3: Homeownership inside and outside of inundation areas across time

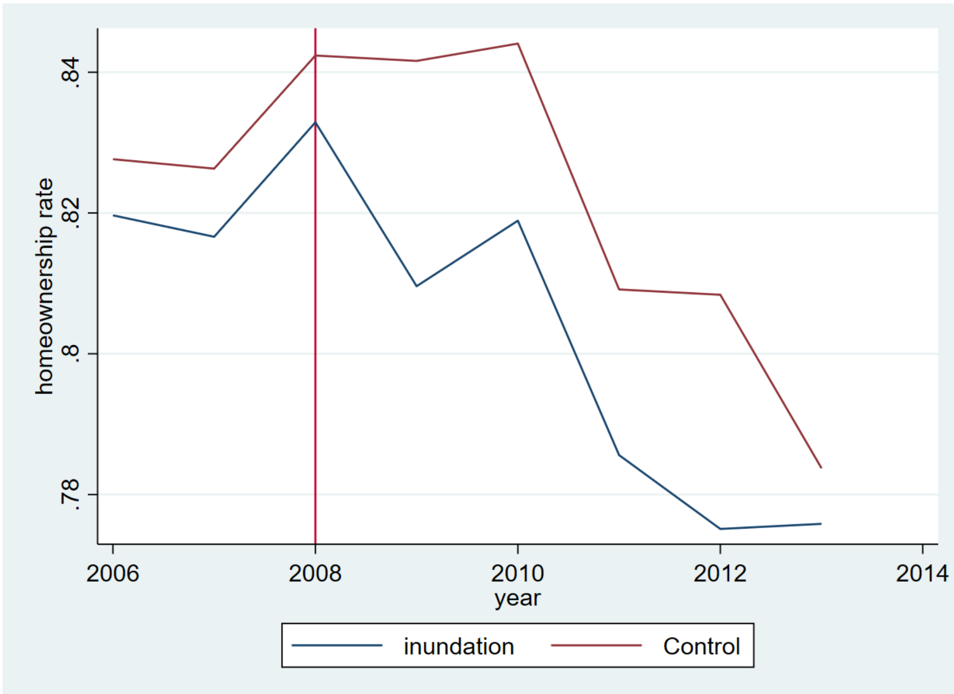


Table 4.2: Effects of the 2008 flood on homeownership rates

	(1) homeownership rate	(2) homeownership rate	(3) homeownership rate	(4) homeownership rate
SFHA × Inundation	-0.139** (0.000488)	-0.00645 (0.0155)	0.0162 (0.0166)	-0.0569 (0.0139)
SFHA × Inundation × 09–10	-0.114** (0.000699)	-0.134** (0.00171)	-0.122* (0.00213)	-0.113* (0.00186)
Non-SFHA × Inundation × 09–10	0.00490 (0.000703)	-0.00566 (0.00107)	-0.00003 (0.00137)	-0.00061 (0.00187)
SFHA × Inundation × 11–13	-0.0868** (0.000930)	-0.104** (0.000746)	-0.0924** (0.000896)	-0.0838** (0.000690)
Non-SFHA × Inundation × 11–13	0.00582 (0.000923)	-0.00180 (0.000335)	-0.00679* (0.000405)	-0.00701 (0.000659)
Head of hh age			0.00827* (0.000173)	0.00879* (0.000157)
Child			0.177** (0.00228)	0.205** (0.00309)
Tract-level characteristics	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Zipcode fixed effects	No	Yes	Yes	No
City fixed effects	No	No	No	Yes
Ethnicity fixed effects	No	No	Yes	Yes
Observations	40,705	40,705	40,705	40,705

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
In column (1) and (2), 136 villages are dropped because of missing values in the 2011 Socio-Economic and Caste Census.
In column (3), 4 villages are excluded due to missing elevation data as they are too small.

I then estimate the effect of the 2008 flood on homeownership outcomes for incoming residents (Table 4.2). I first restrict the sample to migrants originating outside Linn County (Columns 1 and 2) and then add within-county movers in the analysis (Columns 3, 4, and 5). Following the method in Sheldon and Zhan (2019), I model homeownership as a binary outcome with household-level controls and origin fixed effects. I find incoming cross-county movers into inundated areas are 80% less likely to purchase a home and prefer to rent immediately after a hazard event (Column 2). For movers within the Linn County, the reduction in probability of homeownership falls to under 62% and is not statistically significant (Column 1), suggesting that households familiar with the local neighborhoods have better information or place-specific attachment. The effects quickly dissipate for both groups after 1 year, suggesting that the flood effect on tenure decision is short lived. Once rebuilding begins and neighborhood signals normalize, incoming households appear to discount recent flood history. Moreover, our result shows that tenure outcomes are closely tied to prior ownership status: among renters prior to migration, only 39% become homeowners after moving, while 61% continue renting. In contrast, over 78% of former homeowners retain ownership status after migration. These patterns suggest that the observed decline in post-flood homeownership is partly driven by the composition of incoming migrants, particularly the higher likelihood that former renters are relocating into affected areas. Thus, the flood's impact reflects not only a shift in housing preferences but also selective migration by households with different ownership histories.

Table 4.3: Effects of the 2008 flood on tenure decisions of incoming residents

	(1) Home ownership	(2) Home ownership	(3) Home ownership
Inundation	-0.168	0.0863	0.0668
	(0.185)	(0.0147)	(0.00901)
Inundation × 2009	-0.624	-0.814**	-0.858***
	(0.162)	(0.00401)	(0.000693)
Inundation × 2010–13	0.137	-0.0619	-0.0781
	(0.186)	(0.0532)	(0.0775)
Inundation × 2009 × *mi_within*		0.652	0.694
		(0.0956)	(0.0857)
Inundation × 2010–13 × *mi_within*		0.0905	0.0745
		(0.0112)	(0.0277)
Head of household age	0.00808*	0.00754*	0.00855*
	(0.000274)	(0.000367)	(0.000224)
Child	0.135*	0.190**	0.271***
	(0.00903)	(0.000918)	(0.000159)
Year fixed effects	Yes	Yes	Yes
Zipcode fixed effects	Yes	Yes	No
City fixed effects	No	No	Yes
Ethnicity fixed effects	Yes	Yes	Yes
Observations	334	1,017	1,017

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Finally, I examine whether flooding events have heterogeneous effects on the outmigration probabilities of existing households (Table 4.3). The number of observations differs from Table 4.1 due to incomplete tracking of some households across consecutive years. The results indicate that renters were 44% more likely to migrate immediately following the flood (Column 2). While owners are statistically less likely to migrate than renters, I do not find significant evidence that owners respond to flood exposure in the year following the 2008 event. This suggests that homeowners face greater constraints in relocating immediately after the flood. These patterns further support the lagged migration response documented for coastal hurricanes in Chapter 3.

Table 4.4: Effects of the 2008 flood on migration decision across homeownership statuses

	(1) Migrate	(2) Migrate	(3) Migrate
Inundation	-0.0402*	-0.0563	-0.0601
	(0.0197)	(0.0381)	(0.0381)
Inundation x 08	0.423***	0.439***	0.440***
	(0.102)	(0.107)	(0.106)
Owner	-0.0896***	-0.121***	-0.126***
	(0.00605)	(0.0129)	(0.0130)
Owner 08	-0.0315	-0.000341	0.000580
	(0.0206)	(0.0236)	(0.0236)
Inundation Owner	0.0400*	0.0517	0.0566
	(0.0199)	(0.0385)	(0.0385)
Owner Inundation 08	-0.312**	-0.324**	-0.326**
	(0.103)	(0.108)	(0.108)
Inundation 09-13		0.0211	0.0210
		(0.0443)	(0.0443)
Owner 09-13		0.0434**	0.0447**
		(0.0147)	(0.0147)
Owner Inundation 09-13		-0.0141	-0.0158
		(0.0448)	(0.0448)
Head of hh age	-0.000819***	-0.000819***	-0.000837***
	(0.0000820)	(0.0000820)	(0.0000819)
Child	-0.00215	-0.00220	-0.00254
	(0.00260)	(0.00260)	(0.00258)
Tract level characteristics	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Zipcode fixed effect	Yes	Yes	No
City fixed effect	No	No	Yes
Ethnicity fixed effect	Yes	Yes	Yes
Observations	32920	32920	32920

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.6 County-Level Analysis on Homeownership Rates

To test whether the household-level patterns identified in Cedar Rapids generalize to broader settings, I conduct a county-level analysis. While the micro-level study offers detailed insights into behavioral responses to flooding, its findings may be context-specific, shaped by local institutions, demographics, and geography. To assess the external validity of these findings, I examine whether inland flooding events are associated with significant shifts in homeownership rates across U.S. counties between 2006 and 2022[13]. This county-level analysis enables me to evaluate whether localized household responses to inland flood risk scale up to aggregate housing outcomes in diverse regional contexts. Following Kocornik-Mina et al. (2020), I use extreme precipitation events as proxies for local flooding. Although extreme precipitation is not a perfect predictor of flooding at a specific location, it provides an exogenous source of variation in the timing and location of flood events. I assemble monthly total precipitation data from the Parameter-elevation Regressions on Independent Slopes Model (Daly et al., 2008), which produces 4 km $\times$ 4 km grid-level estimates by combining ground-based observations with an interpolation model that accounts for topography and other geographic factors. Specifically, I define an

[13]I include the COVID period to capture the long-term effects of extensive extreme precipitation events occurring after 2016.

extreme precipitation event as occurring when at least one grid within a county experiences monthly precipitation exceeding 600 millimeters in a given year[14]. Since I focus on inland flooding events and storm surge cannot be captured in precipitation data, I exclude all counties along the Atlantic and Gulf coasts, where extreme precipitation is more likely to be driven by hurricanes. As shown in Figure 4.4, the West Coast is more susceptible to the defined precipitation events due to significant rainfall originating from the Pacific Ocean.

[14]While the value is 5 times as large as the value used in Kocornik-Mina et al. (2020), the percentiles are similar. Specifically, around 2% of counties have experienced extreme precipitation events during the period 2006-2022.

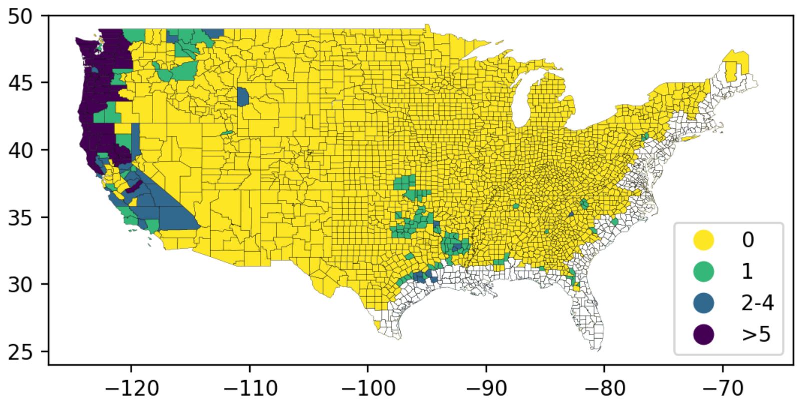
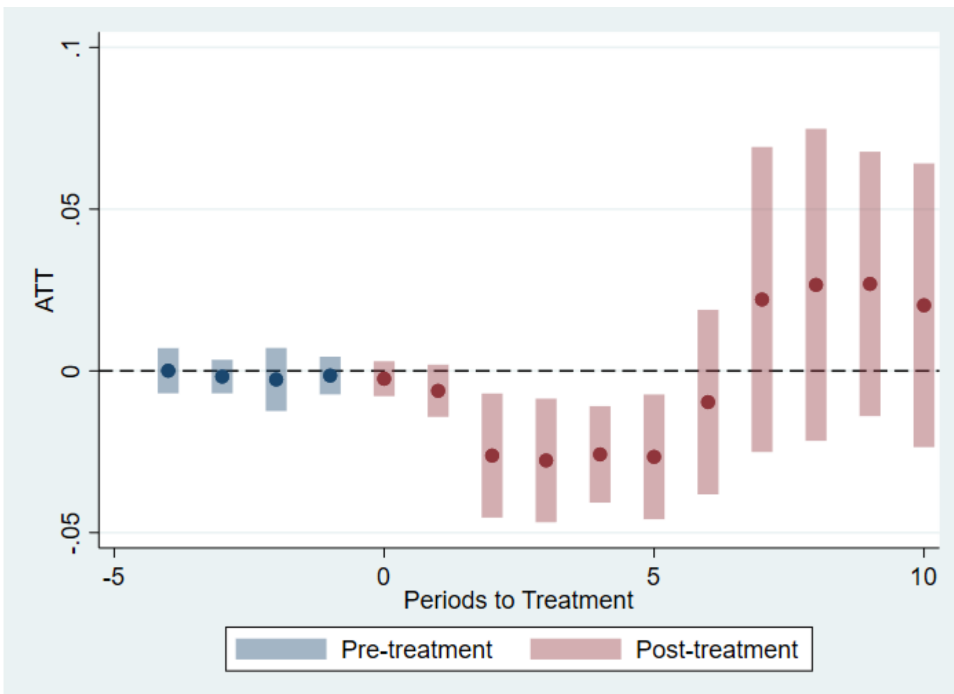


Figure 4.4: Number of extreme precipitation events from 2005 to 2023

Floods are inherently rare, heterogeneous, and staggered, with migration responses often unfolding over multiple years. Conventional two-way fixed-effects (TWFE) estimators are biased when treatment timing and effects vary (Goodman-Bacon, 2021). Specifically, the classical two-way fixed effect estimator becomes a weighted average of all possible two-group/two-period DiD estimators in the data with negative weight if the treatment effect dissipates. I therefore implement a staggered difference-in-differences approach following Callaway and Sant'Anna (2021). This method is well-suited to our context, as the timing of extreme precipitation events varies across counties, and this estimator allows the effect to evolve (and fade) over time. Because some counties may experience multiple extreme precipitation events during the study period, I use the first such event in each county as the treatment. In doing so, I focus on the impact of having ever received the treatment during our sample period and capture the path of treatment effects, even though the treatment itself may be transient. Therefore, our results reflect the long-term effects of a county's first extreme precipitation event on homeownership rates. I control for baseline socioeconomic characteristics, including age structures, income, and vacancy rates. I also include county fixed effects, year fixed effects, and state specific time trends to capture time invariant county heterogeneity, common shocks, and state specific patterns.

Figure 4.5 presents the event study plot of average effects of extreme precipitation events on homeownership rates between 2006 and 2022 using the Callaway and Sant'Anna (2021) estimator. The horizontal axis indicates the number of years since the extreme precipitation event (positive values) or the number of years before (negative values), with zero representing the year of the extreme precipitation event. There is no detectable change in county-wide owner-occupancy in Years 1 and 2, consistent with the lag required to repair, rebuild, or move. Counties that experience extreme precipitation saw a statistically significant 2-percentage-point decline in homeownership rates between years 2 and 5 following the event. The effects dissipate after five years and estimates revert toward zero, indicating that tenure composition gradually rebounds as new construction and in-migration rebalance the market. Results suggest that severe inland floods nudge households tenure toward renting, but the risk perceptions induced by flooding fade over time, consistent with prior evidence (Bin & Landry, 2013).

Figure 4.5: Effects of extreme precipitation events on homeownership rates



Note: This figure illustrates the effects of extreme precipitation events with 95% confidence intervals (vertical lines) on the changes in homeownership rates between 2006 and 2022. The horizontal axis represents the relative year of the extreme precipitation event. The control group consists of counties that did not experience flooding during the study period.

4.7 Discussion and Conclusions

Understanding different mechanisms for households to adapt to heightened natural hazards risks has important implications for local housing development and disaster prevention policies. This chapter demonstrates that severe inland flooding can alter local tenure composition, but the shift is both short-lived and uneven. In Cedar Rapids, owner-occupancy fell by twelve percentage points inside the 100-year floodplain during the two years following the 2008 disaster, a decline driven largely by an influx of renters whereas the higher mobility of existing renters contributes to a increase in homeownership rates a few years after the flooding. A nationwide event-study of extreme precipitation between 2006 and 2022 using staggered difference in difference estimator confirms a parallel, though smaller, pattern: owner-occupancy drops by roughly two percentage points between the second and fifth years after a flood-related shock and then gradually returns to pre-event levels. Taken together, these results suggest that hazard-induced changes in homeownership appear soon after the shock, persist for several years, and stabilize as rebuilding proceeds.

Past research has largely focused on the impact of natural disasters on housing prices and households relocation decisions (Bin & Landry, 2013; Boustan et al., 2020; Gibson & Mullins, 2020; Hornbeck, 2012; Ortega & Taşpınar, 2018; Zhu et al., 2022). Our analysis also suggests that risk perceptions of households could depend on proximity and knowledge of local conditions. Between 2008 and 2009, incoming residents moving into inundated areas from outside the flood affected counties are

80% less likely to purchase homes. For residents making relocation decisions within the county, homeownership rates for migrants moving into inundated areas drop by around 20%. However, this heightened risk sensitivity is temporary. Differences in homeownership rates by origin of migrants largely disappear after 1 year. Unlike some coastal settings where post-disaster rebuilding has attracted high-income newcomers (Graff Zivin et al., 2023), inland floods do not appear to induce gentrification. Instead, rental demand rises and the local income distribution shifts downward, raising concern that repeated floods could erode wealth accumulation in already vulnerable neighborhoods.

The analysis has limitations that should guide future inquiry. The tenure classification relies on probabilistic homeownership scores rather than deed-verified records, and the extreme-precipitation proxy cannot capture flash floods or disentangle concurrent wind and hail damage. The migration measure I use also counts any mailing address change as permanent, so I cannot separate short-term displacement from longer-term migration. Moreover, the data set does not follow households long enough to assess whether tenure stabilizes or continues to fluctuate after multiple flood events.

The findings can inform policy in several ways. First, recovery programs that focus primarily on assistance to homeowners overlook the substantial share of renters who bear the brunt of flood damage and often struggle to secure assistance. Second, more consistent enforcement of flood-insurance requirements beyond the 100-year floodplain, coupled with clearer communication of residual risk, could reduce reinvestment in the most vulnerable neighborhoods. Finally, well-designed and adequately compensated voluntary buy-out programs—paired with affordable relocation options—offer a potential pathway to break the cycle of recurring damage, declining ownership, and worsening inequality.

Homeownership is a key determinant of neighborhood quality and a critical financial asset, especially for marginal homeowners who disproportionately reside in flood-prone areas (Hausman et al., 2022). As climate change intensifies, declines in neighborhood quality due to repeated flooding may exacerbate existing social and economic inequalities, particularly for low-income and minority households that are more likely to live in vulnerable regions. These dynamics suggest a need for policy interventions that address such inequities—such as targeted support and recovery assistance for affected households—to help preserve homeownership and mitigate the compounding effects of climate-related risks.

Chapter 5: Housing Market Dynamics and Supply-Side Responses to Natural Hazards

Much of the economics literature on housing markets treats supply as fixed in the short run and focuses on the demand side – particularly hedonic and sorting models that show how prices and location choices capitalize amenities, environmental risks, and policy interventions. However, population and housing outcomes are jointly determined; where housing development is slow or constrained, prices adjust but people cannot simply move to the risk profile they prefer if adequate housing is unavailable.

Housing supply frictions are acute along the US coastline, where regulatory limits and scarcity of buildable land make new construction relatively inelastic and push prices far above replacement cost (E. Glaeser & Gyourko, 2018). In these settings, most new residents enter the housing market through the reconstruction or renovation of existing housing stock[15] (Graff Zivin et al., 2023). Natural hazards add complexity

[15]While (Parton & Dundas, 2020) find that a policy signal indicating future sea level rise regulation led to a 32% increase in housing permits—until the policy was repealed—in North Carolina, suggesting land was being intentionally preserved for future development, this dynamic may not apply to Miami-Dade County, Florida, where most oceanfront land is already developed.

to housing market dynamics. Theory predicts that heightened awareness of disaster risk from hazards typically reduces housing demand (Bin & Landry, 2013), and curtails new development and housing supply. However, empirical evidence often shows the opposite: housing investment rises shortly after hurricanes, wildfires and floods (Bin & Landry, 2013; Issler et al., 2019; Lazarus et al., 2018). By analyzing hazard-induced renovation and reconstruction decisions, and neighborhood spillover effects, this chapter shows that disasters can accelerate re-development—potentially leading to excessive rebuilding in high-risk areas.

5.1 Housing Supply Responses to Natural Hazards and Neighborhood Change

Foundational work in urban economics (Brueckner, 1980; Wheaton, 1982) shows that redevelopment occurs when the value of land for new development exceeds the value of its current use, net of demolition costs. As high-income households demand high quality housing stocks, the development and redevelopment of housing stock leads to spatial redistribution of population. High income households stay in suburban areas in the initial periods and may eventually move to city center with redevelopment and urban amenities leading to gentrification in urban centers (Brueckner, 1980; Couture et al., 2023).

However, several conditions must hold for these redevelopment dynamics to emerge. In shrinking or stagnant cities, falling demand can forestall redevelopment, resulting in the persistence of aged housing stock due to the durability of built capital

(E. L. Glaeser & Gyourko, 2005). Moreover, since investment in land development is irreversible and the rent is uncertain, the option value can further provide incentive to delay investment to make more informed decisions, thereby delaying reconstruction and renovation decisions (Capozza & Li, 1994; McMillen & O'Sullivan, 2013). Urban decline and revival are then largely driven by disinvestment and subsequent redevelopment decisions of landowners in a neighborhood (Brueckner & Rosenthal, 2009; Rosenthal, 2008).

Because each parcel owner ignores the external effects of their decision on neighboring parcels, redevelopment is prone to coordination failure. The concentration of aged buildings, generally viewed as negative amenity, tend to reduce nearby property prices (Brueckner & Rosenthal, 2009; Hornbeck & Keniston, 2017). Wealthier and more educated households tend to cluster in neighborhoods with newer housing stock (Bayer et al., 2004; Brueckner & Rosenthal, 2009; Diamond & McQuade, 2019), reinforcing patterns of spatial inequality. In more severe cases, distressed or foreclosed properties exert strong negative spillovers on nearby housing price (Anenberg & Kung, 2014; Campbell et al., 2011; Gerardi et al., 2015; Hartley, 2014; Towe & Lawley, 2013; Whitaker & Fitzpatrick Iv, 2013). While some studies suggest that the decrease housing price can also result from competition with increasing housing stock (Hartley, 2014), generally negative amenity due to lack of maintenance is reported as the channel for housing price reduction (Gerardi et al., 2015).

Conversely, the redevelopment of vacant lots and aged structures is a positive neighborhood amenity. Public investment in industrial sites or historic buildings can generate positive externalities for nearby properties (Koster & Rouwendal, 2017; Van Duijn et al., 2016). Similarly, urban renewal and revitalization programs have been shown to benefit untreated areas through spatial spillovers (González-Bailón et al., 2023; Ooi & Le, 2013; Paredes & Skidmore, 2017; Rossi-Hansberg et al., 2010). For example, renovations in Baltimore in before 2008 bolstered nearby redevelopment efforts by 1.8% (Irwin, 2019).

