UNIVERSITY OF MIAMI

NAVIGATING FLOOD HAZARD IN A CHANGING CLIMATE: HOUSEHOLD ASSET EXPOSURE, VULNERABILITIES, AND POLICY OPPORTUNITIES FOR RISK MITIGATION

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Anthropogenic climate change and urban development patterns are increasing flood risks in the United States (US). While mitigation and adaptation measures have the potential to manage these risks and promote climate resilient development, recent evidence suggests current adaptation actions are not keeping pace with growing climate-related risks. This dissertation aims to provide households, firms, and policymakers with relevant information on key aspects of household asset exposure and vulnerability to support decision-making toward effective and equitable flood risk reduction. Chapter 1 contains the introduction. Chapter 2 evaluates housing assets' exposure to anthropogenic sea level rise (SLR), market responses following publication of a watershed scientific report on SLR, and the role of residential property value metrics in Federal flood infrastructure allocation policy processes. Evidence from this chapter indicates acute extant flood risk, not SLR, drives negative price effects, and status quo use of unweighted property values in Federal economic analyses and benefit-cost ratio calculations do not meaningfully account for preexisting property value disparities across socioeconomic groups. Chapter 3 contributes a novel national stocktake of the number and value of household vehicles located in US floodplains, as well as a first analysis of Federal Emergency Management Agency disaster assistance applications and outcomes with respect to vehicle flood damages. Results suggest vehicle flood risk in the US is wide in scope and large in magnitude, and

Federal government expenditures to support uninsured vehicle flood damages are substantial. Chapter 4 gathers novel survey data from coastal vehicle owners and finds robust willingness to pay for a single-peril vehicle flood insurance product, as well as significant auto insurance literacy gaps which may leave many coastal vehicle owners financially vulnerable to flood exposure. Conclusions are provided in Chapter 5. Overall, findings from this dissertation provide insight into key household assets' exposure and vulnerability to climate change-exacerbated flood hazard, and identifies potential policy avenues to achieve future risk reduction.

This dissertation is dedicated to my family, friends, and all flood-prone communities pursuing safe and prosperous lives in close proximity to water bodies.

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The dissertation relies extensively on data products produced by various public agencies, notably FEMA, the National Oceanic and Atmospheric Administration, the United States Army Corps of Engineers, the United States Census Bureau, and the United States Geological Survey. These data would not exist without the dedicated public servants stewarding these data products, nor the tax-paying public who support these public goods. Additionally, Zillow, Inc. and the First Street Foundation have generously provided data used in the research at no cost. Thank you to all of these data providers.

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CHAPTER 1

Introduction

Human settlements and economic activity tend to locate near water due to the essential role water plays in human development (R. Clarke, 2013; Solomon, 2011). Water bodies facilitate transportation and provide access to valuable natural resources, among other economic benefits. However, settlement in close proximity to water also has the potential to increase flood exposure. Thus, water can function as both a resource or a hazard depending on context. In the United States (US), approximately 43 million residents live in areas with a 1% annual exceedance probability of flood exposure, and shore-adjacent counties contain a disproportionately high share of US residents and Gross Domestic Product (GDP) relative to land area (Fleming et al., 2018; Wing et al., 2018). These statistics demonstrate a large portion of US residents and assets are located near water. Correspondingly, the Federal Emergency Management Agency (FEMA) estimates flooding to be the costliest and most frequently-occurring natural hazard in the US (FEMA, 2019). These realities imply holistic water management practices simultaneously require the harnessing of water's benefits and the mitigation of its destructive potential.

At the same time large concentrations of people and assets are already located in floodplains, human emissions of heat-trapping gases are causing an unprecedented rate of global climate change, resulting in a warmer atmosphere, as well as warmer oceans and land surfaces (IPCC, 2021). Anthropogenic climate change is causing mean sea levels to rise and more extreme precipitation events to pour down from the sky, phenomena which are increasing the intensity, frequency, duration, and extent of flood hazard exposure across significant swathes of land across of the US and globally. While climate change impacts are expanding and intensifying flood exposure, status quo urban development patterns are leading to growth of the number of people and assets in extant floodplains (Andreadis et al., 2022; IPCC, 2021; Rentschler et al., 2023; Wing et al., 2018), a trend described as the "expanding bull's eye effect" (Strader & Ashley, 2015). These realities highlight growing flood risks are attributable to both an intensifying hydrological cycle driven by anthropogenic climate change as well as human decisions to settle in already-flood-prone areas. Adaptation has the potential to reduce flood risks arising through these dual drivers, however adaptation progress to date has generally not been sufficient to fully mitigate climate risks (USGCRP, 2023)

While some studies have estimated historical and projected monetary damages from flood hazard exposure in macroeconomic terms (Davenport et al., 2021; Desmet et al., 2021; Downton et al., 2005), this dissertation evaluates US flood exposure and vulnerabilities through the lens of households' most valuable tangible assets: residential property and motor vehicles. How will these widely-owned assets, which represent a substantial share of the average US household's net worth, be affected by the country's most costly and frequently-occurring natural hazard under climate change? A key objective of this dissertation is to provide decision-relevant information to individuals, firms, and policymakers that enables swift, effective, and equitable flood risk mitigation with respect to the assets most important to US households.

Among the bottom 99% of US households as measured by wealth, equity in primary residence represents the second-largest[1] share of aggregate household wealth of any asset type, 29% (Eggleston et al., 2020). Thus, residential property is a pivotal

[1]According to these data, retirement accounts represent the greatest share of US household wealth of any asset type among this group.

asset type for US households and the US economy at large. While approximately two-thirds of US households own their primary residence, roughly nine in ten households own a motor vehicle, suggesting the US vehicle ownership rate is substantially higher than the homeownership rate. Though vehicles represent a relatively smaller share of aggregate household wealth than residential property, vehicles' relative economic importance to households is inversely correlated with income. More specifically, vehicles represent a relatively high share of household net worth for relatively low-wealth households. These statistics broadly indicate flooding threats to housing and vehicle assets are salient, and warrant persistent study as global greenhouse gas emissions and associated climate change impacts continue apace. The following dissertation contributes scholarly and policy-relevant insights about these key household assets' flood exposure and vulnerabilities to support decisionmaking. Beyond household-level implications, these chapters also evaluate viable adaptation policy alternatives that may reduce flood risk and improve welfare.

The following research draws from and integrates concepts, methods, and data from multiple disciplines, specifically environmental science, environmental economics, and policy analysis. In particular, policy analysis components of the work rely on the framing from Weimer and Vining, 2017 of market failures as a potential rationale for public policy interventions, towards the pursuit of designing and implementing welfare-enhancing public policies. Two key themes emerge across chapters. First is the potential value of flood and climate risk information to address the canonical market failure of *imperfect information* to support household decision making in ways that may reduce flood risk. A second major theme that emerges is preexisting disparities in vulnerability, and the potential for Federal disaster and flood mitigation programs' design features to influence the distribution of future flood risk. Across chapters, FEMA and US Army Corps of Engineers (USACE) programs and policies are analyzed to understand the ways in which policy design choices may impact household outcomes vis-à-vis flood hazard.

This dissertation contains three main research chapters. The first, Chapter 2, contributes to an emerging literature on the projected impacts of anthropogenic sea level rise (SLR) in coastal housing markets. Specifically, the chapter uses FEMA and National Oceanic and Atmospheric Administration data products in conjunction with a triple-differences econometric approach that exploits temporal variation in scientific consensus about global mean SLR to estimate the extent to which projected SLR exposure erodes coastal property values, if at all. Additionally, the chapter examines SLR exposure and distributional policy implications using property depreciated replacement value, a policy-relevant property value metric used in USACE's Flood Damage Reduction Analysis software and related flood risk management program decisions. This chapter's findings do not provide evidence indicating there is a SLR exposure price effect in isolation; instead, econometric findings suggest negative SLR exposure price effects estimated elsewhere in the literature may be attributable to acute extant flood risk or compositional differences in residential building stock. Chapter 2's findings also estimate substantial pre-existing disparities in property value of considerable magnitude across community indicators of income and race, an insight with implications for application of benefit-cost analysis design and social welfare objectives of Federal flood risk management programs.

The second research chapter, Chapter 3, produces novel national estimates of the number and value of household vehicles exposed to flood hazard in the US. Preferred estimates suggest approximately 13.1 million household vehicles worth $305 billion are located in FEMA Special Flood Hazard Areas (SFHA), with approximately 5.2 million of these vehicles located in census tracts designated by the US Federal government as "disadvantaged." Further, this chapter leverages previously-unstudied FEMA disaster assistance data to comprehensively analyze the extent of Federal disaster assistance provided in connection with uninsured vehicle flood damages, as well as program gaps which may leave certain vehicle owners financially vulnerable to flood hazard. Between 2007-2022, FEMA received more than 160,000 disaster assistance applications from applicants reporting vehicle flood damage, and awarded more than $130 million to eligible applicants in connection with these uninsured vehicle flood damages. Policy analysis of FEMA's Individuals and Households Program and National Flood Insurance Program also highlights the prominence of private auto insurance markets as a primary insurance mechanism supporting vehicle owner financial resilience in the face of flood exposure. Chapter 3 provides evidence that, despite their mobile nature, vehicle assets experience substantial flood exposure and related damages. Further, considerable gaps in comprehensive insurance uptake and Federal program support leave many households financially-vulnerable to uninsured vehicle flood damages.

The final research chapter, Chapter 4, is motivated by findings from Chapter 3. In the absence of granular, peril-specific, publicly-available comprehensive auto insurance policy or claims data describing uptake rates and incidence of flood damages, data from 360 vehicle owners in coastal New York and Texas are collected via a survey instrument to elicit information on the frequency and magnitude of vehicle flood damage experiences, flood insurance literacy, and willingess-to-pay (WTP) for a hypothetical single-peril vehicle flood insurance product. A contingent valuation approach with double-bounded dichotomous choice question format is used to estimate WTP. Findings indicate 59% of respondents have experienced "significant" vehicle flood damage in their lifetimes, and more than one-third of vehicle owners in the sample report being unaware "comprehensive coverage" is the type of auto insurance policy that covers vehicle assets from flood damage. Preferred estimates indicate sample vehicle owners are willing to pay an average of $182.46 per year for a hypothetical single-peril flood insurance policy for their household's most valuable vehicle, with vehicle owners either residing in a FEMA SFHA or exhibiting concern about flooding willing to pay higher prices than the sample-wide average. Overall, this chapter makes a novel contribution by highlighting vehicle flood damage is a significant economic issue in coastal areas. Despite robust WTP for flood insurance coverage, vehicle owners' knowledge gaps about available insurance coverage may lead to suboptimal risk management decisions pertaining to this key household asset.

CHAPTER 2

Estimating effects of projected mean sea level rise exposure on measures of residential property value: evidence from the southeastern United States

2.1 Introductory remarks

Global mean sea level rose an estimated 0.2 meters (m) [~8 inches] between 1901-2018, and global mean sea level rise (GMSLR) over the past century has been dominated by anthropogenic forcing (Jevrejeva et al., 2009). In recent decades, the rate of GMSLR has begun to accelerate (IPCC, 2021). In the contiguous United States (CONUS), the average rate of sea level rise (SLR) this century is expected to exceed global averages, with a recent United States (US) Federal government intermediate projection anticipating a 3.9-foot increase of mean sea level by 2100 relative to 2000 levels (Sweet et al., 2022) and the potential for significantly higher magnitudes depending on greenhouse gas emissions and ice sheet dynamics (DeConto & Pollard, 2016). By the middle of this century, tens to hundreds of thousands of properties are projected to be permanently inundated by GMSLR (Hauer et al., 2016; Ohenhen et al., 2024), suggesting large societal impacts along US coasts.

Tens of billions of dollars' worth of US real estate is projected to be below mean higher high water (MHHW) altogether by 2100 under conservative GMSLR projections, and hundreds of billions of dollars' worth would be below MHHW under more extreme scenarios (Murfin & Spiegel, 2020). Nearly 70% of US households own their home, and home equity comprises a large share of US household wealth, approximately 29% among the bottom 99% of households by total wealth (Bhutta et al., 2020). While successful adaptation may have the potential to reduce substantial portions of property damages associated with future GMLSR-intensified coastal flooding (Fleming et al., 2018; Nicholls & Cazenave, 2010; Yohe et al., 1996), GMSLR appears poised to impose significant costs on many owners and residents of coastal structures through more frequent and intense flood exposure and/or increased spending on adaptive measures to mitigate flood damages. GMSLR's non-stationarity, dynamic nature, and evolving uncertainties (Milly et al., 2008) motivate careful study to inform effective adaptation to protect human life and property along densely-populated US coasts.

In this study, residential property transactions in coastal Florida, Georgia, North Carolina, and South Carolina are analyzed to investigate whether GMSLR exposure risk has been negatively capitalized in buyers' purchases of housing assets. Specifically, this study examines whether properties on land projected to be below MHHW under GMSLR scenarios which may occur this century, i.e. in the "SLR-plain," sell for a discount relative to comparable properties outside the SLR-plain. The analysis provides at least three novel contributions to an emerging literature on GMSLR exposure risk. First, this study controls for current flood risk and considers previously-unstudied impacts of a watershed Intergovernmental Panel on Climate Change (IPCC) report published in 2001. Second, to complement the aforementioned analysis, this study incorporates an alternative property value metric beyond transaction price, "depreciated replacement value" (DRV), to estimate whether residential structures' DRVs vary across SLR-plain status, ceteris paribus. Third, this analysis examines whether effects of being located in a SLR-plain vary with the racial composition or income level of the community in which a property is located, as well as implications for Federal flood mitigation policy.

Section 2.2 describes the background, motivation, and literature review for this study. Section 2.3 provides an overview of the study area and data used in the analysis. Section 2.4 details the empirical approach used to estimate effects of SLR-plain status on measures of residential property value. Section 2.5 presents results of the empirical analysis. Section 2.6 discusses this study's results within the context of relevant literature and highlights avenues for future work. Finally, the article's conclusion is in Section 2.7. Additional information may be found in the Appendix.

2.2 Background and motivation

Markets can facilitate efficient adaptation to climate change through price signals, though access to current, robust information is important for enabling such responses (Anderson et al., 2019). According to the IPCC, continued GMSLR this century is "virtually certain," however there is still a considerable degree of uncertainty about the precise rate and magnitude of future GMSLR (IPCC, 2021). Effects of GMSLR are emerging in real time and intersect with existing flood hazards, resulting in a complex, evolving set of best-available information on coastal flood hazards (Buchanan et al., 2016) which may be difficult for the average homebuyer to incorporate in their purchasing decisions. Thus, pricing GMSLR risk in housing markets is an evolving phenomenon and a challenge for individuals concerned about coastal housing assets and the US coastal economy.

A wide range of empirical research has previously studied various dimensions of the impacts of potential and actual flood hazard exposure on residential property values (Atreya et al., 2013; Beltrán et al., 2018; Bin & Kruse, 2006; Bin & Landry, 2013; Donnelly, 1989; Fell & Kousky, 2015; Gibson & Mullins, 2020; Ortega & Taṣpınar, 2018), including the price effects of being located in a Federal Emergency Management Agency (FEMA) flood zone, which have been found to be negative (Hino & Burke, 2021; Shr & Zipp, 2019).

Complementary to studies on housing and general flood risk, there is a related and growing literature focused on estimating the price effects of anthropogenic GMSLR, a phenomenon projected to impact many coastal areas which already experience flood risk. While price signals may facilitate efficient adaptation, heterogeneous beliefs and preferences have been shown to lead some households to sort into flood-prone areas (Bakkensen & Ma, 2020). Yohe et al., 2011 further posit that the efficiency of coastal adaptation solutions depends on decisionmakers' aversion to risk. Empirical evidence suggests heterogeneous beliefs and preferences (Bakkensen & Barrage,

2021) as well as an actuarially-unsound National Flood Insurance Program (NFIP) (Chivers & Flores, 2002) may lead markets to imperfectly price residential property assets relative to expected future damages. The existing literature indicates complex human and physical factors influence pricing of GMSLR exposure risk.

Academic research on the observed price effects of GMSLR is nascent, but expanding. Bernstein et al. (2019) find residential properties projected to be inundated by MHHW under six feet of SLR sold for approximately 4.4% less than "observably equivalent" unexposed properties, with properties in nearer-term SLR-plains experiencing larger discounts. Bernstein et al.'s conclusions suggest negative SLR exposure capitalization is largely driven by "sophisticated buyers," i.e. non-owner occupiers and condo owners, as well as properties in counties in which "unsophisticated" buyers exhibit greater worry about climate change. While some national studies find further evidence of a SLR-plain penalty driven by heterogeneous beliefs about climate change (Baldauf et al., 2020) and case studies at the sub-state level similarly find negative price effects (Tarui et al., 2023), a number of studies at national and sub-national scales estimate price effects of GMSLR exposure that are indistinguishable from zero (Filippova et al., 2020; Fuerst & Warren-Myers, 2021; Murfin & Spiegel, 2020). In addition to private residential property markets, recent research also indicates GMSLR exposure risk began to be priced in US municipal bond markets starting in 2013 (Goldsmith-Pinkham et al., 2023). Lack of uniform consensus about the price effects of GMSLR implies there is ample room for additional research to improve our understanding of the impacts of GMSLR on residential property values as this climate change impact continues to unfold.

This paper advances the current state of knowledge regarding residential property market responses to GMSLR and adaptation implications in three important ways. First, it adds to the emerging literature on the impacts of GMSLR by estimating price effects of GMSLR exposure using a triple-difference model that controls for current storm risk and exploits temporal variation in global scientific consensus about GMSLR as represented by a watershed IPCC report. Anthropogenic GMSLR is dynamic, difficult to observe as "turning on" discontinuously, and is a process that has been ongoing for more than a century. The IPCC's Third Assessment Report (AR3), published in 2001, is the first IPCC assessment report that concluded it is "very likely" anthropogenic warming "...contributed significantly to the observed sea-level rise" in previous decades (IPCC, 1995, 2001). As a result, AR3's publication is used as a temporal delineator after which buyers of coastal property may have taken this key indicator of global scientific consensus about GMSLR into account when purchasing coastal properties.[2]

The second contribution of this paper is to conduct a policy-relevant comparison of results across two distinct measures of residential property value: 1. transaction prices and 2. DRV. While a transaction price represents the amount a buyer pays a seller for the right to all current and future benefits conferred by ownership of the transferred property, DRV is a distinct measure defined by the the US Army Corps of Engineers (USACE) as: "...the cost of restoring or replacing a property with something of equivalent value, accounting for physical deterioration and functional obsolescence brought on by age or lack of maintenance" (Cannon et al., 1995). Thus, DRV is a correlate, but not sole determinant, of transaction price. Scholars have highlighted DRV metrics contain market and non-market elements, including "...extensive subjective input by the valuer..." which leads this value to be distinct from market values represented by transaction price (Wyatt, 2009). Transaction prices may also reflect dimensions of non-structural property value, such as land value. Importantly, DRVs–not transaction prices– are used by Federal agencies in benefit-cost analysis (BCA) calculations which influence allocation of Federal flood

[2] While data describing the pre-2004 period are unavailable, Google Trends data shown in Figure A.1 indicate the term "sea level rise" was searched with significant frequency from 2004 onward. While only representing information from Google search users, these data imply there has been significant awareness of SLR as a phenomenon among this population since the early 2000s.

mitigation project investments, such as those deployed through USACE Civil Works Mission works and FEMA Hazard Mitigation Assistance programs (FEMA, 2023c; USACE, 2000). DRVs play an important role in Federal flood mitigation decisions and serve as key inputs in the economic analyses which influence the distribution of flood mitigation project benefits. Improving our understanding of whether DRV varies according to SLR-plain status or demographic factors may inform future policy design and the influence of these property value measures on adaptation interventions. Additionally, contrasting transaction price results with DRV results may inform future researchers concerned about GMSLR price effects and adaptation implications with respect to the most appropriate property value metric(s) to consider in empirical analyses. This study hypothesizes SLR-plain status should have no effect on structures' DRVs, as future costs from flood damage and/or adaptation are not expected to be explicitly captured by this valuation approach.

The third contribution of this analysis investigates whether there is a meaningful relationship between price effects of GMSLR exposure and the racial or income profile of a community. While other studies have examined GMSLR discounts across dimensions of "climate change beliefs" or "buyer sophistication" (Baldauf et al., 2020; Bernstein et al., 2019), this research makes a contribution by investigating whether GMSLR exposure of residential property value and price effects thereof vary across dimensions of community race and income. On average in the United States, low-income and non-Hispanic Black or African-American (BAA) households have lower homeownership rates and less housing wealth than the median US household (Bhutta et al., 2020). Housing wealth and property value disparities across race are in many cases significantly attributable to individual-level and systemic discrimination (Darity Jr & Mullen, 2020; Rothstein, 2017), and empirical analysis of the potential for climate change impacts to exacerbate housing disparities is nascent. Household property wealth and property values can be key determinants of infrastructure allocation

(Junod et al., 2021), therefore housing wealth has implications for where future adaptation benefits may accrue. Previous research indicates certain adaptation measures, such as buyout programs, are more likely to occur in communities of color and/or low-income communities (Mach et al., 2019; Siders & Keenan, 2020), which raises procedural and consequentialist justice concerns in flood mitigation and adaptation policy processes (Paavola & Adger, 2002). This study hypothesizes that properties in the SLR-plain with more low-income and/or BAA residents will sell for steeper SLR-plain discounts relative to comparable properties in the SLR-plain with higher incomes and fewer BAA households. Such a discount, if borne out by the data, may be due to buyers' anticipation of disinvestment in climate adaptation infrastructure in low-income and/or BAA neighborhoods.

2.3 Data description and study area

2.3.1 Zillow ZTRAX data

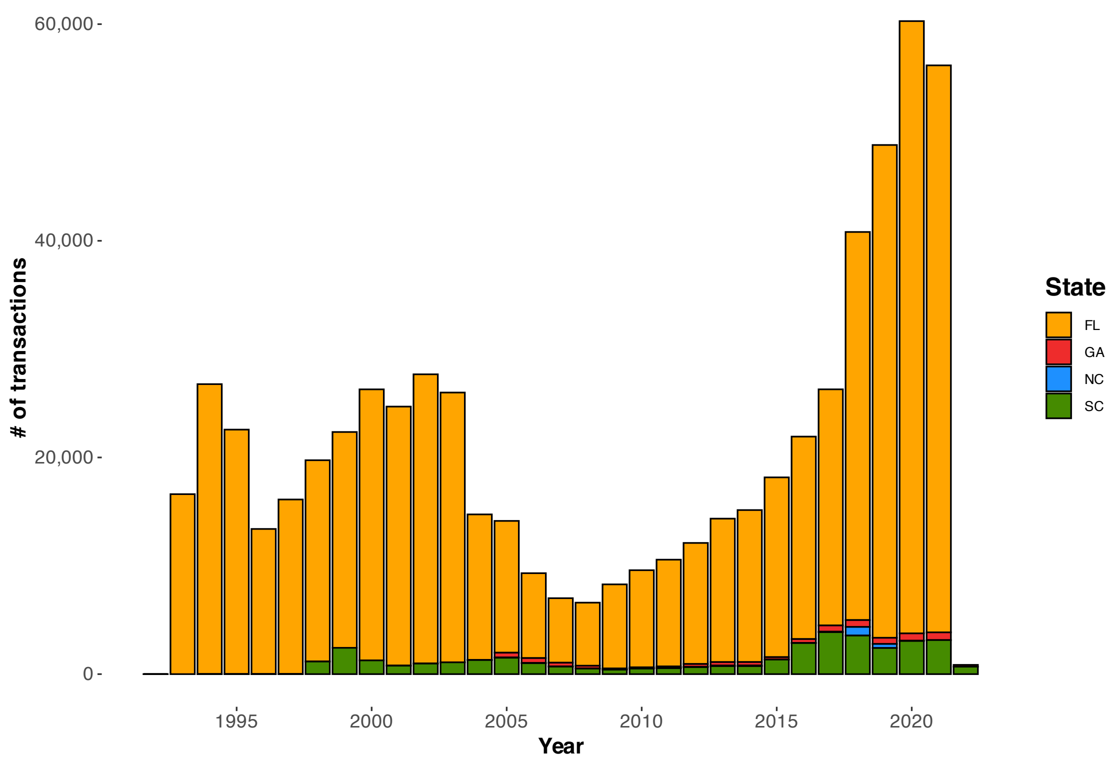
Individual property transaction data, as well as data describing property-level characteristics, are sourced from Zillow, Inc.'s Zillow Transaction and Assessment Database (ZTRAX). This data set has been used widely by empirical researchers (W. Clarke & Freedman, 2019; Nolte, 2020; Zheng, 2022) and contains more than 374 million detailed public property-level transaction records across more than 2,700 US counties. In addition to transaction data, ZTRAX contains property-level assessor information about properties' specific attributes (e.g., latitude/longitude coordinates, number of bedrooms) that provide rich detail on a wide range of housing units. Data from the states of Florida, Georgia, South Carolina, and North Carolina are analyzed due to the fact the eastern Gulf of Mexico and southeastern US coasts are projected to experience some of the highest rates of regional relative SLR in the US through 2050 (Sweet et al., 2022).

In this analysis, the Zillow ZTRAX data are filtered in four key ways. First, transactions with closing documents indicating sale prices below $50,000 and above $10,000,000 are excluded from the sample, as the broad center of the property market distribution is the segment of interest. Second, only properties located within 0.25 miles of the shoreline are included. Third, only property transactions designated for residential use are included in the sample. Fourth and last, only properties and property transactions with non-missing information for the variables of interest for each statistical model have been included (i.e., no data have been imputed or inferred beyond what is provided in ZTRAX and other data sources described below).

Table 2.1 provides descriptive information about the full sample of ZTRAX transactions (N= 637,451) after filtering according to the four criteria listed above. Florida transactions (N=591,991) represent the overwhelming share of observations in the sample , more than 90%. This is intuitive as Florida has the largest number of residents residing in areas projected to be inundated by roughly three and six feet of SLR, respectively (Hauer et al., 2016). Table 2.1 compares sample property transaction summary statistics according to transacted properties' six-foot SLR-plain statuses, while Table 1S shows these summary statistics according to three-foot SLR-plan statuses. 236,348 (37.1% of) transactions in the sample are projected to be inundated by MHHW under six feet of SLR and 39,934 property transactions in the sample (6.3% of all transactions) are projected to be underwater with three feet of SLR as shown in Table A.1. Approximately 99% of property transactions in the three-foot SLR-plain and 79% of property transactions in the six-foot SLR-plain are in a FEMA SFHA. Samplewide, properties in the three-foot and six-foot SLR-plains, respectively, have higher average transaction prices and smaller building areas than those outside each SLR-plain.

Figure 2.1 illustrates temporal variation in the sample and shows annual volume of transactions by state. Figure 2.2 displays the 236,348 property transactions in the sample that are in the projected six-foot SLR-plain, while Figure A.2 in the Appendix displays the 401,103 property transactions that are outside the six-foot SLR-plain.

Figure 2.1: Annual transactions by state (total N=637,451)



2.3.2 USACE National Structure Inventory data

In addition to Zillow's ZTRAX database, the 2022 USACE National Structure Inventory (NSI) is used. This database contains information on structure DRV, an alternative measure of property value that contrasts with transaction price. The data are compiled and maintained by the USACE, and the inventory serves as a repository for information about both residential and commercial structures. NSI data for residential structures in Florida, Georgia, North Carolina, and South Carolina that are within 0.25 miles of the shoreline are included, and summary statistics for structures included in the sample are shown below. The NSI data were further filtered to exclude structures with fewer than 100 square feet and more than 111 stories.

Figure 2.2: Sample transactions exposed to six feet of SLR (total N=236,348)

These filters were applied to remove records with erroneous values and/or those corresponding to very small structures. Additionally, all observations containing DRVs of less than $6,000 and more than $10,000,000 were excluded. Table 2.2 below shows summary statistics for relevant NSI variables included in the analysis according to six-foot SLR-plain status. Table A.2 shows these summary statistics according to three-foot SLR-plain status. In the full sample of residential coastal NSI structures in Florida, Georgia, North Carolina, and South Carolina, 497,687 structures with aggregate DRV of $115.5 billion (priced in 2021 US dollars) are located in the six-foot SLR-plain. More than four in five of these structures are located in Florida. 81,418 structures with aggregate DRV of $18 billion are located in the three-foot SLR-plain.

2.3.3 SLR data

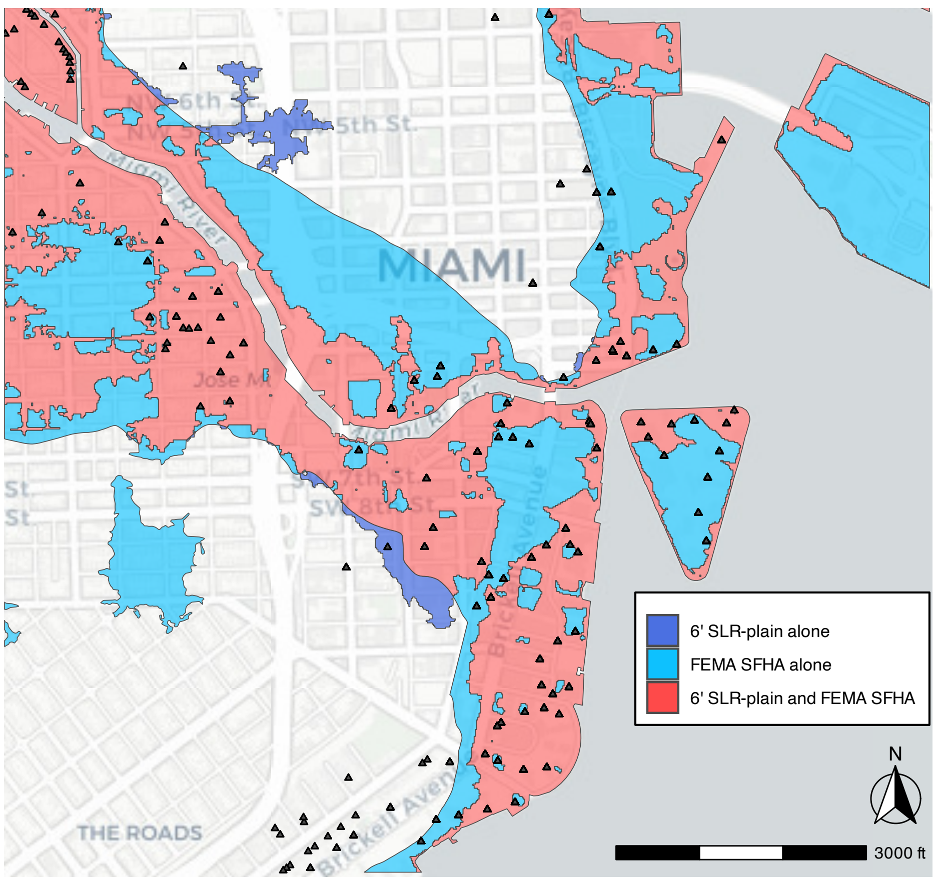
SLR scenarios produced by the National Oceanic and Atmospheric Administration (NOAA) are employed to determine which properties and structures are in the SLR-plain and "exposed" to GMSLR, i.e. projected to be below MHHW under three feet and six feet of mean SLR, respectively, relative to a baseline of the current National Tidal Datum Epoch. These projections are a credible tool produced collaboratively between multiple US Federal agencies. The product includes a disclaimer noting projections do not account for erosion nor subsidence, and also may not capture detailed local hydrologic or hydraulic features (NOAA, 2020; Sweet et al., 2022). However, these projections are still recommended for use for planning purposes and have been frequently employed as a proxy for future exposure to anthropogenic SLR in academic research (Bernstein et al., 2019; McAlpine & Porter, 2018; Murfin & Spiegel, 2020). This paper explores the price effects of exposure to three feet (0.9m) and six feet (1.8m) of SLR, respectively, because comparison of these distinct SLR magnitudes accounts for the continuous nature of GMSLR risk and the differing time horizons on which impacts of different magnitudes of GMSLR may occur (Pistrika et al., 2014). Observed price effects are interpreted to be the present value of expected future damages and/or expected adaptation costs driven by anthropogenic GMSLR.

2.3.4 Other geographic data

Variables for properties' elevations above vertical datum North American Vertical Datum 1988 (NAVD88) are also constructed using the US Geological Survey's The National Map – Elevation Point Query Service (USGS, 2022). In addition to elevation, transacted properties' distances to the nearest shoreline are calculated using NOAA's National Shoreline Data, specifically the "NOAA Medium Shoreline" data set. The NOAA Medium Shoreline data set represents more than 75,000 nautical miles of coastline covering CONUS (NOAA, 2016). Last, FEMA's National Flood

Hazard Layer (NFHL) is used to determine properties' SFHA statuses based on maps downloaded from FEMA's website in March 2023 (FEMA, 2023e). As shown in Tables 2.1 and 2.2, SLR-plain status and SFHA status are highly correlated, but SLR-plain status does not perfectly predict SFHA status and vice versa. Tables A.1 and A.2 show large majorities of transacted properties and structures in the three-foot SLR-plain are also in SFHAs. Figure 2.3 illustrates transacted properties in a section of Miami, FL near the mouth of the Miami River according to their six-foot SLR-plain and FEMA SFHA statuses.

Figure 2.3: Illustrative transactions in Miami, FL based on SFHA and six-foot SLR-plain status (N=6,564) [triangle symbol denotes transacted property]



2.4 Empirical approach

A primary goal of this analysis is to develop unbiased, reliable parameter estimates for the price effects of residential property exposure to three and six feet of future anthropogenic SLR in the southeastern US during the sample period 1993-2022 using property transaction prices as the response variable of interest. A hedonic model with comprehensive fixed effects taking into account property-level characteristics, as well as spatial and temporal fixed effects, is used to isolate price effects of being located in projected SLR-plains. Hedonic property value analysis has been applied in a wide variety of settings to estimate the value of environmental disamenities (K. Bishop et al., 2020), including flood hazard risk (Bin & Polasky, 2004; Kousky, 2010). In a main specification, a triple-difference estimator (Olden & Møen, 2022) is employed to disentangle confounding effects of existing storm risk as proxied by FEMA SFHA status and to identify the effects of GMSLR exposure in isolation, which are hypothesized to emerge in the post-AR3 period. The triple-difference estimator is an approach which has been applied in the environmental hedonic property value literature (Muehlenbachs et al., 2015).

Below is the main econometric model representing a framework which generates core results. The identification strategy to isolate the price effect of being located in a SLR-plain on residential properties relies on control covariates (property age, building square footage, and SFHA status) and a comprehensive set of interacted fixed effects (transaction year, distance to coast, elevation, property zip code, condominium status, and number of bedrooms) to plausibly compare properties that are observably equivalent except for their status regarding exposure to future GMSLR. The mechanism through which we might expect to see a discount emerge is buyer consideration of climate risk about properties' anticipated GMSLR exposure status following AR3's publication, which might then lead to subsequent negative capitalization due to expected future losses or adaptation costs attributable to GMSLR.

A brief explanation of the terms in the main specification, shown in Equation (2.1), follows and aligns with presentation and derivation of the triple-difference estimator from Olden and Møen (2022). A more detailed description may be found in Section A.1 of the Appendix. The dependent variable is the natural log of the final transaction price ($) for property transaction i in year Y. The variable "Exposure" is a dummy variable that takes on a value of 1 if the property in transaction i is exposed to SLR of magnitude m, where m takes on a value of three or six feet. A property is categorized as "exposed" if its latitude and longitude coordinates fall within NOAA's projected layer of inundation below MHHW under corresponding SLR magnitude m. The variable "IPCC" is a dummy variable taking on a value of zero for transactions taking place in 2001 and preceding years, and one in years thereafter. Thus, in this specification, it is most intuitive to view properties in the SLR-plain for magnitude m as the treatment group and those outside the SLR-plain as the control group, with the "pre-period" occurring in 2001 and before, and "post-period" occurring after 2001.

$$\begin{aligned} \text{Ln(price)}_{i,Y} = \beta_0 + \beta_1 \text{Exposure}_{m,i} + \beta_2 \text{IPCC}_Y + \beta_3 \text{SFHA}_i + \\ \beta_4 (\text{IPCC}_Y * \text{Exposure}_{m,i}) + \beta_5 (\text{SFHA}_i * \text{Exposure}_{m,i}) + \beta_6 (\text{IPCC}_Y * \text{SFHA}_i) + \\ \beta_7 (\text{IPCC}_Y * \text{Exposure}_{m,i} * \text{SFHA}_i) + \beta_8 \text{Age}_{i,Y} + \beta_9 \text{SF}_i + \lambda_{BR,CN,D,E,Y,Z} + \epsilon_{i,Y} \end{aligned} \tag{2.1}$$

"Age" and "SF" represent property age and building square footage. The λ term represents the unique slopes for the interaction of fixed effects, including number of bedrooms in the property, "BR;" whether or not a property is a condominium, "CN;" distance to shoreline, "D;" elevation above NAVD88, "E;" year of transaction, "Y;" and zip code in which the property is located, "Z." For both distance to coast, "D," and elevation, "E," values are binned to produce categorical variables to ease computational burden. In the case of elevation, the categorical variable contains five six-foot bins and in the case of distance to shore, the categorical variable contains six bins. “SFHA” is a dummy variable indicating whether the property’s latitude and longitude coordinates are located in one of FEMA’s SFHAs. The combination of covariates and interacted fixed effects help mitigate selection problems and account for compositional differences between groups across SFHA and SLR-plain status (Olden Møen, 2022). Figures A.5 to A.9 in the Appendix provide more detail about parallel trends assumptions for difference-in-differences and triple-difference estimations. A key distinguishing characteristic of this study’s approach is the interaction between “SFHA” and “Exposure” which has been included to understand potential interactive effects between these two correlated variables and to explore whether emergence of GMSLR price effects depends on SFHA status. This study hypothesizes that a statistically significant negative parameter estimate for β_4 or β_7 would be suggestive of a negative GMSLR exposure price effect emerging post-AR3 among properties in the SLR-plain.

2.5 Results

2.5.1 Main results and estimated IPCC AR3 price effects

Table 2.3 contains results from model estimations employing Equation (2.1), with sets of results corresponding to three feet and six feet of SLR, respectively. Each of the estimations contains interacted fixed effects for number of bedrooms, condominium status, distance to coast, elevation, zip code, and transaction year as well as covariates controlling for property age, building square footage, and SFHA status. Across model results shown in Table 2.3, property age is negatively correlated with transaction price at the 1% significance level, and building square footage is positively correlated with transaction price at the 1% significance level.

While naive specifications shown in columns 1a, 1b, 2a, and 2b show negative and significant ($p<0.05$) parameter estimates for being located in the three-foot and six-foot SLR-plains, respectively, incorporation of interaction terms with FEMA SFHA status in columns 1c, 1d, 2c, and 2d call into question whether GMSLR exposure alone is truly a mechanism causing negative capitalization in the sample observations. Columns 1a and 2a, respectively, estimate baseline results that properties in the three-foot and six-foot SLR-plains sold for -4.5% (-8.0% to -0.9%, 95% confidence interval [CI]) and -5.2% (-7.5% to -2.7%, 95% CI) relative to comparable properties outside the SLR-plain over the sample period. However, these parameter estimates are indistinguishable from zero as shown in columns 1c and 2c when incorporating an interaction term with SFHA status to investigate whether being located in both a SFHA and SLR-plain is associated with additional negative capitalization.

Further, estimates of β_4 and β_7 in Table 2.3 columns 1b, 1d, 2b, and 2d do not suggest a negative GMSLR exposure price effect emerged discontinuously following the release of IPCC's AR3 in 2001. Contrary to hypothesized results, estimates for β_4 in columns 1b and 2b imply the presence of negative price effects of being located in the three-foot and six-foot SLR-plains before publication of IPCC's AR3, with this effect attenuating toward zero in the post-AR3 period. It is unlikely coastal home buyers in the pre-AR3 period would price GMSLR risk given limited scientific consensus and public awareness about observed impacts of GMSLR at the time. Rather than a negative price effect post-AR3, a positive post-AR3 price effect is observed in the specification shown in column 1b along with no discernible post-AR3 price effect in column 2b.

When considering the preferred triple-difference estimations in columns 1d and 2d, statistically significant ($p<0.05$) and negative β_5 estimates indicate across the sample period negative price effects of SLR-plain status are only observed when properties are also located in a SFHA. Results in column 1d indicate properties in both the SFHA and three-foot SLR-plain sold, on average, for -5.1% (-9.4% to -0.7%, 95% CI) relative to observably equivalent properties neither in a SFHA nor the SLR-plain across the sample period. Properties in both the SFHA and three-foot SLR-plain sold for -13.0% (-27.9% to +2.0%, 95% CI) compared to observably equivalent properties only in the three-foot SLR-plain (not in a SFHA). Similarly, properties in both the SFHA and three-foot SLR-plain sold for -8.7% (-12.6% to -4.8%, 95% CI) compared to otherwise observably equivalent properties only in a SFHA (not in the three-foot SLR-plain). Estimates in column 2d further suggest properties in both the six-foot SLR-plain and a SFHA sold for -7.5% (-11.5% to -3.3%, 95% CI) compared to observably equivalent properties only in a SFHA. These interactive effects suggest negative price effects are only present in the portions of SFHAs which are most acutely vulnerable to GMSLR, and neither being located in the SLR-plain nor a SFHA alone is associated with a price discount.

Due to the highly-correlated nature of existing storm risk and GMSLR exposure, and parameter estimates for β_4 and β_7 that are statistically indistinguishable from zero across specifications, there is insufficient evidence to infer the existence of a post-AR3 negative price effect solely attributable to GMSLR exposure. Since β_5 estimates reflect the interactive price effect of being in both a SFHA and the SLR-plain across the sample period, with no estimated change following AR3, it is possible acute extant flood risk as represented by FEMA flood maps may in fact be the mechanism driving observed negative price effects in other studies in the literature, as opposed to perceived climate risk in the form of future GMSLR exposure. For example, FEMA's SFHA "V" designation corresponds to "coastal high hazard flooding," which is characterized by higher and more damaging potential wave action than other SFHAs, such as Zone A (FEMA, 2023a).

Figure 2.4 depicts the estimated price effects of GMSLR on coastal property transactions and presents estimates from the specification shown in Table 2.3 column 1b, with slight modification that interacts "Exposure" with each year with 2001 as the illustrative baseline year. These estimates provide visual evidence further suggesting no discernible price effect of GMSLR exposure emerged following publication of AR3 in 2001. In the Appendix, this study also provides novel estimates of GMSLR exposure price effects across community race and income. While results do not suggest there is a SLR exposure price effect, let alone one that meaningfully varies with community race or income, these estimates overwhelmingly find coastal properties—including those in the SLR-plain— tend to sell for less in census tracts with larger BAA populations and lower-income census tracts relative to otherwise observably equivalent properties. On average, a 10% increase in a census tract's BAA population share is associated with a -4.3% (-6.5% to -2.0%, 95% CI) change in transaction price, holding other observed factors constant. Further, a 10% increase in census tract median household income corresponds to an approximate 2.9% (2.4% to 3.4%, 95% CI) increase in transaction price, holding other observed factors constant. Similar findings are observed when restricting the samples to only SLR-exposed properties. These findings highlight the existence of preexisting property value disparities of considerable magnitude across community income and race in areas exposed to GMSLR.

Figure 2.4: Estimated price effects of exposure to three feet of sea level rise by year (reference year: 2001)

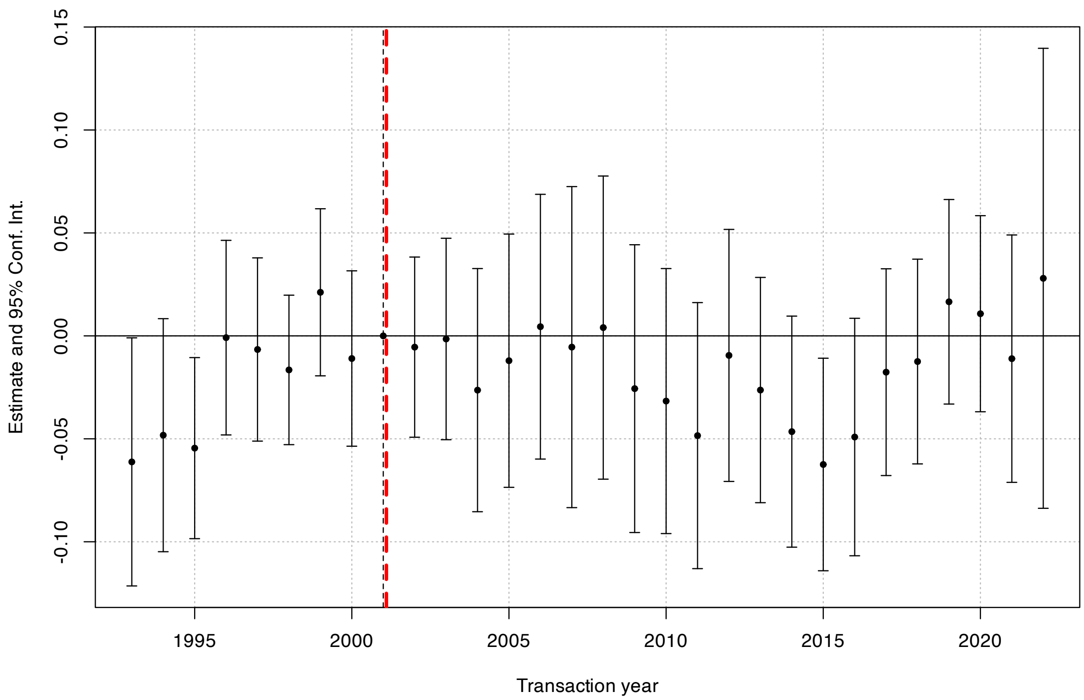


Table 2.1: Summary statistics, property transactions, 1993-2022

	Inside six-foot SLR-plain			Outside six-foot SLR-plain		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Sales price ($, thousands)						
Florida	224,141	444.5	642.9	367,850	360.3	548.6
Georgia	2,176	394.7	274.0	4,462	318.0	263.0
North Carolina	9,410	412.0	555.0	27,866	400.0	493.6
South Carolina	621	512.5	425.5	925	342.9	449.1
Total	236,348	446.6	636.8	401,103	358.7	539.8
# of bedrooms						
Florida	224,141	2.6	1.0	367,850	2.8	0.9
Georgia	2,176	3.1	0.9	4,462	3.0	0.8
North Carolina	9,410	3.3	1.1	27,866	3.3	1.3
South Carolina	621	2.9	1.4	925	2.5	1.1
Total	236,348	2.6	1.0	401,103	2.8	1.0
Building area sq. ft.						
Florida	224,141	1,799	1,119	367,850	1,900	1,076
Georgia	2,176	2,035	948	4,462	1,999	915
North Carolina	9,410	2,248	909	27,866	1,929	1,031
South Carolina	621	621	1,933	925	1,802	1,293
Total	236,348	1,820	1,131	401,103	1,894	1,091
Distance to shore (ft.)						
Florida	224,141	350.2	325.6	367,850	577.7	380.4
Georgia	2,176	660.2	382.2	4,462	793.0	
North Carolina	9,410	470.7	357.0	27,866	677.5	368.3
South Carolina	621	543.6	365.8	925	626.2	362.2
Total	236,348	361.1	331.4	401,103	583.7	379.9
Elevation (ft.)						
Florida	224,141	5.5	1.5	367,850	11.6	11.5
Georgia	2,176	6.7	2.5	4,462	31.4	48.9
North Carolina	9,410	4.6	2.6	27,866	13.0	7.5
South Carolina	621	6.1	3.0	925	14.4	10.9
Total	236,348	5.5	1.6	401,103	12.1	12.7
Property age (years)						
Florida	224,141	28.9	21.3	367,850	27.0	21.2
Georgia	2,176	29.7	22.9	4,462	37.0	33.1
North Carolina	9,410	21.2	18.7	27,866	28.1	19.6
South Carolina	621	27.3	22.0	925	21.8	17.8
Total	236,348	28.6	21.4	401,103	26.7	21.2
Special Flood Hazard Area status						
Florida	224,141	0.78	0.41	367,850	0.24	0.43
Georgia	2,176	0.93	0.26	4,462	0.06	0.24
North Carolina	9,410	0.66	0.47	27,866	0.20	0.4
South Carolina	621	0.91	0.28	925	0.25	0.43
Total	236,348	0.79	0.41	401,103	0.24	0.43

Table 2.2: National Structure Inventory summary statistics, 2022

	Inside six-foot SLR-plain			Outside six-foot SLR-plain		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Structure value ($, thousands)						
Florida	416,513	229.9	339.1	616,398	221.6	292.8
Georgia	7,987	283.0	277.6	13,657	280.4	390.5
North Carolina	43,355	187.3	172.1	88,348	212.5	318.3
South Carolina	29,832	315.0	302.5	43,617	342.7	530.8
Total	497,687	232.1	325.8	761,930	228.5	317.5
Distance to shore (ft.)						
Florida	416,513	340.3	325.4	616,398	599.7	384.0
Georgia	7,987	658.0	387.6	13,567	762.6	365.0
North Carolina	43,355	415.3	341.4	88,348	629.7	380.2
South Carolina	29,832	589.5	376.0	43,617	738.3	364.7
Total	497,687	366.9	338.8	761,930	614.0	384.1
Building area sq. ft.						
Florida	416,513	2,142	3,404	616,398	2,109	2,737
Georgia	7,987	2,676	2,737	13,567	2,598	3,177
North Carolina	43,355	1,965	2,528	88,348	2,173	2,627
South Carolina	29,832	2,659	2,386	43,617	3,025	4,164
Total	497,687	2,166	3,277	761,930	2,178	2,843
Elevation (ft.)						
Florida	416,513	4.3	2.0	616,398	11.7	7.5
Georgia	7,987	6.4	2.4	13,567	32.4	51.4
North Carolina	43,355	4.4	1.6	88,348	14.1	7.4
South Carolina	29,832	6.8	1.7	43,617	17.3	20.8
Total	497,687	4.4	2.1	761,930	12.7	11.5
Number of stories						
Florida	416,513	1.26	0.90	616,398	1.24	0.76
Georgia	7,987	1.49	1.14	13,567	1.48	1.23
North Carolina	43,355	1.40	0.82	88,348	1.59	0.99
South Carolina	29,832	1.58	0.82	43,617	1.59	0.99
Total	497,687	1.30	0.90	761,930	1.28	0.80
Special Flood Hazard Area status						
Florida	416,513	0.61	0.49	616,398	0.19	0.40
Georgia	7,987	0.91	0.28	13,567	0.20	0.40
North Carolina	43,355	0.79	0.41	88,348	0.07	0.25
South Carolina	29,832	0.73	0.44	43,617	0.20	0.40
Total	497,687	0.64	0.48	761,930	0.13	0.34

Table 2.3: Baseline results and estimated IPCC price effects, 1993-2022

Dependent variable: Ln(Price) [$]

Column:	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
SLR Exposure (three feet)	-0.046**	-0.081***	0.058	0.079	–	–	–	–
	(0.019)	(0.019)	(0.086)	(0.046)				
SLR Exposure (six feet)	–	–	–	–	-0.053***	-0.058***	-0.015	-0.022
					(0.013)	(0.017)	(0.016)	(0.016)
SFHA dummy	0.021	0.021	0.22	0.037***	0.036*	0.036*	0.057***	0.067***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.019)
SFHA dummy x SLR Exposure (three feet)	–	–	-0.106	-0.167**	–	–	–	–
			(0.089)	(0.076)				
SFHA dummy x SLR Exposure (six feet)	–	–	–	–	–	–	-0.058****	-0.056**
							(0.020)	(0.025)
SLR Exposure (three feet) x IPCC dummy	–	0.051**	–	-0.031	–	–	–	–
		(0.023)		(0.156)				
SLR Exposure (six feet) x IPCC dummy	–	–	–	–	–	0.007	–	0.010
						(0.014)		(0.018)
SFHA dummy x IPCC dummy	–	–	–	-0.020	–	–	–	-0.014
				(0.014)				(0.018)
SLR Exposure (three feet) x IPCC x SFHA	–	–	–	0.087	–	–	–	–
				(0.158)				
SLR Exposure (six feet) x IPCC x SFHA	–	–	–	–	–	–	–	-0.002
								(0.023)
Property age	-0.0019***	-0.0018***	-0.0019***	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.0018***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Property sq. ft.	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(8.4x10^{-6})	(8.4x10^{-6})	(8.4x10^{-6})	(8.4x10^{-6})	(8.3x10^{-6})	(8.3x10^{-6})	(8.3x10^{-6})	(8.5x10^{-6})
Fixed effects								
BR*CN*D*E*Y*Z	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of fixed effects	161,182	161,182	161,182	161,182	161,182	161,182	161,182	161,182
Fit statistics								
Observations	637,451	637,451	637,451	637,451	637,451	637,451	637,451	637,451
Adj. R^2	0.815288	0.814312	0.815297	0.815329	0.815499	0.81550	0.815599	0.815602

*Significance codes: ***:0.01; **:.05, *:0.1. Standard errors in parentheses and clustered at the zip code level.*

Note: Abbreviation/acronym definitions: "SLR" = sea level rise; "sq. ft" = square feet; "IPCC" = Intergovernmental Panel on Climate Change Third Assessment Report; "CN" = condominium dummy; "Z" = zip code; "Y" = transaction year; "SFHA" = Special Flood Hazard Area. Note: the "distance to coast" variable is categorical with five categories. All observations with elevations of 6 feet or less take on a value of 1, all observations with elevations from 6-12 feet take on a value of 2, etc., and all observations with elevations greater than 24 feet take on a value of 5. The "elevation" variable is categorical with six categories. All observations with distance to shore values of 0-53 feet take on a value of 1; 54-106 feet a value of 2; 107-211 a value of 3; 212-422 a value of 4; 423-845 feet a value of 5; greater than 845 feet a value of 6.

2.5.2 NSI results

Table 2.4 presents results from a modified version of model specification shown in Equation (2.1) using cross-sectional NSI data and describes a similar regression model as shown in the previous section with property value metric as the dependent variable, except without temporal variation. These estimates use a similar, but slightly different, suite of detailed structure-level characteristics sourced from the USACE NSI described in the table footnote. The dependent variable in Table 2.4's estimations is DRV, not transaction price. Contrary to the initial hypothesis, estimation results shown in Table 2.4 column 1d suggest an average effect of -3.2% (-5.5% to -1.1%, 95% CI) on DRV for being located in the three-foot SLR-plain. However, results shown in column 2d indicate a precisely-estimated null effect for being located in the six-foot SLR-plain. This finding suggests structures at risk of permanent inundation by three feet of SLR in the southeastern US are valued less by the USACE than observably equivalent structures outside the three-foot SLR-plain. This result implies there could be compositional differences in housing stock quality across three-foot SLR-plain status, which could perhaps explain estimates of negative SLR exposure price effects found elsewhere in the literature. If structures in the three-foot SLR-plain are of poorer quality and/or valued less by assessors than other structures for other reasons, then this could imply existence of an unobserved factor inherent to the building stock in the three-foot SLR-plain that is positively correlated with SLR-plain status and negatively correlated with property value.

Section A.1 of the Appendix extends this line of inquiry by analyzing results across census tract income and demographics. This analysis finds a 10% increase in census tract BAA population share is associated with a -3.8% (-4.8% to -2.9%, 95% CI) change in DRV, while a 10% increase in census tract median income is associated with a 2.4% (2.7% to 2.1%, 95% CI) increase in DRV. Similar to the above, these results have implications for adaptation policy due to the fact USACE

NSI DRV values are commonly used in decision criteria, such as benefit-cost ratios, for allocation of Federal flood mitigation measures. Therefore, disparities in DRV across socioeconomic groups may influence the distribution of Federal flood mitigation project funding and related equity objectives.

2.6 Discussion

2.6.1 Contextualizing empirical results

A number of this study's empirical results do not align with hypotheses which guided the research ex ante, nor other findings in the literature. While the above results do estimate negative price effects of being located in the three- and six-foot SLR-plains under some naive baseline specifications within a few percentage points of other studies' estimates (Baldauf et al., 2020; Bernstein et al., 2019; Tarui et al., 2023), incorporating additional covariates—notably properties' FEMA SFHA status according to a recent version of FEMA's NFHL—into a specification with an intuitive functional form suggests a GMSLR exposure discount did not emerge in the coastal residential property market in the southeastern US following publication of the IPCC's AR3. It is perhaps unsurprising that FEMA flood zone status and SLR-plain status are highly correlated, notably among transactions in the three-foot SLR-plain, and that estimates are sensitive to inclusion of FEMA flood zone data. Despite the salience of FEMA flood maps and their highly-correlated relationship with SLR-plain status, some studies which estimate non-zero effects of GMSLR exposure do not include controls for FEMA flood zone status (Baldauf et al., 2020; Bernstein et al., 2019, 2022) and instead include other variables (e.g., NOAA storm surge simulations) which aim to noisily control for current or shorter-term flood risk. Other studies have focused more squarely on existing flood risks and exploited temporal variation in FEMA flood map updates to estimate the price effects of residential properties mapped *into*

Table 2.4: National Structure Inventory regression results

Dependent variable: Ln(Depreciated replacement value) [$]

Column:	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
SLR magnitude:	3 ft.	3 ft.	3 ft.	3 ft.	6 ft.	6 ft.	6 ft.	6 ft.
SLR exposure	-0.141***	-0.114***	-0.080	-0.033***	-0.010***	0.025***	0.017	0.006
	(0.005)	(0.005)	(0.042)	(0.012)	(0.001)	(0.001)	(0.012)	(0.007)
SFHA dummy	0.036***	0.024***	0.014	-0.006	0.042***	0.062***	0.054***	-0.001
	(0.001)	(0.001)	(0.011)	(0.007)	(0.001)	(0.001)	(0.017)	(0.009)
SFHA dummy x	0.004	-0.006	-0.023	-0.012	-0.133***	-0.094***	-0.094***	-0.017*
SLR exposure	(0.006)	(0.006)	(0.048)	(0.014)	(0.003)	(0.002)	(0.017)	(0.009)
Structure sq. ft.	–	1.1×10^{-4}***	1.0×10^{-4}***	1.8×10^{-4}***	–	1.1×10^{-4}***	1.1×10^{-4}***	1.8×10^{-4}***
		(3.3×10^{-6})	(8.4×10^{-6})	(9.3×10^{-6})		(3.3×10^{-6})	(8.4×10^{-6})	(9.4×10^{-6})
Fixed effects								
Z	No	No	Yes	No	No	No	Yes	No
BT**D*E*OT*Z	No	No	No	Yes	No	No	No	Yes
# of fixed effects	0	0	675	103,465	0	0	675	103,465
Fit statistics								
Observations	1,259,617	1,259,617	1,238,640	1,238,640	1,259,617	1,259,617	1,238,640	1,238,640
Adj. R^2	0.003091	0.296701	0.442215	0.853183	0.002552	0.295747	0.442042	0.853027

*Significance codes: ***:0.01; **:.05, *:0.1. Standard errors in parentheses and clustered at the zip code level when "Z" fixed effects included. Otherwise, standard errors are heteroskedasticity-robust using White correction.*

Note: Abbreviation/acronym definitions: "SLR" = sea level rise; "sq. ft" = square feet; "Z" = zip code; "OT" = occupancy type; "BT" = building type; "S" = number of stories; "SFHA" = Special Flood Hazard Area. Note: the "distance to coast" variable is categorical with five categories. All observations with elevations of 6 feet or less take on a value of 1, all observations with elevations from 6-12 feet take on a value of 2, etc., and all observations with elevations greater than 24 feet take on a value of 5. The "elevation" variable is categorical with six categories. All observations with distance to shore values of 0-53 feet take on a value of 1; 54-106 feet a value of 2; 107-211 a value of 3; 212-422 a value of 4; 423-845 feet a value of 5; greater than 845 feet a value of 6. "Building type" represents the primary material associated with exterior walls and structure stability functions; values include wood, steel, masonry, manufactured, and concrete. "Occupancy type" may take on one of nineteen distinct categorical values, each of which corresponds to a different residential designation based on the number of units and stories in a residential structure.

a FEMA SFHA (Gourevitch et al., 2023; Hino & Burke, 2021; Shr & Zipp, 2019). Within the climate risk literature, still some studies have controlled for FEMA SFHA status in their hedonic models estimating GMSLR price effects, though temporal variation in FEMA flood zone designations is either excluded or unspecified (Murfin & Spiegel, 2020; Tarui et al., 2023).

The employed methodology highlights the importance and sensitivities of controlling for FEMA flood zone status in estimates of GMSLR price effects, as well as the difficulty of estimating the price effects of climate change impacts in isolation using hedonic approaches. Indeed, previous stated preferences research on the US Gulf Coast region finds GMSLR is a "temporally distant" concern for residents and FEMA flood maps are a salient risk communication tool (Shao et al., 2020). However, FEMA flood maps are known to have shortcomings with respect to representing actual potential flood exposure, with multiple studies highlighting the fact that alternative flood models provide different representations of flood risk (Noonan et al., 2022; Wing et al., 2018). This underscores the importance of credible, accurate data underlying both existing hydrologic and hydraulic processes, as well as projected future ones, when estimating GMSLR price effects.

Further, differing results across measures of residential property value highlight the importance of selecting the appropriate property value metric in alignment with objectives of the analysis at hand. This study's findings compare and contrast results across different measures of "property value," which are generated from different valuation processes. An analyst's decision to select, for example, transaction price instead of DRV in statistical or policy analysis may significantly affect inference and/or program outcomes. Thus, this study contributes to a growing literature by incorporating a unique empirical design that distinguishes between GMSLR exposure and extant flood risk, as well as an analytical component focused on multiple policy-relevant measures of residential property value with implications for Federal flood mitigation.

If price effects of GMSLR exposure in the southeastern US are, indeed, null as this study's results estimate, at least two possible phenomena may explain such findings. First, a property's latitude and longitude coordinates falling within a NOAA projection of future SLR inundation does not mean flood damage is a foregone conclusion; adaptive actions can be, and often are, taken to reduce vulnerability and mitigate effects of anticipated flooding (Fell & Kousky, 2015; Jin et al., 2015; Kelly & Molina, 2023; Kim, 2020; Walsh et al., 2019). Thus, awareness and concern about future sea level rise may catalyze adaptative actions which protect vulnerable exposed areas, preserve residential property values, and stave off negative price effects.

Second, lack of awareness or belief heterogeneity have the potential to lead to a null effect of SLR-plain status. Previous empirical studies have found lack of access to information about potential flood exposure inflates transaction prices in flood-prone areas above fundamentals (Gourevitch et al., 2023; Hino & Burke, 2021), while related research indicates residents with relatively little concern about flooding and strong preferences for coastal living sort into areas prone to coastal flooding (Bakkensen & Barrage, 2021). Similarly, beliefs and levels of concern appear to influence GMSLR risk capitalization, with negative price effects primarily emerging in areas where buyers are more concerned about climate change (Baldauf et al., 2020; Bernstein et al., 2019). Thus, it is possible levels of concern or awareness about GMSLR among buyers in this study area do not rise to levels that would lead to meaningful price effects, highlighting the key distinction between objective risk and subjective risk perceptions in hedonic analysis.

2.6.2 Policy implications

As previously noted, property value is a key input when considering where and when to invest limited funds for flood mitigation measures (Junod et al., 2021). Across Federal agencies– notably USACE and FEMA which are the primary agencies through which Federal funds flow for flood risk reduction projects– BCA is an integral analytical component conducted during the project planning phase (Miller et al., 2023). Across programs in both agencies, projects rarely advance if they do not meet a benefit-cost ratio (BCR) of 1.0 or nearly 1.0 on the grounds of economic justifiability.

The above NSI results highlight preexisting disparities in the value of residential property across communities, with lower-income communities and communities with larger BAA populations exhibiting relatively lower DRVs on average. Avoided damages to structures' unweighted DRV is a primary economic benefit considered in the USACE Hydrologic Engineering Center's Flood Damage Reduction Analysis (HEC-FDA) software, the main tool used to conduct economic analyses and calculate project BCRs during formulation of Corps flood risk management plans (USACE, 2016). These plans include SLR adjustments and consider costs across a 50-year economic period of analysis (Durden & Fredericks, 2009). Similarly, residential structure DRV is a main input in the avoided "physical damage" category of FEMA's Hazard Mitigation Assistance BCA tool and recommended approach (FEMA, 2023b). In the case of FEMA HMA programs, for example, recent scholarship indicates the BCR effectively functions as an eligibility criterion, and is one of many factors considered during the selection phase among eligible HMA project submissions (Miller et al., 2023). In the case of the USACE's comparison of flood risk management plans and ultimate selection of alternatives, BCR is similarly one of multiple factors considered during projection selection, and in some cases high BCR has been cited as justification for project selection (USACE, 2022b). These policy realities underscore the fact that relatively lower DRVs in communities with lower incomes and/or higher BAA population shares are likely to lead to lower BCR calculations, which has implications for project alternatives' eligibility and/or salience of perceived project economic benefits during the selection stage. Among economically-justifiable project alternatives, considerations of both economic efficiency and equity must still be balanced.

The Justice40 Initiative brought into effect by Executive Order 14008 represents a significant Federal policy shift, operationalizing the goal to direct "40 percent of the overall benefits" of certain Federal investments to disadvantaged communities, including FEMA HMA programs and USACE's Flood Risk Management Program (The White House, 2021). Current Office of Management and Budget (OMB) guidance and agency implementation leads to somewhat coarse calculations of the distribution of these benefits by determining the share of invested dollars flowing to census tracts defined by the White House's Climate and Economic Justice Screening Tool (CEJST) as "disadvantaged" (US OMB, 2023; US Army, 2022). This current approach appears to resemble an accounting of the distribution of Federal investment rather than benefits.

Adler, 2016 argues equating unweighted monetary values (e.g., avoided damages to residential structure DRV) with "benefits" espouses implicit moral values, as each marginal dollar of investment or avoided damage does not necessarily provide the same amount of utility or personal benefit to individuals within a community or communities experiencing significant wealth inequality. Though incompatible with agency policies, Adler posits society may prefer to apply an underlying "social welfare function" in BCA approaches which, for example, might include an inequality aversion parameter or income-weighted calculation of benefits to prioritize mitigation of pre-existing disparities as a substitute or complement to Kaldor-Hicks efficiency criteria. When acknowledging property value disparities across socioeconomic groups, both the metric used to quantify "benefits" and the entry point of equity considerations in the project evaluation and selection process seem likely to influence adaptation outcomes. Communities with lower average DRVs may have more difficulty securing Federal investment or meeting eligibility requirements to even be considered for such funding when submitting project applications. Critical study and scholarly transparency with respect to BCA and other quantitative selection criteria employed in

Federal flood mitigation programs will be crucial as Justice40 implementation and guidance is refined in future program cycles. As GMSLR accelerates and incentives to mitigate flood risks in SLR-exposed areas grow stronger, agencies' quantitative analyses and the values embedded within them will be tools through which national flood risk reduction priorities are expressed.

2.7 Conclusions

This study examines the effects of exposure to projected anthropogenic SLR on measures of residential property value in Florida, Georgia, North Carolina, and South Carolina using detailed property- and transaction-level information from multiple data sources. The price effects of two magnitudes of projected SLR—three and six feet— are evaluated using a hedonic regression analysis. The preferred triple-difference estimations' results do not provide conclusive evidence to suggest negative price effect solely attributable to GMSLR exposure risk emerged following publication of the IPCC's AR3 in 2001. However, over the 1993-2022 sample period, properties in both a SFHA and the three-foot SLR-plain sold, on average, for -5.1% relative to observably equivalent properties neither in a SFHA nor the SLR-plain. Similarly, properties in both a SFHA and three-foot SLR-plain sold for -8.7% compared to comparable properties only in a SFHA. These observations suggest negative price effects are only present in the portions of FEMA SFHAs which are most acutely exposed to GMSLR, which are also areas with exposure to current coastal storm risk. These results highlight the highly-correlated relationship between extant flood risk and slow-onset GMSLR risk, and underscores the difficulty as well as importance of controlling for existing storm risk when estimating climate change impacts in hedonic studies.

When conducting a novel comparison of regression estimates across multiple measures of coastal residential "property value"— transaction price and DRV— results indicate USACE structure values appear to vary with three-foot SLR-plain status even when controlling for a host of structure-level characteristics. On average, structures in the three-foot SLR-plain were valued at 3.0% less than comparable properties outside the SLR-plain. These results run contrary to what had originally been hypothesized, and call into question whether there are unobserved elements of USACE's NSI evaluation methods or systemic compositional differences in residential housing stock across SLR-plain status which lead to these outcomes. These findings have implications for future research with respect to choice of appropriate "property value" measures as well as potential confounding unobserved factors leading to estimates of SLR exposure price discounts.

When considering heterogeneity in the effects of SLR-plain status across community race and income, estimations using distinct measures of residential property value—transaction price and DRV—find positive effects from being located in relatively higher-income census tracts and negative effects from being located in census tracts with relatively higher BAA populations. On average, a 10% increase in census tract BAA population is associated with an estimated 4.3% decrease in transaction price and a 3.8% decrease in DRV. The effect of a 10% increase in census tract median income is associated with an estimated 2.9% increase in transaction price and a 2.4% increase in DRV. These findings underscore the embedded nature of DRV as a correlate and determinant of transaction price, and highlight preexisting property value disparities across community race and income in areas exposed to GMSLR. Findings are relevant to researchers studying public policy processes that influence Federal flood mitigation infrastructure allocation and distributional outcomes.

This study's results have important hazard mitigation and climate policy implications regarding adaptation interventions which seek to mitigate damages from anthropogenic GMSLR efficiently and achieve equity objectives. Going forward, policy interventions such as buyout programs, publicly-funded flood mitigation measures, and climate risk disclosure requirements will need to consider preexisting homeownership and property value disparities, heterogeneous buyer beliefs and preferences, extant flood risk, appropriate property value measures, and quality of risk information products to effectively manage emergent GMSLR impacts. Additionally, while BCA is a quantitative tool used to support decisionmaking about adaptation interventions, ultimately difficult and value-laden decisions will need to be made about where to allocate limited funds to provide protection against GMSLR impacts.

CHAPTER 3

Driving up flood risks? Examining vehicle flood exposure, vulnerability, and disaster assistance in the United States

3.1 Introductory remarks

Motor vehicles are the most commonly-owned non-financial asset in the United States (US) and are essential to most households, as well as the US economy at large. In 2019, approximately 85% of US households owned at least one vehicle[3] (Bhutta et al., 2020), while in 2020 84% of US workers commuted to their place of employment in a privately-owned vehicle (US Census Bureau, 2020). In 2020 there were an estimated 276 million highway-ready vehicles on the road in the US, the result of substantial growth in the number of US vehicles in both absolute and per capita terms in recent decades (US BTS, 2023). Projections indicate absolute annual motor vehicle sales in the US will continue to see robust growth in the coming years (Archsmith et al., 2022), suggesting the number of vehicles in the US is likely to increase in the near term. Motor vehicles also transport the vast majority of children (ages 5-17) to school (Jenkins, 2019), and these assets support critical public services such as firefighting, policing, and medical assistance. Thus, vehicle assets are ubiquitous and essential to the US economy and society at large.

Flooding is already estimated to be the costliest and most frequently-occurring natural hazard in the US (FEMA, 2019). Anthropogenic climate change impacts such as global mean sea level rise (GMSLR) and more extreme precipitation (IPCC, 2021), as well as urban development in existing flood-prone areas (Andreadis et al., 2022; Rentschler et al., 2023), are contributing to an increasing number of people and assets in floodplains (Wing et al., 2018). While many studies have focused on the impacts of potential or actual flood hazard exposure on "property value" in the form of residential and/or commercial building structures (Atreya et al., 2013; Baldauf et al., 2020; Beltrán et al., 2018; Bernstein et al., 2019; Bin & Landry, 2013; Bin & Polasky, 2004; Fell & Kousky, 2015; Gibson & Mullins, 2020; Gourevitch et al., 2023; Hino

[3]In this study, the term "vehicle" means a a highway-ready motor vehicle as defined by the United States Department of Transportation Bureau of Transportation Statistics. The vast majority of vehicles in the US are light duty and privately-owned.

& Burke, 2021; Kelly & Molina, 2023; Murfin & Spiegel, 2020; Ortega & Taşpınar, 2018; Shr & Zipp, 2019; Wing et al., 2018), a relative paucity of research has focused on potential and actual impacts of flooding to other important forms of household property, such as vehicles. This chapter argues motor vehicles are a crucial household asset warranting comprehensive study in the context of US flood risk management. In addition to their critical role as a mode of transportation, vehicle assets represent an important financial asset for many low-wealth households for whom an owned vehicle may constitute a relatively large share of household net worth. Converging trends of increasing number of US household vehicles, urban development patterns, and an intensifying hydrological cycle driven by anthropogenic climate change underscore the need for increased study of vehicle assets' exposure and vulnerability to flood hazard.

The present study provides two foundational contributions to the literature on household asset exposure to flood hazard in the face of climate change. First, the research provides novel estimates of the number and value of vehicle assets located in flood-prone areas in the contiguous US (CONUS). Second, this article undertakes the first analysis of vehicle flood damage-related data from the Federal Emergency Management Agency's (FEMA) Individuals and Households Program (IHP) to better understand the scope and magnitude of US vehicle flood damages and effectiveness of related disaster assistance programs. This analysis considers public policy and market factors which may or may not contribute to household financial resilience in the wake of vehicle flood damages. This second contribution provides quantitative insight into where, when, and how much Federal disaster assistance is disbursed to eligible households in connection with vehicle flood damages following presidentially-declared disasters. Additionally, application-level data are analyzed to improve understanding of the factors that contribute to IHP application submission decisions and outcomes when these disasters incur vehicle flood damages. Collectively, findings from this research can inform vehicle owners, insurance professionals, infrastructure planners, and emergency managers about vehicle flood exposure issues, and may also inform FEMA program design.

Section 3.2 describes the role of vehicles in the US economy, their vulnerability to flood hazards, and the insurance markets as well as Federal disaster programs which may provide financial support to affected vehicle owners for recovery post-flood. This section also out lines the main hypotheses to be tested in the research. Section 3.3 describes the data used in the analysis. Section 3.4 explains the empirical methods and approaches used to conduct the data analysis and test the stated hypotheses. Section 3.5 presents and interprets results from the analysis. Section 3.6 discusses policy implications and limitations of this line of inquiry, as well as opportunities for future research. Section 3.7 contains the conclusion.

3.2 Background and hypotheses

3.2.1 Vehicle assets and relative value

As noted above, vehicles are widely-owned and economically important household assets. Of the approximately 276 million highway-ready motor vehicles in the US, US Census Bureau (USCB) data indicate households in the CONUS had access to at least 209.6 million vehicles in 2020 (USCB, 2022). Motor vehicles are “normal goods,” meaning consumer demand for them increases with income (Samuelson & Nordhaus, 2009). While some analysts and advocates have highlighted the fact that replacing widespread private motor vehicle use with alternative transportation modes (e.g., public rail) has the potential to meet societal objectives such as air quality improvements or greenhouse gas emissions reductions (Bleviss, 2021), evidence suggests consumers place considerable value on their owned private vehicles relative to current alternative transportation modes (Moody et al., 2021). The number of vehicles on the road in the US continues to grow in both absolute and per capita terms (US BTS, 2023), suggesting robust US consumer preferences for travel via private passenger vehicles. This trajectory, in conjunction with expanding and intensifying flood hazard in many regions in the US, motivates Hypothesis 1 (H1) below:

> ***Hypothesis 1: A large quantity of vulnerable vehicles at sizable aggregate value are located in US floodplains.***

Recent research suggests more than 40 million US residents live in areas with a 1% annual exceedance probability (AEP) of flood exposure (Wing et al., 2018), and this figure has the potential to increase due to urban growth in existing floodplains (Zhang et al., 2018) and/or expanding flood hazard driven by anthropogenic climate change (Davenport et al., 2021; Strauss et al., 2021). Given high rates of vehicle ownership in the US, H1 hypothesizes vulnerable vehicle assets are subject to widespread flood exposure comparable to exposure of human populations.

While the value of vehicle assets in the US represents just 3.2% of total household wealth, as compared with equity in primary residences which represents 28.5% of total household wealth,[4] the absolute aggregate market value of vehicle assets in the US is non-trivial at trillion-dollar scale.[5] Further, the relative value of vehicle assets is high for low-wealth households. The national household vehicle ownership rate of approximately 83.1% is higher than the household home ownership rate of 61.8%.[6] (Sullivan et al., 2023), implying many households are vehicle owners but not homeowners. Figure 3.1 below uses US Federal Reserve Survey of Consumer Finances data to describe the relationship between household net worth and asset ownership rates for vehicle and housing assets. Among households in the bottom 25% by net worth, the vehicle ownership rate is 68.8%, while the homeownership rate is just 8.1% (Fed SCF, 2022). Figure 3.2 presents the average value of households'

[4]This statistic only pertains to the bottom 99% of US households according to wealth.

[5]Conservatively assuming all registered vehicles in the US are worth ~$4,000 each leads to aggregate vehicle value in excess of $1 trillion; the true monetary value is likely much higher.

[6]"Homeownership" is defined here as a non-renter household owning at least some equity in their primary residence.

owned vehicle assets[7] as a share of aggregate household owned asset value. These data suggest that as a household's net worth[8] increases, the value of owned vehicle assets tends to increase in absolute value but decrease as a share of the value of the household's gross assets. For example, in 2019 the average household in the top 10% of US households by net worth owned $56,799 worth of vehicles, but those vehicles represented less than 1.0% of the household's gross assets (e.g., including real estate, retirement savings, etc.). In contrast, the average household in the bottom quartile of net worth owned $8,274 worth of vehicle assets, and those vehicles represented approximately one-quarter of the value of the household's gross assets. Thus, while vehicles make up a relatively small share of aggregate US asset wealth, on average they represent a relatively high percentage of total net worth for low-wealth vehicle-owning households.

3.2.2 Vehicle flood damage

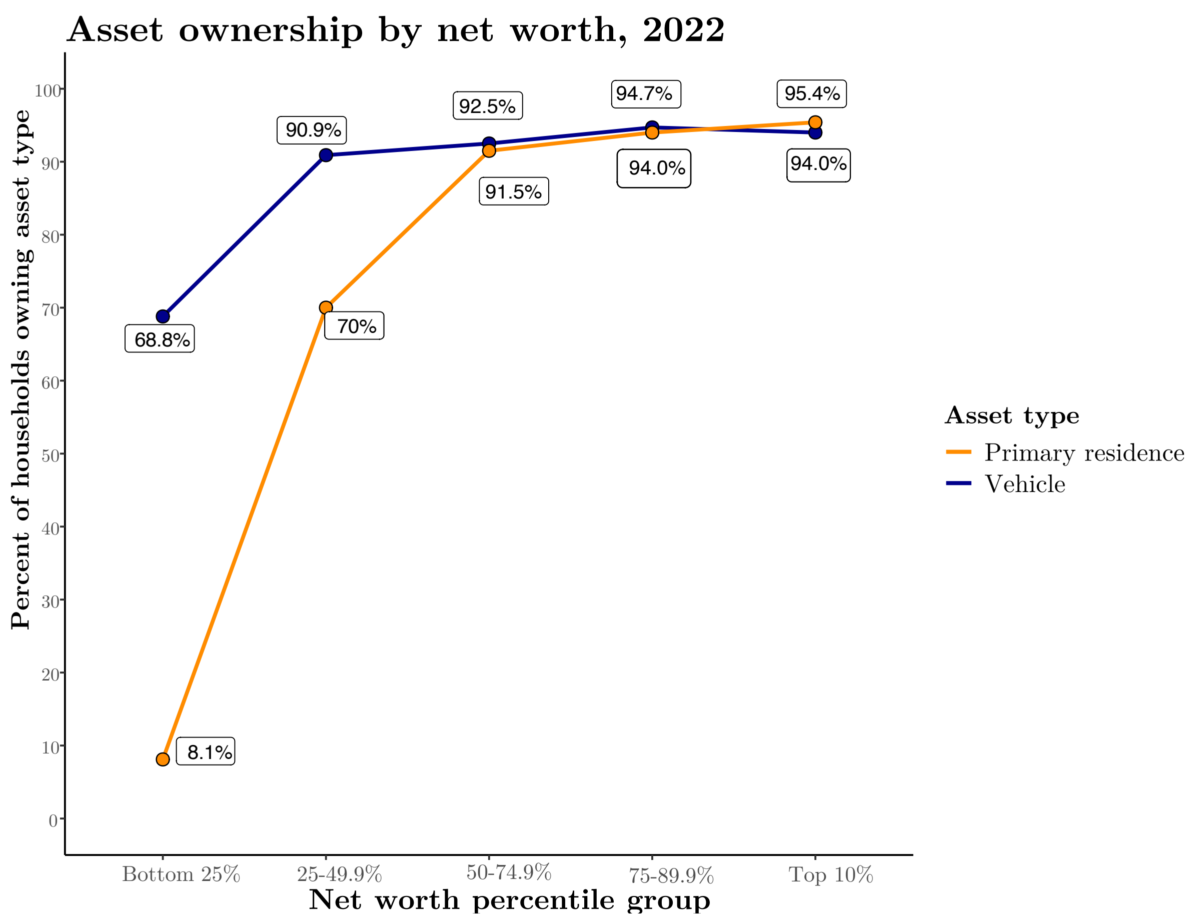
Figure 3.3 describes US Army Corps of Engineers (USACE) estimates of the flood-vehicle depth-damage relationship across vehicle types. According to these Corps estimates, on average a single flood event causes damages of 20% to a sports utility vehicle (SUV)[9], with the same flood level causing an average of nearly 40% to sedans (USACE, 2009). Corps estimates suggest five feet of inundation generally leads to what would be considered a "total loss" in many states (Policy Genius, 2023), which in the insurance industry typically implies the cost of repairing the flooded vehicle exceeds the post-repair value of the vehicle (Oxford Reference, 2023). Thus, a single flood event has the potential to impose sizable damages on a vehicle, with significant financial ramifications for households without commensurate insurance.

[7] These averages include households owning no vehicles and do not only reflect average values for vehicle-owning households.

[8] According to the 2019 Survey of Consumer Finances, the median net worth for a household in the bottom 25% was $300 while the median net worth for a household in the top 10% was approximately $2.6 million.

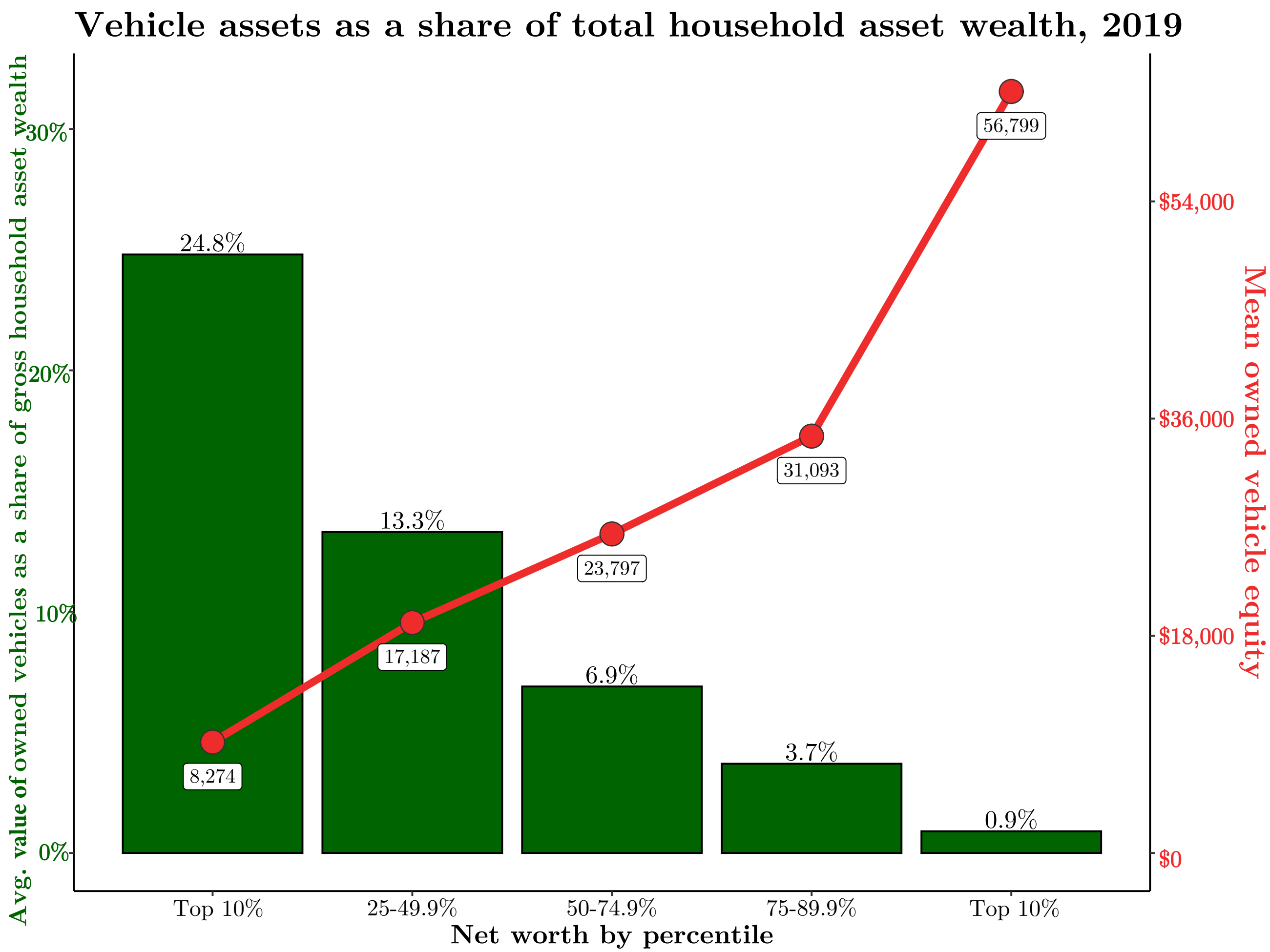
[9] This means the cost of the damage represents approximately 20% of the vehicle's pre-flood value.