Taken together, the durability of housing, option values, and spatial externalities often result in inefficient voluntary investment, contributing to persistent urban decline and spatial concentration of poverty, especially in regions experiencing slow growth or economic downturns (Ambrus et al., 2020; E. L. Glaeser & Gyourko, 2005; Owens et al., 2020). To counteract this decline, policymakers have employed various strategies, including public investment in infrastructure and housing (Koster & Rouwendal, 2017; Rossi-Hansberg et al., 2010; Van Duijn et al., 2016), demolition (Almagro et al., 2023; Collins & Shester, 2013; Sandler, 2017), and other place based policies (Busso et al., 2013), trying to combat population loss, disinvestment, decaying infrastructure, and increasing socioeconomic disparities.

Natural hazards, while destructive, can also act as exogenous shocks that force redevelopment decisions. With spillover effects, post-hazard renovation and reconstruction efforts can release local economic potential and lead to higher welfare gain, especially where properties are outdated, and individual renovation actions do not account for their externality. The great Boston fire of 1972, which devastated a portion of downtown Boston, presented opportunities for beneficial redevelopment and a virtuous circle of building upgrades that encouraged further upgrades of nearby buildings (Hornbeck & Keniston, 2017). Rebuilding assistance after Hurricane Katrina also encouraged more development for ineligible homeowners (Fu & Gregory, 2019). In Japan, the 1995 Hanshin Earthquake in Japan removed redevelopment barriers in the Kyoto–Osaka–Kobe urban core, shifting growth back from the periphery to the center (Xu & Wang, 2019). Similarly, the 1906 San Francisco Fire increase also released the frictions and increased housing density in affected regions (Siodla, 2015).

The same forces that drive positive feedbacks and improve neighborhood quality can also lead to maladaptive outcomes. In coastal areas with repetitive hurricanes and storm surge risks, hazard-induced renovation and reconstruction are often incentivized by post-disaster assistance, which may unintentionally encourage overinvestment (Fu & Gregory, 2019; Kates et al., 2006; Kydland & Prescott, 1977). For example, the introduction of the National Flood Insurance Program (NFIP) led to a near doubling of coastal development in some regions (Cross, 1989). By reducing the financial consequences of loss, disaster aid and insurance can create a moral hazard, encouraging continued development in hazard-prone areas (Ehrlich & Becker, 1972; Henkel et al., 2022; Hsiao, 2023). Since its inception, the NFIP has paid out approximately $9 billion in housing repair assistance and $1 billion in reconstruction support through individual assistance programs (FEMA, 2021). Low-interest disaster loans offer additional support (Billings et al., 2022), helping households recover from devastating events like Hurricane Katrina (Gallagher & Hartley, 2017). Yet, the scale of reliance is concerning—just 1% of properties covered by NFIP, labeled "repetitive loss properties," account for over 38% of total claims (Jenkins, 2004), highlighting how a small subset of properties repeatedly depend on federal support to maintain or rebuild in the face of persistent hazards.

This chapter examines neighborhood spillover effects from post-hurricane renovations in a high-risk, supply-constrained market. Using Hurricane Irma's 2017 landfall in Miami-Dade County as an exogenous shock I test whether the storm accelerated renovations and redevelopment in flood-affect areas and then treat Irma-induced renovation activity as an instrument to estimate the effect of neighborhood renovations on the probability that an unaffected parcel gets renovated. This analysis speaks directly to the debate over whether post-disaster assistance should prioritise rebuilding in place or facilitate retreat, and it quantifies the neighbourhood-level benefits and costs that standard cost-benefit analyses often overlook.

5.2 Background and Data

Miami-Dade County, Florida is an active coastal housing market with chronic exposure to hurricanes, storm surge, flood risk, and sea level rise. Being the most populous county in Florida and the seventh most populated in the United States, Miami-Dade has experienced significant and uneven demographic growth across the income distribution[16]. These shifts have intensified housing demand in high-amenity and low-lying neighborhoods (Haer et al., 2017; Hallegatte et al., 2013).

The county contains over 1.07 million housing units, ranging from luxury oceanfront properties in Coral Gables and Miami Beach to aging and often deteriorated housing in historically lower-income communities. While the total number of single-family homes has continued to grow, most new development is concentrated in the southeastern part of Miami-Dade County. In contrast, along the coastline, growth in housing supply often takes the form of redevelopment. Redevelopment is subject to zoning and building regulations (Graff Zivin et al., 2023), requiring all new construction and major renovations in coastal and flood-prone zones to meet strict standards for wind resistance, elevation, and structural resilience. Combined with NFIP requirements for redevelopment in floodplains (Kousky, 2019), these rules mean that redeveloped properties are often of higher construction quality than the original structures they replace. Although coastal redevelopment remains relatively sparse, the process of redevelopment and gentrification in higher-elevation regions such as Little Haiti has sparked growing concern over displacement and housing affordability. These areas, less vulnerable to flood risk, have increasingly attracted investment and redevelopment interest, contributing to patterns of climate gentrification (Keenan et al., 2018)

[16]Populations and housing units increase both by around 20% from 2000 to 2020 (U.S. Census Bureau, 2019).

Hurricane Irma made landfall in Florida in September 2017, with widespread impacts across the state, including Miami-Dade County. Notably, Hurricane Irma was the first major hurricane to affect the county in over a decade, following a relatively quiet period since Hurricane Wilma in 2005. This long gap likely decreased the perception of hurricane risk among residents and policymakers, making Hurricane Irma a plausibly exogenous shock. Although Irma reached Category 4 status in the Florida Keys, Miami-Dade experienced comparatively less wind damage, with maximum wind speeds at 85 knots at Miami International Airport and Key Biscayne, while most areas experiencing sustained winds between 48 and 60 mph (Rabin, 2017). While wind damage to property was limited, substantial flooding caused significant property damage, as storm surge inundated low-lying coastal areas, particularly immediate beachfront regions. Inundation levels ranged from 1 to 5 feet in most coastal areas, with some regions like Coconut Grove and Brickell experiencing over 6 feet of flooding. This surge flooded streets, damaged properties, and caused significant damage to landmarks such as the Vizcaya Museum and Gardens (NWS, 2017).

5.2.1 Parcel Data

I obtain parcel-level tax assessment records for 300,046 single family homes from 2013 to 2021 from Miami Dade County Tax Assessors public records. To avoid confounding effects of Hurricane Ian that hit Florida in September 2022, I limit the analysis to 2013-2021. After dropping parcels that are vacant or merged, the sample contains 283,743 lots, of which 47,874 lie within the 2017 Hurricane Irma-induced inundation radius in my main analysis.

Renovation: I identify renovation activity from detailed property tax assessment data, which includes annual appraised land and structure values from 2020 to 2024, and structural information on the construction year of the primary building and any detached buildings. Figure 5.1 presents tax assessment records for a property affected by Hurricane Ian from 2022 to 2023. In the top panel (2022), the assessment indicates that the patio was built in 2011. However, in the bottom panel (2023), the records suggest that the landowners constructed a new patio in 2022 and expanded the living area of the structure. By comparing detailed tax assessment reports across years, I am thus able to generate different renovations and development decisions across time. Specifically, I define *Remodel* as the addition of a detached building or a significant change in sub-area of the primary building[17]. I classify a property as undergoing *Renovation* if it involves the construction or significant repair of patios, fences, walls, or remodel. *Redevelopment*—full demolition and rebuilding—is identified when the structure built-year in the assessment file jumps forward and is cross-validated against demolition permits (match rate > 90 %). Because I cannot track earlier maintenance decisions, this data may underestimate investment in maintenance.

[17]The property in Figure 5.1 underwent a remodel in 2022, as part of the main building was altered.

Figure 5.1: Property decomposition for inundated property during Hurricane Ian

BUILDING INFORMATION

Building Number	Sub Area	Year Built	Actual Sq.Ft.	Living Sq.Ft.	Adj Sq.Ft.	Calc Value
1	1	2011	5,435	4,674	4,755	$1,497,825
Current Building Sketches Available						

EXTRA FEATURES

Description	Year Built	Units	Calc Value
Dock - Concrete Griders on Concrete Pilings	2011	176	$5,343
Aluminum Modular Fence	2011	70	$2,190
Patio - Brick, Tile, Flagstone	2011	610	$6,039
Wall - CBS unreinforced	2011	70	$258
Pool 6' res BETTER 3-8' dpth, tile 250-649 sf	2011	1	$27,000

BUILDING INFORMATION

Building Number	Sub Area	Year Built	Actual Sq.Ft.	Living Sq.Ft.	Adj Sq.Ft.	Calc Value
1	1	2011	5,470	4,819	4,807	$1,497,380
1	2	2022	609	512	509	$178,150
Current Building Sketches Available						

EXTRA FEATURES

Description	Year Built	Units	Calc Value
Patio - Brick, Tile, Flagstone	2022	980	$10,780
Patio - Wood Deck	2022	692	$4,844
Glass fences in backyard applications	2022	70	$4,900
Pool 6' res BETTER 3-8' dpth, tile 250-649 sf	2011	1	$26,700
Wall - CBS unreinforced	2011	70	$255
Aluminum Modular Fence	2011	70	$2,166
Dock - Concrete Griders on Concrete Pilings	2011	176	$5,285

Because patios are highly susceptible to flood damage but rarely to wind damage, the first post-Irma patio addition/repair serves as an instrument for flood-induced repair costs. Flooding from storm surge was the primary source of property damage from Hurricane Irma. Patios, being attached to residential properties and often situated at ground level, are especially vulnerable to water damage, making them a reliable indicator of flooding impact. As shown in Table F.1, 63% of patios are made by concrete while the remaining are generally made by bricks, tiles, and flagstones. While most of property owners choose to have concrete or brick patios to prevent damage from heavy storms and termites, concrete patios can be damaged during hurricanes. Storm surge and resulting standing water may erode the underlying soil, causing the slab to crack or settle. Repeated saturation can also lead to mildew or staining, particularly if the surface is not properly sealed. Consequently, concrete and brick patios are typically replaced every 10–15 years, with severe storms often triggering immediate repairs or replacement. In contrast, wind damage primarily affects elevated and structural parts of the home, such as roofs and walls, which are less relevant to my analysis of flood-driven rebuilding. Since patios are rarely damaged by winds but are commonly affected by floodwater, they provide a consistent measure of the flood-induced impact on residential properties.

All types of renovation activity— the addition of pools and patios, remodeling, redevelopment, and general renovations—increased in 2017 and then gradually declined (Table 5.3). This spike suggests a strong response to Hurricane Irma, likely to restore damage and increase resilience, facilitated through disaster assistance or insurance payouts. Figure 5.2 illustrates the probability of constructing a new patio and redeveloping a house across different structure age groups. Consistent with my hypothesis, the probability of redevelopment increases monotonically with the age of the structure, while the probability of new patio remains stable around 2%. Figure 5.3 displays the spatial distribution of these activities, suggesting a positive correlation between housing quality and the rates of new patio construction and redevelopment.

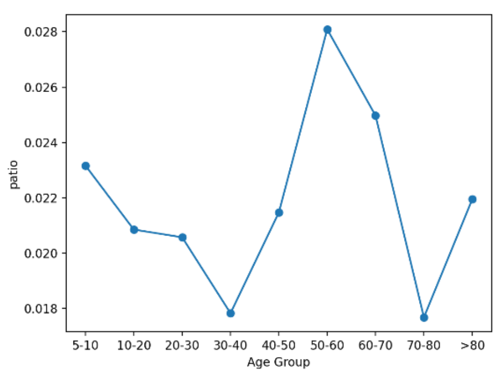
Table 5.1: Distribution of renovation and redevelopment activity across years.

Year	New pool	New patio	Remodel	Redevelopment	Renovation	Total
2015	955	4,013	2,421	144	7,050	283,743
2016	1,150	5,000	2,914	162	8,568	283,743
2017	1,980	10,263	6,806	208	16,299	283,743
2018	1,494	6,365	3,043	229	10,497	283,743
2019	1,561	6,734	3,640	238	10,311	283,743
2020	1,171	3,860	1,639	215	6,067	283,743
2021	1,709	3,451	1,338	248	4,888	283,743
2022	2,310	3,092	1,381	212	4,034	283,743

Note: Renovation indicates all kinds of renovation and remodel activities except for redevelopment

Figure 5.2: Number of parcels experiences renovation and redevelopment activity across years

a. New patio



b. Redevelop

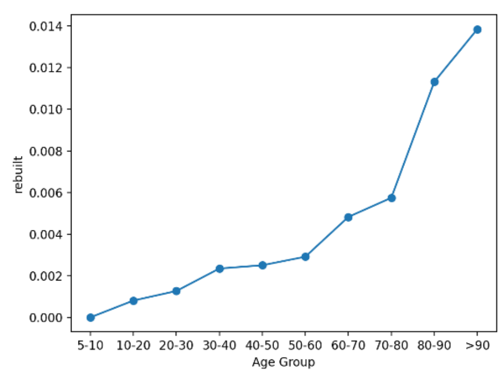
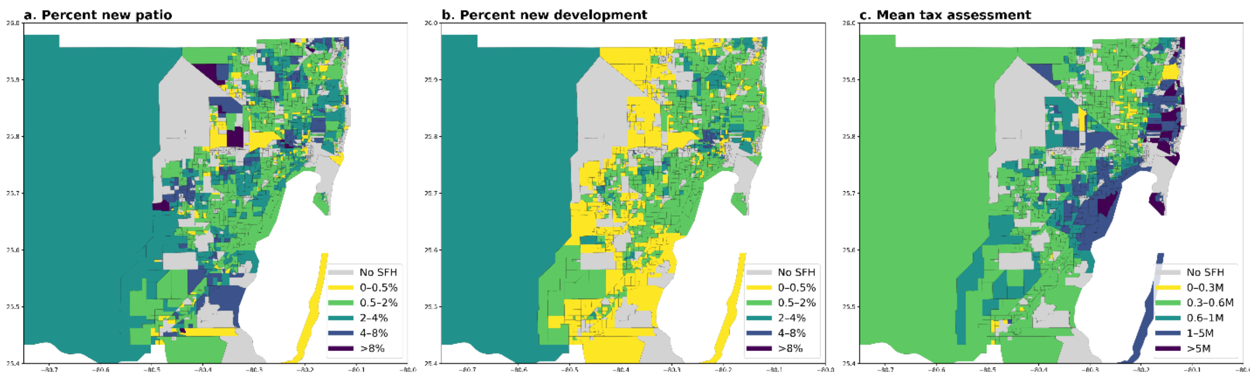


Figure 5.3: Distribution of new patio construction, redevelopment, and property value in Miami-Dade County

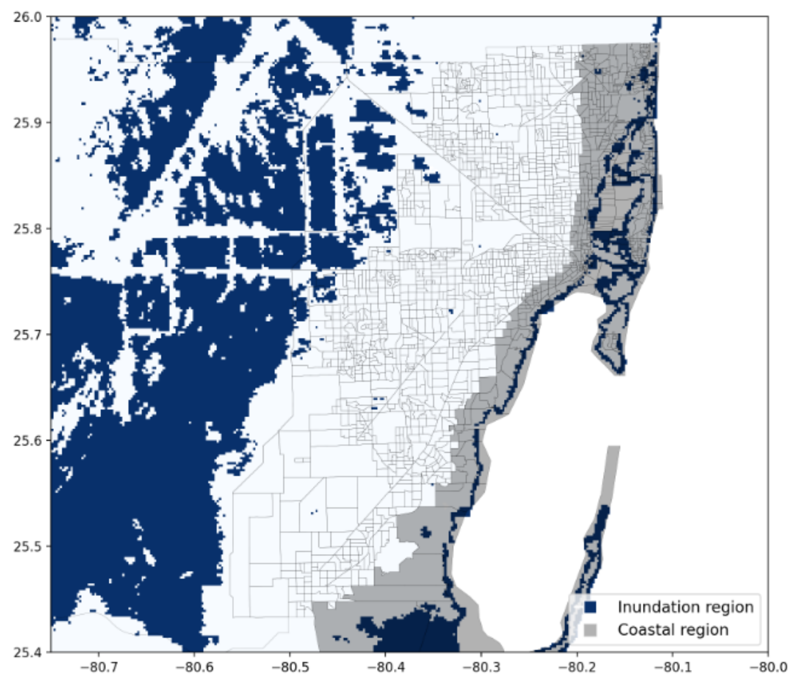


*Note:*Block group boundaries are from the 2010 U.S. Census Bureau.

Owner-occupancy: I identify single-family homes as owner-occupied if they claim homestead exemption in their property tax, a benefit available only to primary residents and claimed by more than 90 percent of eligible owners in Florida (Ihlanfeldt, 2021; Turnbull & van der Vlist, 2022). Further, I classify properties as owned by institutional buyers if they do not have a homestead exemption and if the name of the tax bill payer contains "LLC" or "INC".

Hurricane Irma Damage: In Figure 5.4 the inundated areas from Hurricane Irma are highlighted in blue. Property damage is largely confined to oceanfront and nearshore parcels, with minimal inundation in the lower-lying inner-city areas. Although the inundation extended into the county's western boundary, the area is largely rural, with relatively few properties affected. My study is therefore confined to coastal block groups in Miami-Dade County located within 1 km of the coastline. Specifically, while wind damage from hurricanes tends to be spatially correlated across large areas, it affects a wide range of properties regardless of topography. In contrast, flood damage can only occur when a property is directly inundated by floodwaters. As such, the delineated inundation zone provides a clear spatial boundary for identifying flood exposure based on similar wind damage.

Figure 5.4: Distribution of Irma induced inundation regions and coastal regions



*Note:*Block group boundaries are from the 2010 U.S. Census Bureau.

Neighborhood Spillover: The demand-side spillover effects of housing investments and renovations are largely driven by changes in perceived neighborhood quality and associated shifts in expectations. As new construction or major upgrades occur, nearby property owners may respond by investing in their own properties, anticipating future appreciation and aligning with the neighborhood's evolving image. This localized revitalization often signals improved safety, stability, and aesthetic value—factors that directly influence household willingness to remain or invest. Moreover, as property values rise, so does the local property tax base, which enables municipalities to enhance public amenities, such as parks, schools, and street infrastructure. These improvements, in turn, reinforce the attractiveness of the neighborhood and generate additional demand-side momentum. This positive feedback loop has been observed in both market-rate developments (Hornbeck & Keniston, 2017; Pennington, 2021)and subsidized homeownership programs (Ellen et al., 2001), where targeted housing investment helped reverse neighborhood decline through endogenous upgrades and public reinvestment.

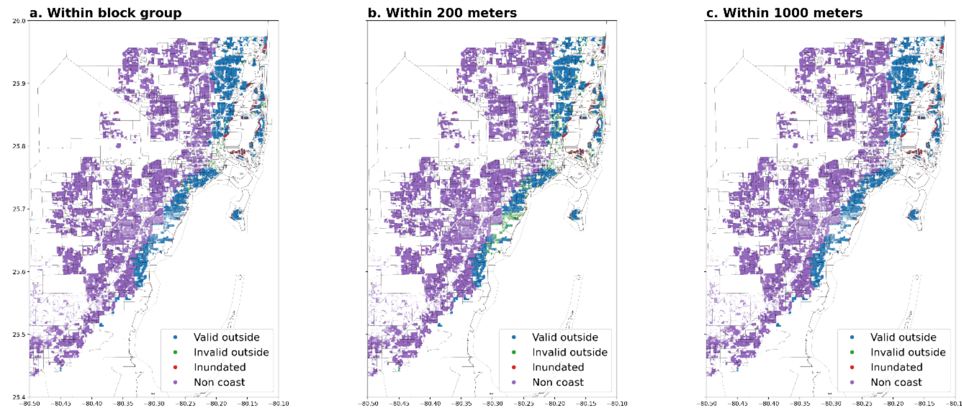
In this study, I measure neighborhood spillover effects using two complementary approaches that reflect distinct underlying mechanisms: administrative boundaries and spatial proximity. The first approach captures spillovers within the same Census block group, which serves as the smallest jurisdiction in which public service improvements and land use decisions—such as tax-financed amenities or code enforcement—are likely to be coordinated and internalized. These jurisdictional boundaries reflect the institutional channel through which renovations may influence neighboring properties via shared amenities or policy responses. Moreover, since the average block group in dense coastal regions covers approximately 2 square kilometers, the administrative boundary is likely to also capture nearby aesthetic spillovers. For each parcel, spillover effects are defined as occurring within the same block group (thick black lines in Figure 5.5).

The second approach uses geographic buffers to capture localized behavioral and perceptual effects, such as perceived quality from nearby construction or the influence of neighborhood appearance on renovation incentives. I define spatial proximity using a 200-meter radius as the primary distance band, with 400-meter and 1-kilometer buffers used for robustness checks. This physical distance-based measure is particularly relevant in urban contexts like Miami-Dade County, where households may be influenced by visible nearby improvements. To ensure reliable estimates, I restrict the sample to parcels located in neighborhoods with at least 30 single-family homes, ensuring that each unit of analysis captures a meaningful social and built environment. The spatial distribution of parcels included in the analysis with different neighborhood definitions is shown in Figure 5.6. Since most block groups have more than 30 single family homes, I use block group as the preferred neighborhood definition, which suggests that property renovation decisions only influence properties within their block groups through aesthetic spillover and benefit within the tax base.

Figure 5.5: Illustration for instruments through neighborhood inundation area

*Note:*Block group boundaries are from the 2010 U.S. Census Bureau.

Figure 5.6: Distribution of parcels for spillover effect analysis



Note: Block group boundaries are from the 2010 U.S. Census Bureau.

Other Controls: Following the literature (Bakkensen & Ma, 2020; Graff Zivin et al., 2023; Turnbull & van der Vlist, 2022), I control for the number of bedrooms and the age of the property. I also include lot size, distance to the shoreline, whether the parcel is oceanfront, and elevation to control for parcel characteristics. Additionally, I use the 2016 aggregated tax assessed value of the building and all auxiliary features, before any exemptions, as a proxy for housing quality. As shown in Table 5.2, while properties inundated by Hurricane Irma—predominantly located closer to the shoreline and often oceanfront—tend to be of higher quality, they do not exhibit systematically different renovation patterns compared to neighboring properties that were not inundated. Inundated homes are characterized by larger assessed school values, greater lot sizes, more bedrooms, and closer proximity to the beach and shorelines, with higher prevalence of luxury features such as pools and brick patios. These features reflect their premium location and structural attributes. However, despite their higher baseline quality, the probability of pre-Irma renovations—including new patios and redevelopment—remains statistically similar to non-inundated properties, as shown in the lower panel of the table. This finding is reinforced by the parallel trends displayed in redevelopment probabilities and new patio probabilities between inundated and non-inundated regions before and after Irma, with a temporary spike in 2017 for both but no persistent divergence (Figure 5.7).