Figure 3.1: Household asset ownership by net worth, 2022



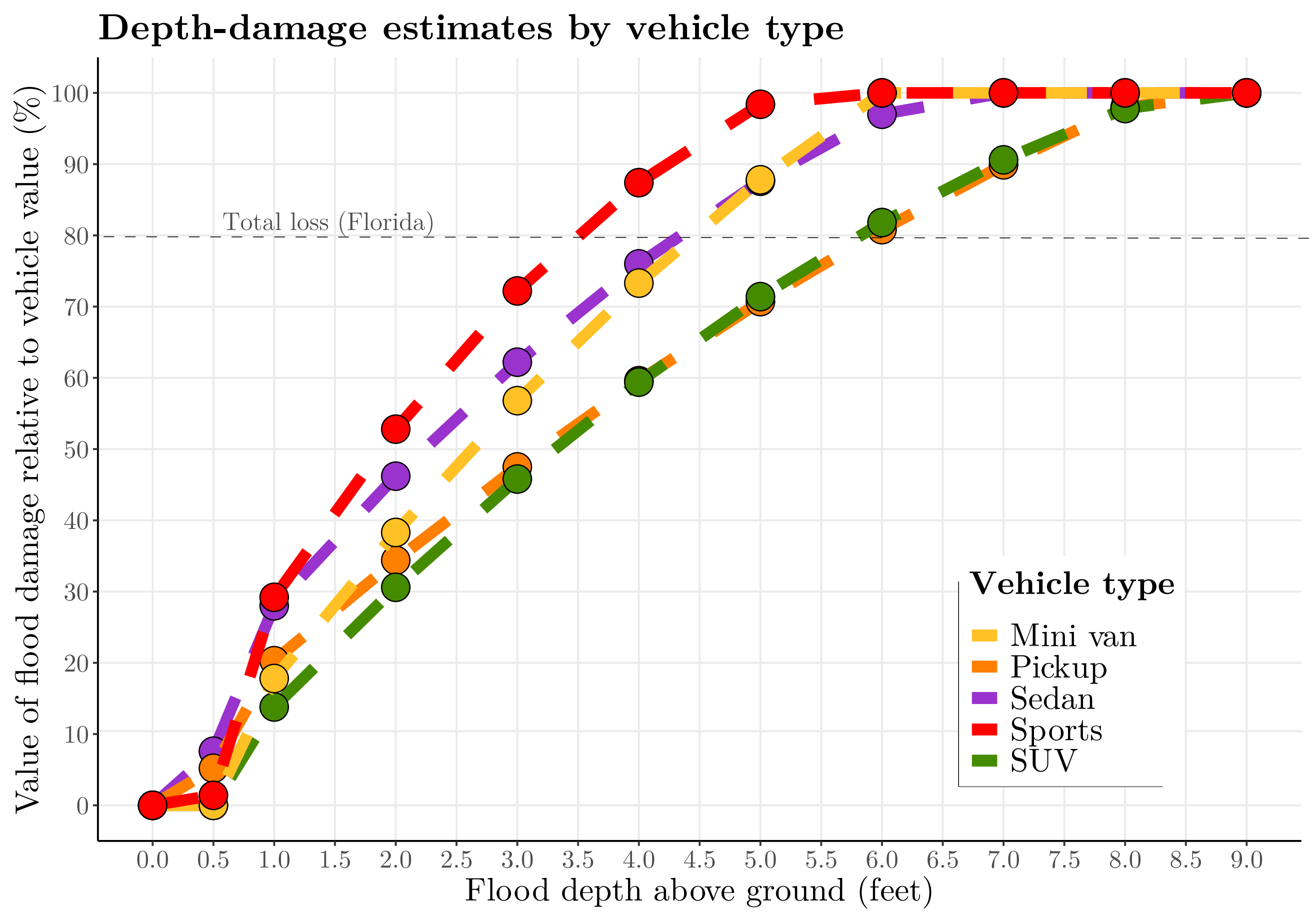
Source: US Federal Reserve Bank Survey of Consumer Finances, 2022.

Figure 3.2: Owned vehicle assets as a share of total household asset wealth, 2019



Source: US Federal Reserve Bank Survey of Consumer Finances, 2019.

Figure 3.3: Depth-damage estimates by vehicle type

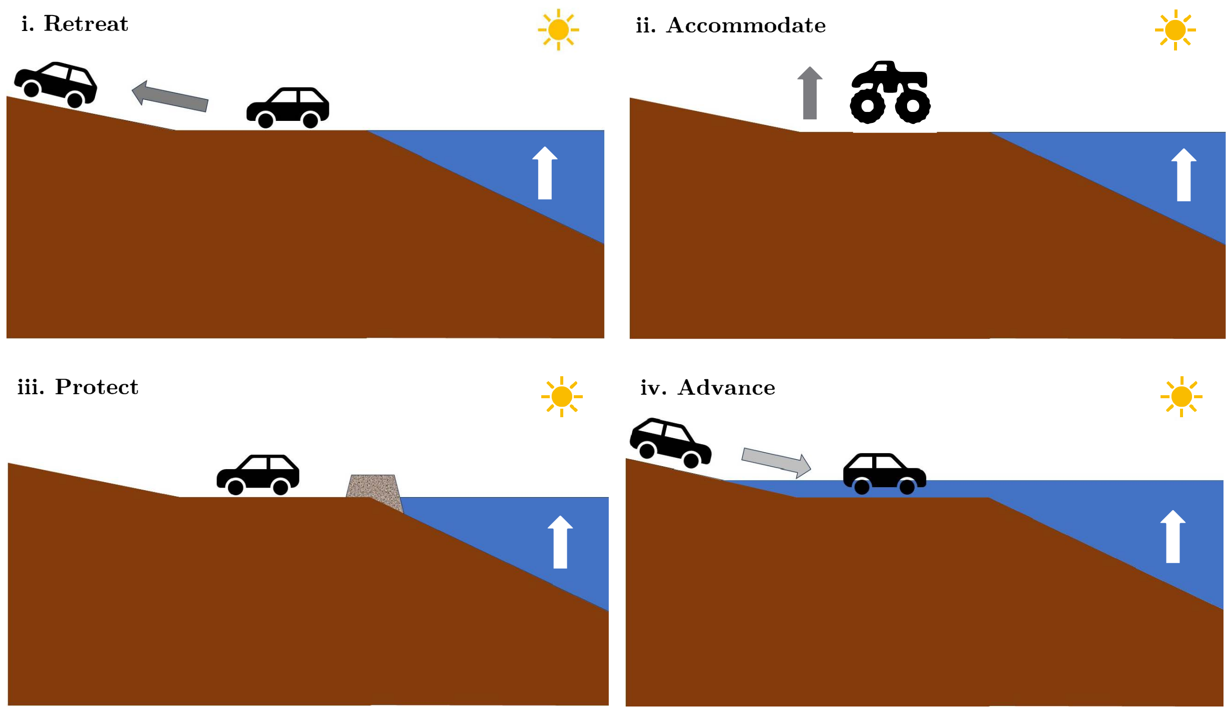


Source: US Army Corps of Engineers, 2009.

In the prevailing climate hazard mitigation literature, hazard risk is defined as the product of a human or ecological system's exposure to a climate hazard coupled with that individual or system's vulnerability to the hazard (IPCC, 2022). Figure 3.3 demonstrates vehicles are generally vulnerable to flood hazard when exposed. This study argues conceptual application of the canonical strategic framework of climate change adaptation and hazard risk mitigation responses— accommodate, protect, retreat, advance— may be extended to vehicle assets to inform future risk reduction activities. This application is illustrated in Figure 3.4.

In practice, these adaptive responses in the context of vehicles are inherently different from applications vis-à-vis relatively immobile assets (e.g., real estate) given vehicles' greater capacities for mobility and flood avoidance. While the economic justification for large-scale infrastructure investments to protect vehicle assets may be weaker than for structures, it is possible other adaptive responses may increasingly emerge among vehicle owners to facilitate temporary *retreat*, such as flood warning systems, or *accommodation*, such as vehicles with higher ground clearances or amphibious capabilities. Notably, while the "advance" adaptation strategy in the context of managing GMSLR risks is typically associated with seaward expansion measures, e.g. land reclamation or engineered artificial islands (Haasnoot et al., 2021; Sengupta et al., 2023), this chapter contributes an alternative interpretation of the "advance" strategy in the context of vehicle assets. Specifically, vehicle owners may drive their vehicles *into* inundated areas, which has the potential to be a maladaptive behavior if the vehicle is vulnerable to the flood hazard. Indeed, when considering research about increased disruption to vehicles and road networks due to flooding (Hauer et al., 2023; Pregnolato et al., 2017), as well as evidence indicating the most common flood fatalities in the US occur in vehicles (CDC, 2020), it is clear the issues of vehicle vulnerability and exposure to flood hazard warrant further study to promote safe transportation alternatives and reductions in loss of property and human life.

Figure 3.4: General framework of vehicle flood adaptation approaches.



Source: Modified from Nicholls, 2018.

3.2.3 Disaster assistance and insurance

Unlike residential and commercial real estate assets, the structures and contents of which may be covered by FEMA's National Flood Insurance Program (NFIP), vehicle assets are not eligible for NFIP coverage (FEMA, 2022). In order to insure a vehicle against flood damages, vehicle owners must purchase a multi-peril "comprehensive auto insurance policy" from a private insurer (Car and Driver, 2020), which typically covers damages from multiple sources such as flood, fire, and vandalism. This coverage is not legally required in any US state, though is often required by lenders and lessors (Insurance Information Institute, 2018). According to the National Association of Insurance Commissioners (NAIC), in 2020 the average price of a comprehensive auto insurance policy in the US was $174.26 per year, with average prices ranging by state from $97.26 in California to $353.10 in South Dakota (NAIC, 2023). The total reported collected premiums across more than 178 million vehicle-years of comprehensive insurance policies in 2020 was more than $31 billion, suggesting comprehensive auto insurance is a market of substantial size. While aggregated data on comprehensive insurance policies are available via the NAIC, firms' comprehensive insurance data describing claims and payouts are generally proprietary, not publicly-available, and have not been made available by large insurers[10] for this analysis. Additionally, the multi-peril nature of comprehensive auto insurance presents an added layer of complexity for researchers interested in claims and payouts specifically pertaining to flood hazard, as publicly-available information on policies and claims are not disaggregated at the peril-level.

In the event a motorist experiences vehicle flood damage, a number of pathways to financially recover from the shock may be available. Figure 3.5 describes these pathways in a simple conceptual diagram. As described above, a vehicle owner pos-

[10]The largest auto insurers by number of policies written, e.g. State Farm, Geico, Progressive, along with smaller insurers such as Lemonade were contacted but no data provided.

sessing a comprehensive insurance policy may be eligible for a claim payout from their insurance company, the funds from which may be used at the policyholder's discretion (e.g., to repair or replace the damaged vehicle). However, not all motorists have comprehensive coverage. Figure 3.6 below shows the estimated share of motorists driving in the US without comprehensive coverage, which according to the Insurance Information Institute (III) is roughly 31%[11] (III, 2023a, 2023b). If a vehicle owner experiences uninsured vehicle flood damages in connection with a flood event that is not a presidentially-declared disaster nor emergency under the Stafford Act (FEMA, 2021), the costs of the damage are likely to be borne by the owner.

However, if uninsured vehicle flood damages occur during a presidentially-declared disaster or emergency, the vehicle owner may be able to access funds from FEMA through the IHP, a sub-program of the agency's larger Individual Assistance (IA) program. According to the 2021 Individual Assistance Program and Policy Guide:

> *IHP assistance provides financial assistance and direct services to eligible individuals and households who have uninsured or underinsured necessary expenses and serious needs. IHP assistance is not a substitute for insurance and cannot compensate for all losses caused by a disaster; it is intended to meet basic needs and supplement disaster recovery efforts.* (FEMA, 2021)

Thus, IHP assistance can help smooth the financial shock of uninsured vehicle flood damages and associated recovery expenses. However, by program design, IHP awards are not intended to make eligible applicants whole post-disaster. Following a disaster or emergency declaration, vehicle owners in eligible counties may apply for disaster assistance to repair or replace a vehicle through FEMA's IHP, specifically in the "Other Needs Assistance" (ONA) category and the "Transportation Assistance" (TA) subcategory.[12] An applicant with vehicle flood damage may receive TA from

[11] Due to data availability, this statistic crudely relies on III's national estimate of 12.6% uninsured motorist rate in 2019 and their estimate from 2020 that 21% of insured motorists have no comprehensive auto insurance coverage.

[12] In Fiscal Year 2023, FEMA's maximum allowable amount of financial assistance to one individual or household under the ONA category within the IHP was $41,000.

FEMA if a number of eligibility conditions are met, including but not limited to: (i) legal compliance with applicable state registration and insurance requirements for the damaged vehicle; (ii) disaster-caused uninsured damage that renders the vehicle inoperable, and; (iii) prior unsuccessful application for a US Small Business Administration (SBA) loan. Additionally, FEMA IHP guidance indicates TA awards are "usually limited to one vehicle." Previous scholarship focusing broadly on FEMA's IHP with respect to housing assistance has found that, for example in the case of Hurricane Maria in Puerto Rico, approximately 60% of all applicants for IHP assistance were ineligible and therefore received no disaster assistance (García, 2022). Rejected applicants were found to be ineligible primarily due to failure to produce necessary documentation (e.g., proof of ownership) required by IHP. The present study is the first to focus exclusively on the incidence of IHP applications with reported vehicle flood damages and determinants of outcomes among this set of IHP applications.

The substantial percentage of motorists driving without comprehensive auto insurance coverage, coupled with the growing reported costs of large-scale climate-mediated disasters in the US (NOAA NCEI, 2021) motivates Hypothesis 2 (H2) below. Additionally, previous research on the positive income elasticity of demand for auto insurance (Showers & Shotick, 1994) motivates Hypothesis 3 (H3), as we might expect to see lower comprehensive auto insurance coverage rates among lower-income households and greater need for IHP assistance among this population. The work of García (2022) further motivates H3 as some applicants, e.g. those who do not meet minimum state auto insurance requirements and/or do not have up-to-date vehicle registration, may be ineligible to receive assistance due to lack of required documentation (e.g., proof of ownership, effective minimum insurance coverage).

> ***Hypothesis 2: A significant number of vehicles experience uninsured flood damages during presidentially-declared disasters, and these cases only represent a portion of uninsured vehicle flood damages.***

Figure 3.5: Conceptual diagram of post-flood vehicle owner financial recovery options

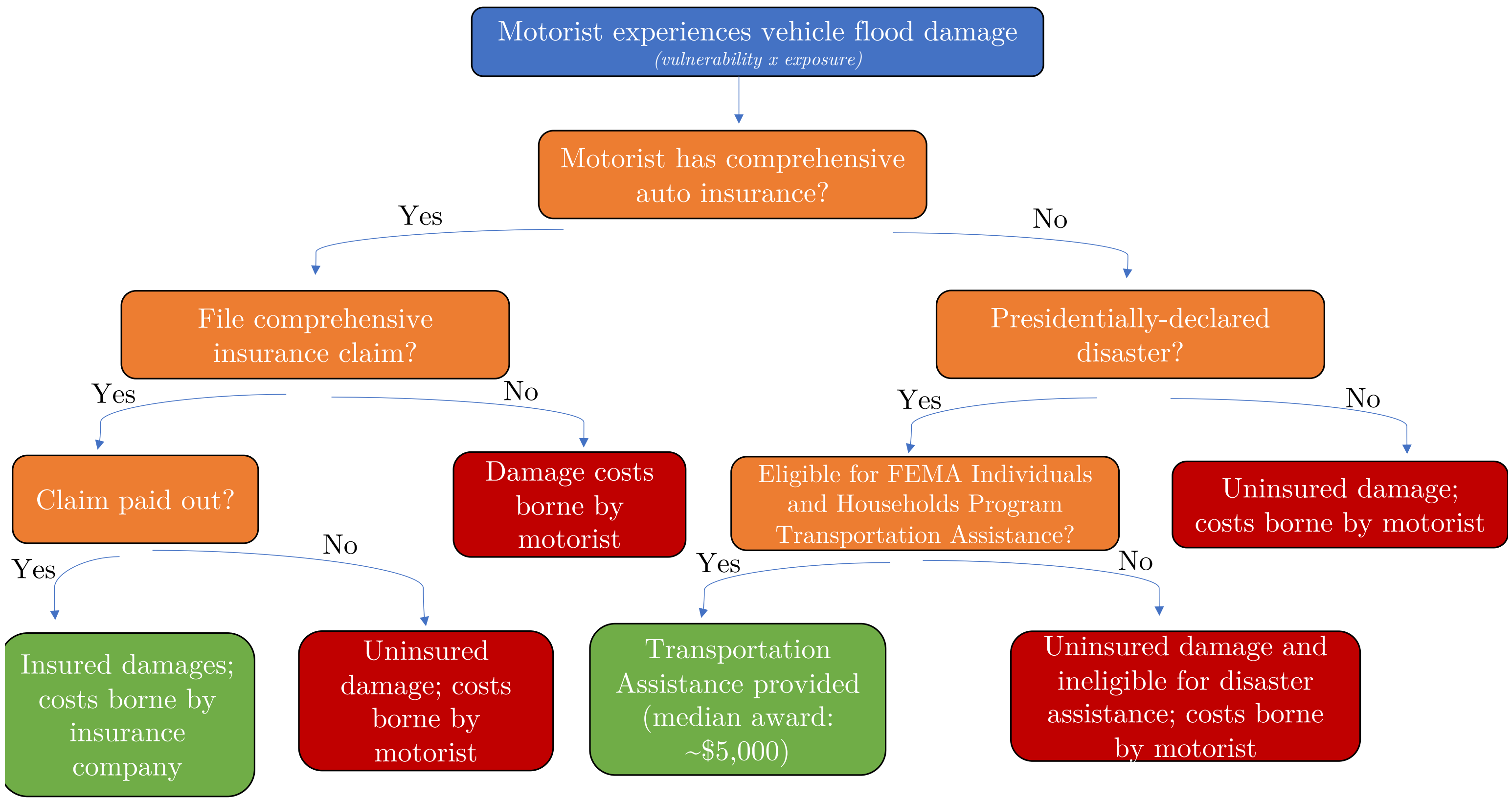
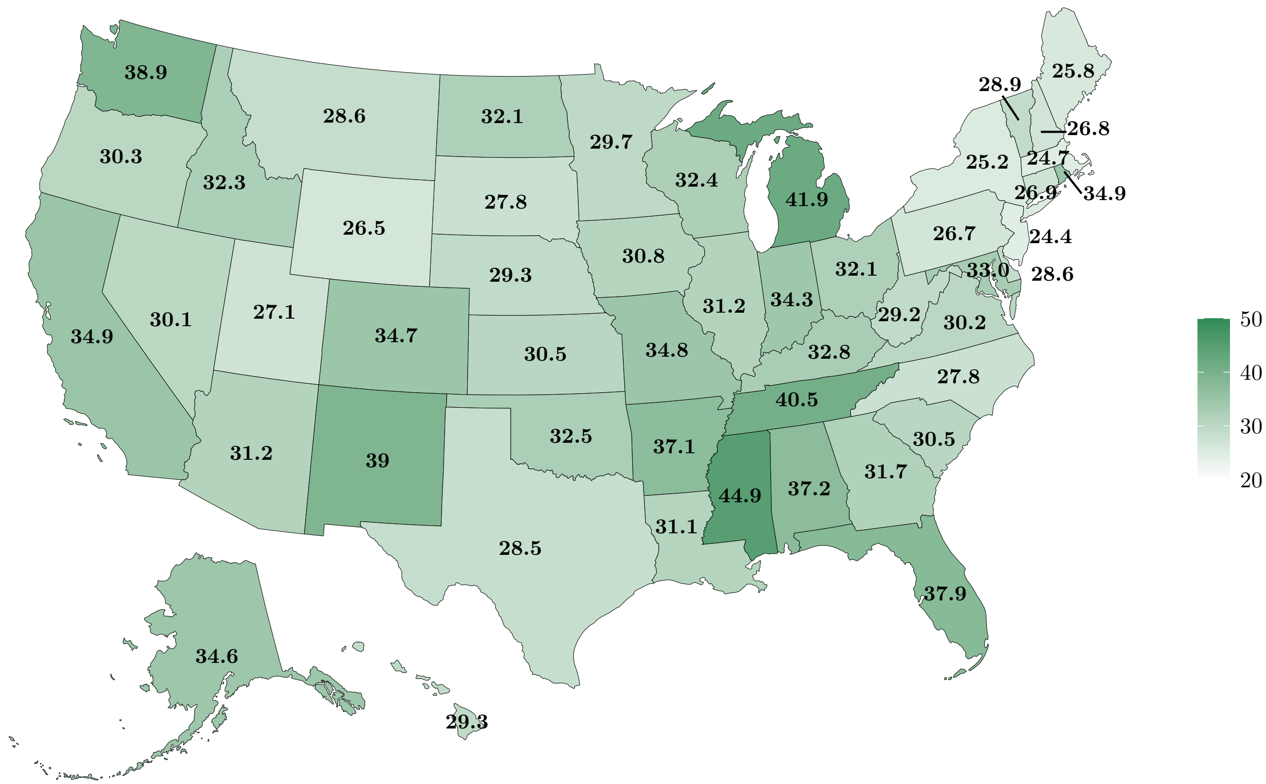


Figure 3.6: Estimated percentage of motorists in US states without comprehensive auto insurance coverage



Source: Insurance Information Institute, 2021. These are approximations; the 2018 nationwide rate of insured motorists without comprehensive coverage, 22%, is applied to each US state and this amount is added to the state uninsured rate.

and

Hypothesis 3: Low-income households will be overrepresented among IHP applicants experiencing vehicle flood damage, but underrepresented among awardees due to ineligibility.

3.3 Data

3.3.1 Study area and land use

The study area in which H2 and H3 will be tested is the entire US, while H1 will be tested in the 48 states in CONUS. In 2020, the US population was approximately 331.1 million people, while the population of CONUS was approximately 328.2 million people (USCB, 2023). A central data source in this analysis is the USCB's Topologically Integrated Geographic Encoding and Referencing (TIGER) database, from which I access the legal boundaries for 83,287 census tracts in CONUS. To understand communities' level of social vulnerability, census tracts' Centers for Disease Control and Prevention (CDC) 2020 Social Vulnerability Index (SVI) scores are incorporated as well (CDC, 2023).

In order to represent variation in land use types across study area tracts, the United States Geological Survey's (USGS) National Land Cover Database (NLCD) is employed (USGS, 2023). This product covers the entirety of CONUS's land area and categorizes the country's territory across 16 land cover types at 30-meter resolution. The 2019 NLCD data product is used in the analysis.

3.3.2 Vehicle data

This study focuses primarily on household vehicles, as opposed to commercial or publicly-owned vehicles. Of the approximately 276 million vehicles on the road in the

US in 2020, fewer than 2% of those were publicly-owned and the rest were privately-owned (US DOT, 2020). In 2022, there were approximately 33.1 million commercial vehicles on the road in the US (S & P Global Mobility, 2023), suggesting roughly five out of six registered vehicles in the US are privately-owned household vehicles. To estimate the number of household vehicles available in each CONUS census tract, USCB 2020 American Community Survey (ACS) five-year estimates are accessed. Specifically, the ACS provides estimates of the number of occupied housing units with no vehicles available, one vehicle available, two vehicles available, or three or more vehicles available. In this analysis, the total number of household vehicles in a census tract is calculated to be the sum of all vehicles available at occupied housing units in 2020. This calculation assumes a value of three vehicles available for households in occupied housing units corresponding to the "three or more vehicles available" USCB category. By construction, this truncation biases final estimates using these inputs downward, as household vehicles beyond the third vehicle are not captured. Additionally, margins of error are calculated in accordance with recommended USCB methodology (USCB, 2020).[13]

While in this analysis UCSB data are primarily used to estimate the *number* of household vehicles in US floodplains, two other data sources are incorporated to provide estimates of the *value* of vehicles in flood-prone areas. First, data from the popular and widely-cited research firm Kelley Blue Book (KBB) are used to construct a weighted average of the annual average used vehicle sale price in the US from 2019-2021 (Kelley Blue Book, 2023), which is estimated to be $23,367.[14] Second, the USACE 2022 National Structure Inventory (NSI) is used to provide an alterna-

[13] Specifically, margins of error (MOE) for count estimates are calculated using the following formula: $\mathrm{MOE}(\mathrm{Est}_1 + \mathrm{Est}_2) = \sqrt{MOE(Est_1)^2 + MOE(Est_2)^2}$. Margins of error for count estimates of the number of household vehicles available at the census tract level are multiplied by the fraction $\left(\frac{\mathrm{Developedlandinfloodzone(km^2)}}{\mathrm{Totaldevelopedlandarea(km^2)}}\right)$ shown in Equation (3.1.)

[14] In comparison, Table 1-17 in the US Department of Transportation's "National Transportation Statistics 2021" report indicates the average price in 2021 dollars of new passenger car and light truck sales in 2019 was $38,003 while the average price of used passenger car and light truck sales in the same year was $20,600 (US BTS, 2023).

tive source of broad vehicle value estimates (USACE, 2022a). The USACE inventory synthesizes data from across multiple sources and includes georeferenced information about approximately 123 million structures across the entire US, approximately 122 million of which are in CONUS states. Included in the inventory are estimates of the "value in [2021] dollars of the cars at the structure." According to USACE, this structure-specific value is estimated based on the number of housing units per residential structure and the number of employees per commercial structure, and does not adjust for variation in vehicle ownership rates nor income across the country. Thus, a key distinction is that estimates using USACE NSI georeferenced vehicle values reflect the value of vehicles at commercial structures. Additionally, while KBB represents a vehicle value derived from market prices, the USACE NSI data aim to represent vehicle depreciated replacement value.[15]

3.3.3 Flood hazard

First, FEMA's National Flood Hazard Layer (NFHL) is used to portray the likelihood of potential flood exposure across CONUS (FEMA, 2023e). Previous flood modelling research has highlighted a number of shortcomings of FEMA flood maps, such as the fact they are not universally available,[16] are of varying age and quality (Wing et al., 2018), and do not reflect all relevant phenomena influencing flood hazard probabilities (e.g., extreme precipitation-driven flood events) (US GAO, 2021). However, the NFHL covers the majority of the relevant study area and is highly policy-relevant due to the fact it supports the NFIP and underpins flood insurance rate making, floodplain management regulations, and mandatory purchase requirements of flood insurance for applicable homeowners.

[15] This information was communicated via email correspondence from Nick Lutz, USACE Hydrologic Engineering Center economist on May 31, 2023. USACE NSI data do not include estimates for the number of vehicles located at structures, only value.

[16] According to FEMA, the NFHL's digital data cover "over 90 percent of the U.S. population."

The NFHL is a vector shapefile containing various categorizations of flood zones, which are broadly characterized into two groups for the purposes of this analysis: (i) Special Flood Hazard Areas (SFHAs), and (ii) moderate flood hazard areas (MFHAs). SFHAs are generally defined by FEMA as "the area that will be inundated by the flood event having a 1-percent chance of being equaled or exceeded in any given year." There are various subcategories of SFHA flood zones (e.g., Zones A, AE, V, VE) that correspond to different degrees of flood hazard exposure driven by specific physical conditions. Similarly, MFHAs are represented by multiple FEMA-designated zones (e.g., Zone B or Zone X [shaded]), and these are defined as "areas between the limits of the base flood and the 0.2-percent-annual-chance (or 500-year) flood" (FEMA, 2023a). A critical shortcoming of these FEMA mapping products is the absence of flood depths or base flood elevations for some SFHA and MFHA flood zones (e.g., Zone A, Zone X [shaded]).

Second, to provide an alternative representation of potential flood hazard exposure, property-level outputs from the First Street Foundation's Flood Model (FSF-FM) are incorporated. While detailed raster or mesh files showing flood depths and probabilities were not made available by FSF, point data representing estimated property-level flood exposure were acquired for the study area. FSF property-level flood hazard exposure estimates rely on geolocated Lightbox data from November, 2021 and employ the probabilistic hydraulic and hydrologic FSF-FM, which incorporates finest inputs at 3-meter resolution. The FSF-FM additionally includes an explicit precipitation model to capture potential hazard driven by pluvial flooding, an analytical component missing from FEMA NFHL products (First Street Foundation, 2023). Only properties with "major flood risk" as denoted by property-level FSF "Flood Factor"® score are analyzed in this study[17]

[17]Specifically, properties with Flood Factor® scores of 5 or greater are included. According to FSF's documentation, "Properties with at least an 80% chance of flooding over 30 years will have a Flood Factor of 5 or higher."

3.3.4 FEMA Individuals and Households Program overview

To test hypotheses H2 and H3, application data from FEMA's IHP are leveraged. The IHP application data available on FEMA's OpenFEMA IHP webpage do not include information about applicants' vehicle flood damage experiences nor TA awards explicitly pertaining to vehicle flood damage, therefore Freedom of Information Act (FOIA) request 2022-FEFO-00281 was submitted to acquire these application-level details. Approximately 1.1 million records reporting vehicle damage were received in connection with the FOIA request, and 160,565 of these applications reported vehicle flood damage.

Table 3.1 presents summary statistics of the IHP application data received via FOIA, specifically those applications reporting vehicle flood damage. The final sample data only represent applications with reported vehicle flood damage. Across the sample period 2007-2022, just 3% of applicants qualified for a SBA disaster loan[18] and only 18% of applications received a TA award, suggesting most applications reporting vehicle flood damage do not receive any Federal financial support in connection with their case. The mean and median TA award amounts across the sample period among applicants receiving an award are \$4,624 and \$5,000, respectively.

Figure A.13 in the Appendix depicts the distribution of TA award amounts, and the shape of the distribution exhibits multimodal characteristics with relatively high shares of the distribution of awards falling in the \$0-\$1,000, \$6,000-\$8,000, and \$9,000-\$10,500 ranges. Figure A.14 in the Appendix also shows the number of TA applications with reported vehicle flood damage by income group, and shows that approximately 70% of applications come from individuals or households making <\$30,000 per year. Across 28,474 TA awards to applicants with vehicle flood damage, a total

[18] In the FEMA IA program, certain forms of ONA, such as TA, are "SBA-dependent." This means an IA applicant is only eligible to receive the SBA-dependent form of IA if they have first unsuccessfully applied for a SBA disaster loan.

of \$131.7 million was awarded by FEMA from 2007-2022. These findings provide compelling evidence to suggest H2 is true. Further, Figure A.15 indicates more than half of all TA award dollars were awarded in connection with just four disaster-state cases: Hurricane Sandy in New York (2012), Hurricane Harvey in Texas (2017), severe unnamed storms in Louisiana (2016), and Hurricane Ike in Texas (2008). According to results in Table 3.1, the average water level at sample applicants' residences during the flood event that damaged their vehicle(s) was 17.4 inches. However, as the plot in Figure A.16 highlights, relatively large TA awards were disbursed to some applicants reporting little or no flood damage at their residence, while other applicants with high reported water levels at their residence received no TA award. These results suggest vehicles and residences are not always co-located, and in some cases households' vehicles and residences may experience different depth or intensity of flood exposure. Additionally, these results imply the potential for applicants to experience significant flood exposure, but not receive requested assistance due to ineligibility.

3.4 Methods

3.4.1 Dasymetric mapping

A dasymetric mapping approach is adopted to test H1 and provide tractable estimates for the number and value of vehicles located in US floodplains. Vehicles, like people, are dynamic in space and time, so the true number of vehicles in US floodplains is not static. While the frontiers of remote sensing data and machine learning techniques are advancing such that researchers are able to observationally identify the number of vehicles in a limited geographic area at a specific point in time with considerable accuracy (Froidevaux et al., 2020), such approaches are not currently viable at scale using publicly-available data.

Table 3.1: Individuals and Households Program summary statistics, applications with recorded vehicle flood damage

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	**Mean TA award***	**Median TA award***	**# of applications**	**Applications receiving TA†**	**Applications eligible for SBA loan†**	**Mean water level (inches)**	**Flood insurance†**	**Homeowners insurance†**
2007	$2,849	$1,075	9,626	0.13	0.07	20.0	0.16	0.51
2008	$2,839	$600	41,462	0.13	0.04	18.6	0.19	0.40
2009	$3,395	$1,689	9,743	0.15	0.04	16.4	0.08	0.40
2010	$3,680	$2,267	22,999	0.08	0.04	14.9	0.09	0.43
2011	$3,628	$2,144	5,655	0.21	0.02	17.4	0.11	0.31
2012	$7,921	$10,000	15,607	0.33	0.06	30.6	0.23	0.39
2013	$4,806	$3,828	1,331	0.24	0.01	13.5	0.04	0.19
2014	$2,341	$645	4,161	0.15	0.01	8.3	0.01	0.10
2015	$4,068	$4,263	1,996	0.31	0.01	8.9	0.03	0.11
2016	$4,764	$6,000	11,352	0.29	0.02	16.9	0.05	0.13
2017	$4,712	$4,659	24,640	0.22	0.03	12.0	0.05	0.11
2018	$4,194	$1,786	1,623	0.27	0.02	9.9	0.04	0.11
2019	$5,000	$6,000	1,292	0.20	0.02	11.8	0.06	0.11
2020	$4,330	$4,000	1,526	0.04	0.01	14.4	0.02	0.03
2021	$5,879	$6,000	6,916	0.10	0.02	17.1	0.03	0.12
2022	$5,848	$7,500	636	0.03	0.00	25.1	0.02	0.08
2007-2022	$4,624	$5,000	160,565	0.18	0.03	17.4	0.12	0.31

*among applicants receiving any Transportation Assistance amount >$0.
† number represents share of applications.
Note: data obtained from FEMA via FOIA request 2022-FEFO-00575.

Dasymetric mapping can be employed to improve the spatial accuracy of data that are aggregated into arbitrary geographic units, such as population estimates produced by USCB. A binary division dasymetric mapping approach is used at the census tract level (Sleeter & Gould, 2007; Swanwick et al., 2022), with the land area of each CONUS state designated as "developed" or "not developed" at 30-meter resolution based on USGS's NLCD. Such a measure assumes the US vehicle population is located entirely on land that is "developed" as defined by USGS, and takes into account the fact the US vehicle population is not evenly distributed across each census tract's land area.

The number of vehicles located in FEMA's SFHA and MFHA in each census tract is estimated using Equation (3.1). "Developed land in flood zone" refers to the land area of each census tract that is both developed *and* in a FEMA-designated flood zone (i.e., SFHA or MFHA). It is important to note this equation assumes there is a homogeneous distribution of household vehicles across all developed areas regardless of land use intensity and may bias the estimates of the floodplain population (Flores et al., 2023), however this is an assumption that has been used elsewhere in the flood hazard exposure literature to produce credible spatially-explicit human population flood exposure estimates (Tate et al., 2021).

To produce estimates of the value of vehicles in FEMA flood zones using dasymetric mapping results, the number of exposed vehicles as calculated by Equation (3.1) is multiplied by the 2019-2021 KBB average used vehicle sale price referenced above. An illustrative example describing the data inputs used in Equation (3.1) is shown for 13 census tracts in Miami Beach, FL in Figure 3.7. Panel (a) includes the census tracts' land boundaries and FEMA flood zone areas,[19] while Panel (b) shows the same tracts' land use statuses according to USGS's 2019 NLCD product. Table 3.2 shows results from Equation (3.1), in Panel (a) showing the illustrative census

[19]This area does not contain MFHA zones.

tracts' estimated 2020 human and vehicle populations, land area (km^2), developed land area (km^2), share of developed land in a SFHA, and estimated number of vehicles in a SFHA. Panel (b) shows mean and median values for these same metrics across the 83,267 census tracts in the CONUS study area. Estimates indicate 100% of developed land area for ten of the illustrative Miami Beach tracts is located within FEMA SFHAs, therefore all household vehicles in these tracts are estimated to be in SFHAs. Sample-wide estimates in Panel (b) underscore these Miami Beach tracts are more flood-exposed, and contain a much higher share of household vehicles in the SFHA, than the average sample census tract.

$$\text{\# of exposed vehicles}_{CONUS} = \sum_{i=1}^{n} \left[\left(\text{Total vehicles}_i \right) \text{ x } \left(\frac{\text{Developed land in flood zone (km}^2)_i}{\text{Total developed land (km}^2)_i} \right) \right] \tag{3.1}$$

where:

i = census tract

n = total number of census tracts, 2020 (83,287)

3.4.2 Spatial matching

To complement the dasymetric mapping approach for estimating the value of vehicles in flood-prone areas, simple spatial matching techniques are used to determine the flood exposure of estimated vehicle value at USACE NSI structures relative to both the FEMA flood mapping product and FSF-FM flood mapping outputs. First, a spatial subset technique using a geographic information system identifies USACE NSI structures that are located within FEMA SFHA and MFHA boundaries. Second, as shown in Figure 3.8, geolocated FSF property-level Flood Factor scores (shown in orange) are matched to geolocated USACE NSI structure data (shown in green) if certain spatial criteria are met. In the scenario with more stringent criteria, denoted

Figure 3.7: 13 illustrative census tracts in South Beach, Miami Beach, Florida by FEMA flood zone (left) and USGS NLCD land use designation (right)

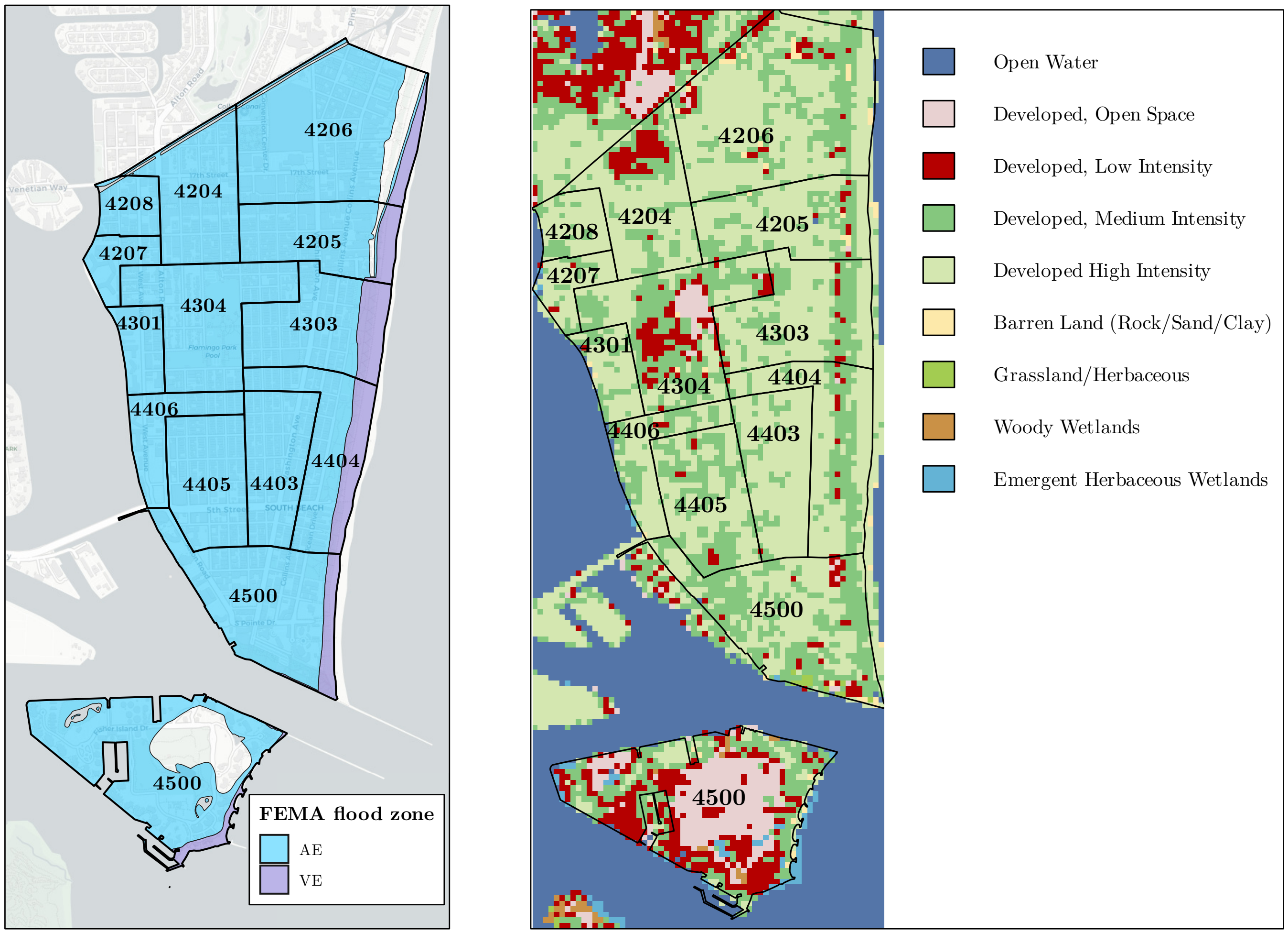


Table 3.2: Summary statistics for census tracts' land area and number of vehicles in FEMA Special Flood Hazard Areas

Panel (a): 13 illustrative census tracts in South Beach, Miami Beach, Florida.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Census tract GEOID	**Population (est.)**	**Land area (km^2)**	**Developed land (km^2)**	**Developed share**	**Developed & SFHA (km^2)**	**SFHA share of developed**	**Total household vehicles (est.)**	**Vehicles in SFHA**
4204	2,368	0.39	0.39	1.0	0.39	1.0	871	871
4205	2,111	0.37	0.37	0.99	0.36	0.98	730	711
4206	2,079	0.87	0.85	0.98	0.78	0.92	1,233	1,128
4207	2,797	0.11	0.11	0.96	0.11	1.0	1,600	1,600
4208	1,411	0.13	0.12	0.99	0.12	1.0	837	837
4301	2,449	0.13	0.13	0.96	0.13	1.0	1,333	1,333
4303	2,749	0.43	0.43	1.0	0.43	1.0	972	972
4304	2,209	0.50	0.49	1.0	0.49	1.0	1,143	1,143
4403	3,481	0.32	0.32	1.0	0.32	1.0	1,285	1,285
4404	2,206	0.40	0.40	1.0	0.40	1.0	941	941
4405	3,763	0.35	0.35	1.0	0.35	1.0	1,468	1,468
4406	2,493	0.19	0.19	0.96	0.19	1.0	1,308	1,308
4500	3,983	1.54	1.35	0.88	1.18	0.87	2,382	2,082

Panel (b): All census tracts in the sample (N=83,267)

	Population (est.)	**Land area (km^2)**	**Developed land (km^2)**	**Developed share**	**Developed & SFHA (km^2)**	**SFHA share of developed**	**Total household vehicles (est.)**	**Vehicles in SFHA**
Mean	3,887	92.17	5.60	0.62	0.34	0.07	1,457	157.0
Median	3,782	4.65	3.28	0.75	0.07	0.02	1,407	49.5

by “NSI-FSF-A” in Table 3.4 and Table A.8, USACE NSI and FSF observations are matched if they are within five meters of one another in horizontal space (i.e., within five-meter buffer polygons surrounding the USACE NSI structure-level data as shown in Figure 3.8) *and* within one meter of one another in vertical space vis-à-vis structure foundation height above NAVD88. Figure 3.8 presents examples of USACE NSI vehicle value observations which are excluded from the more stringent spatial matching criteria on the basis of the horizontal space criterion; USACE NSI structures, their buffers shown in green, without a corresponding overlapping FSF-FM property are not included in “NSI-FSF-A” estimates. In a less stringent spatial matching criteria scenario, denoted “NSI-FSF-B” in Table 3.4 and Table A.8, USACE NSI and FSF observations are matched if they are within fifteen meters of one another in horizontal space and two meters of one another in vertical space.

3.4.3 Regression models

The below estimation approaches are informed by guidance described in Wooldridge, 2010. In the case of FEMA IHP TA application outcomes, the appropriate estimation techniques depend on the specific research questions being asked. Recent scholarship underscores the importance of distinguishing between the intensive and extensive margins when evaluating outcomes with continuous values that can also equal zero (Chen & Roth, 2023), such as IHP TA applications. As noted in the previous section, more than 80% of the 160,565 IHP TA applications reporting vehicle flood damage did not receive an award, and the median award among award recipients was $5,000. In this chapter, both the extensive and intensive margins of IHP TA application outcomes are of interest. The selected model approaches described below are therefore motivated by a desire to understand the (i) factors that influence whether an application successfully receives a TA award, and (ii) factors that predict a smaller or larger award amount given the application received an award >$0.

Figure 3.8: Illustrative example of spatial matching with five-meter buffer, Dare County, NC

3.4.3.1 Probit

A standard Probit model is used to evaluate the extensive margin, specifically factors that may influence whether an application for TA ultimately receives an award. As described in Wooldridge (2010), a Probit model can be used to model binary response probabilities. Etymologically, the term “Probit” is a portmanteau of “probability” and “unit” representing a “probability unit” (Bliss, 1934). In this research setting, use of a nonlinear model, such as Probit, is preferred over a linear probability model (LPM) due to the fact LPM may erroneously estimate fitted values outside the true binary response interval [0,1]. Further, LPM coefficient estimates are of limited value with respect to interpretability given inherent shortcomings of LPM model construction, notably LPM’s estimation of constant marginal effects regardless of explanatory variable values. In this study, the response probability of interest estimated via Probit is the probability an applicant reporting vehicle flood damage receives a TA award conditional on a set of observed characteristics about the application. Equation (3.2) below provides general intuition for the Probit model:

$$P(y = 1|x) = G(x\beta) \tag{3.2}$$

where x is (1 x K) representing the explanatory variable vector, β is (K x 1) representing the parameter vector, the first element of x is unity (i.e., one), and G(.) is the cumulative distribution function of the standard normal distribution, the link function of the Probit model. β parameter estimates are numerically determined via maximum likelihood estimation (Wooldridge, 2010).

$$\text{Award}_{i,d,c,y} = \beta_1\gamma_d + \beta_2\lambda_{c*y} + \alpha X_{i,y} + \epsilon_{i,y} \tag{3.3}$$

Equation (3.3) represents the Probit model employed to test H3 and explore related determinants of receiving a TA application award. The response variable, *Award*, may take on a value of either 0 or 1, and corresponds to IHP application i in connection with FEMA disaster number d submitted in year y from an applicant in county c. The γ term corresponds to a FEMA disaster fixed effect and the λ term corresponds to a county-year fixed effect. X represents a vector of application-specific characteristics, including: (i) a categorical variable describing applicant's annual household income; (ii) reported water depth above ground level at applicant residence during disaster event; (iii) number of members in household; (iv) household flood insurance status; and (v) household homeowners insurance status. ϵ is an idiosyncratic error term.

3.4.3.2 Ordinary least squares

An ordinary least squares (OLS) approach is used to examine the intensive margin on a subset of observations which received a TA award. In Equation (3.4), the response variable is no longer a binary as above, but instead a continuous value representing the natural log of the TA award amount received by an applicant given the award amount is > \$0.

$$Ln(\text{Award amount})_{i,d,c,y} = \beta_1\gamma_d + \beta_2\lambda_{c*y} + \alpha X_{i,y} + \epsilon_{i,y} \tag{3.4}$$

As outlined in Chen & Roth (2023), when considering estimation approaches to evaluate an outcome variable that is weakly-positive but can also equal zero, estimating separate effects (e.g., via OLS and Probit such as above) to study the intensive and extensive margins is presented as one tractable approach. Additionally, estimating a model using Poisson regression and expressing the average treatment effects in levels as a percentage is also presented as an alternative. Results using this approach are shown in Appendix Table A.9.

3.5 Results

3.5.1 Estimated number and value of vehicles in floodplains

3.5.1.1 Dasymetric mapping

Table 3.3 presents estimates of the dasymetric mapping approach from Equation (3.1) for the top five and bottom five CONUS states by estimated number of vehicles in FEMA SFHAs[20]. Table A.7 shows these values for all 48 CONUS states. The margins of error for the 95% confidence interval are shown, and the only source of uncertainty included in these intervals originate from the USCB ACS population sampling process. Results provide convincing evidence to support the claim H1 is true, specifically that a large number of vehicles are located in US floodplains. Main estimates find approximately 13.1 million (±19,907), 95% confidence interval [CI]) household vehicles are in SFHAs in CONUS states, and approximately 23.3 million (±31,768, 95% CI) household vehicles are in MFHAs. Figure 3.9 Panel (a) displays state-level results from Table A.7 rounded to the nearest hundred-thousand vehicles.

The three most populous states in the US are also the states with the highest estimated number of household vehicles in SFHAs. Florida has the highest estimated number of vehicles in floodplains by a wide margin, with approximately 2.9 million (±16,744 95% CI) vehicles in SFHAs and more than 4.1 million (±23,845, 95% CI) in MFHAs. California and Texas are the only other two states estimated to have approximately one million or more household vehicles in SFHAs. While for most states the total estimated number of vehicles in MFHAs is higher than the number of vehicles in SFHAs by a factor of two or less, Arizona is an outlier. Approximately 163,600 (±1,401, 95% CI) household vehicles are estimated to be in SFHAs in Arizona, however nearly three million (±11,864, 95% CI) are estimated to be in MFHAs. Upon

[20] "Top five" and "bottom five" determinations are made according to estimated values shown in column (1)

detailed inspection of the state's NFHL maps, this large disparity between the number of vehicles in SFHAs and MFHAs is likely due to the fact the vast majority of the city of Phoenix, along with the surrounding metropolitan region, lies in MFHAs. Figure 3.9 Panel (b) illustrates the estimated value of vehicles in SFHAs by state, reflecting the product of Table A.7 column (1) estimates multiplied by the aforementioned KBB price of $23,367. Analogous results showing the number and value of vehicles in MFHAs in CONUS states may be found in the Appendix in Figure A.17.

Findings also indicate a sizable share of vehicles in flood-prone areas are located in communities which meet a key US Federal government regulatory definition of "disadvantaged." Specifically, the metric used to make this determination is the 2020 census tract-level CDC Social Vulnerability Index (SVI) score, with tracts exhibiting SVI scores above 0.6 considered "disadvantaged." This metric and threshold is selected because it was the interim criterion used by FEMA in their FY2022 Building Resilient Infrastructure and Communities (BRIC) program cycle to categorize areas as "disadvantaged" in compliance with Executive Order 14008 and subsequent guidance (FEMA, 2023g). In 2020, nearly 40% of the CONUS population resided in a disadvantaged census tract according to this criterion. Estimates in Table 3.3 and Table A.7 suggest approximately 5.2 million (±9,850, 95% CI) vehicles in disadvantaged census tracts are located in SFHAs, while 10.0 million (±20,770, 95% CI) vehicles in disadvantaged census tracts are in MFHAs. These findings imply many vehicles in flood-prone areas are owned by disadvantaged populations.

3.5.1.2 Spatial matching

The spatial matching techniques outlined above do not generate estimates for the number of vehicles in flood-prone areas, but they do produce estimates for the value of vehicles in flood-prone areas across multiple flood mapping products. These results serve as a robustness check to the above dasymetric mapping estimates. Table

Table 3.3: Estimated number of vehicles in FEMA Special Flood Hazard Area and Moderate Flood Hazard Area, thousands

	(1)	(2)	(3)	(4)	(5)	(6)
State	**Est. in SFHA**	**95% CI ME**	**Est. in SFHA, disadvantaged**	**Est. in MFHA**	**95% CI ME**	**Est. in MFHA, disadvantaged**
Top five states						
Florida	2,917.4	±16.7	1,269.5	4,144.0	±23.8	1,849.0
Texas	1,355.4	±4.6	735.7	2,116.9	±7.2	1,144.5
California	999.6	±3.3	531.6	3,339.4	±8.9	1,951.3
Louisiana	631.4	±4.5	269.4	923.1	±6.2	441.4
New York	436.8	±3.3	168.4	721.5	±4.6	288.1
Bottom five states						
Wyoming	11.6	±0.2	2.5	22.0	±0.4	5.2
Maine	15.9	±0.2	3.4	18.3	± 0.2	4.3
Vermont	16.4	±0.2	4.3	20.3	±0.5	5.2
Montana	29.6	±0.4	6.1	50.3	±0.6	9.1
Idaho	32.5	±0.5	9.7	78.2	±1.3	23.9
All 48 CONUS states	13,074.9	±19.9	5,174.2	23,341.3	±31.8	10,000.2

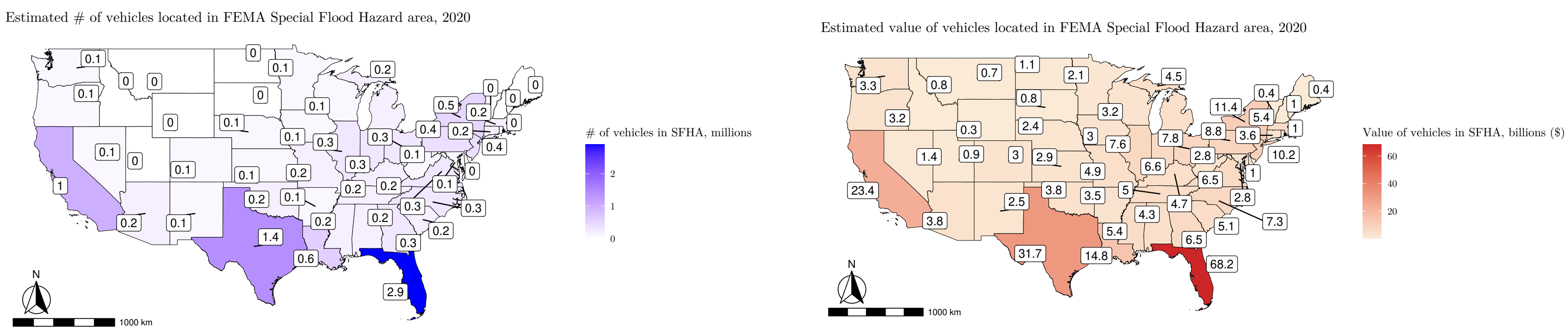


Figure 3.9: Panel (a) shows the estimated number of vehicles in FEMA SFHA, millions, 2020. Panel (b) shows the estimated value of vehicles in FEMA SFHA, billions ($), 2020 using the dasymetric mapping technique.

3.4 provides estimates of the value of vehicles across techniques and data products for the top five and bottom five CONUS states according to estimated values in column (1). Results for all 48 CONUS states may be found in Table A.8.

Columns (1) and (2) show estimates of the value of flood-exposed vehicles from the previous section using the dasymetric mapping technique estimates and the aforementioned KBB weight average price. Columns (3) and (4) include the estimated value of vehicles from USACE NSI structures that are within FEMA SFHAs and MFHAs, therefore they rely upon the same flood mapping product as columns (1) and (2), but a different vehicle value data source. Last, columns (5) and (6) represent estimates based on matched USACE NSI and FSF-FM property-level data for properties determined by FSF to have "major" flood risk. Column (5) shows results from the matches meeting the more stringent spatial criteria (five-meter horizontal space radius; one-meter vertical space radius) while column (6) shows estimates from the approach using less stringent spatial criteria (fifteen-meter horizontal space radius; two-meter vertical space radius).

While there is some variation across estimates indicating results are moderately sensitive to vehicle data sources as well as flood mapping data sources, there are a number of consistent insights across methods and data products which imply robust findings. First, these findings provide further evidence H1 is true. Even in the lowest national estimate shown in Table 3.4, the value of vehicles in SFHAs according to USACE NSI georeferenced values, an estimated \$227.6 billion worth of vehicles in CONUS state areas are estimated to have a 1% AEP of flood exposure each year. At the highest end, column (2) findings indicate more than half a trillion dollars' worth of household vehicles are estimated to be in areas estimated by FEMA to have at least a 0.2% AEP of flood exposure.

A number of sensitivities worth discussing are present in these results. While the dasymetric mapping-derived estimates in column (2) suggest the value of vehicles in MFHAs is greater than the value in SFHAs by a factor of approximately 1.7, the USACE NSI estimates in column (4) estimate the value of vehicles in MFHAs is greater than the value in SFHAs by a factor of nearly 2.2, suggesting the results using USACE NSI inputs are more sensitive to SFHA and MFHA status than dasymetric mapping vehicle value inputs. Additionally, CONUS-wide results in column (6) are greater than those in column (5) by a factor of 1.4, highlighting the sensitivity of results using FSF-FM outputs to stringency of spatial matching criteria.

Despite sensitivities, clear patterns are evident at both the state and CONUS level. Florida persists as the state with the greatest estimated value of vehicles in flood-prone areas across all methods and data inputs shown in Tables 3.4 and A.8. Even the lowest estimate finds approximately $60 billion worth of vehicle assets in the state are in areas with FSF-defined "major" flood risk, while the highest estimate indicates more than $100 billion worth of vehicles are in Florida FEMA SFHAs and MFHAs. California, Texas, Louisiana, and New York are all also consistently among the states with the greatest aggregate vehicle value exposed to potential flooding, at scales in the tens of billions of dollars.

While technical comparison of estimates across flood models is difficult due to limited available information regarding methodology and precise exposure probabilities within the FEMA flood zone designations and FSF-FM Flood Factor scores, the estimates across methods and data sources are similar enough in magnitude to imply a convergence toward credible insight in the aggregate. When comparing what are arguably the most conservative estimates in Table 3.4, columns (1), (3), and (5), estimated values differ from one another by no more than a factor of 1.45. Thus, these findings point toward general agreement: hundreds of billions of dollars' worth of vehicles are estimated to be located in flood-prone areas in CONUS.

While multiple key uncertainties remain about vehicle owners' vehicle flood damage mitigation behaviors in advance of and during flood events, as well as true spatial distribution of vehicles and their value, constructing a simple back-of-the-envelope estimate of average annual losses (AAL) may be instructive for intuition and to inform future research, recognizing much more refinement is needed to improve the accuracy and actionability of such estimates. By applying the probability of exposure to a 1% AEP flood event with depth of two feet[21] to the estimated population of vehicles in SFHAs, and assuming a conservative depth-damage estimate of 30% based on USACE estimates illustrated in Figure 3.3, we may move toward an AAL estimate for vehicle flood damages. This approach, among other assumptions, does not assume any vehicles move into nor out of the floodplain during the flood event, all vehicles are located at ground level, and assumes statistical independence between vehicles' flood exposure probabilities such that 1% of all vehicles in SFHAs are exposed to a two-foot flood in a given year. Critically, this simple calculation does not account for heterogeneity in vehicle type, which has important implications for vehicle value and vulnerability. Data from Table A.8 column 1 are used in this simple method multiplying these three terms–(i) estimated value of vehicles in SFHA, (ii) approximate annual probability of exposure to a two-foot flood event, and (iii) estimated damages associated with exposure to a two-foot flood event–to arrive at a crude AAL estimate of nearly one billion dollars per year.

3.5.2 FEMA Individuals and Households Program outcomes

3.5.2.1 Extensive margin analysis

Table 3.5 below presents results from the Probit regression model specified in Equation (3.3). As noted in Section 3.4.3.1, interpretation of Probit results is different

[21] While FEMA flood zones unfortunately do not universally provide information about expected flood depths of the 1% AEP flood event in all flood zones, this information is available for some zones such as Zone AO and AH. In these SFHA zones the anticipated depths of the 1% AEP flood event are 1-3 feet. Zones V, VE, and V1-30 all carry risk from additional hazard from wave action. For the purposes of this exercise, a magnitude of 2 feet is selected as this is the central advertised modeled depth in FEMA SFHA zones AO and AH.

Table 3.4: Estimated value of flood-exposed vehicles (millions) [$]

State	DM-SFHA	DM-MFHA	NSI-SFHA	NSI-MFHA	NSI-FSF-A	NSI-FSF-B
	(1)	(2)	(3)	(4)	(5)	(6)
Top five states						
Florida	$68,172	$81,410	$67,214	$103,362	$59,840	$78,630
Texas	$31,673	$49,465	$18,360	$34,207	$21,721	$32,878
California	$23,357	$78,031	$14,992	$65,280	$44,084	$64,327
Louisiana	$14,754	21,570	$11,325	$19,251	$15,831	$21,827
New York	$11,368	$16,860	$7,075	$11,935	$16,242	$21,707
Bottom five states						
Wyoming	$270	$515	$223	$579	$927	$1,197
Maine	$373	$428	$243	$315	$1,012	$1,481
Vermont	$383	$474	$325	$448	$770	$1,191
Montana	$691	$1,176	$574	$1,100	$2,315	$2,832
Idaho	$759	$1,826	$610	$1,901	$2,979	$3,618
CONUS total	$305,521	$529,841	$227,599	$493,461	$330,536	$467,586
Vehicle data source	DM	DM	USACE NSI	USACE NSI	USACE NSI	USACE NSI
Flood data source	FEMA NFHL	FEMA NFHL	FEMA NFHL	FEMA NFHL	FSF-FM	FSF-FM

from OLS results due to the non-linear nature of the link function. Results presented in Table 3.5 represent estimated marginal effects of explanatory variables on the extensive margin regarding TA award receipt among IHP applications reporting vehicle flood damage, evaluated in more detail below.

Results from the preferred specification are shown in column (6), with a reference level scenario of an application submitted by an applicant with a reported household income of $30,0001-$60,000 per year in a household of three individuals with no flood insurance, no homeowners insurance, and zero inches of floodwater at the applicant's residence. This model includes disaster number fixed effects as well as county-year fixed effects to control for unobserved heterogeneity in these groups which may be correlated with both explanatory variables and TA award outcome. This preferred specification predicts an applicant from the reference level values described above has a 10% probability of receiving a TA award. Findings across specifications generally indicate at a 0.01 significance level that applicants from households making $0 per year were less likely to receive a TA award than similar applicants from the reference level income category. In the preferred specification, the estimated probability of an applicant from a household making $0 is approximately 1.6 percentage points lower than a similar applicant at the reference level values.[22] As hypothesized in H3, this suggests that while the majority of IHP applications in the sample originate from households making <$30,000 per year–generally considered to be "low-income" by Federal standards (US DOE, 2023)–the lowest-income applicants have a relatively lower probability of receiving a TA award than low- and moderate-income households with relatively higher incomes.

However, contrary to hypothesized results, applications from low-income households in the $1-$30,000 per year range appear to have significantly higher probability of receiving a TA award relative to the reference level values as well as higher-income applicants. For example, preferred estimates in Table 3.5 column (6) show that holding other reference level variables constant, an application from a household making $1-$15,000 per year (low-income) is estimated to have a probability of receiving a TA award that is approximately 14 percentage points higher than a similar application from a household making $30,001-$60,000. On the higher end of the income distribution, estimates indicate an applicant from a household making $120,001-$175,000 per year has a probability of receiving a TA award that is approximately 7.3 percentage points lower than an otherwise observably equivalent applicant making $30,001-$60,000 per year. These findings imply that while the lowest-income applicants (i.e., applicants with no reported income) appear to have a marginally lower probability of receiving a TA award than applicants in the $1-$60,000 per year range, applicants making more than $60,000 per year appear to have significantly lower success rates than lower-income applicants even when controlling for other factors. Thus, along the extensive margin, having an income that is too low (i.e., $0) or too high (i.e., >$60,000 per year) may negatively impact TA award outcomes.

[22]This probability is calculated by adding the z-score associated with estimated baseline response probability 0.10 produced by the specification in Table 5 column (6), -1.275, to the coefficient estimate and deriving the value of the standard normal cumulative distribution function at this z-score.

Besides income, a number of other control variables are consistently correlated with successful TA applications across specifications. Notably, while the preferred specification does not indicate household size influences probability of receiving a TA award among applications from households with two individuals or more, applications from single-person households persistently are estimated to have relatively higher probability of success. Interpretation of these results in the context of IHP program design follows in Section 3.6. While specifications in Table 3.5 columns (1) through (4) indicate a positive, statistically significant relationship between floodwater depth at applicant residence and the response probability of interest, this association is not present when county-year fixed effects are included in columns (5) and (6). These results do not suggest floodwater depth at applicant residence to be a robust predictor of TA award receipt. Last, applicants with homeowners insurance appear to have lower probabilities of TA award success.

3.5.2.2 Intensive margin analysis

Table 3.6 presents results from the model specification shown in Equation (3.4) with the same reference levels outlined in Section 3.5.2.1. While the previous section analyzed factors influencing IHP TA application award outcomes along the extensive margin, this section only focuses on the sample of 28,474 IHP applications which received a TA award. The preferred specification is similarly shown in column (6), and this model includes disaster number fixed effects and county-year fixed effects. Most notably, estimates in column (6) indicate a positive correlation between applicant household income and TA award amount at certain income levels. Specifically, model results suggest an applicant coming from a household making \$1-15,000 per year would be expected to receive an award amount that is -16.3% (-22.1% to -10.0%, 95% CI) and an applicant coming from a household making \$15,001-\$30,000 per year would be expected to receive an award that is -9.9% (-15.2% to -4.3%, 95% CI) relative to a

Table 3.5: Probit model results

Dependent Variable:	Applicant received Transportation Assistance award >0? (1=yes; 0=no)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables						
Household income: \$0	-0.0105	-0.0310*	-0.0897***	-0.1101***	-0.1067***	-0.1060***
	(0.0173)	(0.0174)	(0.0177)	(0.0189)	(0.0341)	(0.0342)
Household income: \$1-\$15,000	0.6610***	0.6370***	0.5548***	0.5627***	0.5756***	0.5759***
	(0.0115)	(0.0115)	(0.0121)	(0.0129)	(0.0446)	(0.0447)
Household income: \$15,001-\$30,000	0.4412***	0.4309***	0.3787***	0.4051***	0.4128***	0.4131***
	(0.0117)	(0.0118)	(0.0120)	(0.0128)	(0.0260)	(0.0261)
Household income: \$60,001-\$120,000	-0.3571***	-0.3489***	-0.2892***	-0.3718***	-0.3746***	-0.3739***
	(0.0200)	(0.0201)	(0.0204)	(0.0221)	(0.0216)	(0.0217)
Household income: \$120,001-\$175,000	-0.6000***	-0.5852***	-0.5002***	-0.6477***	-0.6488***	-0.6486***
	(0.0569)	(0.0570)	(0.0575)	(0.0630)	(0.0531)	(0.0531)
Household income: >\$175,000	-0.4280***	-0.4256***	-0.3744***	-0.4828***	-0.4864***	-0.4864***
	(0.0588)	(0.0588)	(0.0591)	(0.0649)	(0.0996)	(0.0997)
Water level (inches)	0.0024***	0.0023***	0.0028***	0.0004**	7.84×10^{-5}	8.25×10^{-5}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Household size: 1 (ref. = 3)	–	0.1513***	0.1524***	0.1386***	0.1357***	0.1358***
		(0.0115)	(0.0115)	(0.0121)	(0.0204)	(0.0205)
Household size: 2 (ref. = 3)	–	0.0134	0.0242**	0.0188	0.0168	0.0170
		(0.0117)	(0.0118)	(0.0123)	(0.0141)	(0.0141)
Household size: 4 (ref. = 3)	–	-0.0057	-0.0055	0.0058	0.0039	0.0043
		(0.0135)	(0.0136)	(0.0141)	(0.0180)	(0.0180)
Household size: 5 (ref. = 3)	–	-0.0341**	-0.0369**	-0.0160	-0.0142	-0.0140
		(0.0161)	(0.0162)	(0.0169)	(0.0185)	(0.0185)
Household size: >5 (ref. = 3)	–	-0.0562***	-0.0638***	-0.0372**	-0.0318	-0.0313
		(0.0170)	(0.0171)	(0.0178)	(0.0197)	(0.0197)
Flood insurance? (ref. = No)	–	–	0.0864***	-0.0149	-0.0068	-0.0071
			(0.0145)	(0.0155)	(0.0350)	(0.0350)
Homeowners insurance? (ref. = No)	–	–	-0.3054***	-0.2200***	-0.2226***	-0.2230***
			(0.0106)	(0.0117)	(0.0340)	(0.0340)
Fixed effects						
Disaster number	No	No	No	Yes	No	Yes
(County)*(application year)	No	No	No	No	Yes	Yes
Fit statistics						
Observations	160,564	160,564	160,564	160,026	155,992	155,872
Pseudo R^2	0.04919	0.05163	0.05765	0.13478	0.14258	0.14284

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

baseline applicant with household income of \$30,001-\$60,000 per year. Thus, among TA awardees in this \$1-\$60,000 per year household income range, evidence suggests household income may positively influence TA award amount.

Unlike results estimated along the extensive margin, water level at applicant residence persists as positively associated with TA award amount across specifications in Table 3.6. In the preferred model in column (6), estimates conclude a one-inch increase in floodwater depth at an applicant's residence is associated with a 0.7% (0.5% to 0.9%, 95% CI) increase in TA award amount. Additionally, having flood insurance is estimated to increase a successful applicant's award amount on average by 22.3% (12.8% to 32.8%, 95% CI) ceteris paribus while having homeowners insurance is estimated to lead to a change in award amount of -9.7% (-14.4% to -4.7%, 95% CI) ceteris paribus.

These results also provide compelling evidence to support the claim that H2 is true. It is important to note due to data limitations I am unable to analyze the extent to which TA award amount correlates with magnitude of vehicle flood damage, as information describing estimated vehicle flood damage is not available in the FEMA data. Based on this analysis of award amounts and knowledge of the key IHP objective to provide assistance to meet basic needs, it appears reasonable to assume TA award amounts are lower than the whole dollar value of actual vehicle flood damages.

3.6 Discussion

3.6.1 Policy implications

The findings above have direct and indirect relevance for public policy at multiple levels of government, as well as for private vehicle owners and manufacturers. This research demonstrates vehicles are widely-owned, economically-important assets with considerable exposure to flood hazard. While hundreds of billions of dollars' worth of household vehicles are estimated to be in US floodplains, these assets are not covered by the NFIP, a cornerstone program of the US Federal government's flood mitigation policy regime. The NFIP's current landing page states:

> *Flood insurance is a separate policy that can cover buildings, the contents in a building, or both, so it is important to protect your most important financial assets — your home, your business, your possessions.* (FEMA, 2023f)

Table 3.6: OLS model results

Dependent Variable:	Ln(Transportation award amount [$])					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Household income: $0	-0.0798**	-0.1179***	-0.1088***	-0.0493	-0.0207	-0.0231
	(0.0407)	(0.0406)	(0.0406)	(0.0381)	(0.0316)	(0.0317)
Household income: $1-$15,000	-0.4499***	-0.5031***	-0.4858***	-0.2472***	-0.1797***	-0.1774***
	(0.0251)	(0.0252)	(0.0254)	(0.0240)	(0.0360)	(0.0367)
Household income: $15,001-$30,000	-0.2596***	-0.2862***	-0.2704***	-0.1394***	-0.1032***	-0.1040***
	(0.0260)	(0.0259)	(0.0260)	(0.0238)	(0.0307)	(0.0309)
Household income: $60,001-$120,000	0.0838*	0.0890*	0.0568	-0.0766*	-0.0661*	-0.0626*
	(0.0503)	(0.0505)	(0.0505)	(0.0448)	(0.0340)	(0.0341)
Household income: $120,001-$175,000	0.2917**	0.3139**	0.2538*	0.1314	0.1654	0.1592
	(0.1364)	(0.1353)	(0.1360)	(0.1341)	(0.1747)	(0.1733)
Household income: >$175,000	0.0988	0.0818	0.0445	0.0858	0.0694	0.0681
	(0.1523)	(0.1532)	(0.1475)	(0.1246)	(0.1106)	(0.1108)
Water level (inches)	0.0164***	0.0163***	0.0159***	0.0096***	0.0070***	0.0070***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0012)	(0.0012)
Household size: 1 (ref. = 3)	–	0.2217***	0.2233***	0.1417***	0.1095***	0.1054***
		(0.0236)	(0.0236)	(0.0219)	(0.0241)	(0.0240)
Household size: 2 (ref. = 3)	–	0.1273***	0.1262***	0.0998***	0.0875***	0.0860***
		(0.0247)	(0.0247)	(0.0226)	(0.0249)	(0.0247)
Household size: 4 (ref. = 3)	–	0.0216	0.0178	0.0441*	0.0602**	0.0588**
		(0.0286)	(0.0286)	(0.0262)	(0.0274)	(0.0271)
Household size: 5 (ref. = 3)	–	-0.0652*	-0.0666**	-0.0283	-0.0052	-0.0077
		(0.0339)	(0.0338)	(0.0312)	(0.0343)	(0.0345)
Household size: >5 (ref. = 3)		-0.0717**	-0.0741**	-0.0500	-0.0251	-0.0256
		(0.0365)	(0.0363)	(0.0337)	(0.0298)	(0.0299)
Flood insurance? (ref. = No insurance)	–	–	0.3675***	0.2519***	0.2025***	0.2018***
			(0.0309)	(0.0282)	(0.0412)	(0.0416)
Homeowners insurance? (ref. = No insurance)	–	–	-0.0988***	-0.1138***	-0.1023***	-0.1021***
			(0.0230)	(0.0210)	(0.0273)	(0.0274)
Fixed-effects						
Disaster number	No	No	No	Yes	No	Yes
(County)*(application year)	No	No	No	No	Yes	Yes
Fit statistics						
Observations	28,474	28,474	28,474	28,474	28,474	28,474
R^2	0.10215	0.10784	0.11170	0.26868	0.33278	0.33527

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

While this language refers to households' "most important financial assets," vehicles are omitted from NFIP coverage despite the financial importance of vehicle assets as demonstrated in Figures 3.1 and 3.2. While the author speculates the prospects for changes at the Federal level that would make vehicle assets eligible for coverage under the NFIP are dim at best in the near term given many criticisms of the program, including some critics recommending program privatization (Born & Klein, 2019; Horzempa, 2018), a contribution of this work is to highlight the gap in resources supporting financial resilience vis-à-vis vehicle asset owners in the wake of flood exposure. To reduce financial vulnerability to vehicle flood damage, Figure 3.5 demonstrates vehicle owners are well-advised to be aware of the scope of coverage provided by available auto insurance policies. The statistics about IHP TA applications and awards in Table 3.1 demonstrate there is a vehicle flood insurance gap that is partially filled by FEMA in the wake of presidentially-declared disasters or emergencies, however no such Federal assistance is available for vehicle owners significantly affected by flood events that do not receive presidential declarations, nor to ineligible applicants in disaster areas. In these cases, vehicle owners without insurance or disaster assistance are likely to bear the financial shock without resources to support recovery. Figure 3.2 demonstrates this financial shock may be particularly substantial for low-wealth vehicle-owning households.

Previous research with a focus on housing also indicates property owners, on average, tend to purchase less insurance after receiving Federal disaster assistance through FEMA's IA programs (Kousky et al., 2018), implying the potential for moral hazard implications. It is possible disaster assistance similarly crowds out vehicle owners from purchasing comprehensive auto insurance coverage, however, limited data availability describing spatially-explicit comprehensive auto insurance policies and related flood-specific claims makes analysis of this topic difficult. While the National Flood Insurance Reform Act of 1994 requires applicants to purchase NFIP coverage for eligible property if they reside in a SFHA as a condition of receiving certain types of IA Federal assistance, no such requirement appears to exist for comprehensive auto insurance and vehicle owners who reside in SFHAs in order to receive IHP TA in connection with vehicle flood damage (FEMA, 2021).

Analysis of FEMA IHP TA applications and awards suggests the program is generally serving populations in alignment with the program objective to "meet basic needs and supplement disaster recovery efforts" when considering vehicle flood damages (FEMA, 2021). More than 70% of IHP TA applicants with vehicle flood damage came from households with household incomes less than $30,000 per year, and contrary to what had been speculated in H3, more than 80% of TA awards were disbursed to applicants in this income bracket. Significantly lower award rates among applicants from higher-income households, as well as relatively higher award rates among applicants from single-person households, implies the program prioritizes awards to individuals and households who are unable to meet necessary expenses and/or serious disaster-caused needs through other means (e.g., alternative vehicle in the household) (Stafford Act, 2019). However, relatively lower probability of receiving a TA award among no-income applicants, as compared with low-income applicants, suggests some of the most financially vulnerable households do not benefit from TA awards (e.g., due to insufficient documentation or insurance coverage per state legal requirements), possibly making post-flood recovery for these applicants difficult.

This work also highlights data limitations which constrain empirical analysis examining issues related to vehicle flood risk. The FEMA IHP data received via FOIA provide some initial insight into the scale and scope of vehicle flood damages in the US, however the FEMA IHP data do not provide detailed information about: 1. type of vehicle that experienced flood damage, 2. depth and duration of vehicle flood exposure, and 3. total amount of vehicle flood damages. Since TA awards are only designed to meet basic needs, award amounts are not intended to represent total vehicle flood damage experienced. Further, widespread missing data on applicants' compliance with insurance and registration requirements limits opportunities to analyze the mechanisms of TA ineligibility. Thus, to enable researchers to produce more valuable insight into issues pertaining to vehicle flood damage and related financial resilience gaps, FEMA might collect, maintain, and disseminate more detailed information about IHP applications reporting vehicle flood damages. Further, insurers and the NAIC might publicly share peril-specific information about comprehensive auto insurance uptake and flood-specific comprehensive insurance claims to increase visibility of insurance gaps in flood-prone areas and/or vehicle flood damage hotspots to inform affected parties as well as potential future policy design.

Last, while research in the residential sector has found flood risk disclosure laws influence risk-aware buyers' decisions such that more efficient market outcomes occur (Hino & Burke, 2021), no such flood risk disclosure laws exist for the millions of vehicle buyers living in SFHAs. Flood risk disclosure at the time of vehicle purchase may be particularly relevant and welfare-enhancing for vehicle-owning renter households, as this segment of the population often does not benefit from existing disclosure laws applicable to sellers and buyers of residential property.

3.6.2 Limits and future work

The present study provides novel insight into vehicle flood exposure at the national level in the US, as well as detailed policy-relevant empirical analysis of FEMA IHP applications reporting vehicle flood damages. However, there are a number of important limitations of the research worth highlighting to contextualize inference and inform future research. First, as noted above, data limitations hamper precise estimates of the number and value of vehicles in US floodplains. Without vehicle-level observational data that are spatially- and temporally-precise, a perfectly-accurate accounting of the number and value of vehicles in US floodplains remains unattainable.

In the the absence of these data, the dasymetric mapping technique approximates the number of vehicles in FEMA-defined floodplains. In addition to incorporating richer remote sensing data, future work may employ the dasymetric mapping technique with more granular assumptions about the density of vehicles within US floodplains (as opposed to relying on the assumption that household vehicles are equally distributed across developed areas), as well as vehicle composition, value, and parking elevation.

Second, a key uncertainty that is not comprehensively addressed in this research is the "retreat" hazard mitigation behavior adopted by vehicle owners before and during flood events. Scholars have long noted the potential for timely warning information to enable adaptive action that can reduce flood damages (Day & Lee, 1976), however the extent to which vehicle owners avoid vehicle flood damage, with and without warning information, is a fertile area for future research. While some studies have assumed 100% of vehicle assets in a given study area would avoid flood damage due to vehicles' mobility (Genovese, 2006), the present chapter's findings demonstrate such assumptions are empirically unjustified. While the above study does not assume a specific avoidance rate among vehicles estimated to be in flood-prone areas, and such an avoidance rate is not included in FEMA's Hazus model (FEMA, 2021) nor USACE's Hydrologic Engineering Center Flood Damage Reduction Analysis (HEC-FDA) tool (USACE, 2016), future work to credibly estimate such a rate may be valuable to place more precise bounds on estimates of aggregate vehicle flood risk, and may also inform broader risk reduction actions. Conversely, given the CDC's statistic indicating a plurality of flood deaths in the US occur in vehicles (CDC, 2020), in the future it may also be worthwhile to explore the extent to which motorists drive *into* flood-prone areas or already-flooded areas, which represents an understudied dimension of flood risk. Thus, given the dynamic and mobile nature of flood hazard and vehicles, it will be a challenge for future empirical researchers to precisely estimate the flow of vehicles entering and exiting flooded areas, in addition to estimating the aggregate number of vehicles in flood-prone areas.

When considering research limits and potential future work, it is also essential to highlight the role of technological advancements to potentially influence future vehicle flood damages. Entrepreneurial manufacturers in the auto sector have hinted at development of automobiles with amphibious capabilities for the general consumer market (Beckford, 2022), which may facilitate in-situ adaptation, a preferred pathway for many residents in flood-prone areas (Seeteram et al., 2023). The growing autonomous vehicle (AV) market also raises important questions about AV programming, responses, and potential regulation with respect flood hazard mitigation (Schwarting et al., 2018). Figure 3.3 only represents depth-damage relationships for flood-affected vehicles containing internal combustion engines, therefore as we look to the horizon, more work is needed to understand the depth-damage relationship for electric vehicles as these vehicle assets grow in market share. As both flood hazards and private passenger vehicle markets evolve in conjunction with forces shaped by climate change, scholarship at this important nexus can inform policy design to support safe and economically-efficient development of transportation assets.

3.7 Conclusions

Vehicles are a widely-owned and economically-important household asset. At the same time the number of vehicles in the US is growing in both absolute and per capita terms, anthropogenic climate change and urban development patterns are increasing the intensity and extent of flooding across the country. While a wide array of informative research has analyzed the exposure of real estate, such as residential property, to flood hazard, this study is the first to estimate the extent of flood exposure of vehicle assets in the US.

Using a dasymetric mapping technique as well as spatial matching algorithm, vehicle-related data from the USCB, KBB, and USACE NSI are integrated with flood mapping products from FEMA and FSF to estimate the number and value of vehicles in US floodplains. Dasymetric mapping results find an estimated 13.1 million household vehicles worth over $300 billion are located in FEMA-designated SFHAs, with 5.2 million of these vehicles located in census tracts defined by the US Federal government as "socially vulnerable." Results are robust to alternative methods and data sources representing geolocated vehicle value and flood exposure; using flood depth and probability outputs from the FSF-FM and USACE NSI estimates of geolocated vehicle value in CONUS, an estimated $330.5 billion worth of vehicle assets are based at sites with "major flood risk." Florida emerges as the US state estimated to have the greatest number and value of vehicles in floodplains, with main estimates finding approximately 2.9 million vehicles worth nearly $70 billion located in FEMA SFHAs. Results suggest a large quantity of household vehicles at sizable aggregate value are located in US floodplains.