Table 5.2: Summary statistics

Variable	**Mean (Inundated)**	**SD**	**Mean (Uninundated)**	**SD**	**Difference**
Property characteristics					
Assessed value ($ million)	2.206	3.357	1.055	1.719	1.150***
Lot size (sq. meters)	0.018	0.115	0.011	0.009	0.007***
Bedroom	4.215	1.449	3.666	1.284	0.550***
Age	37.947	25.415	42.609	24.922	-4.662***
Distance to shoreline (m)	60.9	82.8	1,638.7	1,588.5	-1,577.9***
Distance to beach (m)	3,153.3	1,811.7	3,376.9	2,400.4	-223.6***
Elevation	4.710	1.697	5.452	3.175	-0.741***
Oceanfront	0.514	0.500	0.255	0.436	0.259***
Have pool	0.555	0.497	0.326	0.469	0.230***
Have wood patio	0.034	0.182	0.021	0.143	0.013
Have concrete patio	0.237	0.425	0.370	0.483	-0.133***
Have brick patio	0.483	0.500	0.243	0.429	0.240***
Have fence	0.500	0.500	0.620	0.485	-0.121***
Have wall	0.306	0.461	0.165	0.371	0.141***
Renovation activities					
Renovated pool	0.007	0.085	0.009	0.093	-0.002
Renovated patio	0.013	0.111	0.019	0.135	-0.006
Renovated fence	0.010	0.099	0.009	0.095	0.001
Renovated wall	0.001	0.026	0.000	0.020	0.000
Remodel	0.001	0.026	0.001	0.028	-0.000
Redevelopment	0.023	0.150	0.019	0.135	0.004
Any renovation	0.044	0.206	0.041	0.199	0.003

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

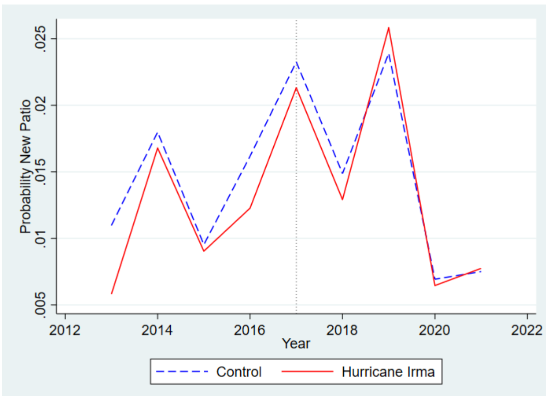
5.3 Methods

5.3.1 Hazard Induced Renovations and Redevelopment

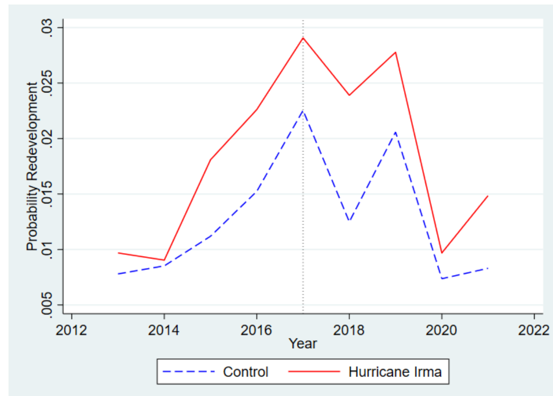
I identify the short-term effect of flooding inundation (similar to Chapter 4) on renovation and redevelopment decisions, exploiting the spatial discontinuity in storm surge from Hurricane Irma (Figure 5.3). Specifically, I examine whether properties that experienced inundation were more likely to undergo renovation, as even limited flooding can degrade soil conditions, damage structural foundations, or compromise property habitability, thereby triggering renovation responses. The identification strategy relies on the exogenous timing of Irma. Specifically, I compare outcomes for properties that were inundated by the storm surge to nearby properties that remained dry. Without the flood, these two groups would have followed parallel trends in housing outcomes, suggesting that post-Irma divergence between the two groups can be attributed to the flood exposure, rather than to pre-existing differences or broader market trends. Figure 5.7 confirms that parcels inundated and uninundated by Hurricane Irma followed parallel trends in the pre-Irma years, especially for patio (Figure 5.7a.), further supporting the use of patio as the instrument for neighborhood renovation trends.

Figure 5.7: Percentage new patio and percentage rebuilt for inundated and control parcels

a. New patio



b. Redevelop



I first estimate the treatment effect of Hurricane Irma with a linear probability model as follows:

$$Y_{iyb} = \alpha_1 Age_{iy} + \alpha_2 Irma_y + \alpha_3 Irma_i Post_y + \beta X_{2iy} + \delta_b + y_t + \epsilon_{iby} \quad (5.1)$$

where Age_{iy} is the structure age for parcel i in year y, $Irma_y$ is a dummy for whether the parcel is in the inundation area and $Post_y$ indicates observations after 2016. I also include block group fixed effects δ_b and year fixed effects y_y to control for time invariant neighborhood amenities and year specific economic shocks. I cluster standard errors at the block group level since properties within the same block groups likely face similar zoning regulations.

I also use duration model to analyze the timing of post-hurricane redevelopment decisions with heterogenous effects of property age on redevelopment decisions over time. I do not model renovation decisions (pool, patio, remodel) in the duration model since I have limited data on prior structure before landowners make patio repairs or renovations. Specifically, I model the probability of property redevelopment with the density function:

$$f(t) = \Pr(T < t < T + dt) \tag{5.2}$$

where T, the survival time, is the interval from the start of the study to when redevelopment is observed for each parcel, or until the study ends for parcels that are not redeveloped. For parcels that are redeveloped, I include both the observation prior to redevelopment and the observation following redevelopment, as they can be treated as two distinct properties. Therefore, I have the survival rate $S(T)$, which is the probability that the parcel remained unrenovated at time T.

$$S(t) = \Pr(t \leq T) \ = 1 - \int_0^t f(t')\, dt' \tag{5.3}$$

Then, I can estimate the probability of redevelopment at $h(t)$ conditional on waiting until time t using Cox proportional hazard model. The semi-parametric duration model is well-suited for analyzing the time until a renovation event occurs, while allowing for flexible baseline hazard estimation.

$$h_{ib}(t) = -\frac{\frac{dS(t)}{dt}}{S(t)} = h_0(t)\, exp\left(\alpha_2 Irma_i + \alpha_3 Irma_i Post_t + \beta X_{2it} + \delta_b + y_t\right) \tag{5.4}$$

Where $h_0(t)$ is the unspecified baseline hazard function and other covariates remain the same. Note that in Equation 5.4, the effect of age on redevelopment outcomes is approximated by the non-parametric baseline hazard rate $h_0(t)$.

5.3.2 Spillover Effects of Neighborhood Renovations

Modeling the spillover effect of neighborhood renovations can be challenging due to endogenous household sorting (Rosenthal, 2008) and clustering of unobserved characteristics (S. Lee & Lin, 2018). Specifically, homeowners tend to cluster with individuals of similar socio-economic characteristics, which increases the likelihood that they will undertake similar strategies to maintain their property. Similarly, developers are more likely to build in areas that are already appreciating (Green et al., 2005), leading to clustered redevelopment efforts. To overcome this endogeneity problem, I exploit the exogenous timing of Hurricane Irma and use a shift-share instrument. While the extent of inundation is correlated with coastal amenities and housing price, the exogenous timing of Hurricane Irma affects the probability and percentage of patio renovations in a neighborhood. I estimate the model in two stages for properties that are not inundated by Hurricane Irma. In the first stage, I regress neighborhood renovation activity on neighborhood and property characteristics:

$$Z_{iyb} = \gamma_1 Age_i + \gamma_2 NIrma_i + \gamma_3 NIrma_i Postyear_t + \beta X_{2it} + \delta_b + y_t + \epsilon_{iby} \quad (5.5)$$

Specifically, I use percentage of nearby properties with patio renovation in the last 5 years Z_{iyb} as a proxy for neighborhood renovation intensity and estimate the hazard induced renovation rate in the neighborhood as a function of the percentage of nearby properties inundated by Irma ($NIrma_i$) and cumulative years after Hurricane Irma $Postyear_t$. For each parcel, I use the percentage of inundated single-family homes (red properties in Figure 5.4) as an instrument for neighborhood renovation activity, since Hurricane Irma triggered an exogenous increase in such renovations. This effect is especially pronounced in the immediate aftermath of the storm, making the instrument a strong proxy for shifts in neighborhood quality after Hurricane Irma. Using a control function approach, I retrieve residuals $\widehat{\epsilon_{iby}}$ from the first stage regression and use it in the second stage for the LPM and Duration models respectively.

$$Y_{iyb} = \alpha_1 Age_{iy} + \rho\widehat{\epsilon_{iby}} + \beta X_{2iy} + \delta_b + y_t + \epsilon_{iby} \tag{5.6}$$

In this case, since I only include households outside of inundation areas in the estimation, I do not include hurricane effects into the model.

5.3.3 Multinomial Logit

Following (Munneke & Womack, 2015), I use a multinomial logit model to analyze landowners' decisions to renovate, redevelop, or wait until the following year. In addition to the previously included covariates, I incorporate the ratio of assessed land value to total assessed property value. A higher land-to-property ratio indicates a more valuable underlying parcel relative to the existing structure, which increases the incentive to redevelop the property. Therefore, I can write indirect utility of landowners i to choose $j \in \{Renovate,\ Redevelop,\ Wait\}$ at time t:

$$V_{ijt} = \alpha_{1j} Age_{it} + \alpha_{2j} Irma_i + \alpha_{3j} Irma_i Post_t + \beta_j X_{it} + \rho\widehat{\epsilon_{iby}} + \epsilon_{ijt} \tag{5.7}$$

I estimate the effect of the hurricane and spillover effects from nearby properties simultaneously using the full sample. The primary reason for this approach is to facilitate more tractable equilibrium simulations where both hurricane risks and neighborhood renovation activities coexist. Assuming that idiosyncratic tastes for choices ϵ_{ijt} follows i.i.d. Type I Extreme Value distribution, the expected probability of choosing option j is (McFadden, 1978):

$$P_{ijt} = \frac{e^{V_{ijt}}}{\sum_{j'} e^{V_{ij't}}} \tag{5.8}$$

and landowners will choose $d_{it} = j$ that maximize utility:

$$d_{it} = j \ if \ V_{ijt} \geq V_{ij't} \ \forall j' \neq j \tag{5.9}$$

5.4 Results

5.4.1 Direct impact of Hurricane Irma on Renovation, Redevelopment, and Owner-Occupancy

The difference-in-differences estimates compare parcels inside the 2017 inundation area with similar parcels within the block group that were not inundated. First, I find that inundated parcels are less likely to have patios or fences, but are more likely to renovate post Hurricane Irma (Table 5.3). Inundated parcels were 0.7 pp more likely to add or replace a patio (Column 2), 0.4 pp more likely to rebuild a fence (Column 3), and 0.8 pp more likely to undertake a full redevelopment (Column 5). While the magnitude of marginal effects is small, these marginal effects account for around 30% of the renovation rates in the sample. Pool upgrades are delayed after the hurricane (Column 1), but the effect is statistically significant only at the 10% level. Owner-occupancy moves in the opposite direction reflecting a 4 pp drop (Column 7) in the homestead exemption rate inside the inundation zone, consistent with a short-run shift toward absentee ownership.

The duration model represents similar effects (Table 5.3, Column 6), where coefficients represent marginal effects, calculated as the product of the hazard ratio and the average redevelopment rate. This analysis focuses solely on redevelopment and does not consider other renovation decisions. Results indicate that landowners are more likely to redevelop a parcel if impacted by hurricane Irma. They are also more likely to redevelop oceanfront homes with greater coastal amenities and larger lot sizes.

Table 5.3: Effects of the 2017 Hurricane Irma on housing renovations and homeownership rate

	(1) Pool	(2) Patio	(3) Fence	(4) Remodel	(5) Redevelop	(6) Redevelop Duration	(7) Owner
Inundation	0.000597	-0.00606***	-0.00403**	-0.000327	-0.00495**	-0.00245*	0.0338*
	(0.000902)	(0.00221)	(0.00172)	(0.000365)	(0.00204)	(0.001356)	(0.0184)
Inundation × Post-Irma	-0.00133*	0.00717**	0.00399*	0.000678*	0.00792***	0.0073***	-0.0395***
	(0.000780)	(0.00323)	(0.00226)	(0.000391)	(0.00266)	(0.00185)	(0.00898)
Lot size	-0.00554	-0.0153	-0.00627	0.0170***	0.0501***	10.195***	0.0443
	(0.0121)	(0.0202)	(0.0199)	(0.00493)	(0.0130)	(2.378)	(0.328)
# of Bedrooms	0.000252**	-0.000187	0.000459**	0.000113**	0.00435***		-0.0141***
	(0.000126)	(0.000225)	(0.000209)	(0.0000454)	(0.000108)		(0.00295)
Age	-0.0000253***	-0.0000214*	0.0000215**	0.0000373***	0.000656***		-0.00111***
	(0.00000603)	(0.0000128)	(0.0000103)	(0.00000549)	(0.000036)		(0.0000972)
Log distance to shoreline	0.000140	0.00109***	0.000607*	0.0000180	0.000548	0.000207	-0.00501
	(0.000183)	(0.000313)	(0.000330)	(0.0000617)	(0.000457)	(0.000339)	(0.00417)
Elevation	0.0000399	-0.0000991	0.0000244	0.00000337	0.000130**	0.000366***	-0.00181
	(0.0000743)	(0.000132)	(0.000109)	(0.0000318)	(0.0000553)	(0.000103)	(0.00138)
Oceanfront	-0.000280	0.00462***	0.00135	-0.0000618	0.00492***	0.00968***	-0.0466***
	(0.000904)	(0.00154)	(0.00154)	(0.000277)	(0.000747)	(0.00163)	(0.0176)
BG fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	486,720	486,720	486,720	486,720	486,720	486,710	486,720

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Coefficients for the duration model (Column 6) are adjusted marginal effects. Age is excluded in the duration model due to its semi-parametric estimation as part of the baseline hazard.

5.4.2 Neighborhood Spillover Effects

Using the share of flood-damaged parcels that repaired patios as an instrument, I find positive spillover effects of on renovation activity in nearby parcels (Table 5.4). Specifically, the coefficient 0.0988 in column (1) suggests that a 1 pp increase in the share of new patios in the block group leads to a 0. 1 pp increase in the patio renovation rate, which has similar magnitude to (Irwin, 2019), who reports that one additional new development leads to a 1% increase in redevelopment probabilities. Similarly, a 1 percentage point increase in the share of new patios in the block group increases redevelopment probability by 0.43 pp. The coefficients remain robust for alternative spillover effect definitions. Spillovers attenuate with distance but remain significant at a 200-metre radius. However, beyond 400-meter radius coefficients inflate, suggesting weaker instrument in control function methods or potential misspecification. First-stage F-statistics exceed 190 in all cases, confirming instrument strength for the preferred distance bands.

Table 5.4: Effects of Hazard-Induced Renovations on Nearby Renovation Activities

	(1) Patio	(2) Patio	(3) Rebuild	(4) Rebuild	(5) Patio	(6) Rebuild	(7) Patio	(8) Rebuild
	Block Group				*200 meters*		*1000 meters*	
Percent properties maintain patio in past 5 years	0.0988***		0.431***	0.110***	0.0740**	0.107***	0.124***	0.0986***
	(0.0184)		(0.00311)	(0.0189)	(0.0355)	(0.0304)	(0.0274)	(0.0238)
Percent properties maintain patio in past 10 years		0.163***						
		(0.0374)						
Age	-0.00000126	-0.00000275		0.0000256***	-0.0000107*	0.0000210***	-0.00000843*	0.0000212***
	(0.00000171)	(0.00000968)		(0.000000852)	(0.00000640)	(0.00000248)	(0.00000494)	(0.00000175)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BG fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	917.128	482.732	196.670	917.128	366.137	366.137	670.450	670.450
N	481,000	481,000	481,00	481,000	437,480	437,480	470,760	470,760

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Coefficients for the duration model (Column 3) are adjusted marginal effects. Age covariate is missing in the duration model since it is semi-parametrically estimated as the baseline.

Table 5.4 shows the results for the multinomial logit models, which simultaneously estimate the effects of Hurricane Irma and the spillover effects of neighborhood renovation activity. Similar to previous specifications, the coefficient on the Inundation is negative and statistically significant for both redevelopment and renovation outcomes, indicating that prior to Hurricane Irma, properties located in inundation zones were less likely to experience property investment. This is consistent with the notion that storm-prone areas may be perceived as riskier investments or have lower baseline neighborhood quality. However, the interaction term is positive, suggesting a substantial increase in the likelihood of investment after the hurricane. As an exogenous shock, Hurricane Irma catalyzed redevelopment and renovation activity, likely due to a combination of insurance payouts, public recovery funding, and homeowner rebuilding incentives. I also find positive spillover effects in both choices, reinforcing the idea of strong local spillover effects. Properties surrounded by homes that had maintained or invested in patios were significantly more likely to undergo redevelopment or renovation themselves.

Older structures are more likely to be redeveloped, as shown by the positive and significant coefficient on Age in the redevelopment model. This is consistent with the idea that aging structures are more likely to be replaced entirely, either because they are nearing the end of their useful life or because new construction can significantly increase their value. However, age is not a significant determinant of renovation activity, suggesting that minor improvements may not be closely linked to structure longevity, which aligns with the trend I observe in the data (Figure 5.2).

Table 5.5: Multinomial logit model of the redevelopment decisions with block group fixed effects

	Redevelopment	Renovate
Inundation	-0.367**	-0.385**
	(0.153)	(0.171)
Inundation × Post-Irma	0.566***	0.427**
	(0.183)	(0.209)
Percent properties maintaining patio in past 5 years	4.500***	4.469***
	(0.326)	(0.360)
Lot size	1.427	-0.779
	(2.423)	(2.129)
# of Bedrooms	0.329***	-0.0102
	(0.0228)	(0.0169)
Age	0.0633***	-0.000289
	(0.00225)	(0.000827)
Log distance to shoreline	0.0606*	0.0630***
	(0.0345)	(0.0217)
Elevation	0.0313***	-0.00153
	(0.0101)	(0.00689)
Oceanfront	0.664***	0.277**
	(0.163)	(0.111)
Observations	486,231	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.5 Discussion and Next Steps

This chapter shows that natural hazards, such as hurricanes, can induce renovation and redevelopment in coastal communities, even supply-constrained, highly regulated market such as Miami Dade County in Florida (Graff Zivin et al., 2023). Flooded parcels are significantly more likely to rebuild patios, fences, and entire structures, and these actions spillover to nearby lots unaffected by the storm, thereby accelerating neighborhood renewal. This pattern is consistent with a "build-back-better" effect in the short run, as individual renovation efforts facilitate post-hazard recovery through spillover effects (Fu & Gregory, 2019). However, when disaster aid and subsidized insurance dampen the risk signal, the same mechanism can encourage overinvestment in locations most exposed to future losses.

Ultimately, this study contributes to a deeper understanding of the dynamics that shape housing markets in the aftermath of natural disasters. It underscores the need for a balanced approach that considers both the benefits and risks associated with hazard-induced development. Policymakers must carefully navigate the complex relationship between disaster recovery, housing market incentives, and long-term resilience to ensure that redevelopment efforts lead to more sustainable and equitable urban outcomes. Future research could expand on these findings by examining the long-term effects of hazard-induced renovations on neighborhood stability and socioeconomic disparities, as well as the broader implications of climate change and sea-level rise for housing markets in coastal regions.

Future work will extend the analysis along three fronts. First, a dynamic simulation calibrated to match observed renovation frequencies will explore whether positive spillovers generate multiple equilibria and potentially chaotic redevelopment cycles. Second, incorporating patio age and depreciation into the state vector should yield more realistic transition paths. Third, I will investigate the role of institutional investors and whether clustered acquisitions amplify over-building. Integrating numerical models of coastal developing with empirical analysis will improve our understanding of post-disaster coastal evolution and help design recovery programs that enhance resilience without deepening inequities.

Chapter 6: Conclusions

Natural hazards affect housing market dynamics, migration patterns, and community-level investments in adaptation and urban development strategies. The impact of repetitive natural hazards on housing decisions and long-term urban resilience requires careful attention, as policymakers aim to balance the need for disaster recovery with the goal of sustainable urban growth. This dissertation examines household- and community responses to environmental risks, and demonstrates that the way natural hazards translate into long-run community outcomes depends on geophysical and behavioral factors. By analyzing climate-induced hazards in settings that range from mangrove-buffered deltas in India to densely built U.S. coastlines and inland flood-plains—how households make location decisions in response to natural hazard risks, how natural disasters affect homeownership dynamics, and how hazard-driven investment patterns shape urban redevelopment. By leveraging high-resolution data and advanced econometric techniques, I not only provide insight into the immediate and long-term effects of natural hazards on housing markets but also develop new methodologies for understanding the broader implications of hazard-induced migration.

6.1 Contributions

Empirical findings highlight the importance of considering both individual and community-level responses to environmental risks when designing policies for disaster recovery and long-term urban planning. I estimate the cyclone risk-reduction benefit from mangroves in India and show that an incremental kilometer of mangrove cover can reduce cyclone damage by 34%. The result provides one of the first causal, spatially explicit estimates of ecosystem protection benefit in an India context and underscores the high return to green-infrastructure investment.

Examining hazard-induced migration from coastal hurricanes (Chapter 3) and inland flooding (Chapter 4), I show an inverted-U response to hurricanes across income groups and a decline in home-ownership rates following a flood. Together, these patterns explain how repeated hazards can widen local inequality and shift community composition.

Finally, I examine supply side housing market response to storms, exploiting Hurricane Irma's storm-surge footprint in Miami-Dade County in Florida. I show that flood damage triggers both direct rebuilding and positive spillovers that accelerate redevelopment nearby. These results reconcile puzzling post-disaster investment booms with economic theory and cautions that hazard-induced rebuilding can lock built capital into high-risk zones.

6.1.1 Methodological Contributions

This work makes three methodological contributions. First, it links an analytical wind field model and flood inundation maps with micro scale parcel and household records, providing a replicable template for causal analysis of natural hazards at fine spatial resolution. Second, by coupling migration elasticities across income groups with a large catalogue of synthetic storm tracks, it provides a forward looking framework to examine the distributional impacts of future climate scenarios. Third, the dissertation takes a first step toward understanding demand and supply side perspectives: I estimate both how hazards alter location choices and how subsequent rebuilding decisions can create positive neighborhood spillovers. Together, these advances allow for a richer, system level understanding of how natural hazards reshape communities.