The study further undertakes a first-of-its-kind analysis of FEMA IHP application data obtained through a FOIA request to better understand the scale and magnitude of vehicle flood damages and related disaster assistance in the US. Summary statistics as well as statistical analyses using Probit and OLS models examine the population of IHP applicants reporting vehicle flood damage in connection with presidentially-declared disasters or emergencies. Between 2007-2022, FEMA received at least 160,565 IHP applications reporting vehicle flood damage, with more than 70% of applications originating from households making less than $30,000 per year. 28,474 TA awards were disbursed in connection with vehicle flood damage cases, more than 80% of these to applicants from households making less than $30,000 per year. While fewer than one in five applications for TA received an award, the median award amount was $5,000, resulting in more than $131 million awarded by FEMA's IHP to address uninsured vehicle flood damages from 2007-2022. When considering IHP application outcomes, findings indicate households making $1-$30,000 per year had the highest estimated probability of success among all income groups when controlling for other factors, suggesting the IHP program is generally meeting its objective of serving populations who are otherwise unable to meet necessary expenses and/or serious disaster caused needs. However, results also indicate applicants reporting no household income have relatively lower probability of receiving a TA award than observably equivalent low-income (non-zero income) applicants. This suggests that while the IHP is designed to facilitate recovery post-disaster for individuals and households of limited means, inability to meet basic eligibility requirements may disqualify the most financially vulnerable applicants from receiving disaster assistance following a vehicle flood damage event.

There are a number of policy implications from this work. First, while the FEMA IHP data received through FOIA provide valuable insight, granular publicly-available data on comprehensive auto insurance policies and claims, as well as detailed information about individuals and households receiving taxpayer-funded Federal assistance in connection with vehicle flood damages following a presidentially-declared disaster, are generally limited. Given the absence of such data sources through which to empirically examine comprehensive auto insurance uptake rates with geographic precision, or incidence of insured and uninsured vehicle flood damages, observation-based estimates bounding the scale of vehicle flood risk in the US prove elusive. While FEMA IHP data provide some insight into the issue of vehicle flood damages, information about the precise magnitude of flood damages, vehicle type, and vehicle location are all missing from the FEMA data set. More robust publicly-available data on insured vehicle flood damages and uninsured vehicle flood damages for which Federal disaster assistance is disbursed would inform vehicle owners, insurance professionals, transportation planners, and policymakers about the scale and scope of this issue, toward improving behavior and policy design for vehicle flood risk mitigation.

Second, this work highlights IHP TA application outcomes relative to program goals and the broader apparatus of Federal hazard mitigation programs. Despite being an economically-important asset for many households, vehicles are not covered by the NFIP; in the absence of comprehensive auto insurance coverage, IHP TA is a key source of Federal financial assistance responding to uninsured vehicle flood damages following a presidentially-declared disaster or emergency. However, IHP resources are unavailable following non-disaster flood events, and such flood events still have the potential to cause substantial damage to vehicles. Additionally, most IHP applicants reporting vehicle flood damages do not receive a TA award, and TA awards are designed to meet basic needs, not serve as an insurance substitute. Thus, while IHP TA provides some financial resilience to affected uninsured vehicle owners in the wake of large-scale flood events, considerable financial resilience gaps remain for the nearly one-third of motorists in the US estimated to lack comprehensive coverage. These findings suggest policies that promote higher penetration of private insurance coverage, greater awareness of vehicles' flood vulnerabilities to incentivize vehicle flood exposure avoiance, or expanded public resources to support recovery for uninsured flood-affected vehicle owners, may be considered to close financial resilience gaps in flood-prone communities.

Last, given the concurrent and converging trends of the number of vehicles on the road in the US increasing along with growing flood exposure due to climate change and urban development patterns, it is likely new adaptation solutions driven by technological advancements or public policy interventions may emerge to mitigate vehicle flood risk. Policy interventions, such as education campaigns or flood disclosure laws, might empower vehicle owners and drivers with information that enables them to mitigate vehicle flood exposure and/or vulnerabilities. Further, technological advances such as improved warning systems or vehicles with amphibious or autonomous capabilities may similarly reduce vehicle flood risk by bending depth-damage curves downward or facilitating vehicle flood avoidance altogether. As the household vehicle market continues to develop in a world of growing climate risks, it will be critical for manufacturers and owners of new generations of vehicles entering the market, such as AVs and EVs, to consider these vehicles' resilience in the face of a more intense hydrological cycle.

CHAPTER 4

The willingness to pay for vehicle flood insurance

4.1 Introductory remarks

As established in Chaper 3, the mobile nature of vehicles does not preclude vehicle assets from adverse impacts caused by flood hazard exposure. While vehicle owners may exploit vehicles' mobility to avoid or mitigate flood hazard exposure and related damages, employing what may be referred to as a form of the "retreat" hazard risk mitigation strategy (Mach et al., 2019), findings from Chapter 3 indicate uninsured vehicle flood damage cases occur with significant frequency in the US. In addition to disaster assistance, risk-pooling in the form of insurance products is a common mechanism through which individuals can mitigate adverse financial impacts from disasters (Kousky, 2022).

While a large and insightful literature evaluates myriad aspects of flood insurance in the context of residential property (Bradt et al., 2021; Browne & Hoyt, 2000; Chivers & Flores, 2002; Hino & Burke, 2021; Kousky, 2018; Kousky & Michel-Kerjan, 2017; Kousky et al., 2018; Landry & Jahan-Parvar, 2011; Pralle, 2019; Shr & Zipp, 2019; Wing et al., 2020), little attention has been paid to insurance literacy, uptake, and recovery outcomes with respect to vehicle flood damage cases. Similarly, engineering scholars have documented the hydrodynamic conditions under which vehicles lose stability (Martínez-Gomariz et al., 2018; Xia et al., 2014) as well as flood-vehicle depth-damage relationships (Martínez-Gomariz et al., 2019; USACE, 2009), though no dollar estimates of actual sustained vehicle flood damages are available in the academic literature, perhaps due to some of the data limitations outlined in Chapter 3.

This chapter advances the hazard mitigation, climate adaptation, and insurance literatures by eliciting novel information from vehicle owners in coastal New York and Texas about their vehicle flood damage experiences and vehicle flood insurance preferences. The present study draws on existing survey methods and contingent valuation literature. At least three main contributions are made through the analysis. First, in the absence of accessible disaggregated flood-specific comprehensive auto insurance policy and claims information, this study is the first to produce estimates of coastal vehicle owners' willingness-to-pay (WTP) for a single-peril vehicle flood insurance product not currently offered on the general insurance market. Second, this study provides new information about coastal vehicle owners' literacy and knowledge regarding currently-offered insurance policies covering flood damage in the auto insurance market. Third, to shed light on the scope and magnitude of vehicle flood damages experienced by coastal vehicle owners, new information about vehicle owners' vehicle flood damage experiences is elicited and analyzed.

The objective of this research is to produce knowledge that informs vehicle owners, insurers, and policymakers toward the ultimate goal of strengthening vehicle owner financial resilience in the face of expanding and intensifying flood exposure. Developing a foundational understanding of the scope of vehicle flood damages, insurance literacy levels, and consumer preferences among coastal vehicle owners can help achieve better risk management decisions for vehicle-owning households, particularly those with limited wealth. Section 4.2 analyzes relevant public laws and policies in the United States (US) which serve as the legal foundations on which auto insurance markets operate. The analysis in this section motivates the data collection process. Section 4.3 describes the study area, which is comprised of 39 zip codes in coastal New York and Texas, and justifies this area's selection. Section 4.4 provides a detailed account of the sampling strategy, contingent valuation methodology motivation, and survey instrument design which took place before deploying the survey to coastal vehicle owners in New York, NY and Houston, TX area. In Section 4.5, information about respondents' vehicle flood damage experiences and WTP for a hypothetical single-peril vehicle flood insurance product, among other survey insights, are statistically analyzed and interpreted. Section 4.6 contextualizes survey findings within the wider public policy and insurance market contexts, as well as within related academic literature. Section 4.7 contains the chapter's conclusion.

4.2 An overview of vehicle flood insurance coverage and public policy foundations

The body of scholarship on flood insurance in the housing sector highlights a number of relevant impediments to insurance penetration among residential property owners, which may be instructive when considering vehicle flood insurance. First, flood insurance affordability is a key determinant of uptake in the residential sector (Atreya et al., 2015; Dixon et al., 2017). Dixon et. al (2017) conducted a survey in a study area which largely overlaps with the New York portion of this chapter's study area, and found, despite positive income elasticity, flood insurance uptake rates are lower in areas where households are relatively cost-burdened by housing expenses. Thus, while homeowners may be interested in purchasing flood insurance to strengthen their financial resilience in the face of potential flood hazard exposure, budget constraints may inhibit uptake (Netusil et al., 2021). Similarly, empirical investigation of auto insurance markets in the US has found auto insurance, including comprehensive coverage, exhibits the positive elasticity of a "normal good" (Sherden, 1984), however insurance penetration gaps persist. These empirical findings imply vehicle owners, like homeowners, may face similar flood-related insurance affordability challenges if their household budget constraints are salient.

Second, insurance literacy gaps may lead to relatively poor insurance penetration and financial vulnerability. A WTP elicitation study by Kousky et al. (2023) in Oregon empirically examines this issue in the context of housing, and finds that a sizable percentage of homeowners in their sample, approximately 38%, were unaware their homeowners insurance policies did not cover flood damage (Kousky &

Netusil, 2023). Homeowners insurance, like comprehensive auto insurance, is typically a multi-peril policy covering damages from perils such as fire, wind, and vandalism, but not flooding. Kousky et al.'s (2023) results found homeowners in Federal Emergency Management Agency (FEMA) Special Flood Hazard Areas (SFHA) were more knowledgeable about the scope of homeowners insurance and flood insurance coverage than homeowners outside SFHAs, which is perhaps the result of lender and agent communication, or other learning mechanisms such as past flood experiences. The issue of flood insurance literacy is highlighted by Kousky et al. (2023) as important for optimal risk management, however no study to date has focused on vehicle owner insurance literacy with respect to comprehensive auto insurance and flood hazard. This chapter intends to advance the flood insurance literacy literature by eliciting relevant information from coastal vehicle owners on the subject.

Figures 3.5 and 3.6 above, as well as discussion in Section 3.6.1, provide an introduction to the flood insurance landscape for vehicle assets. As mentioned, FEMA's National Flood Insurance Program (NFIP) does not offer flood insurance coverage to vehicle assets (FEMA, 2022). As a result, the market for auto insurance that covers against flood damages is entirely private, and vehicle owners seeking coverage against vehicle flood damage must purchase a comprehensive auto insurance policy from an insurance company in this private market. An estimated 31% of motorists on the road in the US do not have comprehensive coverage, though data on comprehensive auto insurance uptake are not publicly-available at a spatial scale more granular than the state level. As previously noted, the average annual price of a multiple-peril comprehensive auto insurance policy in the US in 2020 was $174.26, with state averages ranging from $97.26 to $353.10 per year (III, 2023a). No US state requires comprehensive coverage in their minimum insurance requirements, however individuals financing a vehicle are typically required by their lender to take out a comprehensive auto insurance policy (Progressive Insurance, 2023). More than one-third of US families had an outstanding auto loan in 2022 (Fed SCF, 2022), which suggests a substantial number of vehicles in the US likely have comprehensive coverage due to lender requirements.

Chapter 3 highlights FEMA disaster assistance may extend financial resources to eligible individuals in the wake of uninsured vehicle flood damages, however such disaster assistance is unavailable in many cases, implying the critical role of insurance to provide financial resilience against vehicle flood damages, particularly among households with limited financial means. Insurance firms and the markets in which they operate are generally regulated at the state level in the US. This configuration is largely underpinned by the McCarren-Ferguson Act of 1945 (Macey & Miller, 1993), which broadly exempts insurance firms from Federal regulation. As a result, the insurance regulatory regime in the US is comprised of a constellation of state government agencies (e.g., Florida Office of Insurance Regulation [FLOIR], New York State Department of Financial Services, etc.) which have heterogeneous organizational structures and mandates given different state laws governing insurance markets. Generally, state insurance regulators aim to regulate insurance prices and policies such that they are not excessive, inadequate, unfairly discriminatory, competition-eroding, or financially irresponsible.

Common interests among the various state insurance regulators has led to the creation of the National Association of Insurance Commissioners (NAIC), a 501(c)(3) standard-setting organization governed by chief insurance regulators from the 50 US states, the District of Columbia, and five territories. The organization serves as a forum supporting regulatory excellence that provides expertise, data, and coordination across states. NAIC provides periodic reports and proprietary data access for a fee (NAIC, 2023), however national-scale analysis of comprehensive insurance policies and flood-specific claims is challenging given fragmented data governance and other barriers to access. The challenges of analyzing comprehensive auto insurance uptake and flood-related claims are distinct from challenges analyzing FEMA-maintained NFIP data, as shown in Table 4.1. The two markets for flood insurance covering key household assets contrast across regulatory environments, composition of insurers (FEMA, 2023d; Honka, 2014), rate-setting protocols, data governance, and covered asset characteristics. In the absence of publicly-available, peril-specific, centrally-maintained, spatially-explicit insurance policy and claims data with wide geographic coverage focused on the auto insurance market, the present study aims to fill an existing epistemic gap in the academic literature by explicitly eliciting information from coastal vehicle owners in urban areas about their experienced vehicle flood damages and WTP for a single-peril vehicle flood insurance policy. The following section describes the study area, including motivation for its selection, while Section 4.4 provides information about the survey instrument which aims to fill the aforementioned epistemic gap.

Table 4.1: Comparison of FEMA NFIP structure, contents insurance coverage and private comprehensive auto insurance coverage.

	FEMA NFIP	**Comprehensive auto insurance**
Covered asset type(s)	1. Structures 2. Contents of structures	1. Motor vehicles
Level of regulation	Federal	State/territory
Spatial unit of pricing	FEMA flood zone	Rating territories (varies by state)
Scope of perils covered	Single-peril (flood)	Multiple-peril (e.g., flood, fire, vandalism)
Parties required to have coverage	1. Holders of Federally-backed mortgages in SFHAs 2. Recipients of Federal disaster assistance in SFHAs	1. Lessees 2. Holders of auto loans
Authoritative data source(s)	1. Insurers 2. FEMA	1. Insurers 2. State insurance commissioners 3. NAIC

4.3 Study area

The study area is comprised of 39 coastal zip codes in the New York City region and the Houston, TX region, including the Beaumont-Port Arthur metropolitan area, covering a total estimated population of approximately 1.19 million individuals across an estimated 420,271 occupied housing units according to 2021 US Census Bureau (USCB) American Community Survey (ACS) five-year estimates (United States Census Bureau, 2023). Figures 4.1 and 4.2 show the 13 zip codes in New York and 26 zip codes in Texas included in the study. These zip codes were identified based on three selection criteria measuring: 1. incidence of vehicle flood damages, 2. population, and 3. vehicle ownership rate. Incidence of vehicle flood damages were assessed based on data used in Chapter 3, specifically the cumulative number of FEMA Individuals and Households Program (IHP) applications reporting vehicle flood damages received from residents residing in each zip code between 2007-2022. The total number of IHP applications reporting vehicle flood damages for each sample zip code are shown in Table 4.2, with the number of IHP applications submitted from each zip code ranging from 135 to 2,818.[23] Table 4.2 also shows the estimated populations and shares of households owning a vehicle in sample zip codes. Figure 4.3 shows the total number of FEMA IHP applications reporting vehicle flood damage in New York study area zip codes in connection with Hurricane Sandy as a percentage of the total estimated number of household vehicles available in the zip code in 2013.[24] This figure indicates that in some zip codes, more than 10% of household vehicles may have been damaged by flooding *and* have been correspondingly connected to a FEMA IHP application submission. Nearly 17% of all FEMA IHP applications reporting vehicle flood damage across the 2007-2022 period came from the 39 zip codes in the sample. Unlike the New York zip codes, FEMA IHP applications from the 26 zip codes in Texas were largely spread across two major flood events: Hurricane Ike (2008) and Hurricane Harvey (2017).

[23]For comparison, the median number of IHP applications reporting vehicle flood damage at the zip code level in the full sample of 160,565 applications described in Chapter 3 was 12.

[24]FEMA IHP applications from these 13 zip codes in New York were submitted in 2012 and 2013, with most applications submitted in 2012. Of the 9,970 FEMA IHP applications reporting vehicle flood damage across New York state in connection with Hurricane Sandy (2012), approximately 76% of applications originated from these 13 zip codes.

Table 4.2: Selection criteria variable values and number of survey respondents by study area zip codes.

Texas study area					New York study area				
Zip code	# of respondents	# of IHP applications	Estimated population (2021)	Estimated share of households with a vehicle	Zip code	# of respondents	# of IHP applications	Estimated population (2021)	Estimated share of households with a vehicle
77013	6	352	19,296	0.91	10305	8	218	44,531	0.81
77016	13	484	30,252	0.91	10306	25	566	55,805	0.85
77022	7	403	26,472	0.86	11224	6	961	48,110	0.47
77026	14	577	21,412	0.82	11235	27	924	84,859	0.52
77028	7	490	19,506	0.90	11236	15	599	102,238	0.65
77032	6	237	13,887	0.85	11414	10	486	30,915	0.87
77033	17	298	28,669	0.90	11558	2	302	8,758	0.94
77037	2	413	18,106	0.96	11561	12	941	39,140	0.91
77044	17	574	53,753	0.97	11572	13	251	29,791	0.95
77060	6	1,288	47,349	0.86	11691	12	701	70,797	0.57
77078	8	416	13,738	0.90	11692	4	541	24,639	0.61
77091	5	327	30,008	0.86	11693	5	461	14,147	0.67
77514	3	135	5,818	0.99	11694	1	665	22,432	0.79
77539	16	1,380	45,901	0.97					
77550	6	2,441	22,421	0.84					
77551	11	2,818	23,686	0.91					
77554	1	720	9,001	0.98					
77563	4	484	10,223	0.95					
77565	1	258	6,555	0.99					
77586	6	383	23,364	0.98					
77611	2	1,573	9,829	1.0					
77630	15	1,612	29,480	0.93					
77640	6	397	17,579	0.88					
77642	18	839	37,881	0.90					
77701	10	180	12,930	0.85					
77705	13	557	40,947	0.90					
Total:	220	19,636	618,067	0.91	**Total:**	140	7,616	576,162	0.69

Second, the population of each zip code was evaluated using 2021 USCB ACS five-year estimates of the estimated total population, also shown in Table 4.2. The average sample zip code had an estimated population of more than 30,000 residents in 2021, with the least and most populous zip codes in the sample having estimated populations of 5,818 and 102,238, respectively. Third, the estimated household vehicle ownership rate in the study area was 80.1% in 2021, a rate slightly lower than a credible recent estimate of the national household vehicle ownership rate of 85% (Bhutta et al., 2020). Sample zip codes' estimated household vehicle ownership rates ranged from 47% to nearly 100%. Each of the zip codes included in the sample are thus known to experience vehicle flood damages, as evidenced by their IHP TA applications, and also have sizable urban populations with significant vehicle ownership rates. These selection criteria make these zip codes a fertile area to study the attitudes, experiences, and preferences of coastal vehicle owners residing in flood-prone coastal communities.

Figure 4.1: 13 New York zip codes in survey study area

Figure 4.2: 26 Texas zip codes in survey study area

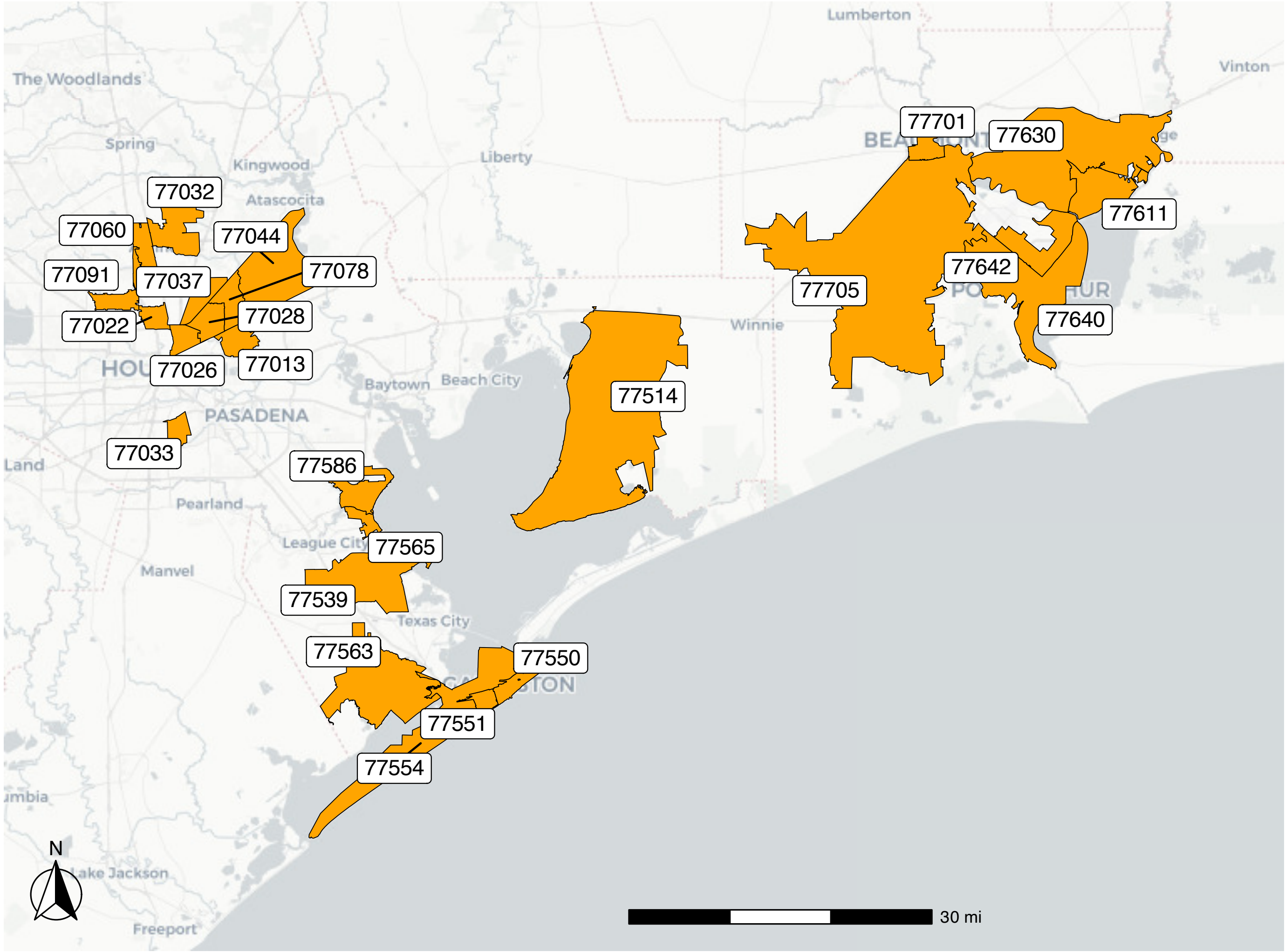
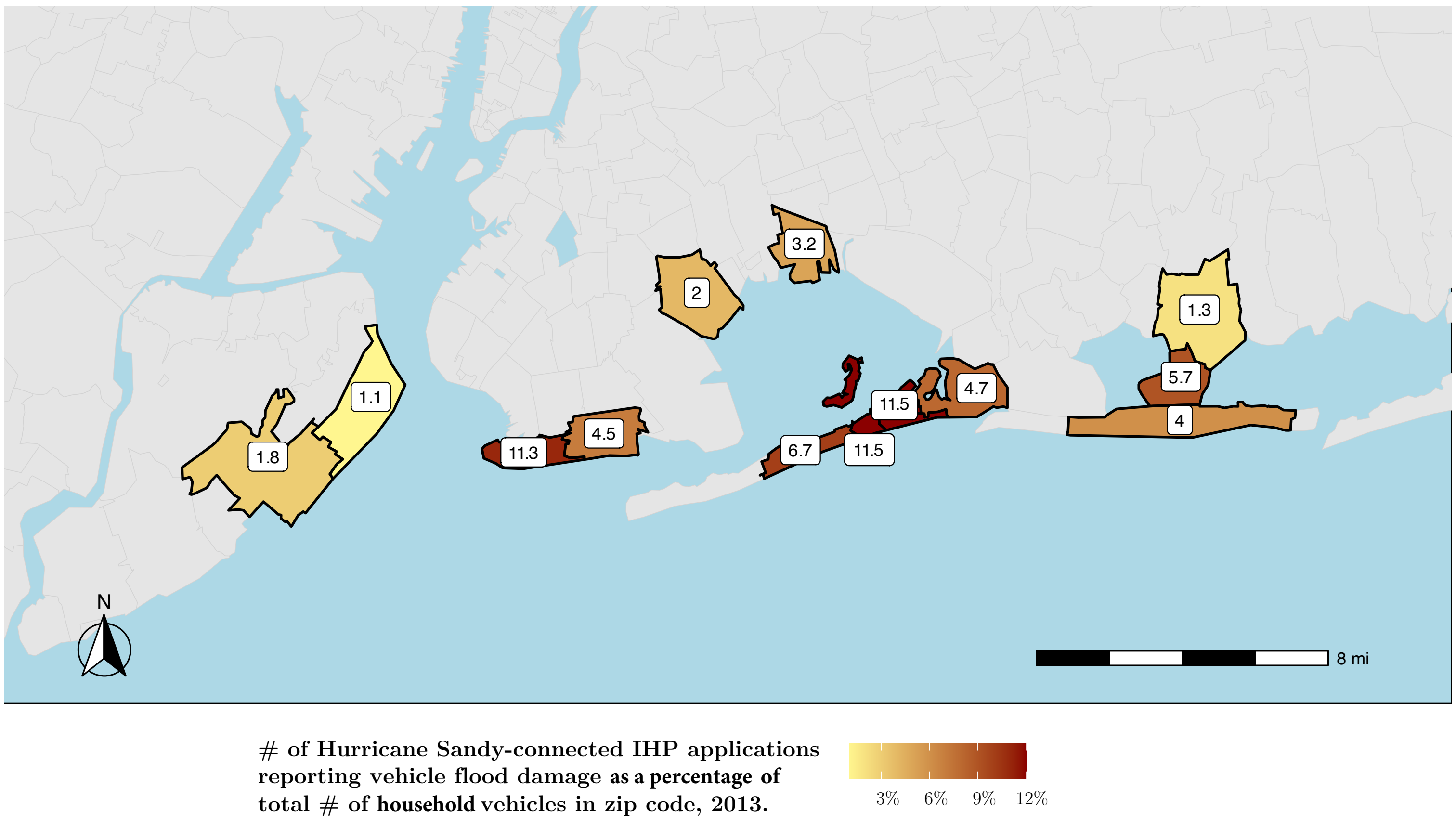


Figure 4.3: New York zip codes in study area - vehicle flood damage impacts of Hurricane Sandy (2012)



4.4 Methods

4.4.1 Sampling strategy

The general population of interest in this study is coastal vehicle owners residing in areas prone to flood hazard exposure. The study area outlined in the previous section was selected to serve as the specific population of interest. There are three main criteria needed to determine the appropriate sample size when collecting survey data to infer population parameters from a sample: confidence level, precision level, and degree of variability of the population parameter(s) of interest (Iarossi, 2006; Israel, 1992). Two of these criteria, confidence level and precision level (sometimes referred to as "sampling error"), are selected by the researcher, while some empirical basis is needed for the degree of variability in order to reasonably determine the appropriate sample size. Below are two formulas from Iarossi (1992), which guide sample size calculations and inference for both population proportions and population means. Please note the terms in these equations are distinct from previous notation (i.e., are not recycled from above).

$$n = \frac{z^2_{\frac{\alpha}{2}} P(1-P)}{e_0^2 + z^2_{\frac{\alpha}{2}} \frac{P(1-P)}{N}} \tag{4.1}$$

and

$$n = \frac{z^2_{\frac{\alpha}{2}} S^2}{e_0^2 + z^2_{\frac{\alpha}{2}} \frac{S^2}{N}} \tag{4.2}$$

where:

N = population size

n = sample size

S^2 = population variance of parameter of interest

P = population proportion parameter of interest

e_0 = desired level of precision (i.e., sampling error)

α = desired level of confidence (e.g., 95%)

$z_{\frac{\alpha}{2}}$ = z distribution (i.e., standard normal distribution) corresponding to α level of confidence

When considering Equation (4.1), a hypothetical population proportion of 50% generally requires a larger sample size to produce population parameter estimates of the same confidence interval and sampling error as smaller or larger proportions. In the present study, assuming a conservative population proportion of 50% and a sample size of 360 respondents (the full sample size eventually analyzed in the study), estimates of population proportions in the study area would be characterized by precision error of approximately 5.2 percentage points with a 95% confidence interval. Such estimates take into account uncertainty resulting from both natural variation in the population as well as sampling error which may be present in the sampling procedure.

Equation (4.2) similarly provides insight into the appropriate sample size needed to reliably estimate a population mean at specified confidence level and precision level, based on the population size and parameter's variance. For certain population means (e.g., average vehicle market value, average maximum vehicle flood damages experienced) referenced in the study, variance parameters are unavailable from the original data source. In these cases, the standard deviation of the sample mean is used as the estimator for the true population variance (Linton, 2017).

Among potential respondents in the study area, two main filtering criteria were applied. First, only respondents stating they own a vehicle are offered the survey. Second, respondents must state they are a current resident of one of the 39 sample zip codes enumerated in Table 4.2, and they must have continuously lived in the zip code for a minimum of one year at the time of survey completion. These screening measures were implemented to ensure the survey instrument elicits information about issues related to vehicle ownership and flooding from members of the population of interest.

4.4.2 Contingent valuation

To understand consumers' preferences and estimate their WTP for a good or service, researchers often employ revealed preferences and/or stated preferences methods (Kroes & Sheldon, 1988). While revealed preference approaches, such as the hedonic pricing estimations conducted in Chapter 2, exploit observed behavior (e.g., purchasing decisions) to make inferences about consumer preferences, stated preferences methods may be suitable in cases where revealed preference methods are unavailable due to interest in conditions, goods, or services which do not exist. In the absence of available data revealed by market transactions, contingent valuation methods relying on survey instruments may be used to estimate the value of non-market goods (Carson, 2000). In the case of this present study, the primary good of interest is a single-peril vehicle flood insurance product, which is currently not commonly available on the auto insurance market.

The primary estimation procedure used by this study to generate WTP bounds employs a utility-differencing approach with binary response model generally guided by M. Hanemann (1984) and Carson and Hanemann (2005). A brief explanation of the theoretical basis for this approach follows. To represent vehicle flood insurance coverage, the term I is introduced where $I = 1$ if an individual has a single-peril vehicle flood insurance policy and $I = 0$ if they do not. The individual's income is denoted by Y; other observable characteristics pertaining to the individual are denoted by the vector X; and the vector of market prices the individual faces in their consumption decisions is represented by P. The general form of the individual's utility function if they have a single-peril vehicle flood insurance policy is $u_1 = u(1,\ Y,\ P;$

X), where utility u_1 is a function of the individual's income, the market prices they face, and their consumption of a single-peril vehicle flood insurance policy given a set of observed characteristics, X. When an individual does not have such an insurance policy, their utility function may generally be described as u_0 = *u(0, Y, P; X)*. Hanemann (1984) observes that since the "econometric observer" cannot observe the true utility function, one must introduce a stochastic component to account for unobservable characteristics. To do so, u_0 and u_1 are viewed as random variables with probability distributions, and means *w(0,Y, P;X)* and *w(1, Y, P; X)*. Thus,

$$u(I, Y, P; X) = w(I, Y, P; X) + \epsilon_I \tag{4.3}$$

where ϵ_I is an independent and identically distributed random variable with mean zero. When faced with a price, C, for a single-peril vehicle insurance policy covering flood damage, an individual is assumed to pay the price if:

$$w(1, Y - C, P; X) + \epsilon_1 > w(0, Y, P; X) + \epsilon_0 \tag{4.4}$$

Following this result, we assume the WTP for a single-peril vehicle flood insurance policy can be written as $w_i(I_i, Y_i, P) = X_i\beta + \epsilon_i$ where the price vector P captures exogenous variation in insurance product prices. The individual's response probability with respect to WTP is then represented by:

$$Pr(\text{individual willing to pay}) = Pr[w(1, Y - C, P; X) + \epsilon_1 > w(0, Y, P; X) + \epsilon_0] \tag{4.5}$$

Equation (4.4) may also be enumerated:

$$Pr(\text{V>C}) = 1 - G_V(C) \tag{4.6}$$

where V is the individual's maximum WTP for the vehicle flood insurance product and $G_V(.)$ is the cumulative distribution function of V across the population of interest. As observed by Carson & Hanemann (2005), the introduction of the stochastic component into the utility model leads to a *WTP distribution* that is then linked to a *binary response probability distribution* that assumes utility-maximizing responses from survey participants. Per Carson & Hanemann (2005), the binary response model can be interpreted as the survivor function of the WTP distribution if it is assumed the "yes" and "no" survey responses are aligned with an economic model of utility maximizing behavior. In the following analysis, main model results leverage a Box-Cox random utility model (RUM) that assumes the error term operates as a random variable with logistic distribution and the response formula becomes a logit model (Box & Cox, 1964; Carson & Hanemann, 2005). As a robustness check to understand sensitivity of the results to model functional form and distributional assumptions, alternative results are shown in Tables A.10 and A.11 in the Appendix which instead employ a Bishop-Heberlein RUM binary response model that assumes the error term is also a random variable with logistic distribution and the response distribution is log-logistic (R. C. Bishop et al., 1983; W. M. Hanemann & Kanninen, 1996). Since there is not clear consensus in the literature about the most appropriate welfare measure (e.g., median, mean) of the cumulative distribution function of respondents' maximum WTP to select for presentation of results and interpretation, I include median, mean, and mean according to Boyle et al.'s adjustment approach to account for distribution truncation at maximum bid (1988) for comparison (Boyle et al., 1988; M. Hanemann, 1984).

To understand the bounds of vehicle owners' WTP for a single-peril vehicle flood insurance product in the study area, a double-bounded dichotomous choice (DBDC) question design is adopted as the central approach. This approach, as opposed to other contingent valuation methods such as single binary-choice, bidding games, or payment cards (Johnston et al., 2017), is selected due to its ability to estimate the bounds of the WTP and its relative efficiency (M. Hanemann et al., 1991). The double-bounded dichotomous choice contingent valuation method has been applied to produce valuable knowledge about WTP for nonmarket environment-related goods (Gelo & Koch, 2015; Molina et al., 2021). In some cases, double-bounded dichotomous choice questions are complemented by an open-ended question (Alberini et al., 2017). The present study adopts this complementary strategy by eliciting WTP from respondents using an open-ended question as well as two valuation questions in the DBDC format.

The DBDC approach begins by providing each respondent with a valuation question in which an initial dollar amount from a pre-determined set of potential initial bid amounts is randomly assigned. Let $B_{initial}$ represent the initial bid amount, which in the present survey can take on a value of either \$20, \$50, \$100, and \$200. If the respondent answers "yes" to the valuation question containing $B_{initial}$, they are provided a follow-up valuation question with a higher bid amount. Let B_{higher} be a higher bid amount that corresponds relative to each value of $B_{initial}$. B_{higher} can take on values of \$30 (corresponding to $B_{initial}$=\$20), \$75 ($B_{initial}$=\$50), \$150 ($B_{initial}$=\$100), or \$300 ($B_{initial}$=\$200) in the deployed survey instrument. If the respondent answers "no" to the first valuation question, they are then provided a follow-up valuation question with a lower bid amount. Let this lower bid amount be represented by B_{lower}, which can take on a value of either \$10 (corresponding to $B_{initial}$=\$20), \$25 ($B_{initial}$=\$50), \$50 ($B_{initial}$=\$100), or \$100 ($B_{initial}$=\$200). Since each respondent who completes the survey will answer two binary choice valuation questions, the response sets include: (yes, yes); (yes, no); (no, yes); (no, no).

$$\Pr(\text{yes, yes}) = \Pr(V \geq B_{higher}) = 1 - G_V(B_{higher})$$
$$\Pr(\text{yes,no}) = \Pr(B_{higher} \geq V \geq B_{initial}) = G_V(B_{higher}) - G_V(B_{initial})$$
$$\Pr(\text{no, yes}) = \Pr(B_{lower} \geq V \geq B_{lower}) = G_V(B_{initial}) - G_V(B_{lower})$$

$$\Pr(\text{no, no}) = \Pr(B_{lower} \geq V) = G_V(B_{lower})$$

$$L = \prod_{k=1}^{K+1} [\psi_k]^{N_k} \tag{4.7}$$

where L is the likelihood function maximizing WTP β parameters, and there are K alternatives of single-peril vehicle flood insurance policy bids that take on the cost C_k. Parameters of the logit model are estimated using maximum likelihood estimation optimized by the Broyden–Fletcher–Goldfarb–Shanno algorithm (Aizaki et al., 2022; Fletcher, 2000). Further, note that $\psi = G_V(C_k) - G_V(C_{k-1})$ for k=1,...,K+1, which represents the increasing probability of a "no" response over the K+1 observed intervals of $G_V(C)$, where bid amount increases with k. We assume the probability of a "no" response at $C_0 = 0$, and the probability of a "no" response at $C_{K+1} = 1$. The superscript, N, in Equation (4.7) denotes a "no" response at amount corresponding to bid k. Further, $G_V(C_k)$ is monotone nondecreasing.

$$\begin{aligned} WTP_i(X_i) = \beta_0 + \beta_1 \text{Income} + \beta_2 \text{Education} + \\ \beta_3 \ln(\text{vehicle value [\$]}) + \beta_4 \text{SFHA} + \beta_5 \text{VFD} + \\ \beta_6 \text{Vehicle type} + \beta_7 \text{Concern} + \beta_8 \text{State} + \beta_9 \text{Bid} + \epsilon_i \end{aligned} \tag{4.8}$$

Equation (4.8) above represents the main logit model used to estimate WTP, where β parameters are maximized according to each individual i's observed characteristics X_i and the random error component ϵ_i which is assumed to be distributed N(0, σ^2). The variable *Income* is categorical with five annual household income bins ranging from "Less than \$25,000" to "More than \$250,000" while *Education* is similarly categorical with six bins ranging from "No high school" to "Postgraduate degree." Further, the natural log of the reported value of the household's most valuable vehicle is included as a control, as is the reported location of each respondent's primary residence with respect to FEMA's SFHA designations.[25] "VFD" represents respondents' answers when asked whether their household has ever experienced significant vehicle flood damages. A covariate is also included for respondent vehicle type (e.g., sedan, sports utility vehicle [SUV], van), and the dummy variable *State* takes on a value of 1 if the respondent lives in Texas and zero if they live in New York. The *Concern* variable corresponds to a question in the survey instrument eliciting information about each respondent's level of concern about flooding in their community.

4.4.3 Survey design

The survey development and design process followed best practices outlined in Dillman et al. (2014). Information was elicited through a web-based survey using the services of Qualtrics. A full enumeration of the questions included in the survey instrument is available in the Appendix. Survey questions were pretested with vehicle-owning economists possessing survey design and contingent valuation expertise, transportation experts working for a government agency in the study area, and multiple scholars with research backgrounds in flood risk mitigation policy and/or survey design. Additionally, a project management team from Qualtrics reviewed survey question logics as well as response information at multiple milestones to ensure quality responses.

The survey was conceptualized in the summer of 2022, with initial question design and scoping taking place in the fall of 2022. Initially, per Dillman et al. (2014), recruitment of respondents through mailing of hard copy survey materials to a random selection of households in the study area was considered. While such an approach proved successful in Netusil et al. (2021), and has the significant analytical

[25] 22% of respondents answered "not sure" when asked if their primary residence is located in a FEMA SFHA.

benefit of randomization which partially addresses concerns about selection bias, the estimated costs of this approach based on response rates in similar studies, mailing costs, and labor costs associated with mailing, screening, and quality control proved prohibitive. Thus, in January 2023, Qualtrics was engaged, and a suitable study area and sampling approach at acceptable cost were identified. Pretesting of the survey instrument occurred in late spring 2023, and a final version of the survey was approved by the University of Miami Institutional Review Board on May 17, 2023. An initial pilot launch of the survey was deployed in collaboration with Qualtrics in June 2023 to ensure soundness of question logics and gather information about respondent completion duration time. Based on pilot results, respondents taking fewer than two minutes to complete the entire survey were terminated from the final sample. All responses in the final sample were collected during June and July 2023.

While many questions in the survey instrument elicit basic information about demographics, attitudes, and experiences, the central questions of the study which elicit information about WTP for a single-peril vehicle flood insurance policy were carefully designed to be grounded in a realistic constructed market setting. Following guidance in K. Bishop et al. (2020), bid amounts were provided in conjunction with information that clearly articulates: 1. monetary amounts and who pays, 2. whether payments are mandatory or voluntary, 3. frequency of payment, 4. the duration of payment, 5. the method of payment, and 6. details of offered product benefits and limits. Amounts and payment vehicles were designed to be credible and salient to respondents. More specifically, the range of bid amounts–from a possible low of $10 per year to a possible high of $300 per year– were selected based on pretesting feedback and average annual comprehensive auto insurance policy prices in the two states comprising the study area. According to NAIC data, the average comprehensive policy premium in 2020 cost $279.44 per year in Texas, and $176.64 per year in New York (NAIC, 2023). Thus, the range of bids included in the final survey instrument bound the average comprehensive insurance policy price in the study area, with the average initial bid amount lower than the average price of comprehensive coverage. This constructed pricing approach aims to reflect the smaller scope of coverage of the single-peril vehicle flood insurance product offered in the survey relative to actual comprehensive insurance policies available in the general marketplace. Additionally, NAIC indicates comprehensive coverage is typically sold with deductibles ranging from \$50 to \$2,000 (NAIC, 2023), and the present survey offers an insurance policy with a \$100 deductible.

4.5 Results

4.5.1 Survey data and summary statistics

As shown in Table 4.2, the final sample following implementation of the various screening and quality control measures outlined above is N=360. Table 4.3 shows the bid amounts offered to each respondent and associated responses. The $B_{initial}$ amounts are randomly assigned, and follow-up bid amounts depend on responses to the question containing $B_{initial}$. Among the 360 respondents in the final sample, the mean completion time for the survey was 7.2 minutes. Table 4.4 presents summary statistics on demographic, flood-related, and vehicle-related information for the total sample, as well as sample results by state. The right-most column provides corresponding information where available from 2021 USCB ACS five-year estimates representing variable estimate averages across the 39 zip codes in the study area.

Overall, the sample appears fairly representative of the study area population based on observed characteristics. The sample has a higher proportion of respondents who are female, have a bachelor's degree, and have a household income greater than \$50,000 per year than the population means. Additionally, the average number of vehicles in each sample household is 2.56, which is greater than the population average of 1.78. However, the population statistics shown in the right-most column of Table 4.4 pertain to the entire population in the study area, not the primary population of interest, vehicle owners, therefore we would expect the average number of households in the sample to be higher than the average across all households in these zip codes, as sample data are only drawn from the vehicle-owning population. The average market value of respondents' most valuable household vehicle, the vehicle of interest with respect to the single-peril vehicle flood insurance WTP elicitation, is approximately $19,600, which is within a factor of 1.2 of the Kelley Blue Book (KBB) average used car sale price previously cited.

Sample respondents report widespread and substantial flood exposure. 46% of respondents reported living in FEMA SFHAs, while 74% reported their household has experienced significant flooding at their primary residence. Importantly, 59% of respondents report their household has experienced significant vehicle flood damages in the past. Among the sub-sample of households who have experienced vehicle flood damage and provided information on the subject,[26] the estimated average maximum amount of vehicle flood damage the household sustained was approximately $9,800, with a sample standard deviation of approximately $12,500. 82% of sample respondents are concerned about flooding negatively impacting their community, suggesting flooding is a meaningful concern and widespread issue in the study area.

When considering comprehensive auto insurance literacy and uptake, only 64% of respondents were aware before taking the survey that comprehensive coverage is the type of auto insurance policy covering vehicles against flood damage. As hypothesized, these findings demonstrate a sizable share of coastal vehicle owners lack knowledge about the type of auto insurance policy that can provide financial resilience in the wake of vehicle flood damages. Further, while the average respondent reported having 2.56 vehicles available in their household, responses indicate only 1.28 vehi-

[26] Data for this variable were only collected from 185 of the 212 respondents reporting vehicle flood damage due to addition of the question following pilot phase.

cles per household have comprehensive coverage, suggesting a considerable share of vehicles in the sample, approximately half, are uninsured against flood damages and other perils covered by comprehensive auto insurance.

Leveraging Equations (4.1) and (4.2) above allows us to make caveated inferences about population parameters from the sample data. Each of the sample proportions described above has an estimated sampling error with 95% confidence interval between 4.0 and 5.2 percentage points, with these levels of precision corresponding to the estimated share of the study area population[27] living in a FEMA SFHA and the share of the population concerned about flooding, respectively. These sampling errors, while of non-trivial magnitude, are small enough such that sample data provide valuable insight when generalizing findings to the study area's population proportions. For example, these results allow population-level inference at a 95% confidence level to support the claims that a majority of vehicle-owning households in the study area have experienced significant vehicle flood damage in the past, and roughly one-third of vehicle owners in the study area do not know comprehensive auto insurance covers vehicle flood damage.

Motivated by findings in Kousky and Netusil (2023) which find a positive correlation between residence SFHA status and homeowner knowledge about NFIP coverage, two-sided t-tests are applied to see if vehicle owners residing in SFHAs, on average, are more knowledgeable about the fact that comprehensive auto insurance covers vehicle flood damages than vehicle owners outside SFHAs. A two-sided t-test comparing knowledge level about comprehensive auto insurance flood coverage between survey respondents in SFHAs (N=166) and those located outside SFHAs (N=114) does not suggest differences between these two groups are statistically dif-

[27]Note: sampling error calculations assume a population of interest that is smaller than the total population, given many individuals in the study area do not drive or own a vehicle. Thus, these calculations assume a total population of interest at a size of approximately 693,800, which assumes the state-level shares of the total population with a driver's license, which are roughly 60.2% and 63.1% for New York and Texas, respectively, in 2020 according to the US Department of Transportation.

ferent from zero ($p<0.05$). However, a comparison between respondents in SFHAs and those responding "not sure" when asked if they reside in a SFHA did produce results suggesting the rate of awareness about comprehensive insurance's flood coverage is significantly higher among respondents who report living in a SFHA ($p<0.05$). More specifically, the t-test finds the rate of awareness about comprehensive insurance's flood coverage is 16.1 percentage points higher ($\pm$ 13 percentage points) among respondents stating they live in a SFHA, as compared with respondents who do not know their SFHA status.

Further, when considering population means using Equation (4.2), the average estimated value of households' most valuable vehicle, approximately $19,600, has a 95% confidence interval of [$18,096.64, $21,115.36]. This average is slightly lower than the 2019-2021 average KBB used vehicle sale price, and may be downward-biased due to the survey instrument's truncation of possible responses at an upper bound of $50,000. When generalizing results regarding maximum sustained vehicle flood damages to the study area population, conditional on the fact the respondent's household has experienced vehicle flood damage, population estimates suggest average maximum vehicle flood damages are $9,800, with a 95% confidence interval of [$7,994.16, $11,595.84].[28] Taken in combination, these survey results suggest vehicle flood damages are common from a cumulative perspective, and have high costs when they do occur.

[28] This application of Equation (4.2) assumes the population of interest is the share of the motorist population in the study area that is estimated to have ever experienced a vehicle flood damage event, which is assumed to be 59% based on Table (4.4) results.

Table 4.3: Bid amounts and responses (N=360)

$B_{initial}$	**Number of $B_{initial}$ responses**	**Proportion accepting** $B_{initial}$	B_{lower}	**Proportion accepting** B_{lower}	B_{higher}	**Proportion accepting** B_{higher}
\$20	86	0.81	\$10	0.38	\$30	0.93
\$50	94	0.80	\$25	0.42	\$75	0.87
\$100	84	0.74	\$50	0.42	\$150	0.77
\$200	96	0.63	\$100	0.58	\$300	0.58

Table 4.4: Survey summary statistics

	New York (N=140)		Texas (N=220)		Total sample (N=360)		ACS, 2021 (N=1,194,229)
Variable	Mean	SD	Mean	SD	Mean	SD	Mean
Demographic information							
Female	0.54	–	0.68	–	0.63	–	0.51
Age	38.1	17.8	39.0	15.4	38.6	16.3	36.9♠
Bachelor's degree or higher	0.47	–	0.18	–	0.29	–	0.16
Household income < $50,000	0.37	–	0.60	–	0.51	–	0.44
Own your home? (1=yes; 0=no)	0.59	–	0.49	–	0.53	–	0.57
Rent your home? (1=yes; 0=no)	0.37	–	0.49	–	0.44	–	0.43
White or caucasian	0.64	–	0.44	–	0.52	–	0.52
Black or African-American	0.31	–	0.38	–	0.35	–	0.29
American Indian or Alaska Native	0.06	–	0.03	–	0.04	–	0.003
Asian or Pacific Islander	0.01	–	0.05	–	0.04	–	0.05
Other race	0.06	–	0.14	–	0.11	–	0.06
Hispanic or Latino (any race)	0.24	–	0.28	–	0.27	–	0.29
Flood-related information							
Live in a SFHA?	0.44	–	0.47	–	0.46	–	–
Primary residence flood damage? (1=yes; 0=no or NA)	0.74	–	0.75	–	0.74	–	–
Vehicle flood damage? (1=yes; 0=no or NA)	0.60	–	0.59	–	0.59	–	–
Maximum vehicle flood damage($1,000s)* $	11.5	13.9	8.7	11.4	9.8	12.5	–
Concerned about flooding? (1=yes; 0=no)	0.79	–	0.84	–	0.82	–	–
Concerned about climate change? (1=yes; 0=no)	0.78	–	0.75	–	0.76	–	–
Know comprehensive insurance (CI) covers flood damage? (1=yes; 0=no)	0.71	–	0.60	–	0.64	–	–
Vehicle information							
# of vehicles owned, free and clear	1.19	0.84	1.47	0.88	1.36	0.88	–
# of vehicles owned, financed	0.45	0.73	0.69	0.86	0.98	0.82	–
# of vehicles leased	0.71	0.82	0.53	0.85	0.60	0.84	–
Total # of vehicles in household	2.36	1.68	2.70	1.86	2.56	1.86	1.78
Total # of household vehicles in household with CI†	1.17	0.86	1.34	1.03	1.28	0.97	–
Market value of most valuable household vehicle ($1,000s)♣	23.3	16.2	17.3	13.0	19.6	14.6	–
Years living in zip code (cumulative)	11.7	7.4	9.7	7.5	10.4	7.5	–

† 12 respondents from New York and 17 respondents from Texas answered "not sure," therefore statistics in this row only reflect non-"not sure" responses.
*Average among respondents reporting any experience of vehicle flood damage (N=185).
♠ This is the median age; mean age not available from ACS.
♣ Note: given question phrasing as shown in Appendix, all responses with values $\leq$\$5,000 take on the value of \$5,000 while all responses with values $\geq$\$50,000 take on value of \$50,000. ACS race categories (e.g., White or caucasian, Other race) reflect "one race only" while sample data reflect survey respondents' ability to select multiple race options.

4.5.2 Willingness to pay estimates

Table 4.5 presents main model results as described in Equation (4.8) in Section 4.4.2, while Table 4.6 column (1) provides preferred WTP estimates for the full sample. These estimates find a mean WTP for a single-peril vehicle flood insurance policy that is \$182.46 (\$167.89 to \$196.88, 95% CI) among sample respondents. Based on constructed market conditions as described in the DBDC elicitation, this policy would cover the respondent's most valuable household vehicle against all forms of flood damage for one year. Confidence intervals for WTP estimates are constructed using methods outlined in Krinsky and Robb (1986), in which mean WTP parameters are computed across 1,000 draws from a multivariate normal distribution with a vector of the parameter estimates as a mean as well as the variance-covariance matrix of the parameter estimates.

As noted above, a scholarly debate exists with respect to selection of the most appropriate welfare measure(s) of the cumulative distribution function of respondents' maximum WTP. While M. Hanemann (1984) highlights the merits of the median as a suitable welfare measure due to its relative robustness over the expected value when results are sensitive to distributional assumptions, Boyle et al. (1988) note the median has an undesirable feature of poorly capturing skewed estimated distributions. Boyle et al. further posit that, in an ideal scenario, the range of integration should not be truncated according to bid amounts in closed-ended survey settings. Thus, Boyle et al. proposed an adjustment that assumes a uniform distribution, a method used effectively in other contingent valuation studies (Bateman et al., 1995; Molina et al., 2021) and which is employed here as well for alternative perspective about result sensitivity to bid design and distributional assumptions. Table 4.6 column (1) shows an estimated median WTP of \$197.44 (\$176.08, \$222.66, 95% CI), which is similar in magnitude to the central mean WTP estimate, within a factor of 1.1. However, mean estimates using the Boyle et al. (1988) adjustment increase the central

WTP estimate by more than 30%, suggesting the bid amounts provided in the survey instrument may not fully capture the tail of the distribution, i.e. individuals with WTP for the offered vehicle flood insurance product that exceed the upper bound of the researcher-selected bid range. Tables A.10 and A.11 in the Appendix show results using the Bishop-Heberlein RUM, which indicate estimates are generally consistent across RUM selection and related distributional assumptions. With respect to inference, comparison of results generally indicate estimates are more sensitive to welfare measure selection than RUM selection.

Table 4.7 provides results from the open-ended WTP elicitation question. While contingent valuation experts advise against relying heavily on this elicitation format to generate WTP estimates due to large number of respondents who provide zero or unrealistically high WTP responses (K. Bishop et al., 2020), and general incentive incompatibility concerns (Carson & Groves, 2007), open-ended estimates can inform the researcher during pretesting and complement results from closed-ended formats. 25 responses are excluded from these calculations as they did not meet a conservative quality control inclusion criterion: maximum stated WTP in the open-ended question cannot exceed 50% of the stated market value of the respondent's most valuable household vehicle, i.e. the vehicle to which the hypothetical flood insurance product pertains.[29] While removing observations may affect the statistical power and representativeness of these estimates, the author's concerns about response validity outweigh these considerations as it is difficult to conceive a vehicle owner would truly spend, for example, $8,000 per year on flood insurance coverage for a vehicle worth $15,000. Unsurprisingly, excluding these 25 observations with unrealistically-high stated WTP lowers the mean, median, and maximum WTP estimates, as well as corresponding standard deviations. Applying Equation (4.2) to these sample statistics leads to a population mean WTP estimate of $434.90 ($\pm$122.16, 95% CI), which is

[29] For comparison, the average annual cost of a multiple-peril comprehensive policy in 2020 was approximately 9% of the value of the average 2019-2021 used vehicle sale price according to KBB.

larger than the baseline mean WTP estimate of $182.46 in Table 4.5 by more than a factor of two. Open-ended results are interpreted with caution, as the relatively higher estimated mean WTP using this format may capture true preferences at the higher-cost tail of the WTP distribution, however the validity of elicited values is suspect due to potential incentive incompatibility.

Table 4.5 provides main estimates from the logit model. These results are presented with a reference scenario in the main specification shown in column (1) in which respondent's household income is $100,001-$250,000 per year, respondent has an Associate's Degree, and respondent has never experienced vehicle flood damage nor is their primary residence located in a FEMA SFHA. The vehicle type driven by the respondent is "other," they live in New York, and they are not concerned at all about flooding. Results in column (1) indicate household income, SFHA status of respondent's primary residence, vehicle type, and level of concern about flooding are all statistically significant at p-values of 0.05 or lower, suggesting it is likely the effect of these variables on WTP is statistically different from zero. Intuitively, bid amount is also negatively correlated with WTP. Notably, results do not suggest statistically different WTP between respondents in New York and Texas. The negative and statistically significant parameter estimate associated with household income below $25,000 per year in column (1) implies a relatively lower WTP among survey respondents in the lowest income bracket. The positive estimated coefficients for *SFHA* and *Very concerned* that are significant at a p-value of 0.01 suggest floodplain status and level of concern about flooding are positively correlated with WTP for vehicle flood insurance. Following results in specification shown in column (1), two separate estimations generally in line with Equation (4.8) are conducted using subsets of the full sample. Specifically, these subsets only include respondents who: 1. report living in a FEMA SFHA, and 2. report being "somewhat concerned" or "very concerned" about flooding in their community. Sample-wide, 166 respondents report living in a SFHA and 295 respondents report being concerned about flooding.

Table 4.6 and companion visualization in Figure 4.4 present results across welfare measures as well as across groupings according to respondents' FEMA SFHA status and level of concern about flood hazard. Mean, median, and mean with Boyle et al. adjustment WTP estimates are all higher among the subset of respondents living in SFHAs and those reporting concern about flooding relative to estimates among the full sample. Specifically, the mean and median WTP estimates for respondents residing in a SFHA are \$243.66 (\$218.69 to \$262.59, 95% CI) and \$308.30 (\$252.14, \$383.65, 95% CI). These estimates are greater than their full-sample counterparts by factors of roughly 1.3 and 1.5, suggesting WTP among vehicle owners residing in areas defined by FEMA as flood-prone is higher than the general population's. These results are generally in line with Netusil et al. (2021), who similarly find WTP for flood insurance is higher among homeowners living in FEMA SFHAs as compared with homeowners residing outside a SFHA. Results in Table 4.6 also suggest concern about flooding increases WTP for vehicle flood insurance, though at a much smaller magnitude than SFHA status.

When considering factors which may influence WTP for vehicle flood insurance beyond SFHA status and flooding concerns, model results in Table 4.5 also show respondent household income and vehicle type are statistically significant in columns (1), (2), and (3). When employing Equation (4.8) using preferred estimation methods previously outlined, truncated mean and median WTP estimates for respondents from households making less than \$25,000 per year (N=82) are \$128.76 (\$103.46 to \$156.78, 95% CI) and \$120.09 (\$83.35 to \$160.41, 95% CI). The average value of households' most valuable vehicle in this income bracket in the sample was \$10,317, roughly half of the sample-wide average and less than half the aforementioned KBB average price. While income constraints may explain these results, it also stands to reason the amount of insurance coverage needed to cover a relatively lower-value vehicle asset would be worth less than the amount needed to cover a relatively higher-value vehicle asset. Findings across the full sample and subsets also indicate a relatively higher WTP for vehicle flood insurance among respondents with a sedan, as compared with those with a van, SUV, or other type of vehicle. While purely speculation, this could perhaps be driven by sedans' lower ground clearances and greater vulnerability to flood damage conditional on exposure, as represented in Figure 3.3.

4.6 Discussion

4.6.1 Policy and insurance market implications

The above results have a number of relevant implications for insurance markets and the regulatory bodies overseeing them, four of which are described in this section. First, despite potential avoidance capabilities enabled by the mobile nature of vehicles, respondents express a considerable willingness to pay for a single-peril vehicle flood insurance product. In the preferred conservative central estimates, mean and median WTP for one year of coverage are approximately \$182 and \$197, respectively. These amounts exceed the average annual cost of a multiple-peril comprehensive auto insurance policy in the US in 2020, suggesting the potential for significant consumer surplus enjoyed by coastal vehicle owners in the comprehensive auto insurance market. Such robust WTP estimates may be of interest to insurance companies and regulators when weighing pricing structures and potential new sources of revenue.

Second, these results have implications for state insurance regulators motivated to accurately price flooding and climate impacts in auto insurance premiums. Underpricing insurance policies can pose solvency risks to insurers, making accurate pricing an important prerogative for multiple parties (Mohey-Deen & Rosen, 2018). Currently, each state has different rate-making rules determining which factors are

Table 4.5: Logit model results

	All	SFHA	Concerned
Variable	(1)	(2)	(3)
Household income: < $25,000 (ref. = $100,001-$250,000)	-1.191*	-4.748***	-1.517*
	(0.518)	(1.360)	(0.594)
Household income: $25,001-$50,000 (ref. = $100,001-$250,000)	-0.411	-3.580**	-0.495
	(0.467)	(1.311)	(0.531)
Household income: $50,001-$100,000 (ref. = $100,001-$250,000)	0.025	-2.677*	-0.322
	(0.429)	(1.253)	(0.492)
Household income: >$250,000 (ref. = $100,001-$250,000)	-1.069	-2.923	-0.728
	(0.775)	(1.869)	(0.901)
Education: No high school (ref. = Associate's degree)	0.802	15.422	-0.374
	(1.114)	(363.360)	(1.306)
Education: Some high school (ref. = Associate's degree)	0.183	2.116*	0.025
	(0.505)	(0.926)	(0.579)
Education: High school diploma or equivalent (ref. = Associate's degree)	0.173	0.984·	0.252
	(0.334)	(0.593)	(0.388)
Education: Bachelor's degree (ref. = Associate's degree)	0.413	0.691	0.307
	(0.413)	(0.755)	(0.487)
Education: Postgraduate degree (ref. = Associate's degree)	0.198	1.886	-0.190
	(0.515)	(1.310)	(0.549)
Ln(Vehicle Value)	-0.124	-0.295	-0.002
	(0.201)	(0.368)	(0.227)
In SFHA: Not sure (ref. = No)	-0.034	–	0.273
	(0.324)		(0.385)
In SFHA: Yes (ref. = No)	0.873**	–	1.172***
	(0.291)		(0.331)
VFD: Not sure (ref. = No)	0.145	0.906	0.280
	(0.646)	(1.522)	(0.886)
VFD: Yes, multiple times (ref. = No)	0.628·	1.109·	0.924*
	(0.378)	(0.628)	(0.419)
VFD: Yes, once (ref. = No)	0.436	1.205*	0.686*
	(0.290)	(0.523)	(0.328)
Vehicle type: Sedan (ref. = other)	1.270**	2.024**	1.701***
	(0.399)	(0.707)	(0.436)
Vehicle type: SUV (ref. = other)	1.062**	2.200	1.297**
	(0.387)	(0.691)	(0.419)
Vehicle type: Van (ref. = other)	0.614	1.796	0.988
	(0.635)	(1.200)	(0.795)
State: Texas (ref. = New York)	-0.254	-0.065	-0.041
	(0.283)	(0.536)	(0.339)
Concern: Not very concerned (ref. = Not concerned at all)	0.911	13.299	–
	(0.719)	(363.356)	
Concern: Somewhat concerned (ref. = Not concerned at all)	1.663*	14.729	–
	(0.679)	(363.355)	
Concern: Very concerned (ref. = Not concerned at all)	2.224**	15.224	–
	(0.696)	(363.355)	
Bid amount	-0.011***	-0.011***	0.012***
	(0.001)	(0.002)	(0.001)
Number of observations:	360	166	295
Log likelihood:	-365.05	-129.00	-284.27
AIC	778.10	302.01	610.54
BIC	871.37	370.47	687.97

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

Table 4.6: WTP estimates by FEMA Special Flood Hazard Area status and level of concern about flooding - logit model

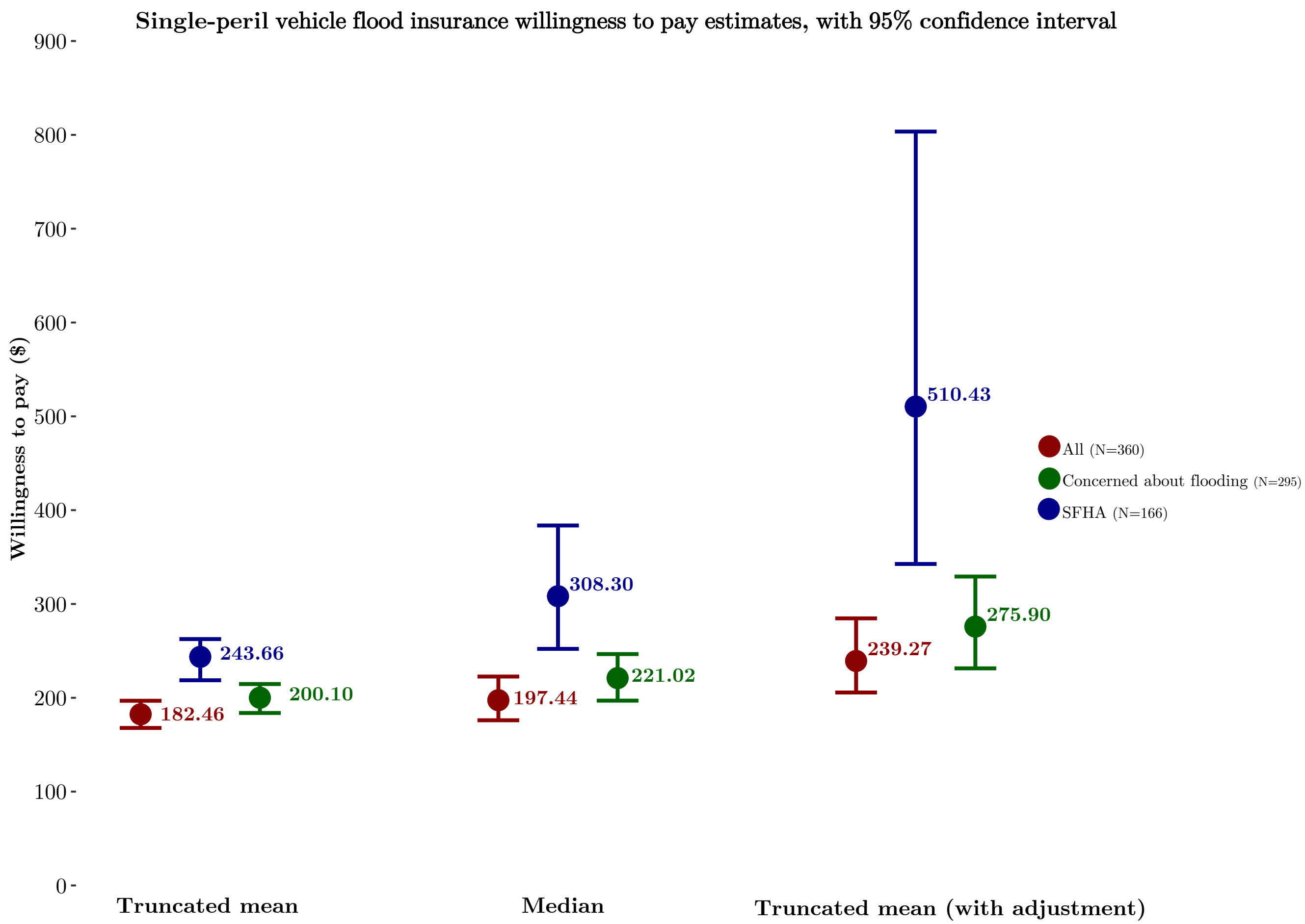
	All (N=360)		**SFHA (N=166)**		**Concerned (N=295)**	
	(1)		(2)		(3)	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
All respondents (N=360)						
Mean (truncated at max. bid)	$182.46	[$167.89, $196.88]	$243.66	[$218.69, $262.59]	$200.10	[$183.84, $214.67]
Median	$197.44	[$176.08, $222.66]	$308.30	[$252.14, $383.65]	$221.02	[$196.99, $246.63]
Mean (truncated at max. bid with adjustment)	$239.27	[$205.66, $284.67]	$510.43	[$342.65, $803.50]	$275.90	[$231.96, $329.24]

62 New York-based respondents and 104 Texas-based respondents reported living in a SFHA. 110 New York-based respondents and 185 Texas-based respondents reported being “somewhat concerned” or “very concerned” about flooding having a negative impact their communities.

Table 4.7: Summary statistics for responses to open-ended WTP elicitation

	Mean	**Median**	**Minimum**	**Maximum**	**Standard deviation**
All (N=335)	$434.90	$100.00	$0.00	$15,000.00	$1,141.03
New York (N=130)	$652.6	$180.00	$0.00	$15,000.00	$1,599.09
Texas (N=205)	$296.80	$100.00	$0.00	$5,000.00	$682.11

Figure 4.4: Central willingness to pay estimates for a single-peril vehicle flood insurance policy across welfare measures.



allowed to influence insurance premium rates, and these rules govern the weight each factor can have in the rate-making decision (Reger, 2015). In some states, insurers are allowed to factor territorial weights into rate-making, which commonly occur at the most granular level of zip code, or coarser geographic units (e.g., the state of Connecticut only had 13 auto insurance rating territories in 2006) (Kaminski, 2006). In California, there is a complex territorial rating process that may include grouping census tracts or zip codes together according to claims severity, however territorial considerations are not a primary nor secondary factor in the ratemaking decision, but a tertiary factor ("California Code of Regulations", 2023). Further, demographic factors such as race and income are not allowed to be factored into ratemaking decisions in any US state (Brobeck & Hunter, 2012). Thus, unlike the NFIP which prices flood insurance for structures and their contents according to modeled physical flood risk as shown in Table 4.1, comprehensive auto insurance prices only reflect physical flood risk at coarse geographic levels. However, since motorists' traffic violations and frequency of at-fault accidents are typically primary factors in ratemaking decisions, pricing likely captures some potential flood risk associated with motorists' propensities to drive *into* or remain in flood-exposed areas, though this only partially addresses flood risk in auto insurance pricing. Accurate pricing or underpricing relative to true risk still does not address "propitious selection" factors which can lead risk-averse individuals into insurance markets and risk-seeking individuals out of them (Hemenway, 1990).

Third, these results motivate consideration of opportunities for policy interventions, such as education campaigns or disclosure requirements, to increase awareness about vehicle flood risks and insurance options among potentially vulnerable vehicle owners in flood-prone areas. For example, while homeowners with Federally-backed or regulated mortgages residing SFHAs are required to purchase flood insurance through NFIP, and many states have enacted flood risk disclosure laws in the residential sector to promote informed consumer decisions vis-à-vis structure-level flood risk (Hino & Burke, 2021), flood risk information is generally not disclosed to vehicle owners at point of sale in cases where comprehensive insurance is not required by a lender or lessor. In combination, the dual insights of considerable WTP for single-peril vehicle flood insurance policies among respondents, and sizable estimated share of the study area population lacking knowledge about auto insurance flood coverage, suggest auto insurance literacy gaps may be leading to suboptimal comprehensive auto insurance penetration. This is perhaps most relevant to vehicle owners in SFHAs, where vehicle flood insurance gaps persist despite relatively high WTP for a single-peril vehicle flood insurance product. If some uninsured consumers opt out of purchasing comprehensive auto insurance due to lack of knowledge about scope of flood coverage, when they would truly prefer having vehicle flood insurance coverage, aggregate welfare may be diminished, leaving uncaptured consumer financial resilience benefits and unrealized revenue to insurers.

Fourth and last, this study's findings highlight gaps in publicly-available auto insurance data, which impairs effective public policy analysis. Unlike NFIP policies and claims data which all pertain to flood peril, granular peril-specific flood-related comprehensive auto insurance claims data are not analogously publicly-available. Additionally, while NFIP data are spatially explicit, with policy and claims data geolocated at the property level, publicly-available comprehensive claims data are only coarsely available at the state level. Increasing the accessibility, transparency, and usability of comprehensive insurance policy and claims data, and producing data products that are both flood-specific and geographically precise, would enable wider empirical analysis unconstrained by high costs of survey data. Such data products provided by insurers and/or state regulators could potentially improve public policy research to inform flood and climate risk exposure and vulnerabilities in auto insurance markets, which have implications for the broader insurance market.

4.6.2 Limitations and future work

The limitations of this chapter are enumerated to inform inference and future research. First, while a randomization element does exist in which Qualtrics randomly contacts potential respondents from the company's market research database about survey participation, there are a number of potential threats to representativeness which need to be acknowledged. Selection bias among contacted potential respondents could systematically overrepresent segments of the population exhibiting greater propensity to participate in the survey, and underrepresent segments less prone to participate. While observable sample characteristics on key variables such as vehicle ownership rates, age, and average vehicle value are close enough to sample zip code-wide estimates to provide reason to assume such sampling biases are not of huge magnitude, the absence of a fully-representative sample frame and the potential for non-response bias cannot be overlooked. Additionally, in certain survey results, such as the open-ended WTP elicitation, it is possible deliberate removal of seemingly-unrealistic responses actually remove valid, representative observations. In making these subjective decisions, the author aimed to equally balance priorities of representativeness and validity.

A second limitation concerns constructed market conditions in the WTP elicitation. While these central questions were designed to mirror a real market setting with fidelity, and attempted to provide ample information to respondents such that informed, valid responses were elicited, a few subjective choices may have impacted outcomes in significant ways which may be of interest to future researchers. In the DBDC elicitation, respondents were asked their WTP for a vehicle flood insurance product with $100 deductible. Since deductibles and premium prices generally have an inverse relationship, and auto insurance policies with larger deductibles of $250 or $500 are commonly selected by consumers, it is likely WTP estimates would be significantly lower if a larger deductible amount were offered. Additionally, this study only requests WTP information about respondents' most valuable household vehicle. As a result, heterogeneity in preferences for insurance coverage between household vehicles among respondents with multiple vehicles is not captured. Further, while the WTP elicitation pertains to one vehicle-year of insurance coverage, households owning multiple vehicles often bundle their vehicles under one policy for a lower cost of coverage per vehicle-year. Thus, this research overlooks WTP for tens of millions of household vehicles, since more than 60% of US households are estimated to have access to two or more vehicles (USCB, 2022). Survey results show, on average, approximately half of household vehicles lack comprehensive auto insurance. Future work in this area might explore the preferences of well-informed consumers which influence decisions to insure, or not insure, household vehicles under a comprehensive policy.

Last, due to lack of data on observed behavior, this work estimates WTP for an insurance product not generally available in the marketplace using a stated preferences approach. While contingent valuation and other stated preferences methods are often suitable in applications where observations describing revealed preferences are not observed (Carson & Hanemann, 2005), results rely heavily on econometric assumptions, quality of elicitation design, and accuracy of stated information provided by respondent as representative of true behavior. Ideally, insights from this chapter could be complemented in the future by empirical analysis of observational records in a revealed preferences approach to complement stated preferences findings, however current data limitations hinder such work at present.

4.7 Conclusions

This study focuses on two distinct urban, coastal regions in New York and Texas that are known to have experienced a relatively high number of uninsured vehicle flood damage cases in the past decade and a half. High vehicle ownership rates, expanding and intensifying flood hazards driven by climate change, and urban development patterns suggest many other communities in the US face similar vehicle flood risk mitigation challenges. While many studies to date have focused on the experiences of residential property with respect to actualized flood damages and flood insurance uptake, this is the first to empirically examine flood damages, literacy rates regarding flood insurance coverage, and WTP for a single-peril flood insurance policy with a focus on vehicle assets.

Responses from 360 vehicle owners across 39 coastal zip codes indicate vehicle flood damages are common and can be of considerable magnitude. Contingent valuation estimates find respondents exhibit robust WTP for a single-peril vehicle flood insurance product currently not available on the general auto insurance market. The preferred mean estimate of WTP per vehicle-year for vehicle flood insurance coverage is \$182.46, a value which exceeds the average price of a comprehensive auto insurance policy in the US in 2020. Estimated WTP for single-peril vehicle flood insurance among respondents living in FEMA-designated SFHAs was approximately 33% higher than the sample-wide average, which is consistent with similar conclusions in the housing literature that find homeowners in SFHAs have higher WTP for flood insurance, on average, than homeowners outside SFHAs (Netusil et al., 2021). Even when controlling for vehicle value, estimates find WTP and vehicle owner household income are negatively correlated, suggesting the potential for income constraints to affect comprehensive auto insurance affordability and penetration in the actual marketplace. 59% of survey respondents report their household has experienced at least one significant vehicle flood damage event, though on average fewer than half of household vehicles are reported to be covered by a comprehensive policy. Among respondents reporting vehicle flood damage, the average maximum cost of experienced vehicle flood damages is nearly \$10,000, suggesting vehicle flood damages are not only common, but can be large in magnitude when they occur.

Empirical results also find approximately one in three vehicle owners in the study area lack the knowledge that comprehensive auto insurance is the type of policy that covers a vehicle against flood damage. While insightful research on homeowner flood insurance literacy has been conducted in the housing literature and finds considerable knowledge gaps exist among homeowners about the type of policy that covers residential structures against flood damage (Kousky & Netusil, 2023), this is the first study to apply analogous research questions to vehicle owners. While results do not suggest vehicle owners residing in SFHAs are more or less informed about vehicle flood insurance coverage than those indicating they reside outside SFHAs, the vehicle flood insurance literacy rate among the population reporting they do not know if their residence is in a SFHA is 16 percentage points lower, on average, than the rate among vehicle owners residing in SFHAs. Thus, despite considerable mean WTP estimates for single-peril vehicle flood insurance, insurance gaps persist, and some segments of the population appear particularly unaware of their key household assets' objective flood risk and pertinent insurance options to mitigate these risks.

These results make at least three notable contributions to the academic literature on climate adaptation, insurance, and flood risk mitigation. First, in the absence of accessible disaggregated flood-specific comprehensive auto insurance policy data describing vehicle owners' revealed preferences, this study elicits and derives novel WTP estimates for a single-peril vehicle flood insurance product using a contingent valuation approach. The magnitude of these estimates suggests coastal vehicle owners may enjoy significant consumer surplus in the comprehensive auto insurance market. Insurers and state insurance regulators may be interested in these WTP estimates, given incentives to identify new viable revenue streams. Additionally, WTP estimates are higher among respondents with greater objective flood exposure and elevated concern about flooding, suggesting demand for flood insurance coverage for vehicles may increase as climate change impacts and urban development patterns expose more areas to flood hazard.

Second, this work fills an epistemic gap resulting from the absence of granular flood-specific auto insurance claims data by providing estimates of the scope and magnitude of vehicle flood damages in an urbanized coastal study area. Inferences to the population level indicate a majority of vehicle-owning households in the 39 zip codes in the study area have at some point experienced significant vehicle flood damages, and the estimated average maximum amount of damage experienced among those having experienced vehicle flood damage is approximately $9,800 ($7,994, $11,596, 95% CI). These results provide compelling evidence that vehicle flood damages are widespread and of significant magnitude. Third, the survey data provide a first examination of vehicle flood insurance literacy rates among vehicle owners, and finds considerable vehicle flood insurance literacy gaps exist. Public policy interventions such as education campaigns or vehicle flood risk disclosure requirements could potentially reduce financial vulnerability to vehicle flood damages by increasing literacy and insurance penetration rates. Future research might examine disaggregated comprehensive auto insurance policies and claims data to help inform design of insurance markets and related public policies, thereby promoting financial resilience in the face of intensifying flood hazards.

CHAPTER 5

Conclusion

This dissertation is motivated by the intersection of existing household vulnerability and growing flood hazard exposure driven by anthropogenic climate change and status quo urban development patterns. At its core, the objective of this research is to inform households, firms, and policymakers in meaningful ways that can improve future climate adaptation and flood risk reduction efforts. The dissertation primarily focuses on exposure, vulnerability, and risk mitigation opportunities with respect to two widely-owned and economically-important household assets: residential property and vehicles. The research is interdisciplinary in nature, leveraging concepts as well as technical approaches from the fields of environmental science, policy analysis, environmental economics, and adaptation science. The following paragraphs briefly describe the main scholarly contributions of each chapter, as well as avenues for future research conceived during the analysis and interpretation of results.

In my first research chapter, I contribute to an emerging body of scholarship on the hedonic pricing of anthropogenic sea level rise (SLR) impacts in coastal residential property markets, specifically by employing a novel application of the econometric triple-differences estimator that exploits temporal variation in global scientific consensus about observed anthropogenic SLR and controls for extant flood risk as represented by Federal Emergency Management Agency (FEMA) flood maps. The chapter focuses on the southeastern United States (US) and for the first time integrates a policy-relevant alternative property value metric, structure depreciated replacement value (DRV), alongside transaction prices as a statistical robustness check and more relevant property value measure when analyzing Federal programs with flood mitigation objectives. While results do not detect a price effect of anthropogenic SLR exposure in isolation, they do suggest negative effects estimated elsewhere in the literature could be attributable to acute extant flood risk or compositional differences in residential building stock. Additionally, across measures of residential property value, coastal property value is positively correlated with census tract income and negatively correlated with non-Hispanic Black or African-American population share with statistical significance, suggesting policy decisions that weight every dollar of property value equally may have the potential to favor higher-value properties in flood risk management decisions and reinforce existing property value disparities.

Chapter 2 may be complemented by future research in at least three avenues. First, future work may build on this revealed preferences study by estimating property owners' "willingness-to-accept" of SLR impacts across varying magnitudes, timescales, and adaptation scenarios through a stated preferences study. Second, while previous researchers have analyzed the impacts of flood risk disclosure laws on residential property markets, the role of high-quality *climate risk* information (e.g., localized impacts of SLR on relevant timescales) and policy interventions requiring the provision of this information to prospective homeowners or renters in SLR-exposed areas, may provide insight germane to future coastal adaptation policies. Third, specific case studies focused on FEMA or US Army Corps of Engineers (USACE) flood mitigation projects that employ alternative benefit-cost analysis (BCA) methods and social welfare functions relative to existing Federal policy guidance might inform policy analysts about the sensitivity of project selection decisions and flood risk reduction outcomes to property value inputs and their weighting (or lack thereof).

Chapter 3 conducts a first-of-its-kind, data-intensive national stocktake of the number and value of household vehicles located in the contiguous US, incorporating data from more than 80,000 US census tracts, 10 billion pixels of US Geological Survey (USGS) land cover data at 30-meter resolution, and more than 100 million property-level observations from the USACE National Structure Inventory (NSI) and First Street Foundation, respectively. While many studies have focused on exposure and impacts of flooding on residential and commercial property, this study is the first to focus exclusively on US households' most widely-owned tangible asset. Preferred estimates suggest approximately 13.1 million household vehicles worth more than $300 billion are located in FEMA SFHAs, and 5.2 million of these vehicles are in census tracts defined by the Federal government as "disadvantaged." Further, this study is the first to analyze previously-unstudied FEMA Individuals and Households Program (IHP) data, which indicate thousands of households apply for disaster assistance in connection with vehicle flood damages every year, and FEMA has paid more than $130 million through IHP to mostly low-income households recovering from uninsured vehicle flood damages.

Going forward, scholars may advance our understanding of US vehicle flood damages and related disaster assistance by acquiring and analyzing granular flood-specific insurance claims data from private firms or state regulators, and/or additional information from FEMA staff about the specific levels of vehicle flood damage experienced by IHP applicants as well as the precise reasons applicants are deemed ineligible. Additionally, as remote sensing data, computing power, and machine learning techniques improve, empirical analysis of observed vehicle owner behaviors before, during, and after flood events may refine these estimates of the number and value of flood-exposed vehicles, and produce valuable insight into the rates at which vehicle owners avoid inundated areas or advance into them.

Finally, Chapter 4 gathers novel information from 360 vehicle owners in coastal New York and Texas about their flood insurance literacy, past experiences regarding vehicle flood damages, and willingess-to-pay (WTP) for a hypothetical single-peril vehicle flood insurance product. This survey fills a key epistemic gap in the academic literature, which has to date predominantly focused on flood exposure, insurance uptake, and related policy opportunities for flood risk mitigation with respect to residential property, with little analogous attention paid to an also-important but understudied household asset: vehicles. Findings suggest vehicle flood damages are both common and substantial in magnitude when they occur in the study area, suggesting the opaqueness of private auto insurance data and the multi-peril nature of comprehensive auto insurance policies may obfuscate public understanding of the scale of insured vehicle flood damages in the US. More than one-third of survey respondents reported a lack of awareness about the type of auto insurance policy that covers flood damages, suggesting the potential for asymmetric information to yield suboptimal risk management decisions. Preferred estimates indicate respondents were willing to pay an average of $182.46 per year for the hypothetical single-peril vehicle flood insurance product, with vehicle owners who are concerned about flooding or reside in FEMA SFHAs willing to pay substantially more for such a policy. These findings suggest insurance firms may consider offering peril-specific auto insurance policies in hazard-prone areas, as respondents' mean WTP for the hypothetical single-peril product is comparable to the average price of a comprehensive auto insurance policy actually available on the market. Additionally, vehicle owners, insurance firms, and state regulators all stand to potentially benefit from increasing consumers' awareness of auto insurance policies' scopes of coverage.

Future research on this topic may extend the contributions of this study in at least three ways. First, a comparable study with larger sample size and randomized dissemination might ask questions that test the sensitivity of respondents' WTP with respect to different values for variables such as deductible amount or scope of coverage (e.g., damages not covered if driver advances *into* inundated area) to better understand generalizability of this chapter's results. Second, an empirical analysis of proprietary insurance claims data disaggregated at the peril-level for flood hazard would complement the sample data describing vehicle owners' individual vehicle flood damage experiences. Third, a microeconomic study of vehicle owners' WTP for peril-specific auto insurance coverage relative to the comprehensive insurance prices they are offered in the marketplace may reveal opportunities for improved pricing of weather and climate risks into auto insurance markets.