6.1.2 Policy Implications

Policymakers need to understand how environmental amenities and risks shape household location choices and homeownership patterns to design policies that not only address immediate disaster impacts but also foster long-term resilience. First, the analyses of hazard-induced migration present cautionary evidence that household relocation decisions can shape community demographics (income distribution and homeownership rates) in ways that can deepen exposure and widen inequality. Second, the study of post-disaster redevelopment underscores the need for policies that account for potential maladaptation, as incentives for private investment in vulnerable areas can lead to both opportunities for revitalization and increased future risk. Third, spatially explicit estimates of mangrove and wetland protection benefits suggest spatially targeted investment in natural capital can be effective in reducing cyclone risk particularly in low- and middle-income countries.

Ultimately, this work underscores the importance of a multi-faceted approach to understanding environmental risks and housing market dynamics. By bridging economic theory and natural hazard risks, this dissertation provides both theoretical contributions and practical applications for managing the effects of natural hazards. As climate change continues to exacerbate the risks faced by communities worldwide, this research contributes to the broader conversation on how to build more resilient, adaptive urban environments in both developed country and developing country contexts.

Appendix A: Additional robustness tests for Chapter 2

To further control for the mitigation benefit from mangrove habitat, we only include 4,679 villages that are historically protected by mangrove in Column (2). As shown in Table A.1, the results are similar to our preferred specification (Table 2.2 Column (3)).

Table A.1: Robustness checks for mangrove habitats

	(1) Log nightlight	**(2)** Log nightlight
Cyclone index	-0.039***	-0.035***
	(0.006)	(0.007)
Distance to shoreline × Cyclone index	0.002***	0.002***
	(0.001)	(0.001)
Lag Mangrove width × Cyclone index	0.021***	0.024***
	(0.007)	(0.007)
Distance to continental shelf × Cyclone index	-0.038***	-0.040***
	(0.002)	(0.002)
Year fixed effect	Yes	Yes
Sd fixed effect	Yes	Yes
Other controls	Yes	Yes
Observations	51,320	37,432
Kleibergen-Paap rk Wald F statistic	149.500	153.100
Adjusted R-squared	0.709	0.715

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

One crucial identification assumption in our model is that cyclones impact nightlight at the end of the year but do not affect nightlight at the end of the following year. To test this assumption, we use Cyclone Hudhud, a Category 4 cyclone that struck in October 2014, as our case study. Hudhud primarily affected the states of Andhra Pradesh and Odisha, making landfall near Visakhapatnam on October 12th with wind speeds reaching up to 100 knots. The cyclone caused significant devastation, resulting in at least 124 fatalities and economic losses estimated at $3.58 billion. We define treated villages as those experiencing local wind speeds exceeding 50 knots. Using propensity score matching without replacement, we identify control villages based on baseline (2011) attributes that are not treated. Specifically, we select control villages that experienced local wind speeds of less than 33 knots, which is consistent with the assumption in our main IV specification. Our identification assumption is thus that the cyclone track of Cyclone Hudhud is random. Consequently, the difference in nightlight levels in villages after October 2014 reflects the impact of cyclone.

As shown in Figure A.1, both the treatment and control groups followed parallel trends before the cyclone. Post-treatment, nightlight intensity in affected areas decreased by 50% in the treated villages, with the effect gradually dissipating over 6-11 months. Since cyclones in India typically occur after May, their impact is likely to reduce nightlight at the end of the year but not affect it in the subsequent year. This assumption is further supported by observations of nightlight intensity change in Visakhapatnam after Cyclone Hudhud (Figure A.1). In October 2014, nightlight levels in Visakhapatnam significantly diminished. Although there was some recovery by December 2014, differences between nightlight levels in December 2014 and September 2014 remained evident. Most recovery was observed by December 2015 when we could not find impacts from the cyclone.

Figure A.1: Parallel trend test for patio replacement and redevelopment

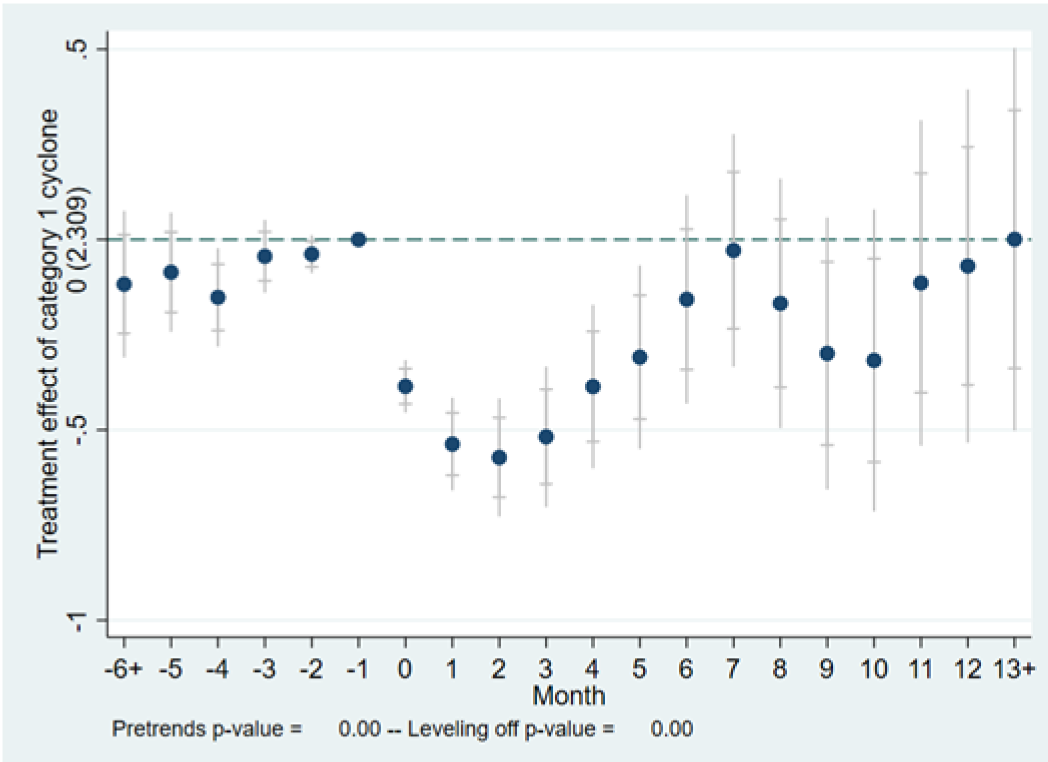
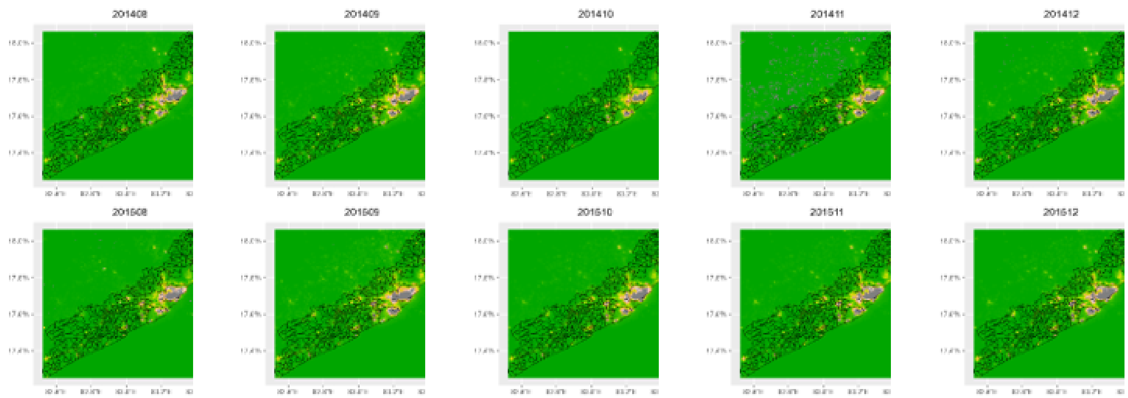


Figure A.2: Nightlight change after Hurricane Hudhud in Visakhapatnam



In main text, we calculate the mangrove width based on shortest distance between each village to the coastline (measured at boundary of exclusive economic zone). We calculate the mangrove width based on distance between the centroid of each village to the coastline instead in Table A.2. Similar to Table 2.2, we include villages within West Bengal in Column (3) and exclude all villages that are not protected by mangroves in 1944 in Column (4).

Table A.2: Robustness checks for alternative mangrove width calculation method

	(1) Log nightlight OLS	**(2)** Log nightlight IV	**(3)** Log nightlight IV	**(4)** Log nightlight IV
Cyclone index	-0.038***	-0.039***	-0.009	-0.035***
	(0.006)	(0.006)	(0.006)	(0.007)
Distance to shoreline × Cyclone index	0.002***	0.003***	0.000	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Lag Mangrove width (centroid) × Cyclone index	0.003	0.021***	0.011***	0.024***
	(0.002)	(0.007)	(0.001)	(0.007)
Distance to continental shelf × Cyclone index	-0.035***	-0.038***	-0.043***	-0.040***
	(0.002)	(0.002)	(0.002)	(0.002)
Year fixed effect	Yes	Yes	Yes	Yes
Sd fixed effect	Yes	Yes	Yes	Yes
Observations	51,320	51,320	68,488	37,432
Kleibergen-Paap rk Wald F statistic	–	240.300	701.400	153.500
Adjusted R-squared	0.709	0.709	0.676	0.714

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Since historical mangrove distribution can be correlated with current economic activity though other channels such as habitat, we further strengthen our result by matching methods. Specifically, to estimate the benefits from mangroves, we use coarsened exact matching to compare 1460 out of the 6415 villages that have mangrove coverage in our study period to other coastal villages with similar soil, bathymetry, geological, and socio-economic characteristics (Table A.3). We cluster the standard errors at matched set levels to correct for post matching standard errors (Abadie & Spiess, 2022).

Table A.3 presents the summary statistics for the matched sample. As shown, most baseline characteristics are well balanced for villages with and without cycloens. Key socio-demographic variables such as population density, percentage male, caste composition, and land ownership show no statistically significant differences post-matching. This indicates that the matching procedure was effective in creating a comparable control group. The only statistically significant differences are found in the mangrove width, as well as in cyclone exposure and log nightlight—where villages with mangroves exhibit lower exposure to cyclones and slightly lower levels of nightlight luminosity. The latter may reflect historical differences in development or land-use regulation associated with mangrove-preserving regions.

To evaluate whether our main findings are sensitive to estimation strategy, Table A.4 compares the regression results from the unmatched sample using ordinary least squares (OLS) with those based on the matched sample. In all specifications, cyclone exposure is negatively and significantly associated with nighttime light intensity, reaffirming the detrimental economic effects of cyclones. More importantly, we find consistent evidence that mangroves mitigate cyclone impacts: the interaction between lagged mangrove width and cyclone exposure is positive and statistically significant in both the unmatched (column 2) and matched samples (column 4). This suggests that mangroves play a protective role in buffering villages from cyclone-induced economic disruptions. Notably, the interaction between distance to shoreline and cyclone exposure, which is significant in the OLS estimates, becomes insignificant in the matched sample—implying that the matching approach better accounts for spatial confounding.

Table A.3: Summary statistics

Variable	Mean (Mangrove)	SD	Mean (No Mangrove)	SD	Difference
Log nightlight	1.298	1.107	1.441	1.206	-0.143*
Cyclone index	4387.912	4512.724	11471.400	16657.130	-7083.489***
Mangrove width (km)	1.929	3.895	0.000	0.006	1.929***
Population density (1000s/sq km)	0.571	0.941	0.610	0.955	-0.039
Distance to nearest town (log km)	2.092	0.896	2.047	0.730	0.045
Percentage male	0.505	0.022	0.506	0.022	-0.001
Percentage younger than 6	0.114	0.027	0.114	0.025	0.000
Percentage scheduled caste	0.245	0.265	0.245	0.243	-0.001
Percentage ag worker	0.180	0.131	0.178	0.117	0.002
Monthly precipitation (mm)	121.833	20.778	121.027	18.011	0.806
Distance to shoreline (km)	8.371	4.087	7.982	4.061	0.390
Baseline electricity hours (2011)	8.461	8.118	8.305	8.015	0.156
Distance to shelf/20m-depth (km)	2.006	1.316	1.988	1.514	0.018
Log area (sq. m)	14.269	1.131	14.339	1.155	-0.071
Elevation (m)	9.534	9.452	9.586	10.356	-0.052
Percentage landowner	0.391	0.259	0.401	0.256	-0.010
Pct. with monthly income > 10k INR	0.054	0.069	0.055	0.068	-0.001

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: Difference between OLS results for matching samples and original samples

	(1) Log nightlight	**(2)** Log nightlight	**(3)** Log nightlight	**(4)** Log nightlight
Cyclone index	-0.032***	-0.038***	-0.003***	-0.003***
	(0.002)	(0.006)	(0.000)	(0.009)
Distance to shoreline × Cyclone index		0.002***		0.002
		(0.001)		(0.010)
Lag Mangrove width × Cyclone index		0.004*		0.003**
		(0.002)		(0.001)
Distance to continental shelf × Cyclone index		-0.035***		0.000
		(0.002)		(0.000)
Year fixed effect	Yes	Yes	Yes	Yes
Sd fixed effect	Yes	Yes	Yes	Yes
Observations	51,320	51,320	17,832	17,832
Adjusted R-squared	0.709	0.710	0.725	0.725

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
In columns (3) and (4), only villages in the matched sample are included.

Appendix B: Robustness tests on Chapter 3

We examine the robustness of our results by estimating a set of alternative specifications. Specifically, we replace the continuous measure of natural hazards with event-level indicators to capture the effects of major natural hazards, which yield similar results (Figure 3.3). We also test alternative wind damage functions (Figure B.1). In addition to the 0-knot and 50-knot thresholds (Emanuel, 2011), we use a 64-knot threshold, corresponding to Category 1 hurricanes or higher, which are more likely to cause local damage. Furthermore, we assume hurricane damage takes a quadratic term following (Emanuel, 2011). We also adopt an alternative wind field model (Holland, 2008) to calculate maximum sustained wind speed as an additional robustness check (Figure B.2).

We also change the definition of migration (Figure B.3), limit the sample to non trailer homeowners (Figure A2.B.4), change the working-age head of household definition around 25-60 (Figure A2.B.5), try different income range cutoffs (Figure A2.B.6), and switch predicted income estimate to predicted wealth indicators (Figure B.7). While we lose statistical significance in the marginal effect for middle-income households, the heterogeneous nature of the effect of natural disasters and the trend in migration response across income groups remains similar. Overall, the robustness checks confirm that the baseline results are qualitatively robust to different specifications, though there are quantitative differences on the top-1-percentile end of the distribution. For all specifications, we cannot reject the hypothesis that the marginal effect of natural disasters on top-1-percentile-income households is statistically different from that on high-income households because of the large standard errors for the top-1-percentile-income estimate, indicating top-1-percentile-income households might migrate because of natural disasters in some specific scenarios. However, we can reject the hypothesis that the effect of natural disasters on low-income households is the same as the effect of natural disasters on high-income households. Thus, we are confident that there is an increase in the probability of migration after exposure to a natural disaster for households with high income. However, we do not know whether the effect of natural disasters becomes flat, increases, or decreases between high-income and top-1-percentile-income households.

Figure B.1: Marginal effect of lag year hurricane damage on migration probability. The terms “50 knots”, “64 knots” and “0 knot” mean that thresholds of 50, 64 and 0 knots are used to compute the measure of hurricane, respectively. The terms “quadratic” and “cubic” indicate the exponent of the damage function.

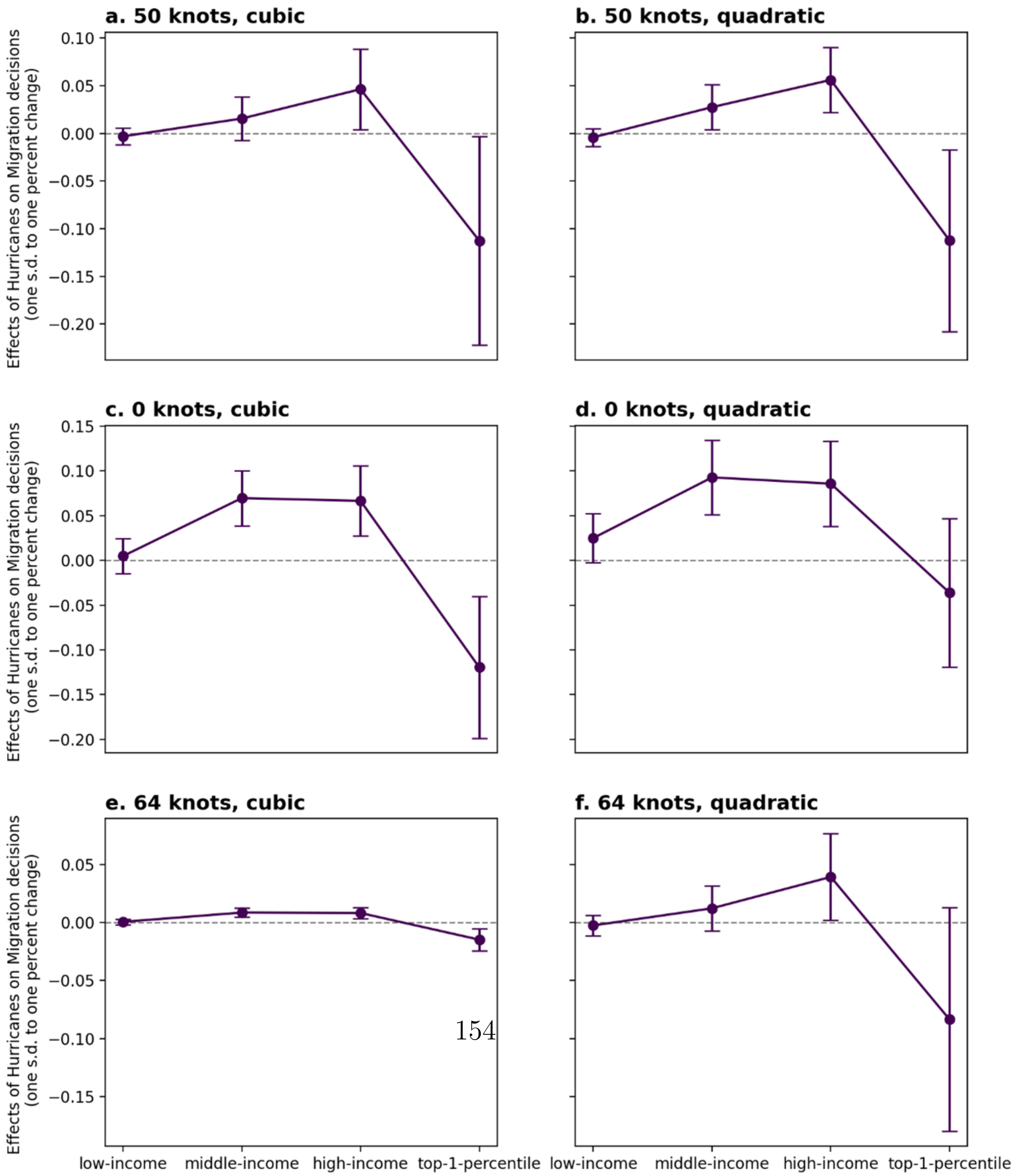


Figure B.2: Marginal effect of lag year hurricane damage on migration probability using Holland wind field model (Holland, 2008) through CLIMADA. The terms "50 knots", "64 knots" and "0 knot" mean that thresholds of 50, 64 and 0 knots are used to compute the measure of hurricane, respectively. The terms "quadratic" and "cubic" indicate the exponent of the damage function.

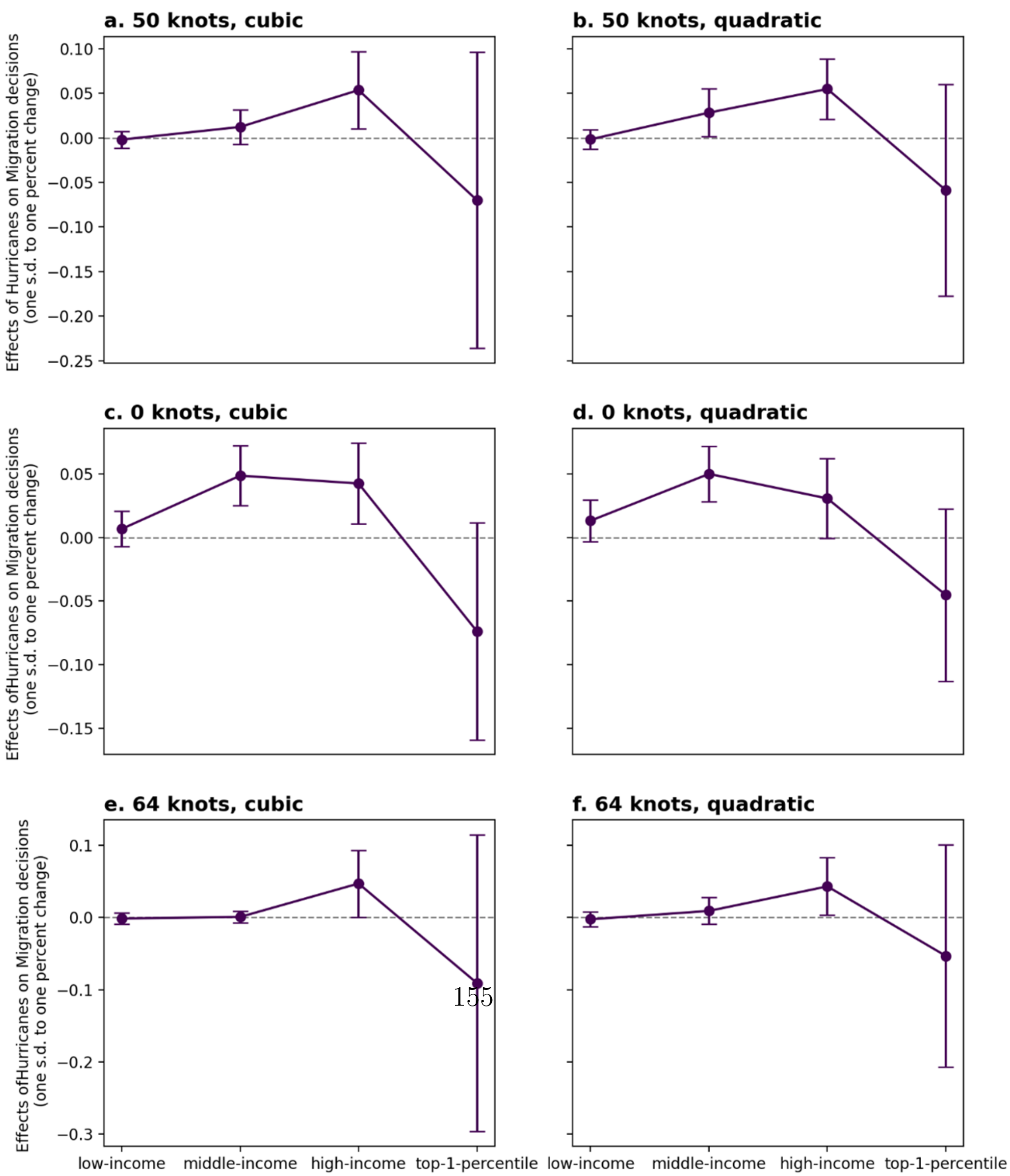


Figure B.3: Robustness tests for alternative migration definition

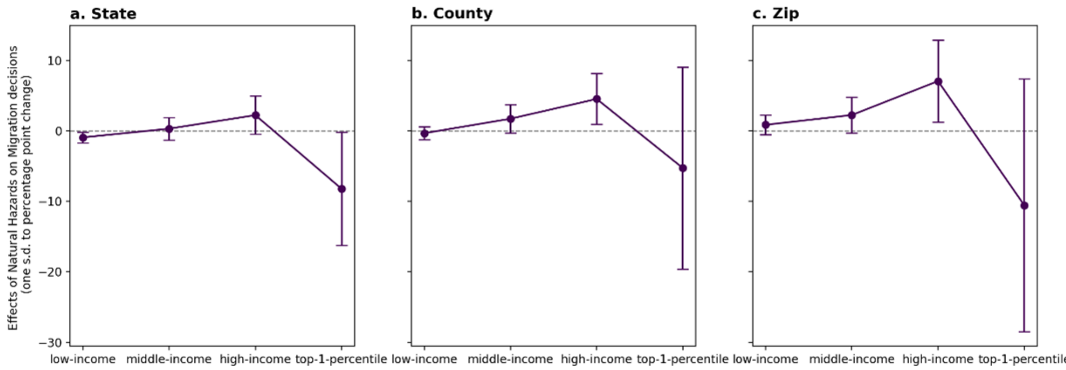


Figure B.4: Marginal effects of hurricane damage on household migration for non-trailor homeowners