This dissertation demonstrates key US household assets of residential property and vehicles have widespread exposure to climate change-intensified flood hazards. Many US households are vulnerable to adverse impacts from flood exposure, including through these assets. Despite current and projected risks, substantial opportunities exist which cana catalyze transformative adaptation actions that will help steer households and society in the direction of equitable, climate resilient development. This dissertation produces, analyzes, and interprets policy-relevant evidence that may support individuals, firms, and policymakers in their flood risk management decisions. Our built environments and the people who rely on them are unlikely to vacate coasts and watersheds overnight– in the coming years and decades, scholarship that is both rigorous and decision-relevant will remain essential to help mitigate future flood losses and promote well-being in waterfront communities.

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APPENDIX

A.1 Chapter one supplemental materials: Estimating effects of projected mean sea level rise exposure on measures of residential property value: evidence from the southeastern United States

A.1.1 Additional description of empirical methods

In Equation 2.1 in the main text, the β_1 parameter represents the difference in the average price of unexposed properties and exposed properties outside the SFHA in the pre-AR3 period. This parameter captures the location effect of being in the sea level rise (SLR)-plain in the pre-AR3 period. β_2 captures changes in transaction prices in the pre-AR3 period and corresponds to the difference between average transaction price among unexposed properties in the pre-AR3 period and post-AR3 period. β_3 represents the price effect of being inside a SFHA relative to being outside a SFHA among properties unexposed to SLR of magnitude m.

β_4 corresponds to an interaction term between the post-AR3 dummy variable and Exposure variables, and captures temporal variation in the price effect of being in the

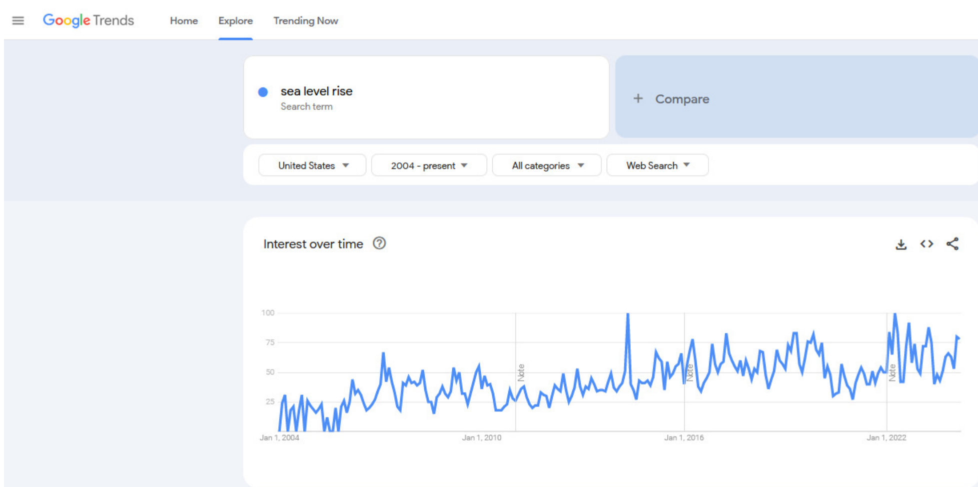
SLR-plain in the post-AR3 period relative to pre-AR3 period. β_5 tests whether price effects of being in the SLR-plain across the sample period are statistically different from zero among properties inside a Federal Emergency Management Agency (FEMA) Special Flood Hazard Area (SFHA) as compared with those outside FEMA's SFHA. β_6 captures temporal variation in the price effects of SFHA status in the post-AR3 period relative to the pre-AR3 period, and are hypothesized to be zero. β_7 is a cornerstone parameter of interest, constituting the triple-difference estimator. This parameter is so-called as it represents the difference between (i) the difference between average transaction price in the post-AR3 and pre-AR3 period of properties both in the SLR-plain and SFHA; (ii) the difference between average transaction price in the post-AR3 period and pre-AR3 period of properties not in the SLR-plain but in the SFHA; and (3) the difference between average transaction price in the post-AR3 and pre-AR3 period among properties in the SLR-plain but not in the SFHA.

The identifying triple-difference parallel trend assumption as noted in Olden and Møen (2022) requires the relative outcome for properties "in the SFHA" vis à-vis properties "outside the SFHA" among SLR-exposed properties to pre-trend in the same way as the relative outcome of properties "in the SFHA" vis-à-vis properties "outside the SFHA" in the unexposed group. Figures A.5-A.9 include parallel trend visualizations for average transaction price by year across SLR-plain status and SFHA status, respectively, as well as the triple-difference parallel trend assumption described above. Inspections of these visualizations do not appear to preclude valid difference-in-differences or triple-difference estimation. The analysis assumes treatment effects are constant over time (Goodman-Bacon 2021).

A simplified example of the derivation for β_7 in Equation 2.1 is shown below in Equation A.1 and draws from Wooldridge (2010).

$$
\begin{aligned}
\hat{\beta}_7 = {} & [(\overline{Price}_{\text{Exposed, SFHA, Post-AR3}} - \overline{Price}_{\text{Exposed, SFHA, Pre-AR3}}) - \\
& (\overline{Price}_{\text{Not exposed, SFHA, Post-AR3}} - \overline{Price}_{\text{Not exposed, SFHA, Pre-AR3}})] - \\
& [(\overline{Price}_{\text{Exposed, Not in SFHA,Post-AR3}} - \overline{Price}_{\text{Exposed, Not in SFHA, Pre-AR3}}) - \\
& (\overline{Price}_{\text{Not exposed, Not in SFHA, Post-AR3}} - \overline{Price}_{\text{Not exposed, Not in SFHA, Pre-AR3}})]
\end{aligned} \tag{A.1}
$$

Figure A.1: Google Trends results for "sea level rise" search term, 2004-2024.

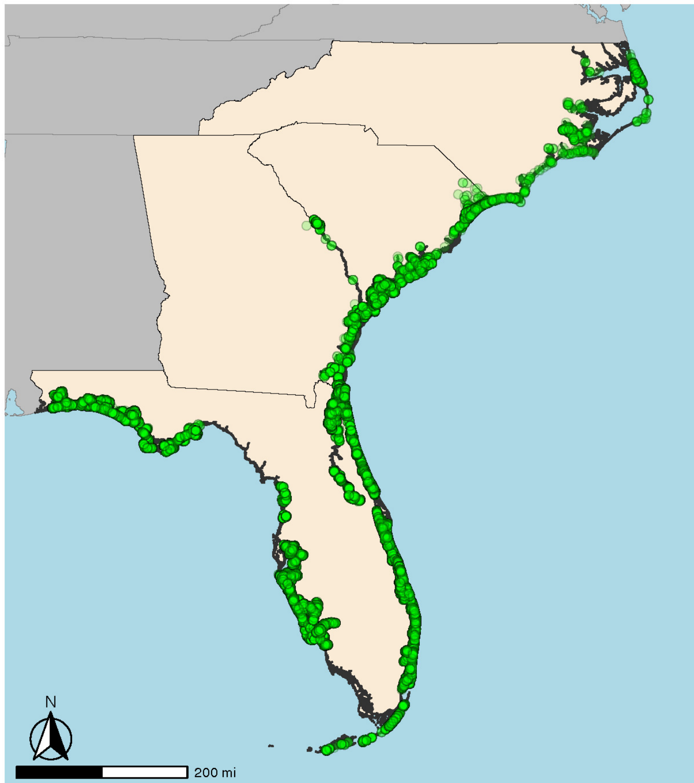


A.1.2 Exploring heterogeneous effects of community race and income on measures of residential property value

A.1.2.1 Description of data

In order to control for local community characteristics and explore heterogeneity in price effects of GMSLR across demographic dimensions—specifically the racial composition and median household income of an area— census tract-level data from the United States Census Bureau's (USCB) American Community Survey (ACS) five-year estimates were sourced for this purpose. According to the US Census Bureau,

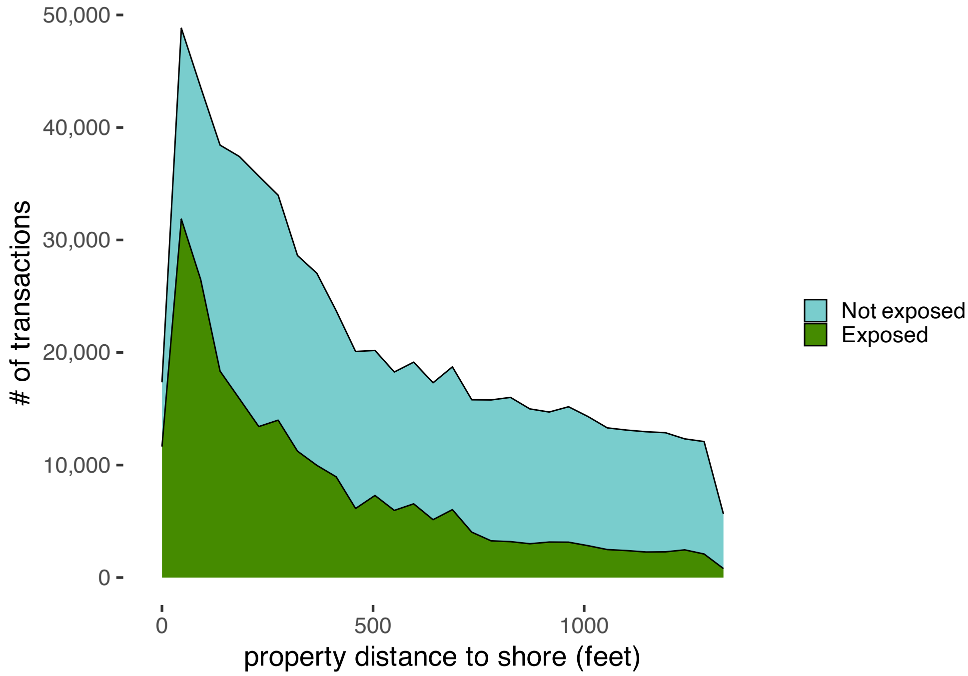
Figure A.2: Sample transactions not exposed to six feet of sea level rise (N=401,103)



census tracts are small subdivisions of a county with an "optimum size of 4,000 people" and generally range from 1,200-8,000 people. Figure A.10 displays the coastal census tracts included in the analysis, all of which contain at least a portion of area that is within a quarter-mile of the shoreline as defined by the National Oceanic and Atmospheric Administration (NOAA). Census tracts typically cover smaller land areas in areas with higher population densities, which explains census tracts that are small by land area in dense urban areas such as Miami-Dade County. Annual tract-level data were accessed for each year for which ACS data were available, in this case 2009-2020 (Walker, 2021).

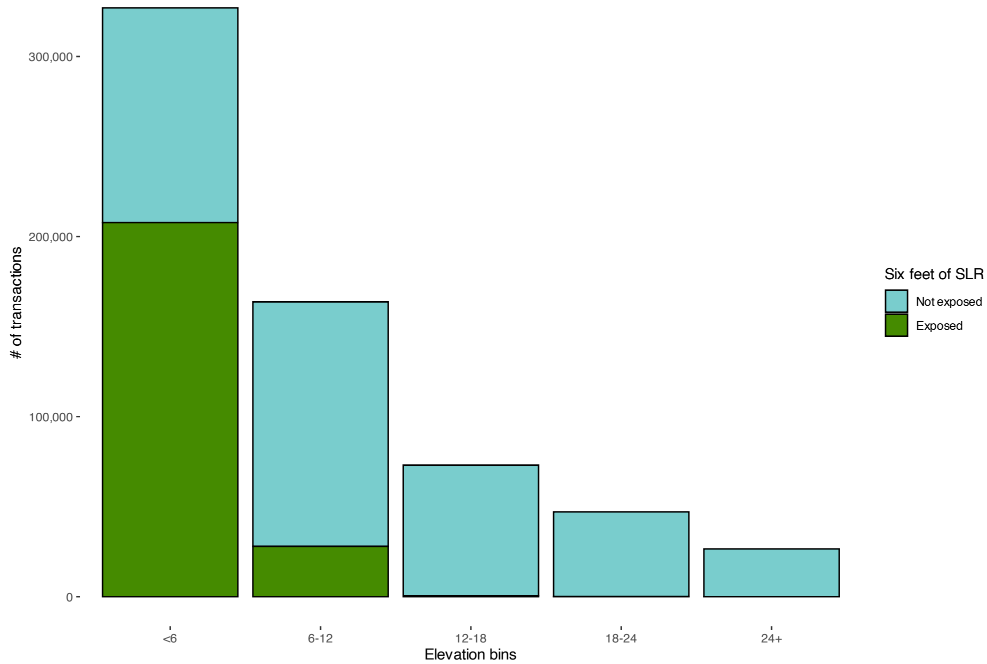
Census data are available for 285,729 of the transactions in coastal tracts shown in Table A.3; this subsample is analyzed in complement with the larger ZTRAX sample. Among transactions in the sample for which census data are available, the average

Figure A.3: Transactions by shore distance and six-foot SLR-plain status (N=637,451)



census tract median income and share of the population identified as non-Hispanic Black or African-American were \$66,794 and 3.9%, respectively. The median household incomes from 2016-2020 in Florida, Georgia, North Carolina, and South Carolina, respectively, were \$57,703, \$61,224, \$54,864, and \$56,642, which suggests the census tracts in which sample transactions occurred tend to have median household incomes above state averages (Walker, 2021). Regarding racial composition, Table A.3 presents statistics about the statewide and coastal census tract populations in 2020, as well as the share of these populations estimated to be non-Hispanic Black or African-American. Table A.3 indicates Florida, Georgia, North Carolina, and South Carolina all have substantial non-Hispanic Black or African-American populations above the national average of 12.1%, however these populations tend to be underrepresented in coastal census tracts relative to the statewide populations. Additionally, Florida has both the largest statewide and coastal census tract population among the four states analyzed, and its population in coastal census tracts represents the

Figure A.4: Six-foot SLR-plain status of sample transactions by elevation above NAVD88 (feet) [N=637,451]



greatest share of the total state population with an estimated 29.2% of Florida residents residing in census tracts within 0.25 miles of the shoreline. Among census tracts in Florida, Georgia, North Carolina, and South Carolina within 0.25 miles of the shoreline for which data were available, approximately 14.4% of the population in 2020 was non-Hispanic Black or African-American (Walker, 2021).

Table A.3 suggests there are substantial non-Hispanic Black or African-American populations in shore-adjacent census tracts in the study area, which is corroborated in the geography literature (Hardy et al., 2017). However, the census tracts in which property transactions took place tended to have smaller non-Hispanic Black or African-American shares of the population than the coastal study area at large. Further, as shown in Figures A.11 and A.12, the vast majority of sample transactions take place in census tracts in which a small share of the tract population is non-Hispanic Black or African-American. One possible explanation for this observation is a low

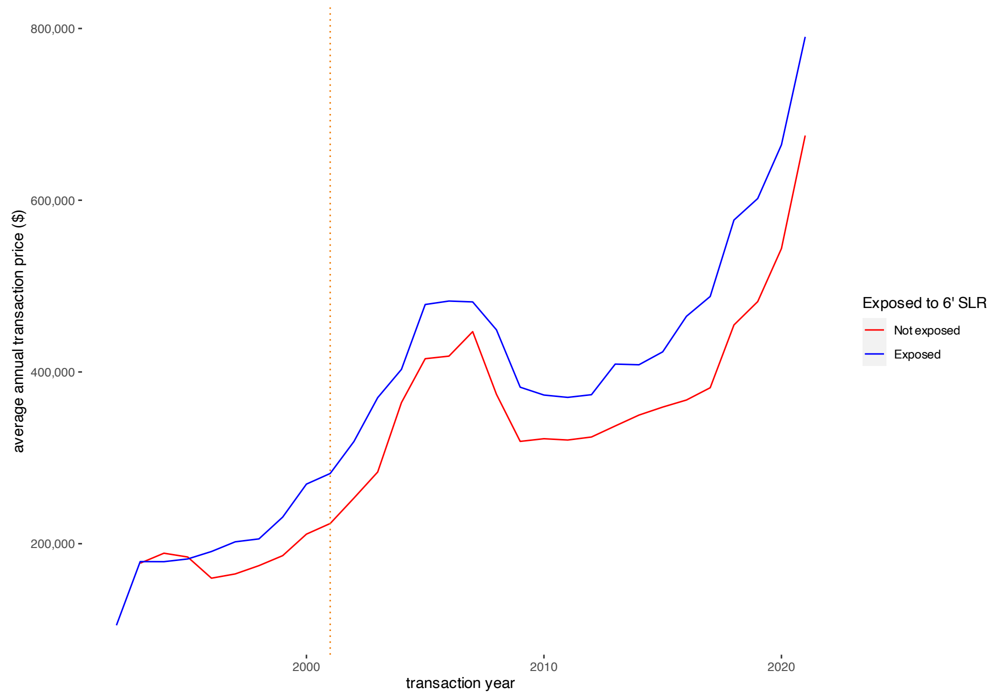
Figure A.5: Parallel trends, transactions inside and outside three-foot SLR-plain (N=637,451)

national homeownership rate among the non-Hispanic Black or African-American population relative to the national average.

Model specifications shown in Equations (A.2) and (A.3) are run to explore heterogeneity in price effects across dimensions of income and race at the census tract-level.

$$\text{Ln(price)}_{i,Y} = \beta_0 + \beta_1 \text{Exposure}_{m,i} + \beta_2 \text{AA}_{c,Y} + \beta_3(\text{Exposure}_{m,i} * \text{AA}_{c,Y}) + \beta_4(\text{SFHA}_i) + \beta_5(\text{Exposure}_{m,i} * \text{SFHA}_i) + \beta_6 \text{Age}_{i,Y} + \beta_7 \text{SF}_i + \lambda_{BR,CN,D,E,Y,Z} + \epsilon_{i,Y} \quad \text{(A.2)}$$

Figure A.6: Parallel trends, transactions inside and outside six-foot SLR-plain (N=637,451)

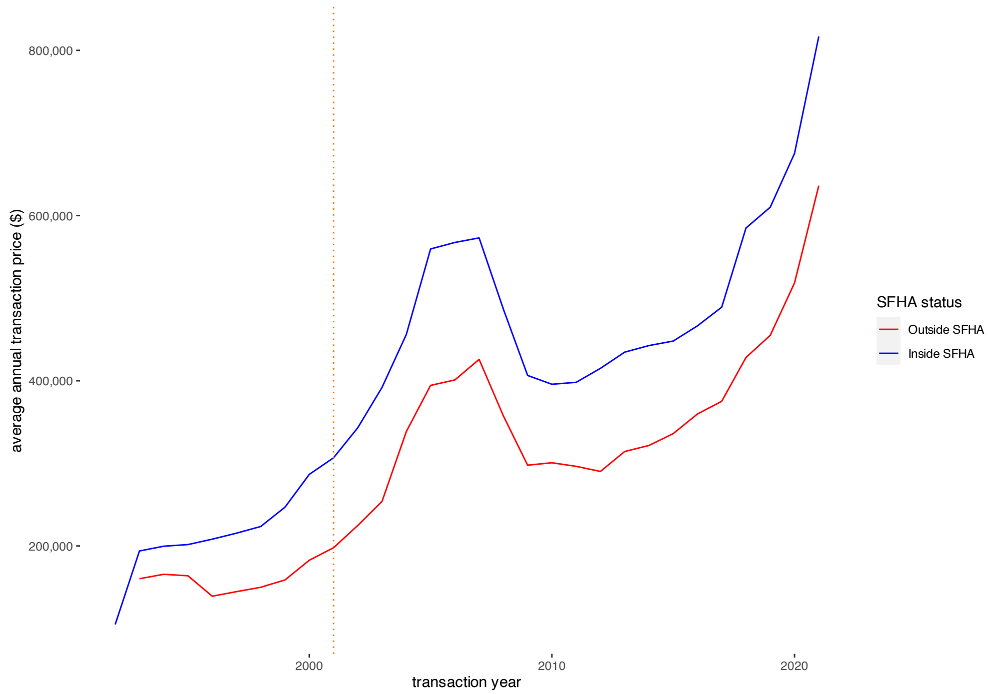


$$\text{Ln(price)}_{i,Y} = \beta_0 + \beta_1 \text{Exposure}_{m,i} + \beta_2 \text{I}_{c,Y} + \beta_3(\text{Exposure}_{m,i} * \text{I}_{c,Y}) + \beta_4(\text{SFHA}_i) + \beta_5(\text{Exposure}_{m,i} * \text{SFHA}_i) + \beta_6 \text{Age}_{i,Y} + \beta_7 \text{SF}_i + \lambda_{BR,CN,D,E,Y,Z} + \epsilon_{i,Y} \tag{A.3}$$

A.1.2.2 Transaction price results by share of census tract non-Hispanic Black or African-American

Table A.4 includes a total of eight sets of estimation results corresponding with variations of model specification shown in Equation (A.2). The sample used in this analysis includes 285,729 transactions from 2009-2020 for which census tract-level demographic data were available, and thus is unable to exploit temporal variation in

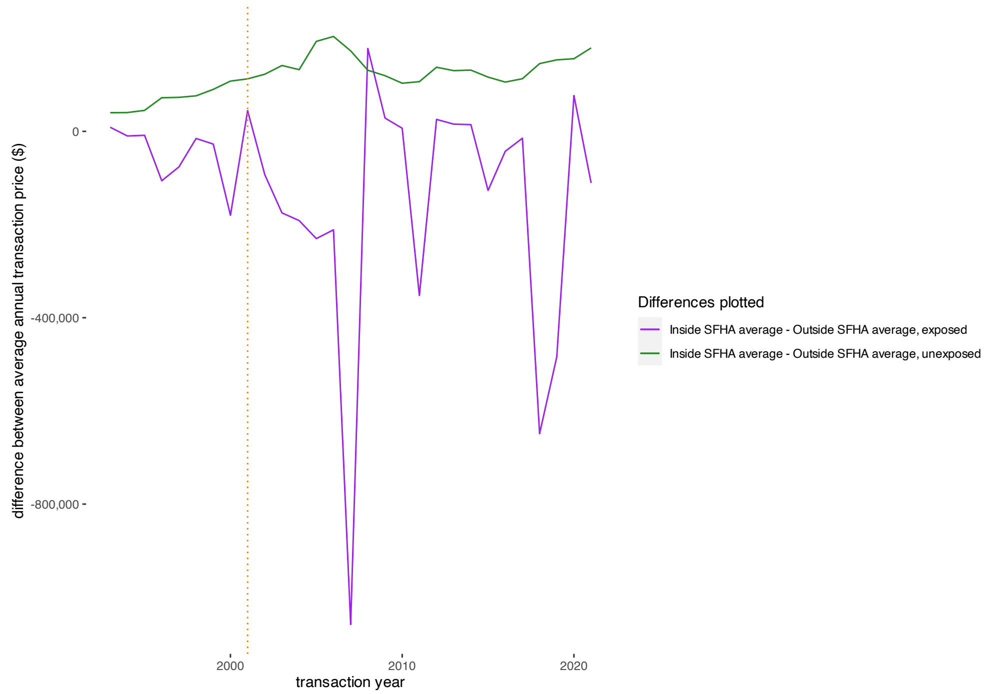
Figure A.7: Parallel trends, transactions inside and outside SFHA (N=637,451)



global scientific consensus about anthropogenic GMSLR as proxied by the Intergovernmental Panel on Climate Change's (IPCC) Third Assessment Report. Columns 1a, 1b, 2a, and 2b present results of reference estimations without the key new independent variable of interest, non-Hispanic Black or African-American share of the census tract population. In estimates of β_1 in columns 1a and 2a, being located in the SLR-plain appears to suggest negative and statistically significant price effects (at $p<0.1$ for three feet of SLR, $p<0.01$ for six feet of SLR) similar to main results shown in Equation (2.1). However, when incorporating the SFHA interaction term in specifications shown in columns 1b and 2b, β_1 estimates are statistically indistinguishable from zero. These findings are consistent with those from model (1) which suggest the possibility that extant flood risk, and not GMSLR alone, may drive negative β_1 parameter estimates when SFHA status is not sufficiently controlled for.

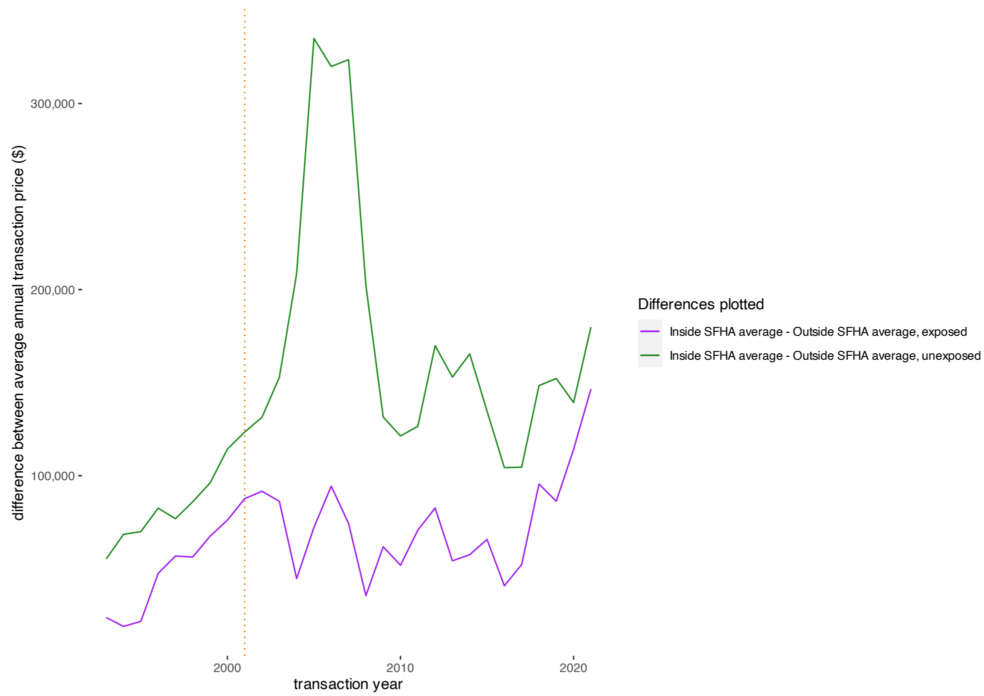
Estimates shown in Table A.4 columns 1c, 1d, 2c, and 2d incorporate Census Bureau data on census tract-level non-Hispanic Black or African-American population

Figure A.8: Parallel trends, triple differences (three-foot SLR-plain) [N=637,451]



share. While these results do not provide compelling evidence of a SLR-plain status discount nor a more pronounced SLR-plain discount in areas with larger non-Hispanic Black or African-American populations as hypothesized, they do indicate substantial differences in otherwise observably equivalent properties based on the share of the Black population in the census tract in which the property is transacted. While estimates of β_3 in model specification Equation (A.2) do not suggest a coherent or meaningful relationship between SLR-plain status and census tract race, β_2 estimates do indicate that a 10% increase in the share of a census tract's non-Hispanic Black or African American population share is associated with a -4.3% (-6.5% to -2.0%, 95% CI) change in transaction price ceteris paribus. These results suggest, on average, as coastal census tracts' non-Hispanic Black or African-American populations increase, property transaction prices decrease. Figure A.11 shows a scatter plot and least fit line representing transaction prices by transactions' exposure statuses vis-à-vis six feet of SLR and share of census tract that is non-Hispanic Black or African-American.

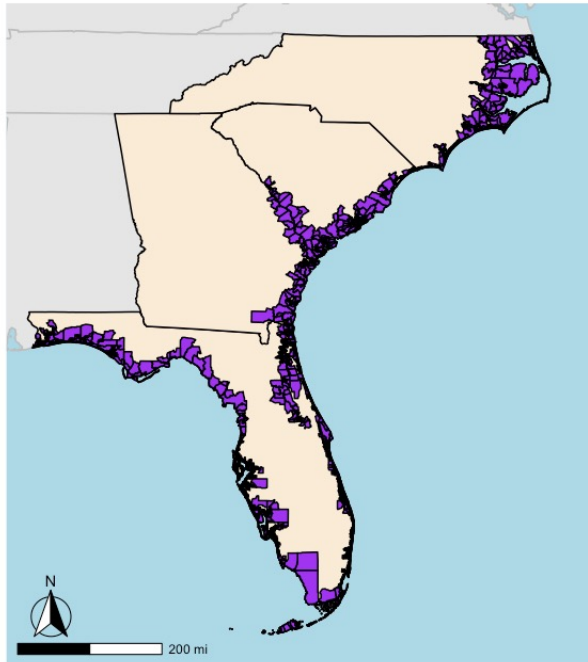
Figure A.9: Parallel trends, triple differences (six-foot SLR-plain) [N=637,451]



This plot indicates there is significant variation in SLR exposure across transaction price and census tract non-Hispanic Black or African-American population. Additionally, the figure clearly illustrates the negative correlation between transaction price and Black population. Figure A.12 shows similar results, but only for the subset of transactions located in the six-foot SLR-plain.

While previous studies have found evidence property values tend to be lower on average in areas with larger Black populations when compared with similar properties in areas with smaller Black populations (Harris, 1999), this study is the first to produce definitive evidence this is also the case in shore-adjacent areas in the southeastern US which face substantial threat of increased flood exposure and/or permanent inundation due to GMSLR. While this study does not provide evidence of a negative price effect of a property being located in the SLR-plain as hypothesized, across specifications I find consistent evidence that coastal properties located in census tracts with larger non-Hispanic Black or African-American populations tend to

Figure A.10: Census tracts represented in demographic data sample (N=1,976)



sell for less than observably equivalent properties with smaller non-Hispanic Black or African-American populations.

A.1.2.3 Transaction price results by census tract income

Table A.5 contains results which correspond to the model in Equation (A.3). Across all four shown specifications in the table, transaction price is positively correlated at p<0.01 with the median income of the census tract in which the transacted property was located. Results are similar for both SLR magnitudes in columns 1b and 2b, suggesting that on average a 1% increase in census tract median household income corresponds to an approximate 0.3% increase in transaction price holding other observed factors constant. Estimates shown in columns 1a and 1b do not provide evidence to suggest properties in the three-foot SLR-plain sold for any discount relative to comparable properties outside the SLR-plain. Similar to findings in the main text, column 2b suggests some interactive negative price effect for being located in both the six-foot SLR-plain and a SFHA. Additionally, the parameter estimate for β_3 from model in Equation (A.3) is statistically significant at ($p<0.1$), and provides some weak evidence that negative price effects of being in the six-foot SLR-plain emerge as census tract income increases. These findings are somewhat consistent with Bernstein et al. (2019) conclusions about negative price effects primarily emerging among "sophisticated" buyers.

Table A.1: Summary statistics, property transactions, 1993-2022

	Inside three-foot SLR-plain			Outside three-foot SLR-plain		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Sales price ($, thousands)						
Florida	38,152	481.0	640.2	553,839	386.0	583.2
Georgia	437	383.4	225.0	6,201	340.3	271.7
North Carolina	141	415.8	399.2	1,405	403.7	473.7
South Carolina	1,204	423.3	399.8	36,072	384.5	486.2
Total	39,934	478.0	630.6	597,517	385.5	575.2
# of bedrooms						
Florida	38,152	2.5	1.0	553,839	2.7	1.0
Georgia	437	3.2	0.8	6,201	3.0	0.9
North Carolina	141	3.4	1.2	1,405	3.3	1.1
South Carolina	1,204	3.1	1.2	36,072	2.5	1.3
Total	39,934	2.5	1.0	597,517	2.7	1.0
Building area sq. ft.						
Florida	38,152	1,706	1,082	553,839	1,872	1,093
Georgia	437	2,118	911	6,201	2,003	927
North Carolina	141	1,939	879	1,405	1,930	994
South Carolina	1,204	2,145	1,156	36,072	1,907	1,333
Total	39,934	1,725	1,086	597,517	1,876	1,108
Distance to shore (ft.)						
Florida	38,152	297.7	295.0	553,839	504.9	378.5
Georgia	437	707.8	387.2	6,201	752.4	377.6
North Carolina	141	532.4	407.1	1,405	600.7	374.0
South Carolina	1,204	551.1	389.7	36,072	607.1	363.9
Total	39,934	310.6	306.1	597,517	27.4	21.1
Elevation (ft.)						
Florida	38,152	5.2	1.2	553,839	9.6	9.9
Georgia	437	4.8	2.1	6,201	24.6	42.9
North Carolina	141	3.4	3.7	1,405	10.3	7.3
South Carolina	1,204	4.6	2.9	36,072	12.5	10.3
Total	39,934	5.2	1.3	597,517	9.9	10.9
Property age (years)						
Florida	38,152	27.8	23.2	553,839	27.7	21.1
Georgia	437	28.5	23.3	6,201	35.2	30.7
North Carolina	141	26.5	17.6	1,405	27.9	19.4
South Carolina	1,204	25.2	27.6	36,072	21.8	18.5
Total	39,934	27.7	23.3	597,517	27.4	21.1
Special Flood Hazard Area status						
Florida	38,152	0.99	0.12	553,839	0.41	0.49
Georgia	437	1.0	0.0	6,201	0.30	0.46
North Carolina	141	0.97	0.19	1,405	0.32	0.47
South Carolina	1,204	0.99	0.12	36,072	0.40	0.49
Total	39,934	0.99	0.12	597,517	0.41	0.49

Table A.2: National Structure Inventory summary statistics, 2022

	Inside three-foot SLR-plain			Outside three-foot SLR-plain		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Structure value ($, thousands)						
Florida	65,155	227.5	368.6	967,756	224.8	308.1
Georgia	1,464	270.1	364.8	20,090	282.2	352.0
North Carolina	9,995	166.6	148.7	121,708	207.3	286.9
South Carolina	4,804	233.8	187.7	68,645	338.3	464.5
Total	81,418	221.2	341.2	1,178,199	230.6	319.3
Distance to shore (ft.)						
Florida	65,155	291.2	297.5	967,756	508.8	384.5
Georgia	1,464	619.4	416.2	20,090	731.4	372.8
North Carolina	9,995	405.8	354.8	121,708	571.7	380.8
South Carolina	4,804	495.3	380.7	68,645	690.7	372.9
Total	81,418	323.2	320.8	1,178,199	529.7	386.8
Building area sq. ft.						
Florida	65,155	2,113	4,051	967,756	2,123	2,942
Georgia	1,464	2,463	3,873	20,090	2,639	2,950
North Carolina	9,995	1,758	2,219	121,708	2,133	2,264
South Carolina	4,804	1,991	1,302	68,645	2,938	3,654
Total	81,418	2,069	3,758	1,178,199	2,180	2,964
Elevation (ft.)						
Florida	65,155	2.6	1.5	967,756	9.1	7.0
Georgia	1,464	4.6	2.1	20,090	24.1	43.9
North Carolina	9,995	2.8	1.1	121,708	11.6	7.6
South Carolina	4,804	4.9	2.1	68,645	13.6	17.3
Total	81,418	2.8	1.7	1,178,199	9.9	10.1
Number of stories						
Florida	65,155	1.37	1.11	967,756	1.24	0.80
Georgia	1,464	1.58	1.05	20,090	1.48	1.21
North Carolina	9,995	1.38	0.85	121,708	1.39	0.81
South Carolina	4,804	1.70	0.95	68,645	1.58	0.92
Total	81,418	1.39	1.07	1,178,199	1.28	0.82
Special Flood Hazard Area status						
Florida	65,155	0.82	0.38	967,756	0.33	0.47
Georgia	1,464	1.0	0.00	20,090	0.34	0.47
North Carolina	9,995	0.93	0.26	121,708	0.35	0.48
South Carolina	4,804	0.62	0.49	68,645	0.36	0.48
Total	81,418	0.83	0.38	1,178,199	0.34	0.47

Table A.3: State and coastal census tract populations, 2020

State	Total population, 2020	Population in coastal census tracts, 2020	Share of total population BAA, 2020	Share of coastal census tract population BAA, 2020
Florida	21,216,924	6,190,920	15.9%	12.7%
Georgia	10,516,579	334,012	31.6%	26.5%
North Carolina	10,386,227	735,012	21.4%	16.0%
South Carolina	5,091,517	790,391	26.4%	20.9%
Total	47,211,247	17.1%	21.7%	14.4%

Note: “BAA” is defined as “non-Hispanic Black or African-American.”
Source: US Census Bureau.

Figure A.11: Transaction price by census tract race and six-foot SLR-plain status, 2009-2020 (N=285,729

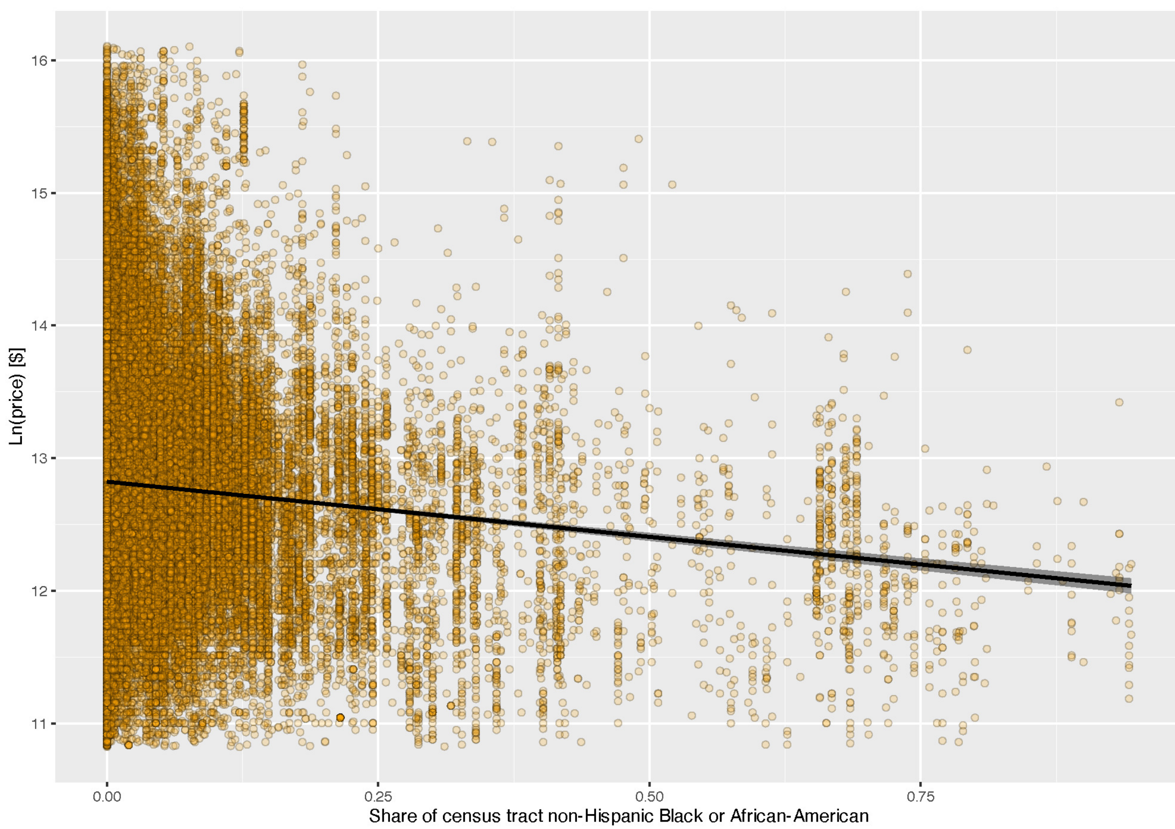


Figure A.12: Transaction price by census tract race, property transactions in six-foot SLR-plain (N=109,259)

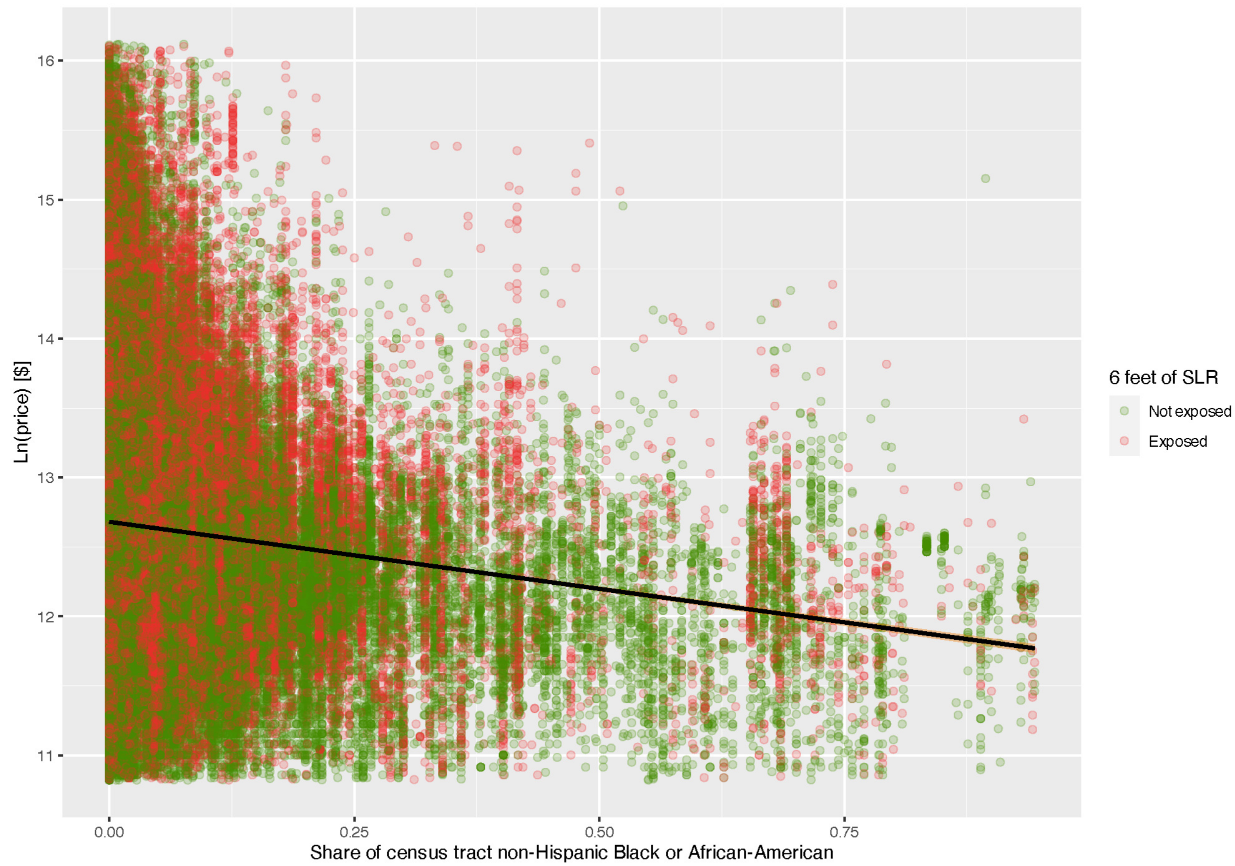


Table A.4: Estimated price effect of SLR exposure by SLR magnitude and BAA share of census tract

Dependent variable: Ln(Price) [$]								
Column:	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
SLR magnitude:	3 ft.	3 ft.	3 ft.	3 ft.	6 ft.	6 ft.	6 ft.	6 ft.
SLR Exposure	-0.031*	0.024	-0.024	0.055	-0.044***	-0.006	-0.008	-0.062
	(0.017)	(0.145)	(0.145)	(0.152)	(0.010)	(0.014)	(0.014)	(0.054)
SFHA dummy	0.016	0.017	0.016	0.017	0.029**	0.051***	0.050***	0.050***
	(0.112)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
SLR exposure x SFHA dummy	–	-0.056	-0.056	-0.056	–	-0.058***	-0.055***	-0.055***
	–	(0.146)	(0.145)	(0.0145)	–	(0.017)	(0.017)	(0.017)
Share census tract BAA†	–	–	-0.044***	-0.044***	–	–	-0.044***	-0.046***
			(0.012)	(0.012)			(0.012)	(0.012)
SLR exposure x (BAA=1)	–	–	–	-0.031	–	–	–	0.055
				(0.049)				(0.054)
SLR exposure x (BAA=2)	–	–	–	-0.031	–	–	–	0.046
				(0.063)				(0.054)
SLR exposure x (BAA=3)	–	–	–	-0.127	–	–	–	-0.011
				(0.079)				(0.073)
SLR exposure x (BAA=4)	–	–	–	$-4.6\text{x}10^{-4}$	–	–	–	0.085
				(0.119)				(0.086)
SLR exposure x (BAA=6)	–	–	–	0.069	–	–	–	0.097
				(0.126)				(0.090)
SLR exposure x (BAA=7)	–	–	–	-0.067	–	–	–	0.035***
				(0.134)				(0.115)
SLR exposure x (BAA=8)	–	–	–	-0.021	–	–	–	-0.037
				(0.136))				(0.086)
SLR exposure x (BAA=9)	–	–	–	-0.347***	–	–	–	-0.104
				(0.123)				(0.086)
SLR exposure x (BAA=10)	–	–	–	–	–	–	–	0.020
								(0.211)
Property age	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	$(3.7\text{x}10^{-4})$	$(3.8\text{x}10^{-4})$	$(3.7\text{x}10^{-4})$	$(3.7\text{x}10^{-4})$	$(3.8\text{x}10^{-4})$	$(3.8\text{x}10^{-4})$	$(3.8\text{x}10^{-4})$	$(3.7\text{x}10^{-4})$
Property sq. ft.	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	$7.3\text{x}10^{-6}$	$7.3\text{x}10^{-6}$	$7.3\text{x}10^{-6}$	$7.3\text{x}10^{-6}$	$7.3\text{x}10^{-6}$	$7.3\text{x}10^{-6}$	$7.3\text{x}10^{-6}$	$7.3\text{x}10^{-6}$
Fixed effects								
BR*CN*D*E*Y*Z	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of fixed effects	80,393	80,393	80,393	80,393	80,393	80,393	80,393	80,393
Fit statistics								
Observations	285,729	285,729	285,729	285,729	285,729	285,729	285,729	285,729
Adj. R^2	0.799081	0.799083	0.799561	0.799573	0.799254	0.799366	0.799836	0.799961

*Significance codes: ***:0.01; **:.05, *:0.1. Standard errors in parentheses and clustered at the zip code level.*

† "BAA" is an abbreviation for "non-Hispanic Black or African-American." This variable takes on discrete values from 1 to 10. A value of 1 indicates between 0-10% of the census tract in which the transacted property is located was non-Hispanic Black or African-American in the transaction year. A value of 10 indicates between 90.1%-100% of the census tract in which the transacted property is located was non-Hispanic Black or African-American in the transaction year. The reference level is BAA=1.