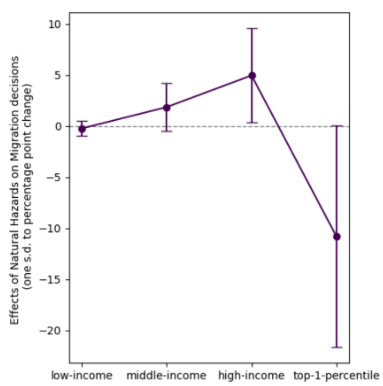


Figure B.5: Robustness tests for alternative working age range

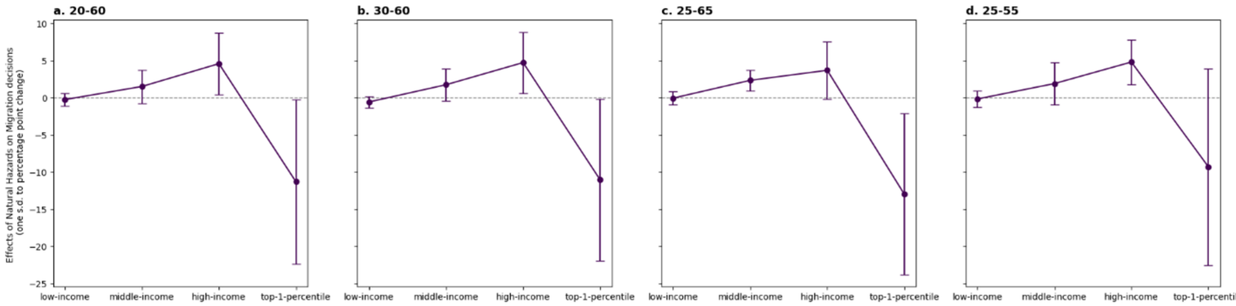


Figure B.6: Robustness tests for alternative income bin cutoffs. In e., we change the cutoff for the top-1-percentile income group to $360,000 per year, which corresponds to the top-2-percentile cutoff

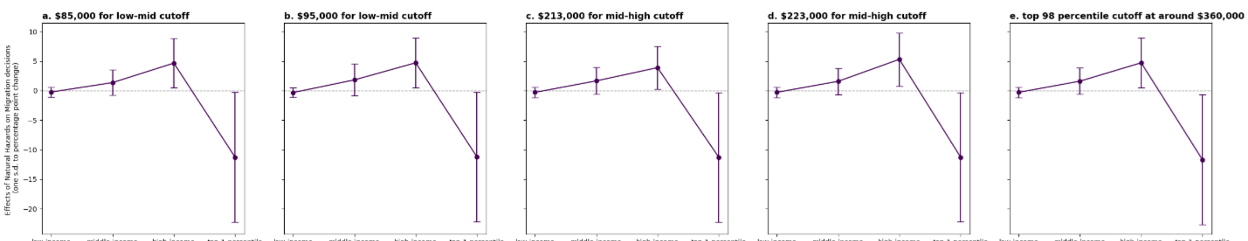
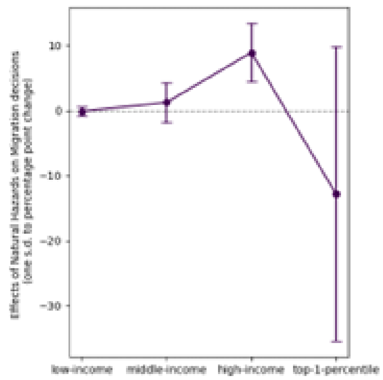


Figure B.7: Robustness tests for wealth indicator at low (0-50 percentiles), middle (50-90 percentile), high (90-99 percentiles) and top-1-percentile



Appendix C: Data Axle data validation

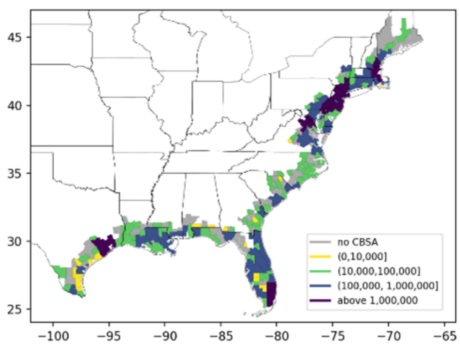
Figure C.1. presents all homeowners included in our main analysis for 2020, along with the overall distributions and those in the top-1-percentile-income group. Several counties outside metropolitan areas have no observations, reflecting the fact that most top 1% income homeowners do not reside in micropolitan regions or in counties not classified within a core-based statistical area. Consequently, we exclude nonmetropolitan regions from the main analysis and focus exclusively on migration across metropolitan areas. This approach ensures that migration patterns of top-1-percentile-income homeowners are not compared with those of lower- and middle-income homeowners residing in fundamentally different geographic and economic contexts. Given the limited population and migration activity in nonmetropolitan regions, we believe this exclusion does not materially affect our simulation results.

In Figure C.2, we obtain all households from the Data Axle sample in all U.S. and compare county-level summary statistics with 2020 census and American Community Survey (ACS) data. Overall, Data Axle provides a representative sample for each county (Figure C.2 a.), and estimated income levels corresponds closely with ACS data (Figure S15c.). While Data Axle offers household-level information on heads of households, age, race, and ethnicity data are reported at the population level, leading to some discrepancies with census data. Specifically, heads of households tend to be older on average compared to the mean age in each county (Figure S15d). However, Data Axle's race and ethnicity distributions generally correspond well with census data, as heads of households often share similar racial and ethnic backgrounds with other household members.

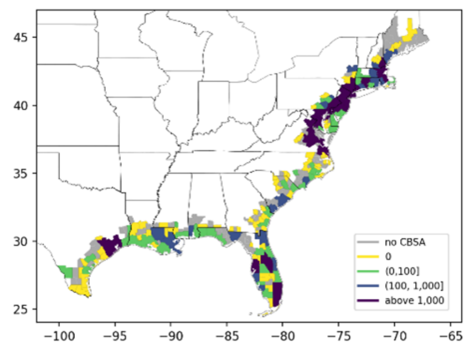
In Figures C.3. and C.4., we compare migration patterns identified in the Data Axle dataset with two commonly used migration data sources: Internal Revenue Service (IRS) migration data and the American Community Survey (ACS) 5-year migration data. We focus on the 2015–2019 period, as the latest ACS migration data is available for the 2015–2019 and 2016–2020 intervals. The high correlation coefficients between Data Axle and the other sources suggest that our migration measures effectively capture general migration trends in the U.S. However, because migration in the Data Axle dataset is identified through changes in credit or billing addresses, it captures a more limited set of migration behaviors. As a result, the across-metropolitan-region migration rate in Data Axle is approximately one-third of that in IRS data and one-eighth of that in ACS data. This underestimation may partly explain the relatively small economic significance of our estimates.

Figure C.1: Number of homeowners in our sample by CBSA. US state and coastal county outlines were obtained from the US Census Bureau. The outlines of CBSAs were obtained using the 2015 CBSA statues.

a. Number of all homeowners



b. Number of top-1-percentile homeowners



Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

Figure C.2: County level Data Axle data validation with 2020 census and 2016-2020 ACS. The grey lines represent where the census data and Data Axle data is equal. The circle for each point in b-f. represents the number of households in each county documented in Data Axle datasets

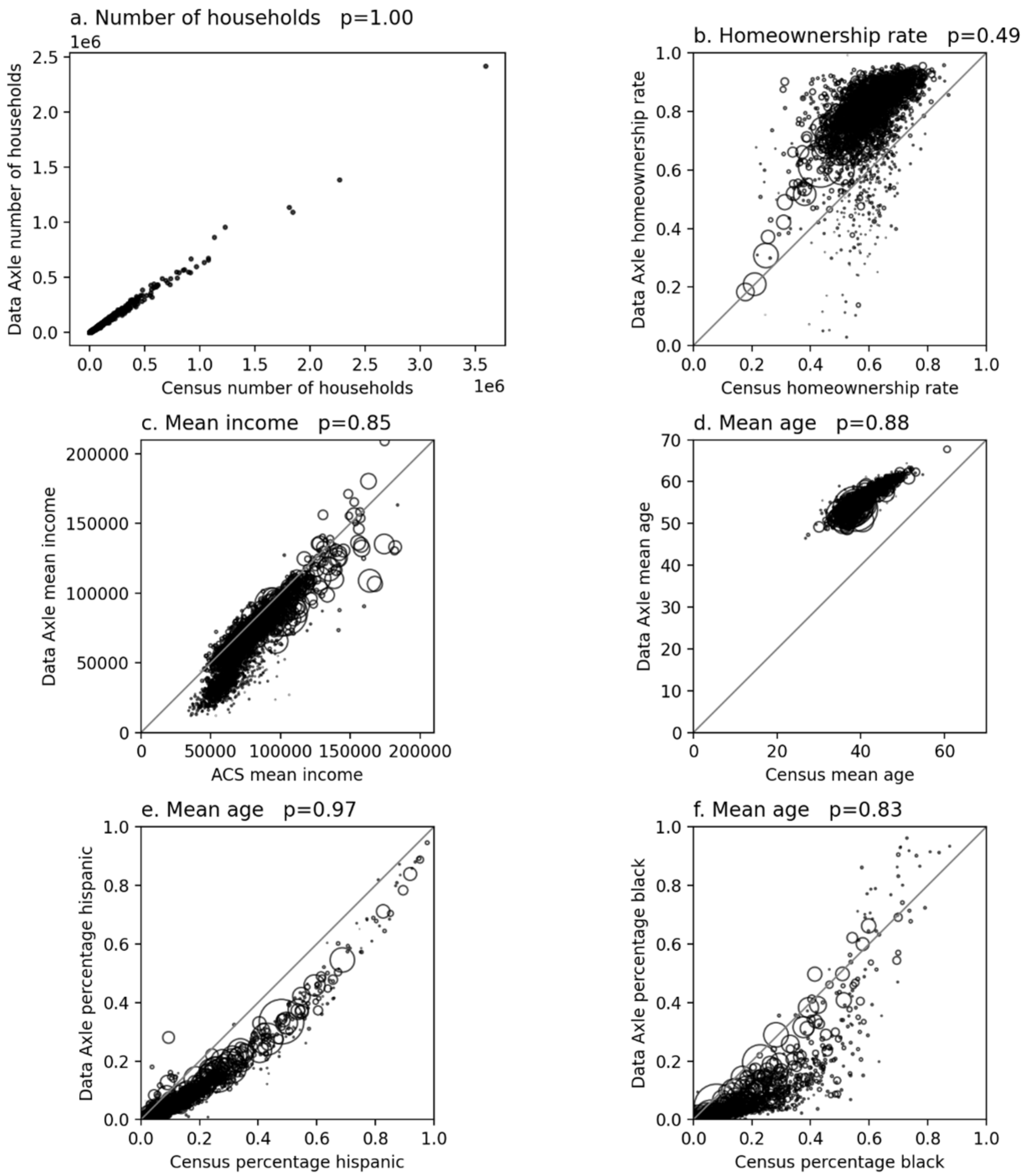


Figure C.3: County level Data Axle data validation with household level IRS migration statistics from 2015-2019. The circle for each point in b-d. represents the number of households in each county documented in Data Axle datasets

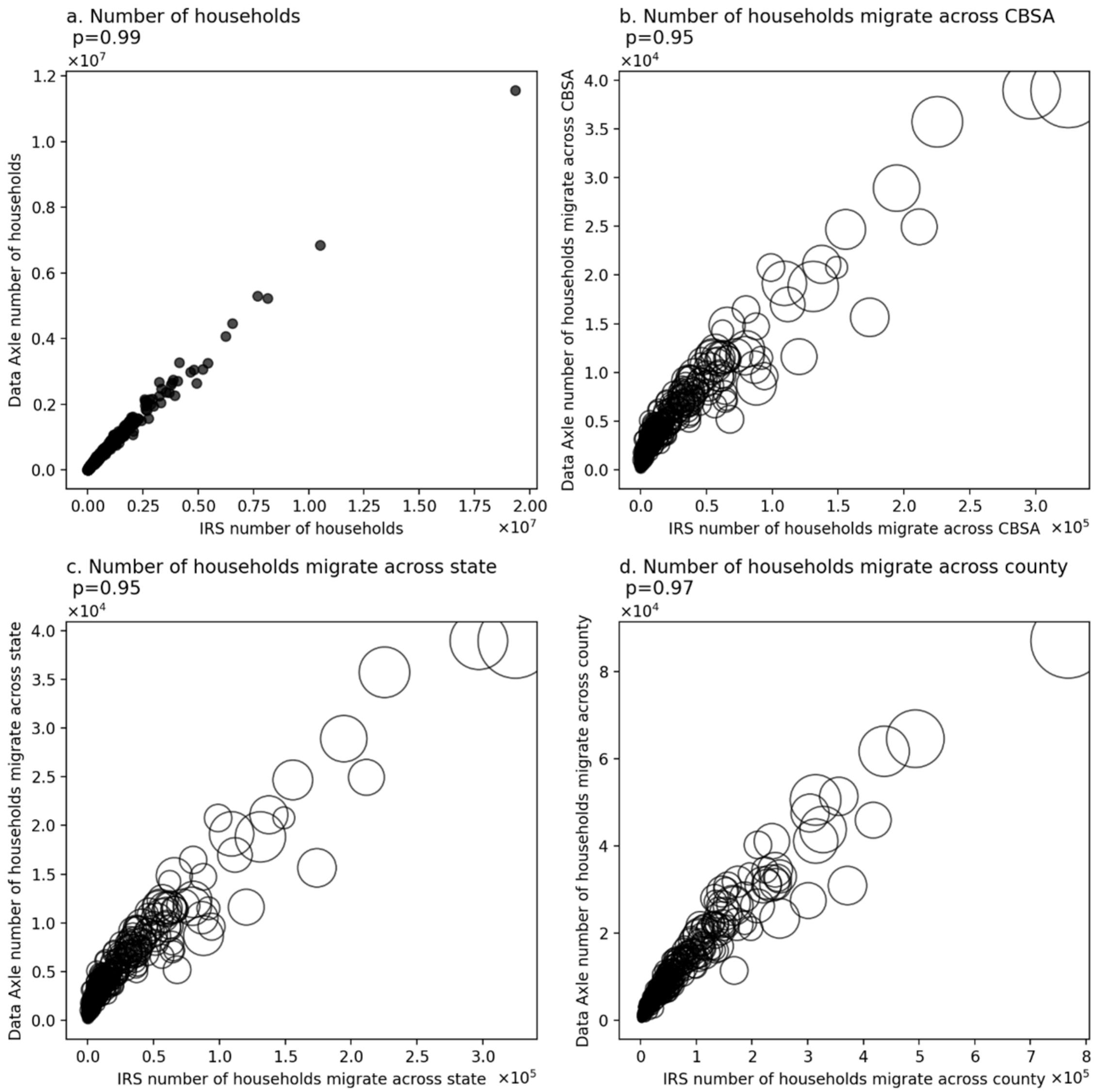
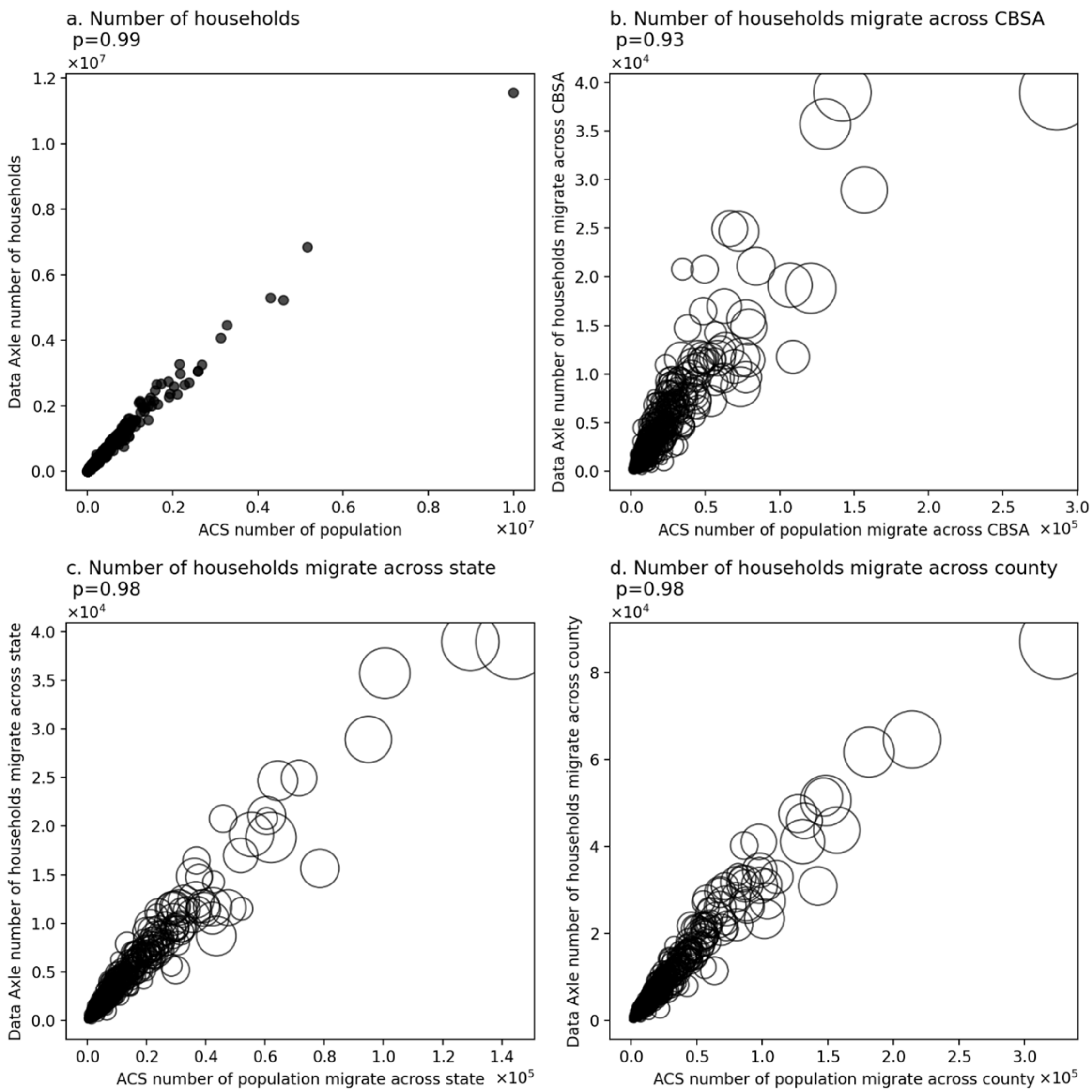


Figure C.4: County level Data Axle data validation with household level ACS migration statistics from 2015-2019. Note that here we are compaing between household level migration in Data Axle dataset and population level migration in ACS dataset. The circle for each point in b-d. represents the number of households in each county documented in Data Axle datasets

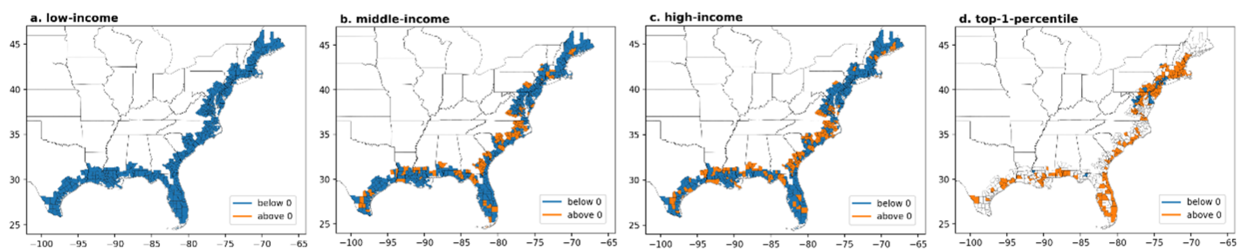


Appendix D: Additional simulation results in Chapter 3

Figures 3.6 and 3.7 show the simulated effects of natural hazards on the 2050 population distribution and income inequality, comparing 2050 population distributions one with and without hazard-induced migration. Both simulations rely on the 2050 baseline population trends derived from a historical migration matrix without hazard-induce migration.

Figure D.1 displays the simulated change in population from 2020 to 2050 across four income groups, excluding the effects of hazard-induced migration. Low-income households exhibit widespread out-migration from coastal counties, suggesting increasing displacement or retreat even without hazard exposure. Middle- and high-income groups show a more mixed pattern, with predominant outflows from high-risk areas but some gains in inland regions, reflecting varying risk tolerance and adaptation capacity. In contrast, top-1-percentile households are more likely to move into coastal areas, indicating that the wealthiest households are either less affected by or more capable of mitigating hazard risks. These patterns underscore how climate-driven migration may reinforce spatial income inequality. The population shifts lead to Gini coefficient change in Figure D.2. At the county level (Figure D.2 a), the majority of coastal counties exhibit an increase in economic inequality, particularly in areas such as coastal Texas and the Carolinas. These increases reflect growing disparities in income distribution, driven by selective migration patterns where lower-income households leave and top-1-percentile-group households remain or concentrate. The pattern is more spatially aggregated at metropolitan and state levels with increased inequality across the East Coas,t except for Northwest regions.

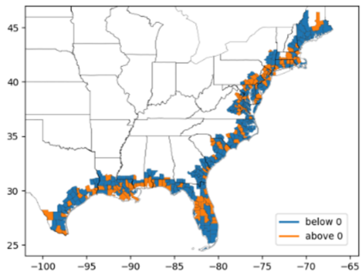
Figure D.1: Figure A3.1. Population change in each income groups between 2050 distribution and 2020 distribution



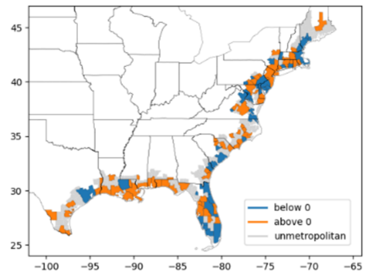
Note: I restrict the top-1-percentile map (d.) to metropolitan counties with above 100 top-1-percentile income households to ensure valid comparisons.

Figure D.2: Gini coefficient changes at county, metropolitan region, and state levels between 2050 distribution and 2020 distribution

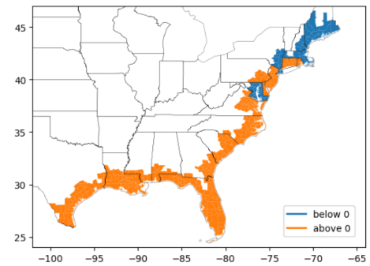
a. County



b. Metro



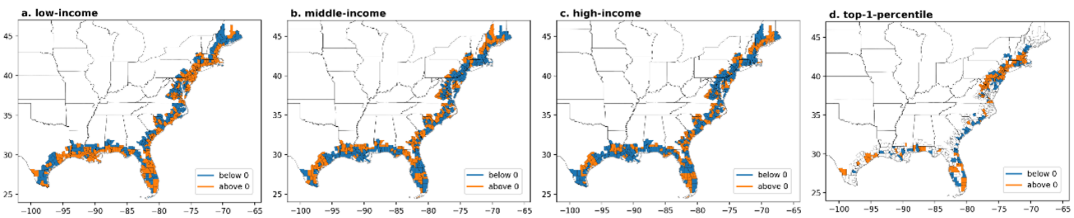
c. State



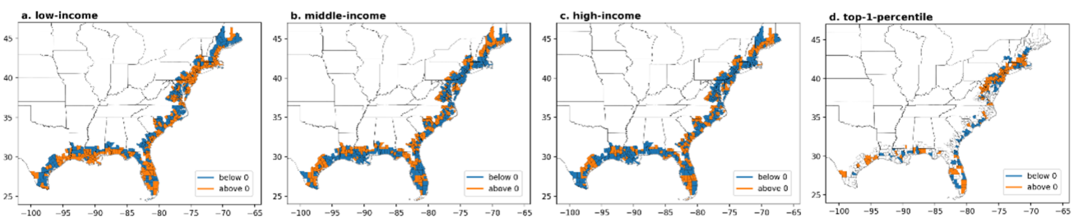
Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

Figure D.3: Predicted population change in each income group under climate scenarios RCP 2.6, RCP 4.5, and RCP 8.5.

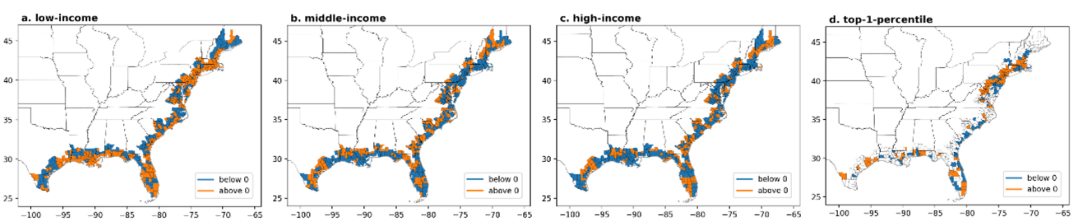
(a) RCP 2.6



(b) RCP 4.5



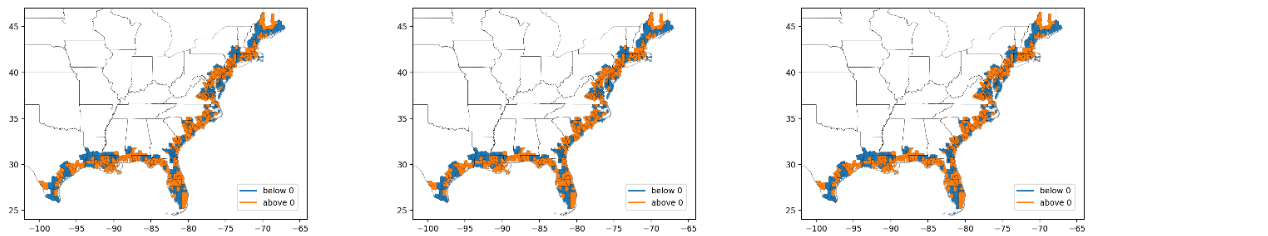
(c) RCP 8.5



Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

Figure D.4: Predicted county level gini coefficients change in each income groups for climate scenarios RCP 2.6, RCP 4.5, and RCP 8.5

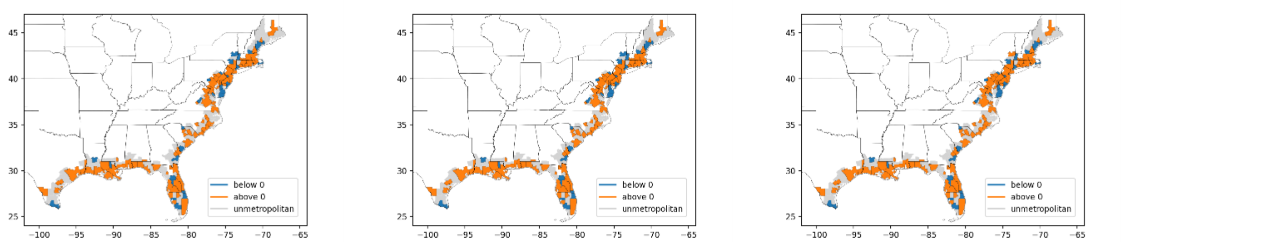
a. County   b. Metro   c. State



Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

Figure D.5: Predicted metropolitan level gini coefficients change in each income groups for climate scenarios RCP 2.6, RCP 4.5, and RCP 8.5

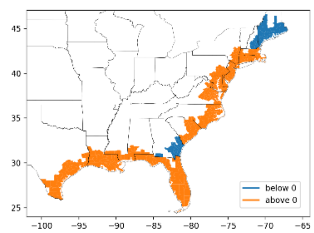
a. County   b. Metro   c. State



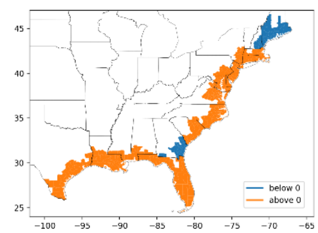
Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

Figure D.6: Predicted state level gini coefficients change in each income groups for climate scenarios RCP 2.6, RCP 4.5, and RCP 8.5

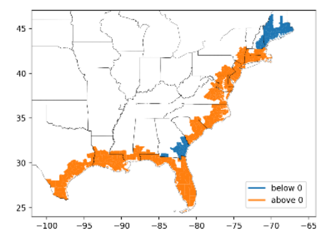
a. County



b. Metro



c. State



Note: State and coastal county boundaries are from the U.S. Census Bureau and coastal county definition adopted from NOAA.

Appendix E: Additional robustness tests for Chapter 4

Table E.1 compares key household characteristics between properties located inside the 2008 inundation area and those in nearby non-inundated areas, conditional on being in the FEMA 100-year Special Flood Hazard Area (SFHA). The results show that, on average, households within and outside the flood zone are largely similar in demographic and housing characteristics. For example, there are no statistically significant differences in the age of the household head, length of residence, whether have children, or racial/ethnic composition. This balance supports the validity of the regression discontinuity design by suggesting that, absent the flood, the two groups would be comparable. However, two key differences emerge: households in the inundated area have lower average homeownership rates and lower average income levels, suggesting that households right inside the inundation boundary might view close to river as disamenity. However, given that the homeownership rate follows parallel trends before 2008 (Figure 4.3), indicating that these pre-existing differences were stable over time and not the result of 2008 Iowa Flood.

Table E.1: Summary statistics

Variable	**Mean (Inundation)**	**SD**	**Mean (Control)**	**SD**	**Difference**
Homeownership	0.780	0.340	0.860	0.410	-0.080**
Head of HH Age	51.260	16.550	50.080	14.930	1.180
Length of Residence	13.850	12.110	12.630	10.810	1.230
Child	0.160	0.370	0.170	0.380	-0.010
Property Value ($1000)	123.880	87.770	134.780	126.090	-10.900
Household Income ($1000)	60.250	38.860	69.280	52.950	-9.040**
SFHA	0.260	0.440	0.030	0.160	0.240***
Black	0.010	0.100	0.000	0.070	0.010
Hispanic	0.010	0.070	0.010	0.100	-0.010

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results remain robust when restricting the analysis to households located even closer to the inundation boundary. Using narrower bandwidths, such as within 100 meters of the flood line (Table E.2 column (3), (4)), yields qualitatively similar estimates of reduced homeownership in inundated areas. This consistency across tighter spatial windows reinforces the credibility of the difference-in-difference design, as it suggests that the estimated effects are not driven by unobserved differences between neighborhoods farther apart. Instead, the results reflect localized changes in tenure decisions caused by direct flood exposure, further supporting the interpretation of a short-term behavioral response to the 2008 flood. I also find that the estimated effects become smaller when using narrower bandwidths around the inundation boundary, compared to the preferred model. This suggests the presence of potential positive spillover effects, as households may also be hesitant to purchase homes in areas adjacent to, but not directly affected by, the flood.

Table E.2: Robustness tests for alternative boundary cutoff

	(1) Homeownership rate	(2) Homeownership rate	(3) Homeownership rate	(4) Homeownership rate
SFHA × Inundation	-0.139**	-0.149**	0.016	-0.057
	(0.000)	(0.000)	(0.017)	(0.014)
SFHA × Inundation × 2009–10	-0.114**	-0.104**	-0.122*	-0.113*
	(0.001)	(0.001)	(0.002)	(0.002)
Non-SFHA × Inundation × 2009–10	0.005	0.004	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)
SFHA × Inundation × 2011–13	-0.087**	-0.001	-0.092**	-0.084**
	(0.001)	(0.007)	(0.001)	(0.001)
Non-SFHA × Inundation × 2011–13	0.006	0.004	-0.007*	-0.007
	(0.001)	(0.001)	(0.000)	(0.001)
Head of HH age			0.008*	0.009*
			(0.000)	(0.000)
Child			0.177**	0.205**
			(0.002)	(0.003)
Tract-level characteristics	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Zipcode fixed effect	No	No	Yes	Yes
City fixed effect	No	No	No	No
Ethnicity fixed effect	No	No	Yes	Yes
Observations	40,705	6,794	40,705	6,764

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
In columns (3) and (4), only households within 100 meters from the inundation boundary are included.

Appendix F: Additional robustness tests for Chapter 5

Table F.1: Distribution and Longevity of Patio Types in Florida

Description	Count in study area before 2017	Count in Irma-flooded area before 2017	Average lifespan (years)
Wood	1,286	56	9.75
Concrete	23,730	418	19.01
Brick	14,190	851	17.34

Among the recorded patios in the study area, concrete is by far the most prevalent material, accounting for over 23,000 installations—more than the combined total of wood and brick patios. This dominant share reflects Florida homeowners' preference for concrete's durability, pest resistance, and low maintenance requirements in the state's hot, humid, and storm-prone environment. Brick patios also appear in significant numbers, likely due to their aesthetic appeal and reliable performance in wet, coastal conditions, although their overall share remains considerably lower than that of concrete. In contrast, wood patios are relatively uncommon, comprising less than

5% of all patio records. This low adoption rate is consistent with wood's susceptibility to rot, warping, and termite damage, particularly in coastal or flood-prone areas.

Although wood decks may occasionally be built in oceanfront or storm-prone regions, their adoption rate is too low to significantly affect our overall results. Notably, the overrepresentation of brick patios in the flooded areas suggests that oceanfront property owners may prioritize resistance to saltwater damage and visual appeal when selecting patio materials. Since there is no statistically significant difference in the average lifespan between brick and concrete patios (p=0.47), our results are not biased by differences in patio types share in the study regions (Table F.2).

Table F.2: Effects of the 2017 Hurricane Irma on housing renovations

	(1) Patio	**(2)** Concrete patio	**(3)** Brick patio
Inundation	-0.006***	-0.009***	-0.004**
	(0.002)	(0.003)	(0.002)
Inundation × Post-Irma	0.007**	0.010***	0.004**
	(0.003)	(0.004)	(0.002)
Lot size	-0.015	-0.012	0.016
	(0.020)	(0.024)	(0.022)
# of Bedrooms	-0.000	0.000*	0.004***
	(0.000)	(0.000)	(0.000)
Age	-0.000*	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Log distance to shoreline	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)
Elevation	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Oceanfront	0.005***	0.005***	0.004***
	(0.002)	(0.002)	(0.001)
BG fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	486,721	486,721	486,721

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Bibliography

Abadie, A., & Spiess, J. (2022). Robust Post-Matching Inference. *Journal of the American Statistical Association*, *117*(538), 983–995. https://doi.org/10.1080/01621459.2020.1840383
econometrics.

Adler, K. F. (2015). *Natural disasters as a catalyst for social capital: A study of the 500-year flood in Cedar Rapids, Iowa*. University Press of America, Inc.
OCLC: ocn889168751.

Agoramoorthy, G., Chen, F.-A., & Hsu, M. J. (2008). Threat of heavy metal pollution in halophytic and mangrove plants of Tamil Nadu, India. *Environmental Pollution*, *155*(2), 320–326. https://doi.org/10.1016/j.envpol.2007.11.011

Allison, P. (2012, February). Logistic Regression for Rare Events.

Almagro, M., Chyn, E., & Stuart, B. (2023, January). *Urban Renewal and Inequality: Evidence from Chicago's Public Housing Demolitions* (tech. rep. No. w30838). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w30838

Ambrus, A., Field, E., & Gonzalez, R. (2020). Loss in the Time of Cholera: Long-Run Impact of a Disease Epidemic on the Urban Landscape. *American Economic Review*, *110*(2), 475–525. https://doi.org/10.1257/aer.20190759
theory.

Andor, M. A., Osberghaus, D., & Simora, M. (2020). Natural Disasters and Governmental Aid: Is there a Charity Hazard? *Ecological Economics*, *169*, 106534. https://doi.org/10.1016/j.ecolecon.2019.106534

Anenberg, E., & Kung, E. (2014). Estimates of the Size and Source of Price Declines Due to Nearby Foreclosures. *American Economic Review*, *104*(8), 2527–2551. https://doi.org/10.1257/aer.104.8.2527

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Aronoff, D., & Rafey, W. (2023). Conservation Priorities and Environmental Offsets: Markets for Florida Wetlands. *NBER*.

Asher, S., Lunt, T., Matsuura, R., & Novosad, P. (2021). Development Research at High Geographic Resolution: An Analysis of Night-Lights, Firms, and Poverty in India Using the SHRUG Open Data Platform. *The World Bank Economic Review*, *35*(4), 845–871. https://doi.org/10.1093/wber/lhab003

Atreya, A., Ferreira, S., & Kriesel, W. (2013). Forgetting the Flood? An Analysis of the Flood Risk Discount over Time. *Land Economics*, *89*(4), 577–596. https://doi.org/10.3368/le.89.4.577

Axle, D. (2021). Data Axle historical residential dataset.

Aznar-Siguan, G., & Bresch, D. N. (2019). CLIMADA v1: A Global Weather and Climate Risk Assessment Platform. *Geoscientific Model Development*, *12*(7), 3085–3097. https://doi.org/10.5194/gmd-12-3085-2019

Bacmeister, J. T., Reed, K. A., Hannay, C., Lawrence, P., Bates, S., Truesdale, J. E., Rosenbloom, N., & Levy, M. (2018). Projected changes in tropical cyclone activity under future warming scenarios using a high-resolution climate model. *Climatic Change*, *146*(3-4), 547–560. https://doi.org/10.1007/s10584-016-1750-x

Bakkensen, L. A., & Barrage, L. (2021). Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics (S. Van Nieuwerburgh., Ed.). *The Review of Financial Studies*, hhab122. https://doi.org/10.1093/rfs/hhab122
theory.

Bakkensen, L. A., & Ma, L. (2020). Sorting over flood risk and implications for policy reform. *Journal of Environmental Economics and Management*, *104*, 102362. https://doi.org/10.1016/j.jeem.2020.102362
empirical.

Balaji, M., Chakraborty, A., & Mandal, M. (2018). Changes in tropical cyclone activity in north Indian Ocean during satellite era (1981-2014). *International Journal of Climatology*, *38*(6), 2819–2837. https://doi.org/10.1002/joc.5463

Barbier, E. B., Koch, E. W., Silliman, B. R., Hacker, S. D., Wolanski, E., Primavera, J., Granek, E. F., Polasky, S., Aswani, S., Cramer, L. A., Stoms, D. M., Kennedy, C. J., Bael, D., Kappel, C. V., Perillo, G. M. E., & Reed, D. J. (2008). Coastal Ecosystem-Based Management with Nonlinear Ecological Functions and Values. *Science*, *319*(5861), 321–323
empirical.

Basher, R. (2006). Global early warning systems for natural hazards: Systematic and people-centred. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *364*(1845), 2167–2182. https://doi.org/10.1098/rsta.2006.1819

Bayer, P., McMillan, R., & Rueben, K. (2004, November). *An Equilibrium Model of Sorting in an Urban Housing Market* (tech. rep. No. w10865). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w10865

Begley, T. A., Gurun, U. G., Purnanandam, A. K., & Weagley, D. (2018). Disaster Lending: The Distributional Consequences of Government Lending Programs. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3145298

Beltrán, A., Maddison, D., & Elliott, R. J. R. (2018). Assessing the Economic Benefits of Flood Defenses: A Repeat-Sales Approach. *Risk Analysis*, *38*(11), 2340–2367. https://doi.org/10.1111/risa.13136

Berlemann, M., & Steinhardt, M. F. (2017). Climate Change, Natural Disasters, and Migration—a Survey of the Empirical Evidence. *CESifo Economic Studies*, *63*(4), 353–385. https://doi.org/10.1093/cesifo/ifx019

Bertinelli, L., Mohan, P., & Strobl, E. (2016). Hurricane damage risk assessment in the Caribbean: An analysis using synthetic hurricane events and nightlight imagery. *Ecological Economics*, *124*, 135–144. https://doi.org/10.1016/j.ecolecon.2016.02.004

Bhattacharjee, K., & Behera, B. (2018). Does forest cover help prevent flood damage? Empirical evidence from India. *Global Environmental Change*, *53*, 78–89. https://doi.org/10.1016/j.gloenvcha.2018.09.004
information.

Billings, S. B., Gallagher, E. A., & Ricketts, L. (2022). Let the rich be flooded: The distribution of financial aid and distress after hurricane harvey. *Journal of Financial Economics*, S0304405X21005067. https://doi.org/10.1016/j.jfineco.2021.11.006

Bin, O., & Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management*, *65*(3), 361–376. https://doi.org/10.1016/j.jeem.2012.12.002

Bin, O., & Polasky, S. (2004). Effects of Flood Hazards on Property Values: Evidence before and after Hurricane Floyd. *Land Economics*, *80*(4), 490–500. https://doi.org/10.2307/3655805

Black, R., Bennett, S. R. G., Thomas, S. M., & Beddington, J. R. (2011). Migration as adaptation. *Nature*, *478*(7370), 447–449. https://doi.org/10.1038/478477a

Bohra-Mishra, P., Oppenheimer, M., & Hsiang, S. M. (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. *Proceedings of the National Academy of Sciences*, *111*(27), 9780–9785. https://doi.org/10.1073/pnas.1317166111

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-Experimental Shift-Share Research Designs (D. Krueger, Ed.). *The Review of Economic Studies*, *89*(1), 181–213. https://doi.org/10.1093/restud/rdab030

Botzen, W. J. W., Deschenes, O., & Sanders, M. (2019). The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*, *13*(2), 167–188. https://doi.org/10.1093/reep/rez004

Boustan, L. P., Kahn, M. E., & Rhode, P. W. (2012). Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century. *American Economic Review*, *102*(3), 238–244. https://doi.org/10.1257/aer.102.3.238

Boustan, L. P., Kahn, M. E., Rhode, P. W., & Yanguas, M. L. (2020). The effect of natural disasters on economic activity in US counties: A century of data. *Journal of Urban Economics*, *118*, 103257. https://doi.org/10.1016/j.jue.2020.103257

Bradt, J. T., Kousky, C., & Wing, O. E. (2021). Voluntary purchases and adverse selection in the market for flood insurance. *Journal of Environmental Economics and Management*, *110*, 102515. https://doi.org/10.1016/j.jeem.2021.102515
theory.

Brennan, M., Srini, T., Steil, J., Mazereeuw, M., & Ovalles, L. (2022). A Perfect Storm? Disasters and Evictions. *Housing Policy Debate*, *32*(1), 52–83. https://doi.org/10.1080/10511482.2021.1942131
empirical.

Brucal, A., & Lynham, J. (2021). Coastal armoring and sinking property values: The case of seawalls in California. *Environmental Economics and Policy Studies*, *23*(1), 55–77. https://doi.org/10.1007/s10018-020-00278-3

Brueckner, J. K. (1980). A vintage model of urban growth. *Journal of Urban Economics*, *8*(3), 389–402. https://doi.org/10.1016/0094-1190(80)90039-X

Brueckner, J. K., & Rosenthal, S. S. (2009). Gentrification and Neighborhood Housing Cycles: Will America's Future Downtowns Be Rich? *Review of Economics and Statistics*, *91*(4), 725–743. https://doi.org/10.1162/rest.91.4.725
theory.

Buchmiller, R. C., & Eash, D. A. (2010). Floods of May and June 2008 in Iowa.

Bunting, P., Rosenqvist, A., Lucas, R. M., Rebelo, L.-M., Hilarides, L., Thomas, N., Hardy, A., Itoh, T., Shimada, M., & Finlayson, C. M. (2018). The Global Mangrove Watch—A New 2010 Global Baseline of Mangrove Extent. *Remote Sensing*, *10*(10), 1669. https://doi.org/10.3390/rs10101669

Busso, M., Gregory, J., & Kline, P. (2013). Assessing the Incidence and Efficiency of a Prominent Place Based Policy. *American Economic Review*, *103*(2), 897–947. https://doi.org/10.1257/aer.103.2.897

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Campbell, J. Y., Giglio, S., & Pathak, P. (2011). Forced Sales and House Prices. *American Economic Review*, *101*(5), 2108–2131. https://doi.org/10.1257/aer.101.5.2108
information.

Capozza, D., & Li, Y. (1994). The Intensity and Timing of Investment: The Case of Land. *The American Economic Review*.

Cattaneo, C., Beine, M., Fröhlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., Millock, K., Piguet, E., & Schraven, B. (2019). Human Migration in the Era of Climate Change. *Review of Environmental Economics and Policy*, *13*(2), 189–206. https://doi.org/10.1093/reep/rez008

Cattaneo, C., & Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, *122*, 127–146. https://doi.org/10.1016/j.jdeveco.2016.05.004

CEMHS. (2022). Spatial hazard events and losses database for the UnitedStates, version 22.0. Arizona State University, Center for Emergency Management and Homeland Security.

Chanda, A., & Kabiraj, S. (2020). Shedding light on regional growth and convergence in India. *World Development*, *133*, 104961. https://doi.org/10.1016/j.worlddev.2020.104961

City of Cedar Rapids. (2023). Flood of 2008 Facts & Statistics.

Collins, W. J., & Shester, K. L. (2013). Slum Clearance and Urban Renewal in the United States. *American Economic Journal: Applied Economics*, *5*(1), 239–273. https://doi.org/10.1257/app.5.1.239

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., & Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. *Proceedings of the National Academy of Sciences*, *116*(43), 21450–21455. https://doi.org/10.1073/pnas.1907826116

Coulson, . (2002). Regional and state variation in homeownership rates; or if California's home prices were as low as Pennsylvania's would its ownership rate be as high? *JOURNAL OF REAL ESTATE FINANCE AND ECONOMICS*, *24*(3), 261–276. https://doi.org/10.1023/A:1015217414878
empirical.

Couture, V., Gaubert, C., Handbury, J., & Hurst, E. (2023). Income Growth and the Distributional Effects of Urban Spatial Sorting. *Review of Economic Studies*, rdad048. https://doi.org/10.1093/restud/rdad048
theory.

Cross, J. A. (1989). Flood Insurance and Coastal Development. *The Florida Geographer*, *23*.

Cusick, D. (2021, April). A small city pays for flood walls at 2 global companies.

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., & Pasteris, P. P. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology*, *28*(15), 2031–2064. https://doi.org/10.1002/joc.1688

Danielsen, F., Sørensen, M. K., Olwig, M. F., Selvam, V., Parish, F., Burgess, N. D., Hiraishi, T., Karunagaran, V. M., Rasmussen, M. S., Hansen, L. B., Quarto, A., & Suryadiputra, N. (2005). The Asian Tsunami: A Protective Role for Coastal Vegetation. *Science*, *310*(5748), 643–643. https://doi.org/10.1126/science.1118387

Das, S., & Crépin, A.-S. (2013). Mangroves can provide protection against wind damage during storms. *Estuarine, Coastal and Shelf Science*, *134*, 98–107. https://doi.org/10.1016/j.ecss.2013.09.021
information.

Das, S., & Vincent, J. R. (2009). Mangroves protected villages and reduced death toll during Indian super cyclone. *Proceedings of the National Academy of Sciences*, *106*(18), 7357–7360. https://doi.org/10.1073/pnas.0810440106
empirical.

DasGupta, R., & Shaw, R. (2013). Changing perspectives of mangrove management in India – An analytical overview. *Ocean & Coastal Management*, *80*, 107–118. https://doi.org/10.1016/j.ocecoaman.2013.04.010

Davis, ,, Lehnert, A., & Martin, . (2008). The rent-price ratio for the aggregate stock of owner-occupied housing. *REVIEW OF INCOME AND WEALTH*, *54*(2), 279–284. https://doi.org/10.1111/j.1475-4991.2008.00274.x
empirical.

Davlasheridze, M., Fisher-Vanden, K., & Allen Klaiber, H. (2017). The effects of adaptation measures on hurricane induced property losses: Which FEMA investments have the highest returns? *Journal of Environmental Economics and Management*, *81*, 93–114. https://doi.org/10.1016/j.jeem.2016.09.005
information.

del Valle, A., Eriksson, M., Ishizawa, O. A., & Miranda, J. J. (2020). Mangroves protect coastal economic activity from hurricanes. *Proceedings of the National Academy of Sciences*, *117*(1), 265–270. https://doi.org/10.1073/pnas.1911617116
empirical.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature*, *52*(3), 740–798. https://doi.org/10.1257/jel.52.3.740

Deppermann, C. E. (1947). Notes on the Origin and Structure of Philippine Typhoons. *Bulletin of the American Meteorological Society*, *28*(9), 399–404.

Deryugina, T., Kawano, L., & Levitt, S. (2018). The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns. *American Economic Journal: Applied Economics*, *10*(2), 202–233. https://doi.org/10.1257/app.20160307

Deshpande, M., Singh, V. K., Ganadhi, M. K., Roxy, M. K., Emmanuel, R., & Kumar, U. (2021). Changing status of tropical cyclones over the north Indian Ocean. *Climate Dynamics*, *57*(11-12), 3545–3567. https://doi.org/10.1007/s00382-021-05880-z

Desmet, K., Kopp, R. E., Kulp, S. A., Nagy, D. K., Oppenheimer, M., Rossi-Hansberg, E., & Strauss, B. H. (2021). Evaluating the Economic Cost of Coastal Flooding. *American Economic Journal: Macroeconomics*, *13*(2), 444–486. https://doi.org/10.1257/mac.20180366
theory.

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Yan, K., Brandimarte, L., & Blöschl, G. (2015). Debates-Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes: A socio-hydrological approach to explore flood risk changes. *Water Resources Research*, *51*(6), 4770–4781. https://doi.org/10.1002/2014WR016416
information.

Diamond, R., & McQuade, T. (2019). Who Wants Affordable Housing in Their Backyard? An Equilibrium Analysis of Low-Income Property Development. *Journal of Political Economy*, *127*(3), 1063–1117. https://doi.org/10.1086/701354

Donaldson, D., & Storeygard, A. (2016). The View from Above: Applications of Satellite Data in Economics. *Journal of Economic Perspectives*, *30*(4), 171–198. https://doi.org/10.1257/jep.30.4.171

Dubey, S. K., Censkowsky, U., Roy, M., Chand, B. K., & Dey, A. (2019). Framework for Rapid Evaluation of a Mangrove Restoration Site: A Case Study from Indian Sundarban. In B. Gul, B. Böer, M. A. Khan, M. Clüsener-Godt,

& A. Hameed (Eds.), *Sabkha Ecosystems* (pp. 363–378, Vol. 49). Springer International Publishing. https://doi.org/10.1007/978-3-030-04417-6_22

Dugoua, E., Kennedy, R., & Urpelainen, J. (2018). Satellite data for the social sciences: Measuring rural electrification with night-time lights. *International Journal of Remote Sensing*, *39*(9), 2690–2701. https://doi.org/10.1080/01431161.2017.1420936

Dumm, R. E., Sirmans, G. S., & Smersh, G. (2011). The Capitalization of Building Codes in House Prices. *The Journal of Real Estate Finance and Economics*, *42*(1), 30–50. https://doi.org/10.1007/s11146-009-9176-0

Dundas, S. J. (2017). Benefits and ancillary costs of natural infrastructure: Evidence from the New Jersey coast. *Journal of Environmental Economics and Management*, *85*, 62–80. https://doi.org/10.1016/j.jeem.2017.04.008

Dundas, S. J., & Lewis, D. J. (2020). Estimating Option Values and Spillover Damages for Coastal Protection: Evidence from Oregon's Planning Goal 18. *Journal of the Association of Environmental and Resource Economists*, *7*(3), 519–554. https://doi.org/10.1086/708092
information.

Ehrlich, I., & Becker, G. S. (1972). Market Insurance, Self-Insurance, and Self-Protection. *Journal of Political Economy*, *80*(4), 623–648. https://doi.org/10.1086/259916

Eilbott, P., & Binkowski, E. S. (1985). The determinants of SMSA homeownership rates. *Journal of Urban Economics*, *17*(3), 293–304. https://doi.org/10.1016/0094-1190(85)90052-X
empirical.

Ellen, I. G., Schill, M. H., Susin, S., & Schwartz, A. E. (2001). Building Homes, Reviving Neighborhoods: Spillovers from Subsidized Construction of Owner-Occupied Housing in New York City. *Journal of Housing Research*, *12*(2), 185–216.

Elliott, J. R., & Pais, J. (2010). When Nature Pushes Back: Environmental Impact and the Spatial Redistribution of Socially Vulnerable Populations*: Environmental Impact and Spatial Redistribution. *Social Science Quarterly*, *91*(5), 1187–1202. https://doi.org/10.1111/j.1540-6237.2010.00727.x

Ells, K., & Murray, A. B. (2012). Long-term, non-local coastline responses to local shoreline stabilization. *Geophysical Research Letters*, *39*(19), 2012GL052627. https://doi.org/10.1029/2012GL052627

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F. C., & Ghosh, T. (2017). VIIRS night-time lights. *International Journal of Remote Sensing*, *38*(21), 5860–5879. https://doi.org/10.1080/01431161.2017.1342050

Emanuel, K. (2011). Global Warming Effects on U.S. Hurricane Damage. *Weather, Climate, and Society*, *3*(4), 261–268. https://doi.org/10.1175/WCAS-D-11-00007.1

Fan, Q., & Bakkensen, L. A. (2021). Household Sorting as Adaptation to Hurricane Risk in the United States. *Land Economics*, 111319–0162R1. https://doi.org/10.3368/le.98.2.111319-0162R1
empirical.

Fell, H., & Kousky, C. (2015). The value of levee protection to commercial properties. *Ecological Economics*, *119*, 181–188. https://doi.org/10.1016/j.ecolecon.2015.08.019

FEMA. (1982). *Flood insurance rate map* (Panel 39089C0301G).

FEMA. (2009). Mitigation Assessment Team Report: Midwest Floods of 2008 in Iowa and Wisconsin.

Forest Survey of India. (2021). *State of Forest Report* (tech. rep.).

Fu, C., & Gregory, J. (2019). Estimation of an Equilibrium Model With Externalities: Post-Disaster Neighborhood Rebuilding. *Econometrica*, *87*(2), 387–421. https://doi.org/10.3982/ECTA14246
theory.

Fung, J. F., Helgeson, J. F., Webb, D. H., O'Fallon, C. M., & Cutler, H. (2021). Does resilience yield dividends? Co-benefits of investing in increased resilience in Cedar Rapids. *Economic Systems Research*, *33*(3), 336–362. https://doi.org/10.1080/09535314.2020.1798359

Gallagher, J. (2014). Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States. *American Economic Journal: Applied Economics*, *6*(3), 206–233. https://doi.org/10.1257/app.6.3.206

Gallagher, J., & Hartley, D. (2017). Household Finance after a Natural Disaster: The Case of Hurricane Katrina. *American Economic Journal: Economic Policy*, *9*(3), 199–228. https://doi.org/10.1257/pol.20140273

Georgic, W., & Klaiber, H. A. (2022). A Flood of Construction: The Role of Levees in Urban Floodplain Development. *Land Economics*, *98*(1), 78–97. https://doi.org/10.3368/le.98.1.071520-0106R1
empirical.

Gerardi, K., Rosenblatt, E., Willen, P. S., & Yao, V. (2015). Foreclosure externalities: New evidence. *Journal of Urban Economics*, *87*, 42–56. https://doi.org/10.1016/j.jue.2015.02.004
information.

Gibson, M., & Mullins, J. T. (2020). Climate Risk and Beliefs in New York Floodplains. *Journal of the Association of Environmental and Resource Economists*,

7(6), 1069–1111. https://doi.org/10.1086/710240
information.

Gillis Peacock, W., Gladwin, H., & Hearn Morrow, B. (2012). *Hurricane Andrew: Ethnicity, Gender and the Sociology of Disasters.* Taylor and Francis. OCLC: 823380438.

Giri, C., Long, J., Abbas, S., Murali, .,, Qamer, .,, Pengra, B., & Thau, D. (2015). Distribution and dynamics of mangrove forests of South Asia. *JOURNAL OF ENVIRONMENTAL MANAGEMENT*, *148*, 101–111. https://doi.org/10.1016/j.jenvman.2014.01.020
writing.

Glaeser, E., & Gyourko, J. (2018). The Economic Implications of Housing Supply. *Journal of Economic Perspectives*, *32*(1), 3–30. https://doi.org/10.1257/jep.32.1.3

Glaeser, E. L., & Gyourko, J. (2005). Urban Decline and Durable Housing. *Journal of Political Economy*, *113*(2), 345–375. https://doi.org/10.1086/427465
seminal.

González-Bailón, S., Lazer, D., Barberá, P., Zhang, M., Allcott, H., Brown, T., Crespo-Tenorio, A., Freelon, D., Gentzkow, M., Guess, A. M., Iyengar, S., Kim, Y. M., Malhotra, N., Moehler, D., Nyhan, B., Pan, J., Rivera, C. V., Settle, J., Thorson, E., ... Tucker, J. A. (2023). Asymmetric ideological segregation in exposure to political news on Facebook. *Science*, *381*(6656), 392–398. https://doi.org/10.1126/science.ade7138
information.

Goodman, L. S., & Mayer, C. (2018). Homeownership and the American Dream. *Journal of Economic Perspectives*, *32*(1), 31–58. https://doi.org/10.1257/jep.32.1.31

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Graff Zivin, J., Liao, Y., & Panassié, Y. (2023). How hurricanes sweep up housing markets: Evidence from Florida. *Journal of Environmental Economics and Management*, *118*, 102770. https://doi.org/10.1016/j.jeem.2022.102770
empirical.

Grames, J., Prskawetz, A., Grass, D., Viglione, A., & Blöschl, G. (2016). Modeling the interaction between flooding events and economic growth. *Ecological Economics*, *129*, 193–209. https://doi.org/10.1016/j.ecolecon.2016.06.014
theory.

Green, R. K., Malpezzi, S., & Mayo, S. K. (2005). Metropolitan-Specific Estimates of the Price Elasticity of Supply of Housing, and Their Sources. *American Economic Review*, *95*(2), 334–339. https://doi.org/10.1257/000282805774670077

Grilli, G., Fratini, R., Marone, E., & Sacchelli, S. (2020). A spatial-based tool for the analysis of payments for forest ecosystem services related to hydrogeological protection. *Forest Policy and Economics*, *111*, 102039. https://doi.org/10.1016/j.forpol.2019.102039
information.

Groen, J. A., & Polivka, A. E. (2008). The Effect of Hurricane Katrina on the Labor Market Outcomes of Evacuees. *The American Economic Review*, *98*(2), 43–48.

Haer, T., Botzen, W. J. W., de Moel, H., & Aerts, J. C. J. H. (2017). Integrating Household Risk Mitigation Behavior in Flood Risk Analysis: An Agent-Based Model Approach: Integrating Household Risk Mitigation. *Risk Analysis*, *37*(10), 1977–1992. https://doi.org/10.1111/risa.12740

Hallegatte, S., Green, C., Nicholls, R. J., & Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. *Nature Climate Change*, *3*(9), 802–806. https://doi.org/10.1038/nclimate1979

Hartley, D. (2014). The effect of foreclosures on nearby housing prices: Supply or dis-amenity? *Regional Science and Urban Economics*, *49*, 108–117. https://doi.org/10.1016/j.regsciurbeco.2014.09.001

Hashida, Y., & Dundas, S. J. (2023). The effects of a voluntary property buyout and acquisition program on coastal housing markets: Evidence from New York. *Journal of Environmental Economics and Management*, *121*, 102873. https://doi.org/10.1016/j.jeem.2023.102873
information.

Hauer, M. E. (2017). Migration induced by sea-level rise could reshape the US population landscape. *Nature Climate Change*, *7*(5), 321–325. https://doi.org/10.1038/nclimate3271

Hauer, M. E., Holloway, S. R., & Oda, T. (2020). Evacuees and Migrants Exhibit Different Migration Systems After the Great East Japan Earthquake and Tsunami. *Demography*, *57*(4), 1437–1457. https://doi.org/10.1007/s13524-020-00883-7

Hausman, N., Ramot-Nyska, T., & Zussman, N. (2022). Homeownership, Labor Supply, and Neighborhood Quality. *American Economic Journal: Economic Policy*, *14*(2), 193–230. https://doi.org/10.1257/pol.20200177
empirical.

Henderson, J. V., & Ioannides, Y. M. (1983). A Model of Housing Tenure Choice. *The American Economic Review*, *73*(1), 98–113
theory.

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring Economic Growth from Outer Space. *American Economic Review*, *102*(2), 994–1028. https://doi.org/10.1257/aer.102.2.994

Henkel, M., Kwon, E., & Magontier, P. (2022). The Unintended Consequences of Post-Disaster Policies for Spatial Sorting. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4237083
empirical.

Hilber, . (2005). Neighborhood externality risk and the homeownership status of properties. *JOURNAL OF URBAN ECONOMICS*, *57*(2), 213–241. https://doi.org/10.1016/j.jue.2004.10.006
empirical.

Hinkel, J., Lincke, D., Vafeidis, A. T., Perrette, M., Nicholls, R. J., Tol, R. S. J., Marzeion, B., Fettweis, X., Ionescu, C., & Levermann, A. (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences*, *111*(9), 3292–3297. https://doi.org/10.1073/pnas.1222469111
information.

Hino, M., Field, C. B., & Mach, K. J. (2017). Managed retreat as a response to natural hazard risk. *Nature Climate Change*, *7*(5), 364–370. https://doi.org/10.1038/nclimate3252

Hochard, J. P., Barbier, E. B., & Hamilton, S. E. (2021). Mangroves and coastal topography create economic “safe havens” from tropical storms. *Scientific Reports*, *11*(1), 15359. https://doi.org/10.1038/s41598-021-94207-3
empirical.

Hochard, J. P., Hamilton, S., & Barbier, E. B. (2019). Mangroves shelter coastal economic activity from cyclones. *Proceedings of the National Academy of Sciences*, *116*(25), 12232–12237. https://doi.org/10.1073/pnas.1820067116
empirical.

Hoffmann, R. (2022). Contextualizing Climate Change Impacts on Human Mobility in African Drylands. *Earth’s Future*, *10*(6), e2021EF002591. https://doi.org/10.1029/2021EF002591

Hoffmann, R., Wiederkehr, C., Dimitrova, A., & Hermans, K. (2022). Agricultural livelihoods, adaptation, and environmental migration in sub-Saharan drylands: A meta-analytical review. *Environmental Research Letters*, *17*(8), 083003. https://doi.org/10.1088/1748-9326/ac7d65

Holland, G. (2008). A Revised Hurricane Pressure–Wind Model. *Monthly Weather Review*, *136*(9), 3432–3445. https://doi.org/10.1175/2008MWR2395.1

Hornbeck, R. (2012). The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe. *American Economic Review*, *102*(4), 1477–1507. https://doi.org/10.1257/aer.102.4.1477

Hornbeck, R., & Keniston, D. (2017). Creative Destruction: Barriers to Urban Growth and the Great Boston Fire of 1872. *American Economic Review*, *107*(6), 1365–1398. https://doi.org/10.1257/aer.20141707
theory.

Howell, J., & Elliott, J. R. (2019). Damages Done: The Longitudinal Impacts of Natural Hazards on Wealth Inequality in the United States. *Social Problems*, *66*(3), 448–467. https://doi.org/10.1093/socpro/spy016

Hsiang, S., & Jina, A. (2014, July). *The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones* (tech. rep. No. w20352). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w20352

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences*, *107*(35), 15367–15372. https://doi.org/10.1073/pnas.1009510107

Hsiao, A. (2023). Sea Level Rise and Urban Adaptation in Jakarta.

Husby, T. G., de Groot, H. L., Hofkes, M. W., & Dröes, M. I. (2014). Do Floods Have Permanent Effects? Evidence from the Netherlands: Do Floods Have Permanent Effects? *Journal of Regional Science*, *54*(3), 355–377. https://doi.org/10.1111/jors.12112

Hutchison, J., Manica, A., Swetnam, R., Balmford, A., & Spalding, M. (2014). Predicting Global Patterns in Mangrove Forest Biomass. *Conservation Letters*, *7*(3), 233–240. https://doi.org/10.1111/conl.12060

Ihlanfeldt, K. (2021). Property Tax Homestead Exemptions: An Analysis of the Variance in Take-Up Rates Across Neighborhoods. *National Tax Journal*, *74*(2), 405–430. https://doi.org/10.1086/714168

Ioannides, Y. M., & Rosenthal, S. S. (1994). Estimating the Consumption and Investment Demands for Housing and Their Effect on Housing Tenure Status. *The Review of Economics and Statistics*, *76*(1), 127–141. https://doi.org/10.2307/2109831

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (tech. rep.). Cambridge University Press.

[H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]

IPCC. (2023, July). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland.* (First, tech. rep.). Intergovernmental Panel on Climate Change (IPCC). https://doi.org/10.59327/IPCC/AR6-9789291691647

Irwin, N. B. (2019). Keeping up appearances: Spatial spillovers and housing renovations. *Papers in Regional Science*, *98*(5), 2115–2134. https://doi.org/10.1111/pirs.12449

Issler, P., Stanton, R. H., Vergara-Alert, C., & Wallace, N. E. (2019). Mortgage Markets with Climate-Change Risk: Evidence from Wildfires in California. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3511843

Jenkins, W. O. (2004). *NATIONAL FLOOD INSURANCE PROGRAM Actions to Address Repetitive Loss Properties* (tech. rep.).

Jin, D., Hoagland, P., Au, D. K., & Qiu, J. (2015). Shoreline change, seawalls, and coastal property values. *Ocean & Coastal Management*, *114*, 185–193. https://doi.org/10.1016/j.ocecoaman.2015.06.025

Kandasamy, K. (2017). Mangroves in India and Climate Change: An Overview. In R. DasGupta & R. Shaw (Eds.), *PARTICIPATORY MANGROVE MANAGEMENT IN A CHANGING CLIMATE: PERSPECTIVES FROM THE ASIA-PACIFIC* (pp. 31–57).
writing.

Kates, R. W., Colten, C. E., Laska, S., & Leatherman, S. P. (2006). Reconstruction of New Orleans after Hurricane Katrina: A research perspective. *Proceedings of the National Academy of Sciences*, *103*(40), 14653–14660. https://doi.org/10.1073/pnas.0605726103

Keeler, A. G., Mullin, M., McNamara, D. E., & Smith, M. D. (2022). Buyouts with rentbacks: A policy proposal for managing coastal retreat. *Journal of Environmental Studies and Sciences*. https://doi.org/10.1007/s13412-022-00762-0
inform.

Keenan, J. M., Hill, T., & Gumber, A. (2018). Climate gentrification: From theory to empiricism in Miami-Dade County, Florida. *Environmental Research Letters*, *13*(5), 054001. https://doi.org/10.1088/1748-9326/aabb32

Kelly, D. L., & Molina, R. (2023). Adaptation Infrastructure and Its Effects on Property Values in the Face of Climate Risk. *Journal of the Association of*

Environmental and Resource Economists, *10*(6), 1405–1438. https://doi.org/10.1086/725109
Kim, S. K. (2020). The Economic Effects of Climate Change Adaptation Measures: Evidence from Miami-Dade County and New York City. *Sustainability*, *12*(3), 1097. https://doi.org/10.3390/su12031097
Knapp, K. R., Diamond, H. J., Kossin, J. P., Kruk, M. C., & Schreck, C. J. (2018). International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4. https://doi.org/10.25921/82TY-9E16
Kocornik-Mina, A., McDermott, T. K. J., Michaels, G., & Rauch, F. (2020). Flooded Cities. *American Economic Journal: Applied Economics*, *12*(2), 35–66. https://doi.org/10.1257/app.20170066
information.
Koster, H. R., & Rouwendal, J. (2017). Historic Amenities and Housing Externalities: Evidence from the Netherlands. *The Economic Journal*, *127*(605), F396–F420. https://doi.org/10.1111/ecoj.12477
Kousky, C. (2019). The Role of Natural Disaster Insurance in Recovery and Risk Reduction. *Annual Review of Resource Economics*, *11*(1), 399–418. https://doi.org/10.1146/annurev-resource-100518-094028
Kousky, C., & Michel-Kerjan, E. (2017). Examining Flood Insurance Claims in the United States: Six Key Findings. *The Journal of Risk and Insurance*, *84*(3), 819–850.
Kousky, C., Michel-Kerjan, E. O., & Raschky, P. A. (2018). Does federal disaster assistance crowd out flood insurance? *Journal of Environmental Economics and Management*, *87*, 150–164. https://doi.org/10.1016/j.jeem.2017.05.010
Krauss, K. W., & Osland, M. J. (2019). Tropical cyclones and the organization of mangrove forests: A review. *Annals of Botany*, mcz161. https://doi.org/10.1093/aob/mcz161
review.
Kulanthaivelu, E. (2023). The impact of tropical cyclones on income inequality in the U.S.: An empirical analysis. *Ecological Economics*, *209*, 107833. https://doi.org/10.1016/j.ecolecon.2023.107833
Kydland, F. E., & Prescott, E. C. (1977). Rules Rather than Discretion: The Inconsistency of Optimal Plans. *Journal of Political Economy*, *85*(3), 473–491.
Laso Bayas, J. C., Marohn, C., Dercon, G., Dewi, S., Piepho, H. P., Joshi, L., van Noordwijk, M., & Cadisch, G. (2011). Influence of coastal vegetation on the 2004 tsunami wave impact in west Aceh. *Proceedings of the National Academy of Sciences*, *108*(46), 18612–18617. https://doi.org/10.1073/pnas.1013516108

Lazarus, E. D., Limber, P. W., Goldstein, E. B., Dodd, R., & Armstrong, S. B. (2018). Building back bigger in hurricane strike zones. *Nature Sustainability*, *1*(12), 759–762. https://doi.org/10.1038/s41893-018-0185-y
information.

Lee, C.-Y., Tippett, M. K., Sobel, A. H., & Camargo, S. J. (2018). An Environmentally Forced Tropical Cyclone Hazard Model. *Journal of Advances in Modeling Earth Systems*, *10*(1), 223–241. https://doi.org/10.1002/2017MS001186

Lee, S., & Lin, J. (2018). Natural Amenities, Neighbourhood Dynamics, and Persistence in the Spatial Distribution of Income. *The Review of Economic Studies*, *85*(1), 663–694. https://doi.org/10.1093/restud/rdx018
theory.

Lewis, T., & Nickerson, D. (1989). Self-insurance against natural disasters. *Journal of Environmental Economics and Management*, *16*(3), 209–223. https://doi.org/10.1016/0095-0696(89)90010-7

Li, X., Gopalakrishnan, S., & Klaiber, H. A. (2023). Local Adaptation and Unintended Coastal Vulnerability: The Effect of Beach Nourishment on Residential Development in North Carolina. *Journal of the Association of Environmental and Resource Economists*, 727357. https://doi.org/10.1086/727357

Lindersson, S., Raffetti, E., Rusca, M., Brandimarte, L., Mård, J., & Di Baldassarre, G. (2023). The wider the gap between rich and poor the higher the flood mortality. *Nature Sustainability*, *6*(8), 995–1005. https://doi.org/10.1038/s41893-023-01107-7

Liu, H., Zhang, K., Li, Y., & Xie, L. (2013). Numerical study of the sensitivity of mangroves in reducing storm surge and flooding to hurricane characteristics in southern Florida. *Continental Shelf Research*, *64*, 51–65. https://doi.org/10.1016/j.csr.2013.05.015

Loder, N., Irish, J., Cialone, M., & Wamsley, T. (2009). Sensitivity of hurricane surge to morphological parameters of coastal wetlands. *Estuarine, Coastal and Shelf Science*, *84*(4), 625–636. https://doi.org/10.1016/j.ecss.2009.07.036

Mach, K. J., Kraan, C. M., Hino, M., Siders, A. R., Johnston, E. M., & Field, C. B. (2019). Managed retreat through voluntary buyouts of flood-prone properties. *Science Advances*, *5*(10), eaax8995. https://doi.org/10.1126/sciadv.aax8995

Mahmud, S., & Barbier, E. B. (2016). Are private defensive expenditures against storm damages affected by public programs and natural barriers? Evidence from the coastal areas of Bangladesh. *Environment and Development Economics*, *21*(6), 767–788. https://doi.org/10.1017/S1355770X16000164

Mallakpour, I., & Villarini, G. (2017). Analysis of changes in the magnitude, frequency, and seasonality of heavy precipitation over the contiguous USA. *Theoretical and Applied Climatology*, *130*(1-2), 345–363. https://doi.org/10.1007/s00704-016-1881-z

Mård, J., Di Baldassarre, G., & Mazzoleni, M. (2018). Nighttime light data reveal how flood protection shapes human proximity to rivers. *Science Advances*, *4*(8), eaar5779. https://doi.org/10.1126/sciadv.aar5779

Maul, G. A., & Duedall, I. W. (2019). Demography of Coastal Populations. In C. W. Finkl & C. Makowski (Eds.), *Encyclopedia of Coastal Science* (pp. 692–700). Springer International Publishing. https://doi.org/10.1007/978-3-319-93806-6_115

McFadden, D. (1978). Modeling the Choice of Residential Location.

McMillen, D., & O'Sullivan, A. (2013). Option value and the price of teardown properties. *Journal of Urban Economics*, *74*, 71–82. https://doi.org/10.1016/j.jue.2012.09.004

McNamara, D. E., Gopalakrishnan, S., Smith, M. D., & Murray, A. B. (2015). Climate Adaptation and Policy-Induced Inflation of Coastal Property Value (J. P. Kropp, Ed.). *PLOS ONE*, *10*(3), e0121278. https://doi.org/10.1371/journal.pone.0121278
information.

McNamara, D. E., Smith, M. D., Williams, Z., Gopalakrishnan, S., & Landry, C. E. (2024). Policy and market forces delay real estate price declines on the US coast. *Nature Communications*, *15*(1). https://doi.org/10.1038/s41467-024-46548-6

Menéndez, P., Losada, I. J., Torres-Ortega, S., Narayan, S., & Beck, M. W. (2020). The Global Flood Protection Benefits of Mangroves. *Scientific Reports*, *10*(1), 4404. https://doi.org/10.1038/s41598-020-61136-6
information.

Mirza, M. U., Xu, C., van Bavel, B., van Nes, E. H., & Scheffer, M. (2021). Global inequality remotely sensed. *Proceedings of the National Academy of Sciences*, *118*(18), e1919913118. https://doi.org/10.1073/pnas.1919913118

Mishra SP, M. S. a. S. K. (2023). The Values and Blue Carbon Ecosystem of the Chilika Lagoon through Ages, India. https://doi.org/10.5281/ZENODO.8256143

Mueller, V., Gray, C., & Kosec, K. (2014). Heat stress increases long-term human migration in rural Pakistan. *Nature Climate Change*, *4*(3), 182–185. https://doi.org/10.1038/nclimate2103
information.

Munneke, H. J., & Womack, K. S. (2015). Neighborhood renewal: The decision to renovate or tear down. *Regional Science and Urban Economics*, *54*, 99–115. https://doi.org/10.1016/j.regsciurbeco.2015.08.001

Nasrin, T., Ramiz, M., Sarif, M. N., Hashim, M., Siddiqui, M. A., Siddiqui, L., Mohibul, S., & Mankotia, S. (2023). Modeling of impact assessment of super cyclone Amphan with machine learning algorithms in Sundarban Biosphere Reserve, India. *Natural Hazards*, *117*(2), 1945–1968. https://doi.org/10.1007/s11069-023-05935-w
information.

Notaro, S., & Paletto, A. (2012). The economic valuation of natural hazards in mountain forests: An approach based on the replacement cost method. *Journal of Forest Economics*, *18*(4), 318–328. https://doi.org/10.1016/j.jfe.2012.06.002

NWS. (2017). Hurricane Irma Local Report/Summary.

Office of the Registrar General and Census Commissioner, India. (2011). Census of india.

Oliveira, J., & Pereda, P. (2020). The impact of climate change on internal migration in Brazil. *Journal of Environmental Economics and Management*, *103*, 102340. https://doi.org/10.1016/j.jeem.2020.102340

Ooi, J. T., & Le, T. T. (2013). The spillover effects of infill developments on local housing prices. *Regional Science and Urban Economics*, *43*(6), 850–861. https://doi.org/10.1016/j.regsciurbeco.2013.08.002

Oppenheimer, M., Campos, M., Warren, R., DeWaard, J., Lubor, G., O'Neill, B., & Takahashi, K. (2014). Emergent risks and key vulnerabilities. In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]* (pp. 1039–1099). Cambridge University Press.

Ortega, F., & Taṣpınar, S. (2018). Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market. *Journal of Urban Economics*, *106*, 81–100. https://doi.org/10.1016/j.jue.2018.06.005

Osama, S. (2023). Economic and Demographic Effects of Increased Flood Susceptibility: Evidence from Rural India.

Owens, R., Rossi-Hansberg, E., & Sarte, P.-D. (2020). Rethinking Detroit. *American Economic Journal: Economic Policy*, *12*(2), 258–305. https://doi.org/10.

1257/pol.20180651
theory.
Paredes, D., & Skidmore, M. (2017). The net benefit of demolishing dilapidated housing: The case of Detroit. *Regional Science and Urban Economics*, *66*, 16–27. https://doi.org/10.1016/j.regsciurbeco.2017.05.009
Parton, L. C., & Dundas, S. J. (2020). Fall in the sea, eventually? A green paradox in climate adaptation for coastal housing markets. *Journal of Environmental Economics and Management*, *104*, 102381. https://doi.org/10.1016/j.jeem.2020.102381
data.
Partridge, M. D., Feng, B., & Rembert, M. (2017). Improving Climate-Change Modeling of US Migration. *American Economic Review*, *107*(5), 451–455. https://doi.org/10.1257/aer.p20171054
Pelli, M., Tschopp, J., Bezmaternykh, N., & Eklou, K. M. (2023). In the eye of the storm: Firms and capital destruction in India. *Journal of Urban Economics*, *134*, 103529. https://doi.org/10.1016/j.jue.2022.103529
empirical.
Pennington, K. (2021). Does Building New Housing Cause Displacement?: The Supply and Demand Effects of Construction in San Francisco. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3867764
Peralta, A., & Scott, J. B. (2024). Does the National Flood Insurance Program Drive Migration to Higher Risk Areas? *Journal of the Association of Environmental and Resource Economists*, *11*(2), 287–318. https://doi.org/10.1086/726155
Petrolia, D. R., Hwang, J., & Landry, C. E. (2015). Wind Insurance and Mitigation in the Coastal Zone.
Pleninger, R. (2022). Impact of natural disasters on the income distribution. *World Development*, *157*, 105936. https://doi.org/10.1016/j.worlddev.2022.105936
empirical.
Qiu, Y., & Gopalakrishnan, S. (2018). Shoreline defense against climate change and capitalized impact of beach nourishment. *Journal of Environmental Economics and Management*, *92*, 134–147. https://doi.org/10.1016/j.jeem.2018.08.013
Rabin, C. (2017, September). Irma, at least in Miami-Dade and Broward, wasn't even a hurricane. But the gusts sure were.
Rahuman, S., Ismail, A. M., Varghese, S. M., Toworfe, G. K., & Sasikumar, B. (2022). Wind Flow Simulation around Rhizophora Mangrove Roots Using Computational Fluid Dynamics (S. J. S. Chelladurai, Ed.). *Journal of Nanomaterials*,

2022, 1–11. https://doi.org/10.1155/2022/5722653
information.

Raker, E. J. (2020). Natural Hazards, Disasters, and Demographic Change: The Case of Severe Tornadoes in the United States, 1980–2010. *Demography*, *57*(2), 653–674. https://doi.org/10.1007/s13524-020-00862-y

Rangel-Buitrago, N., Williams, A., & Anfuso, G. (2018). Hard protection structures as a principal coastal erosion management strategy along the Caribbean coast of Colombia. A chronicle of pitfalls. *Ocean & Coastal Management*, *156*, 58–75. https://doi.org/10.1016/j.ocecoaman.2017.04.006
information.

Raya, J., & Garcia, J. (2012). Which Are the Real Determinants of Tenure? A Comparative Analysis of Different Models of the Tenure Choice of a House. *URBAN STUDIES*, *49*(16), 3645–3662. https://doi.org/10.1177/0042098012446998
review.

Rezaie, A. M., Loerzel, J., & Ferreira, C. M. (2020). Valuing natural habitats for enhancing coastal resilience: Wetlands reduce property damage from storm surge and sea level rise (J. M. Dias, Ed.). *PLOS ONE*, *15*(1), e0226275. https://doi.org/10.1371/journal.pone.0226275

Rosen, H. S., Rosen, K. T., & Holtz-Eakin, D. (1984). Housing Tenure, Uncertainty, and Taxation. *The Review of Economics and Statistics*, *66*(3), 405–416. https://doi.org/10.2307/1924996

Rosenthal, S. S. (2008). Old homes, externalities, and poor neighborhoods. A model of urban decline and renewal. *Journal of Urban Economics*, *63*(3), 816–840. https://doi.org/10.1016/j.jue.2007.06.003
information.

Rossi-Hansberg, E., Sarte, P.-D., & Owens, R. (2010). Housing Externalities. *Journal of Political Economy*, *118*(3), 485–535. https://doi.org/10.1086/653138

ROY, P., MEIYAPPAN, P., JOSHI, P., KALE, M., SRIVASTAV, V., SRIVASATAVA, S., BEHERA, M., ROY, A., SHARMA, Y., RAMACHANDRAN, R., BHAVANI, P., JAIN, A., & KRISHNAMURTHY, Y. (2016). Decadal Land Use and Land Cover Classifications across India, 1985, 1995, 2005. https://doi.org/10.3334/ORNLDAAC/1336

Sadowski, N. C., & Sutter, D. (2005). Hurricane Fatalities and Hurricane Damages: Are Safer Hurricanes More Damaging? *Southern Economic Journal*, *72*(2), 422. https://doi.org/10.2307/20062119

Sandler, D. H. (2017). Externalities of public housing: The effect of public housing demolitions on local crime. *Regional Science and Urban Economics*, *62*, 24–35. https://doi.org/10.1016/j.regsciurbeco.2016.10.007

Schultz, J., & Elliott, J. R. (2013). Natural disasters and local demographic change in the United States. *Population and Environment*, *34*(3), 293–312.
Selvam, V. (2003). Environmental classification of mangrove wetlands of India. *CURRENT SCIENCE*, *84*(6)
information.
Service, U. S. A. M. (1955). *India and Pakistan 1:250,000* (tech. rep.). Washington.
Shah, H., & Ramesh, R. (2022). Development-aligned mangrove conservation strategy for enhanced blue economy: A successful model from Gujarat, India. *Estuarine, Coastal and Shelf Science*, *274*, 107929. https://doi.org/10.1016/j.ecss.2022.107929
Sheldon, T. L., & Zhan, C. (2019). The Impact of Natural Disasters on US Home Ownership. *Journal of the Association of Environmental and Resource Economists*, *6*(6), 1169–1203. https://doi.org/10.1086/705398
Siders, A., Hino, M., & Mach, K. J. (2019). The case for strategic and managed climate retreat. *Science*, *365*(6455), 761–763. https://doi.org/10.1126/science.aax8346
Simmons, K. M., & Sutter, D. (2007). Tornado shelters and the housing market. *Construction Management and Economics*, *25*(11), 1119–1126. https://doi.org/10.1080/01446190701618299
Singhal, A., Sahu, S., Chattopadhyay, S., Mukherjee, A., & Bhanja, S. N. (2020). Using night time lights to find regional inequality in India and its relationship with economic development (S. Goli, Ed.). *PLOS ONE*, *15*(11), e0241907. https://doi.org/10.1371/journal.pone.0241907
Siodla, J. (2015). Razing San Francisco: The 1906 disaster as a natural experiment in urban redevelopment. *Journal of Urban Economics*, *89*, 48–61. https://doi.org/10.1016/j.jue.2015.07.001
Slater, L. J., & Villarini, G. (2016). Recent trends in U.S. flood risk. *Geophysical Research Letters*, *43*(24). https://doi.org/10.1002/2016GL071199
Smith, A. B. (2020). U.S. Billion-dollar Weather and Climate Disasters, 1980 - present (NCEI Accession 0209268). https://doi.org/10.25921/STKW-7W73
Smith, M. (2019). An Iowa Town Fought and Failed to Save a Levee. Then Came the Flood. *The New York Times*.
Smith, R. (2014). Five years, 1,356 property purchases later.
Spalding, M., Kainuma, M., & Collins, L. (1997). *World atlas of mangroves*. Routledge.
OCLC: 1053731504.
Sun, F., & Carson, R. T. (2020). Coastal wetlands reduce property damage during tropical cyclones. *Proceedings of the National Academy of Sciences*, *117*(11),

5719–5725. https://doi.org/10.1073/pnas.1915169117
empirical.

Suresh, ., & Sahu, . (2015). Mangrove Area Assessment in India: Implications of Loss of Mangroves. *Journal of Earth Science & Climatic Change*, *06*(05). https://doi.org/10.4172/2157-7617.1000280

Sutton, P. C., Elvidge, C. D., & Ghosh, T. (2007). Estimation of Gross Domestic Product at Sub-National Scales using Nighttime Satellite Imagery. *International Journal of Ecological Economics & Statistics*.

Tate, E., Strong, A., Kraus, T., & Xiong, H. (2016). Flood recovery and property acquisition in Cedar Rapids, Iowa. *Natural Hazards*, *80*(3), 2055–2079. https://doi.org/10.1007/s11069-015-2060-8

Taylor, C. A., & Druckenmiller, H. (2022). Wetlands, Flooding, and the Clean Water Act. *American Economic Review*, *112*(4), 1334–1363. https://doi.org/10.1257/aer.20210497
empirical.

Temmerman, S., Meire, P., Bouma, T. J., Herman, P. M. J., Ysebaert, T., & De Vriend, H. J. (2013). Ecosystem-based coastal defence in the face of global change. *Nature*, *504*(7478), 79–83. https://doi.org/10.1038/nature12859

Ton, M. J., De Moel, H., De Bruijn, J. A., Reimann, L., Botzen, W. J. W., & Aerts, J. C. J. H. (2024). Economic damage from natural hazards and internal migration in the United States. *Natural Hazards*. https://doi.org/10.1007/s11069-024-06987-2

Towe, C., & Lawley, C. (2013). The Contagion Effect of Neighboring Foreclosures. *American Economic Journal: Economic Policy*, *5*(2), 313–335. https://doi.org/10.1257/pol.5.2.313

Turnbull, G. K., & van der Vlist, A. J. (2022). Bargaining power and segmented markets: Evidence from rental and owner-occupied housing. *Real Estate Economics*, *50*(5), 1307–1333. https://doi.org/10.1111/1540-6229.12380
empirical.

Turner, T. M. (2003). Does Investment Risk Affect the Housing Decisions of Families? *Economic Inquiry*, *41*(4), 675–691. https://doi.org/10.1093/ei/cbg036

Van Duijn, M., Rouwendal, J., & Boersema, R. (2016). Redevelopment of industrial heritage: Insights into external effects on house prices. *Regional Science and Urban Economics*, *57*, 91–107. https://doi.org/10.1016/j.regsciurbeco.2016.02.001

Vancutsem, C., Achard, F., Pekel, J.-F., Vieilledent, G., Carboni, S., Simonetti, D., Gallego, J., Aragão, L. E. O. C., & Nasi, R. (2021). Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. *Science Advances*, *7*(10), eabe1603. https://doi.org/10.1126/sciadv.abe1603

Vinnakota, M., & Ziff, A. (2024). Levees: Infrastructure and Insurance as Adaptation to Flood Risk.

Washington, T. L., Smedley, B. D., Alvarez, B., & Reece, J. (2006). *The State of Housing in New Orleans One Year After Katrina* (tech. rep.). KIRWAN INSTITUTE FOR THE STUDY OF RACE and ETHNICITY.

Wheaton, W. C. (1982). Urban spatial development with durable but replaceable capital. *Journal of Urban Economics*, *12*(1), 53–67. https://doi.org/10.1016/0094-1190(82)90004-3
theory.

Whitaker, S., & Fitzpatrick Iv, T. J. (2013). Deconstructing distressed-property spillovers: The effects of vacant, tax-delinquent, and foreclosed properties in housing submarkets. *Journal of Housing Economics*, *22*(2), 79–91. https://doi.org/10.1016/j.jhe.2013.04.001

White, G. F. (1942). *Human Adjustment to Floods: A Geographical Approach to the Flood Problem in the United States* [Doctoral dissertation, The University of Chicago].
T-07550.

Xu, H., & Wang, S. (2019). Urban redevelopment and residential location choice: Evidence from a major earthquake in Japan. *Journal of Regional Science*, *59*(5), 850–882. https://doi.org/10.1111/jors.12424
information.

Yamamoto, Y. (2023). Living under ecosystem degradation: Evidence from the mangrove–fishery linkage in Indonesia. *Journal of Environmental Economics and Management*, *118*, 102788. https://doi.org/10.1016/j.jeem.2023.102788
information.

Zhang, W., & Villarini, G. (2021). Greenhouse gases drove the increasing trends in spring precipitation across the central USA. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *379*(2195), 20190553. https://doi.org/10.1098/rsta.2019.0553

Zhao, X., Yu, B., Liu, Y., Yao, S., Lian, T., Chen, L., Yang, C., Chen, Z., & Wu, J. (2018). NPP-VIIRS DNB Daily Data in Natural Disaster Assessment: Evidence from Selected Case Studies. *Remote Sensing*, *10*(10), 1526. https://doi.org/10.3390/rs10101526

Zhu, K., Gopalakrishnan, S., & Smith, M. (2022). Natural Disasters and Inequality in U.S. Coastal Communities. https://doi.org/10.22004/AG.ECON.322424