Note: Abbreviation/acronym definitions: "SLR" = sea level rise; "sq. ft" = square feet; "IPCC" = Intergovernmental Panel on Climate Change Third Assessment Report; "CN" = condominium dummy; "Z" = zip code; "Y" = transaction year; "SFHA" = Special Flood Hazard Area. Note: the "distance to coast" variable is categorical with five categories. All observations with elevations of 6 feet or less take on a value of 1, all observations with elevations from 6-12 feet take on a value of 2, etc., and all observations with elevations greater than 24 feet take on a value of 5. The "elevation" variable is categorical with six categories. All observations with distance to shore values of 0-53 feet take on a value of 1; 54-106 feet a value of 2; 107-211 a value of 3; 212-422 a value of 4; 423-845 feet a value of 5; greater than 845 feet a value of 6.

Table A.5: Estimated price effect of SLR exposure by SLR magnitude and census tract median household income

Dependent variable: Ln(Price) [$]				
Model:	(1a)	(1b)	(2a)	(2b)
SLR magnitude:	3 ft.	3 ft.	6 ft.	6 ft.
Variables				
SLR Exposure	0.037	0.299	-0.001	-0.500*
	(0.150)	(0.483)	(0.014)	(0.270)
SFHA dummy	0.018	0.0176	0.048***	0.047***
	(0.011)	(0.012)	(0.013)	(0.013)
SLR exposure x SFHA dummy	-0.063	-0.059	-0.51***	-0.050***
	(0.151)	(0.152)	(0.017)	(0.017)
Ln(Median census tract income)[$]	0.301***	0.303***	0.298***	0.320***
	(0.027)	(0.027)	(0.027)	(0.028)
SLR exposure x Ln(Median census tract income) [$]	–	-0.024	–	-0.046*
		(0.041)		(0.024)
Property age	-0.003***	-0.003***	-0.003***	-0.003***
	($3.7\text{x}10^{-4}$)	($3.7\text{x}10^{-4}$)	($3.7\text{x}10^{-4}$)	($3.7\text{x}10^{-4}$)
Property sq. ft.	0.0004***	0.0004***	0.0004***	0.0004***
	($7.1\text{x}10^{-6}$)	($7.1\text{x}10^{-6}$)	($7.1\text{x}10^{-6}$)	($7.1\text{x}10^{-6}$)
Fixed effects				
BR*CN*D*E*Y*Z	Yes	Yes	Yes	Yes
# of fixed effects	80,393	80,393	80,393	80,393
Fit statistics				
Observations	285,729	285,729	285,729	285,729
Adj. R^2	0.802987	0.802991	0.803212	0.803255

*Significance codes: ***:0.01; **:.05, *:0.1. Standard errors in parentheses and clustered at the zip code level.*
Note: Abbreviation/acronym definitions: “SLR” = sea level rise; “sq. ft” = square feet; “IPCC” = Intergovernmental Panel on Climate Change Third Assessment Report; “CN” = condominium dummy; “Z” = zip code; “Y” = transaction year; “SFHA” = Special Flood Hazard Area. Note: the “distance to coast” variable is categorical with five categories. All observations with elevations of 6 feet or less take on a value of 1, all observations with elevations from 6-12 feet take on a value of 2, etc., and all observations with elevations greater than 24 feet take on a value of 5. The “elevation” variable is categorical with six categories. All observations with distance to shore values of 0-53 feet take on a value of 1; 54-106 feet a value of 2; 107-211 a value of 3; 212-422 a value of 4; 423-845 feet a value of 5; greater than 845 feet a value of 6.

A.1.2.4 NSI results

Table A.6 presents results from modified estimations of the models in Equations (A.2) and (A.3) using National Structure Inventory (NSI) data. Estimates for β_1 shown in columns 1a, 1c, and 2d provide some evidence that structures in the three-foot and six-foot SLR-plains were valued less than comparable structures outside the SLR-plain, on average. Similar to main text results, results in columns 1b, 1d, and 2d are suggestive that there is an negative interactive valuation effect for a structure being located in both a SLR-plain and a SFHA. However, these findings are not consistent across specifications.

Across results shown in columns 1a through 2d, the parameter estimates for β_2 indicate strong statistically and economically significant associations between structure depreciated replacement value (DRV) and the median income and race of the census tract in which the structure is located. For example, in column 1c results find that a 10% increase in census tract non-Hispanic Black or African-American population share is associated with a -3.8% decrease in DRV at significance level $p<0.01$. In column 1d, estimates indicate a 10% increase in census tract median income is associated with a 2.5% increase in DRV, also at $p<0.01$ significance level. This findings have policy implications, given the fact lower DRVs in census tracts with lower incomes and higher shares of the population that are non-Hispanic Black or African-American may influence the benefit-cost ratios of flood mitigation projects. Improving our understanding of the DRV valuation processes which lead to these statistical relationships may better inform policy design and meet equity objectives where applicable.

Table A.6: National Structure Inventory regression results

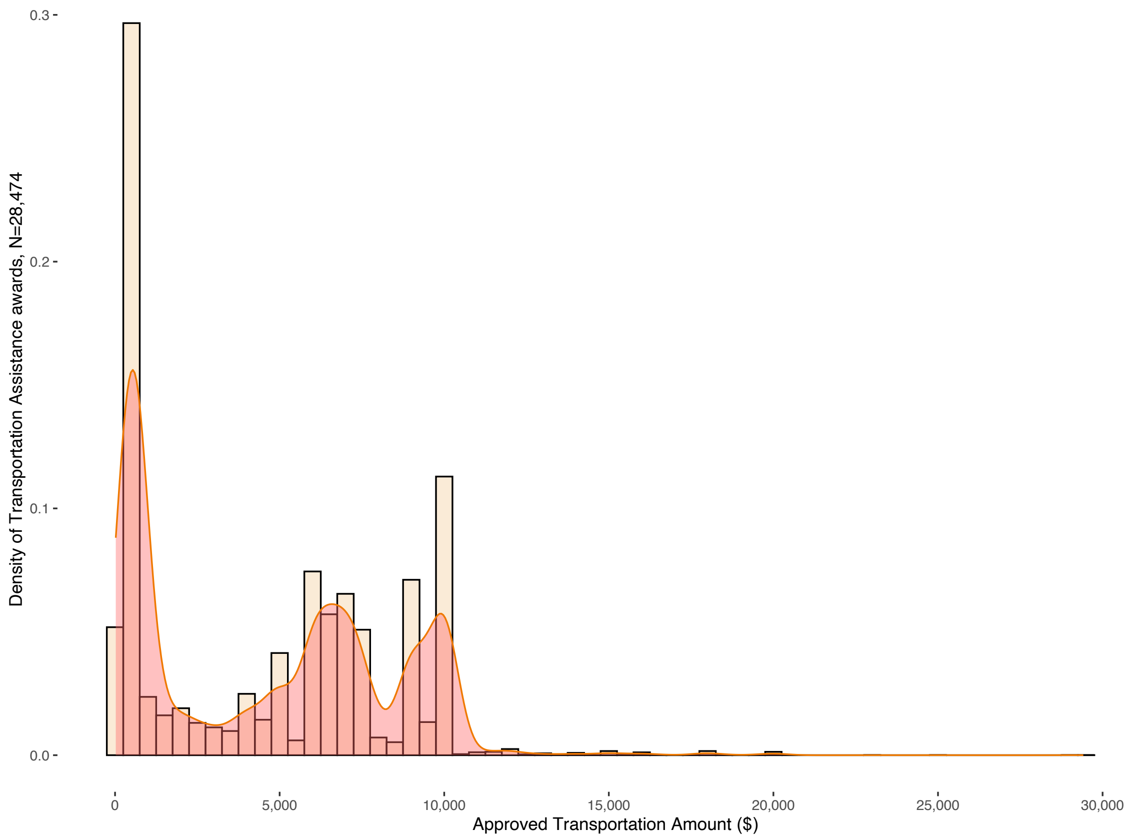
Dependent variable: Ln(structure DRV)[$]								
Model:	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
SLR magnitude:	3 ft.	3 ft.	3 ft.	3 ft.	6 ft.	6 ft.	6 ft.	6 ft.
Variables								
SLR exposure	-0.023**	-0.016	-0.030**	0.270	0.005	-0.004	0.004	0.664***
	(0.011)	(0.012)	(0.013)	(0.191)	(0.007)	(0.007)	(0.011)	(0.155)
SFHA dummy	-0.010	-0.010	-0.010	-0.010	-0.006	-0.006	-0.006	-0.004
	(0.007)	(0.006)	(0.007)	(0.006)	(0.009)	(0.008)	(0.009)	(0.008)
SFHA dummy x SLR exposure	-0.020	-0.025*	-0.021	-0.026*	-0.014	-0.016	-0.014	-0.018*
	(0.013)	(0.014)	(0.013)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)
Structure sq. ft.	$1.9*10^{-4}$***	$1.9*10^{-4}$***	$1.9*10^{-4}$***	$1.9*10^{-4}$***	$1.9*10^{-4}$***	$1.9*10^{-4}$***	$1.9*10^{-4}$***	$1.9*10^{-4}$***
	($6.8x10^{-6}$)	($6.7x10^{-6}$)	($6.7x10^{-6}$)	($6.7x10^{-6}$)	($6.8x10^{-6}$)	($6.7x10^{-6}$)	($6.8x10^{-6}$)	($6.7x10^{-6}$)
Share census tract AA	-0.038***	–	-0.039***	–	-0.038***	–	-0.038***	–
	(0.005)		(0.005)		(0.005)		(0.004)	
Ln(Census tract median income)[$]	–	0.247***	–	0.249***	–	0.248***	–	0.270***
		(0.015)		(0.015)		(0.002)		(0.017)
SLR exposure x Share BAA	–	–	0.006	–	–	–	$1.6x10^{-4}$)	–
			(0.005)				(0.005)	
SLR exposure x Ln(income)	–	–	–	-0.026	–	–	–	-0.059***
				(0.017)				(0.014)
Fixed effects								
BT*D*E*OT*S*Z	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of fixed effects	100,419	99,467	100,419	99,467	100,419	99,467	100,419	99,467
Fit statistics								
Observations	1,185,496	1,175,813	1,185,496	1,175,813	1,185,496	1,175,813	1,185,496	1,175,813
Adj. R^2	0.860855	0.86707	0.860858	0.86708	0.860719	0.866956	0.860719	0.86709

*Significance codes: ***:0.01; **:.05, *:0.1. Standard errors in parentheses and clustered at the zip code level when "Z" fixed effects included. Otherwise, standard errors are heteroskedasticity-robust using the White correction.*

Note: Abbreviation/acronym definitions: "SLR" = sea level rise; "sq. ft" = square feet; "IPCC" = Intergovernmental Panel on Climate Change Third Assessment Report; "CN" = condominium dummy; "Z" = zip code; "OT" = occupancy type; "BT" = building type; "S" = number of stories; "SFHA" = Special Flood Hazard Area. Note: the "distance to coast" variable is categorical with five categories. All observations with elevations of 6 feet or less take on a value of 1, all observations with elevations from 6-12 feet take on a value of 2, etc., and all observations with elevations greater than 24 feet take on a value of 5. The "elevation" variable is categorical with six categories. All observations with distance to shore values of 0-53 feet take on a value of 1; 54-106 feet a value of 2; 107-211 a value of 3; 212-422 a value of 4; 423-845 feet a value of 5; greater than 845 feet a value of 6

A.2 Chapter two supplemental materials: Driving up flood risks

Figure A.13: Distribution of FEMA IHP TA awards by dollar amount



"TA" = Transportation Assistance

Figure A.14: Number of IHP applications reporting vehicle flood damage by income group, percentage receiving an award in parentheses

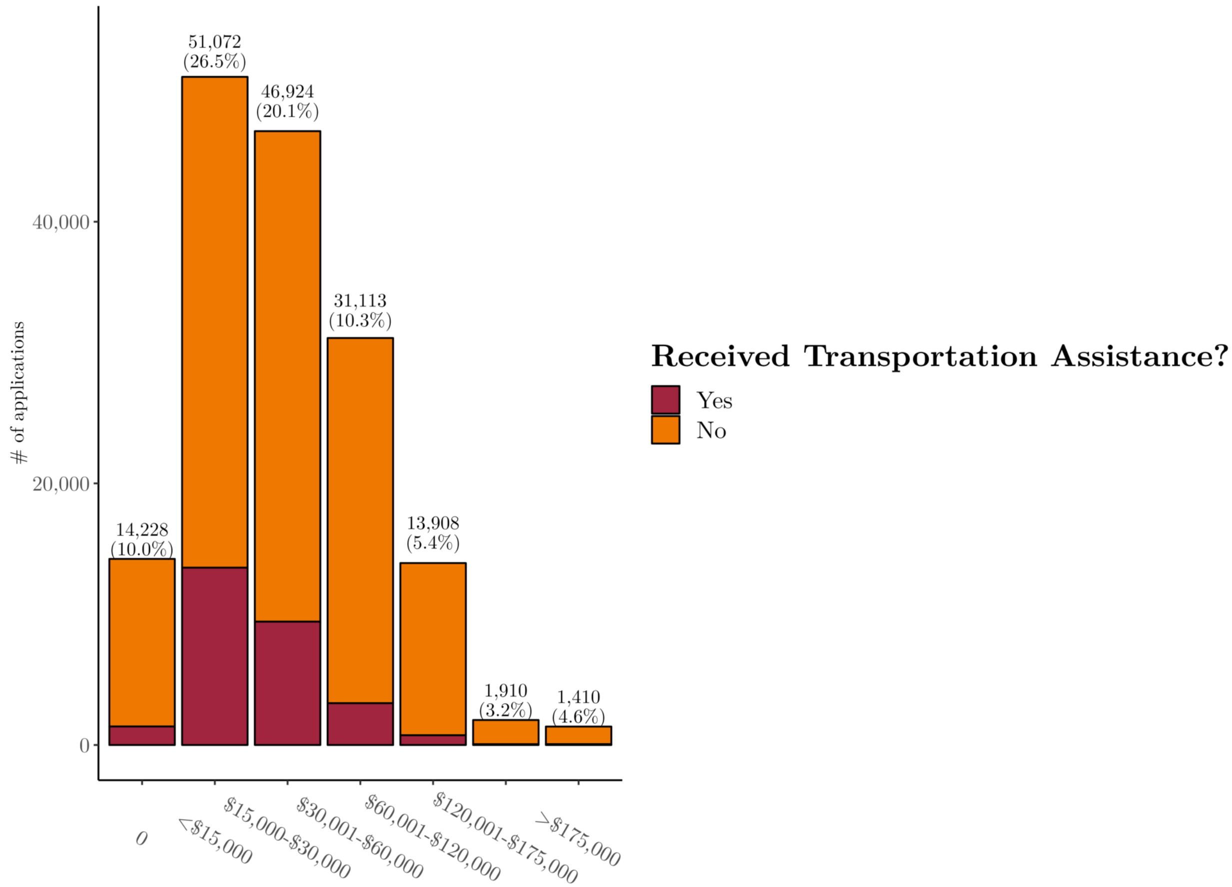


Figure A.15: Top 12 disaster-state or disaster-territory cases by amount of TA awarded to applicants with vehicle flood damage

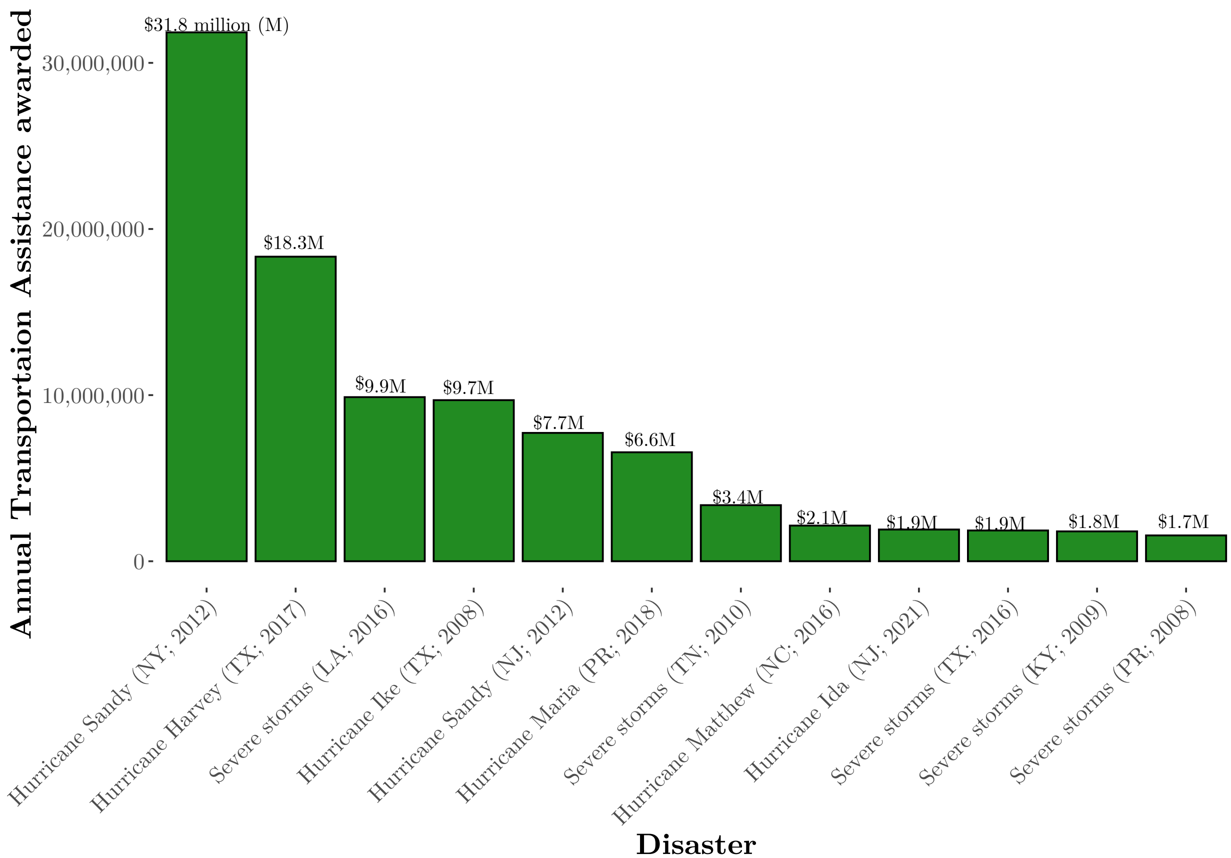


Figure A.16: Approved TA amount by reported water level at IHP applicant primary residence (N=160,565)

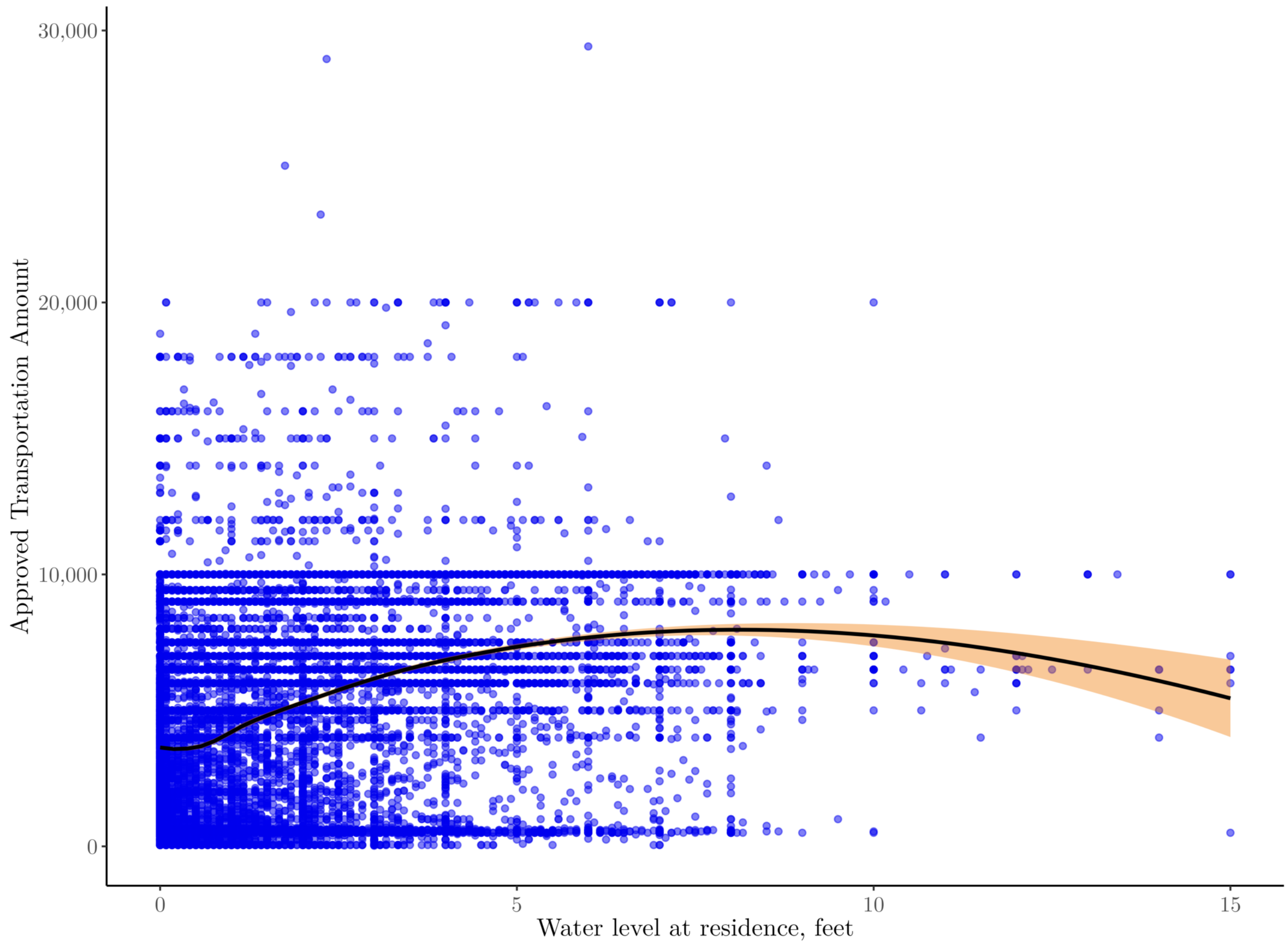
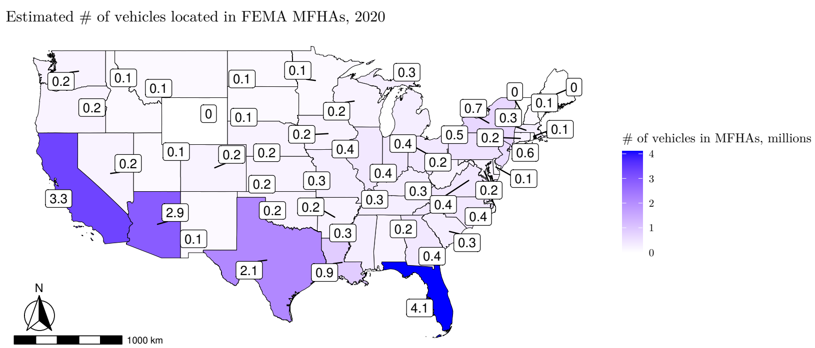


Table A.7: Estimated number of vehicles in FEMA SFHA and MFHA, thousands

	(1)	(2)	(3)	(4)	(5)	(6)
State	**Est. in SFHA**	**95% CI ME**	**Est. in SFHA, disadvantaged**	**Est. in MFHA**	**95% CI ME**	**Est. in MFHA, disadvantaged**
Alabama	185.9	±1.1	81.1	235.5	±1.5	103.1
Arizona	163.6	±1.4	72.5	2,941.5	±11.9	1,193.5
Arkansas	149.0	±1.0	71.8	224.1	±1.9	118.7
California	999.6	±3.3	531.6	3,339.4	±8.9	1,951.3
Colorado	129.8	±0.8	41.1	202.5	±1.4	73.2
Connecticut	153.1	±1.2	48.7	199.8	±1.5	63.2
Delaware	40.9	±0.8	11.5	50.2	±0.9	15.5
Florida	2,917.4	±16.7	1,269.5	4,144.0	±23.8	1,849.0
Georgia	276.7	±1.3	127.5	386.5	±2.1	176.6
Idaho	32.5	±0.5	9.7	78.2	±1.3	23.9
Illinois	325.7	±1.2	96.9	424.1	±1.7	134.2
Indiana	280.9	±1.4	72.5	362.5	±1.8	102.0
Iowa	127.3	±0.6	27.0	159.3	±0.8	34.7
Kansas	124.5	±0.7	35.0	199.9	±1.4	74.6
Kentucky	199.5	±1.1	70.6	265.2	±1.7	99.3
Louisiana	631.4	±4.5	269.4	923.1	±6.2	441.4
Maine	15.9	±0.2	3.4	18.3	±0.2	4.3
Maryland	121.0	±0.8	33.2	154.2	±1.0	43.9
Massachusetts	232.6	±1.5	58.2	325.9	±1.9	85.2
Michigan	191.8	±1.0	45.1	255.7	±1.4	62.3
Minnesota	90.4	±0.5	18.9	136.6	±0.9	33.4
Mississippi	232.6	±1.9	132.4	325.9	±2.9	185.5
Missouri	208.6	±1.0	59.7	254.1	±1.2	71.9
Montana	29.6	±0.4	6.1	50.3	±0.6	9.1
Nebraska	104.1	±0.8	31.2	163.7	±1.5	58.0
Nevada	59.2	±0.8	25.7	222.8	±2.3	99.6
New Hampshire	42.0	±0.4	6.6	60.1	±0.5	11.3
New Jersey	436.8	±2.8	109.4	581.4	±3.4	157.7
New Mexico	105.5	±1.3	71.6	133.9	±1.5	89.5
New York	486.5	±3.3	168.4	721.5	±4.6	288.1
North Carolina	312.0	±1.4	139.0	401.6	±1.9	184.1
North Dakota	49.0	±0.9	5.2	125.2	±2.2	18.1
Ohio	333.9	±1.4	90.9	420.8	±1.7	116.3
Oklahoma	161.8	±0.8	82.7	236.8	±1.4	129.1
Oregon	138.9	±0.9	63.3	221.8	±1.8	108.4
Pennsylvania	376.0	±1.4	88.0	511.6	±2.0	132.4
Rhode Island	43.5	±0.5	9.8	69.8	±0.9	14.2
South Carolina	218.0	±1.9	57.1	338.6	±3.0	84.3
South Dakota	33.8	±0.4	8.1	50.6	±0.6	11.9
Tennessee	214.5	±1.0	85.0	275.9	±1.3	114.3
Texas	1,355.4	±4.6	735.7	2,116.9	±7.2	1,144.5
Utah	38.8	±0.3	9.5	91.7	±0.9	26.6
Vermont	16.4	±0.2	4.3	20.3	±0.3	5.2
Virginia	272.7	±1.7	69.8	368.9	±2.1	94.5
Washington	142.8	±0.9	53.7	185.8	±1.1	68.7
West Virginia	121.6	±0.9	34.5	164.4	±1.4	49.3
Wisconsin	136.2	±0.6	28.8	181.1	±1.0	41.2
Wyoming	11.6	±0.2	2.5	22.0	±0.4	5.2
Total	13,074.9	±19.9	5,174.2	23,341.3	±31.8	10,000.2

Table A.8: Estimated value of flood-exposed vehicles (millions) [$]

State	DM-SFHA	DM-MFHA	NSI-SFHA	NSI-MFHA	NSI-FSF-A	NSI-FSF-B
	(1)	(2)	(3)	(4)	(5)	(6)
Alabama	$4,345.0	$5,675.2	$5,503.1	$5,943.7	$524.3	$667.9
Arizona	$3,822.1	$68,734.5	$4,732.5	$82,735.3	$4,182.0	$5,779.8
Arkansas	$3,480.5	$5,236.9	$2,039.0	$4,002.1	$1,538.8	$2,358.7
California	$23,356.7	$78,031.4	$14,992.1	$65,279.8	$44,084.0	$64,327.3
Colorado	$3,033.3	$4,731.7	$3,624.0	$6,460.1	$2,702.6	$4,021.1
Connecticut	$3,576.5	$4,644.7	$1,983.3	$2,982.3	$2,992.3	$4,988.9
Delaware	$955.0	$1,173.4	$1,642.2	$1,928.8	$885.1	$2,196.3
Florida	$68,172	$81,409.7	$67,213.5	$103,362.4	$59,840.0	$78,630.3
Georgia	$6,465.6	$9,030.4	$5,373.1	$8,961.4	$7,865	$10,472.5
Idaho	$759.4	$1,826.2	$610.3	$1,901.0	$2,979.2	$3,617.8
Illinois	$7,610.2	$9,909.8	$2,781.0	$4,599.0	$10,191.9	$13,932.7
Indiana	$6,564.4	$8,470.8	$2,843.3	$4,539.4	$4,450.8	$6,181.7
Iowa	$2,975.5	$3,722.3	$1,725.0	$2,583.3	$3,737.6	$4,902.9
Kansas	$2,909.7	$4,672.0	$1,239.7	$3870.6	$2,421.6	$3,231.0
Kentucky	$4,662.4	$6,197.9	$3,117.1	$4,900.2	$3,591.0	$5,486.8
Louisiana	$14,753.9	21,570.1	$11,324.5	$19,250.6	$15,830.5	$21,826.8
Maine	$372.5	$427.9	$242.8	$315.4	$1,011.7	$1,481.4
Maryland	$2,826.8	$3,603.1	$1,412.3	$2,269.5	$3,430.0	$5,132.1
Massachusetts	$5,434.2	$7,426.6	$3,542.6	$5,424.8	$7,438.0	$11,605.1
Michigan	$4,481.5	$5,975..4	$2,536.1	$3,748.7	$6,194.2	$9,149.9
Minnesota	$2,112.4	$3,191.1	$751.2	$1,728.9	$4,794.4	$6,414.2
Mississippi	$5,434.5	$7,614.3	$4,516.6	$7,192.8	$3,042.3	$4,241.0
Missouri	$4,873.3	$5,936.7	$2,435.8	$3,424.1	$4,459.3	$6,252.4
Montana	$691.1	$1,176.0	$573.5	$1,100.1	$2,314.9	$2,831.5
Nebraska	$2,431.5	$3,825.0	$1,290.0	$2,425.9	$804.0	$1,324.4
Nevada	$1,383.7	$5,205.5	$1,053.8	$6,043.4	$1,538.1	$2,369.9
New Hampshire	$982.4	$1,404.5	$719.6	$1,059.1	$1,065.5	$1,860.5
New Jersey	$10,206.8	$13,585.9	$6,974.2	$9,512.3	$8,455.3	$11,003.9
New Mexico	$2,465.0	$3,128.6	$3,326.5	$4,139.3	$2,306.6	$3,363.9
New York	$11,368.4	$16,859.5	$7,075.0	$11,934.7	$16,242.1	$21,707.4
North Carolina	$7,290.1	$9,383.5	$4,765.9	$7,112.9	$9,337.7	$12,737.4
North Dakota	$1,144.9	$2,924	$527.2	$2,660.8	$569.4	$712.8
Ohio	$7,801.4	$9,833.0	$4,094.6	$6,249.9	$8,294.4	$11,484.5
Oklahoma	$3781.0	$5,533.3	$1,447.7	$3,094.1	$1,468.5	$2,674.7
Oregon	$3,245.4	$5,182.1	$6,154.7	$11,550.7	$7,391.2	$10,289.9
Pennsylvania	$8,785.2	$11,954.0	$5,080.3	$8,058.8	$12,839.0	$19,342.5
Rhode Island	$1,015.5	$1,632.1	$708.5	$1,265.8	$1,014.1	$1,362.7
South Carolina	$5,094.3	$7,911.5	$6,439.1	$11,074.9	$5,156.8	$8,210.4
South Dakota	$790.0	$1,182.0	$463.0	$1,076.7	$608.1	$847.9
Tennessee	$5,012.3	$6,446.2	$2,633.8	$4,539.1	$4,596.3	$7,412.6
Texas	$31,672.5	$49,465.4	$18,359.5	$34,206.9	$21,721.3	$32,878.1
Utah	$905.6	$2,143.5	$379.0	$1,452.9	$1,918.4	$2,737.5
Vermont	$383.3	$474.2	$324.6	$448.0	$770.4	$1,191.0
Virginia	$6,372.8	$8,619.2	$3,849.8	$7,080.1	$6,269.7	$9,402.4
Washington	$3,336.8	$4,341.2	$2,230.3	$3,188.1	$8,426.5	$11,535.1
West Virginia	$2,842.4	$3841.0	$2,451.0	$4,208.4	$4,852.4	$7,269.7
Wisconsin	$3,181.7	$4,232.7	$1,199.4	$1,994.6	$3,461.2	$4,939.5
Wyoming	$270.2	$514.7	$223.1	$578.7	$927.3	$1,197.4
CONUS total	$305,521.4	$529,840.5	$227,599.4	$493,461.0	$330,536.1	$467,586
Vehicle data source	DM	DM	USACE NSI	USACE NSI	USACE NSI	USACE NSI
Flood data source	FEMA NFHL	FEMA NFHL	FEMA NFHL	FEMA NFHL	FSF-FM	FSF-FM



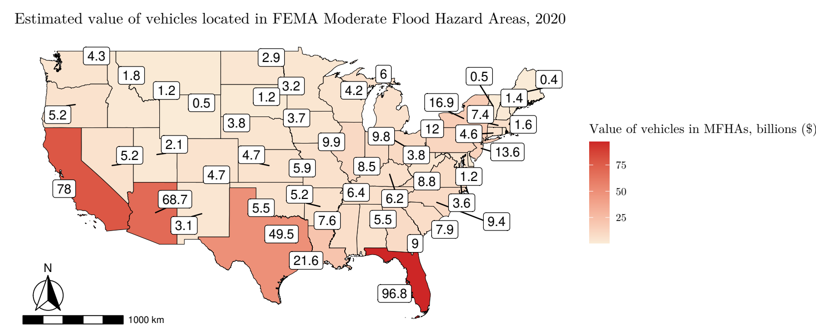


Figure A.17: Panel (a) shows the estimated number of vehicles in FEMA MFHA, millions, 2020. Panel (b) shows the estimated value of vehicles in FEMA MFHA, billions ($), 2020 using the dasymetric mapping technique.

Table A.9: Poisson model results

Dependent Variable:	Approved Transportation Assistance amount ($)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Household income: $0	-0.0631*	-0.0967**	-0.1878***	-0.2013***	-0.1888***	-0.1884***
	(0.0379)	(0.0379)	(0.0385)	(0.0366)	(0.0623)	(0.0624)
Household income: $1-$15,000	0.6596***	0.6163***	0.4966***	0.6157***	0.6429***	0.6436***
	(0.0235)	(0.0235)	(0.0250)	(0.0231)	(0.0673)	(0.0673)
Household income: $15,001-$30,000	0.5213***	0.5025***	0.4285***	0.5009***	0.5121***	0.5124***
	(0.0242)	(0.0242)	(0.0250)	(0.0230)	(0.0374)	(0.0374)
Household income: $60,001-$120,000	-0.5311***	-0.5139***	-0.4408***	-0.6104***	-0.6082***	-0.6073***
	(0.0469)	(0.0469)	(0.0472)	(0.0451)	(0.0507)	(0.0506)
Household income: $120,001-$175,000	-1.022***	-0.9937***	-0.9139***	-1.193***	-1.189***	-1.189***
	(0.1429)	(0.1430)	(0.1434)	(0.1413)	(0.1193)	(0.1193)
Household income: >$175,000	-0.8007***	-0.7903***	-0.7404***	-0.9588***	-0.9603***	-0.9598***
	(0.1424)	(0.1424)	(0.1421)	(0.1410)	(0.1778)	(0.1779)
Water level (inches)	0.0098***	0.0096***	0.0096***	0.0045***	0.0030***	0.0030***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0008)	(0.0008)
Household size: 1 (ref. = 3)	–	0.2898***	0.2940***	0.1707***	0.1470***	0.1473***
		(0.0219)	(0.0219)	(0.0203)	(0.0440)	(0.0442)
Household size: 2 (ref. = 3)	–	0.0714***	0.0890***	0.0620***	0.0494*	0.0500**
		(0.0232)	(0.0233)	(0.0213)	(0.0253)	(0.0253)
Household size: 4 (ref. = 3)	–	0.0217	0.0224	0.0611**	0.0645**	0.0651**
		(0.0273)	(0.0273)	(0.0254)	(0.0282)	(0.0280)
Household size: 5 (ref. = 3)	–	-0.0542*	-0.0584*	0.0041	0.0150	0.0148
		(0.0328)	(0.0328)	(0.0306)	(0.0332)	(0.0332)
Household size: >5 (ref. = 3)	–	-0.0741**	-0.0853**	-0.0048	0.0192	0.0197
		(0.0349)	(0.0349)	(0.0328)	(0.0406)	(0.0406)
Flood insurance? (ref. = No)	–	–	0.3723***	0.1682***	0.1625***	0.1613***
			(0.0276)	(0.0259)	(0.0463)	(0.0464)
Homeowners insurance? (ref. = No)	–	–	-0.5286***	-0.3348***	-0.3397***	-0.3397***
			(0.0222)	(0.0214)	(0.0489)	(0.0489)
Fixed effects						
Disaster number	No	No	No	Yes	No	Yes
County*Year	No	No	No	No	Yes	Yes
Fit statistics						
Convergence	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE
Observations	160,564	160,564	160,564	160,037	156,110	155,991
Squared Correlation	0.01215	0.01485	0.01576	0.15699	0.17139	0.17168
Pseudo R^2	0.04490	0.04893	0.05736	0.22928	0.24690	0.24740
BIC	533,078,392.4	530,827,464.8	526,123,389.4	429,505,642.7	414,772,379.1	414,348,927.7

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.3 Chapter three supplemental materials: The willingness to pay for vehicle flood insurance

Table A.10: WTP estimates by FEMA Special Flood Hazard Area status and level of concern about flooding - log-logistic response model Bishop-Heberlein

	All (N=360)		**SFHA (N=166)**		**Concerned (N=295)**	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
All respondents (N=360)						
Mean (truncated at max. bid)	$180.31	[$ 164.47, $197.36]	$239.51	[$212.67, $260.55]	$ 196.82	[$180.91, $211.56]
Median	$183.96	[$147.33, $241.09]	$463.17	[$279.35, $967.30]	$221.08	[$179.02, $285.82]
Mean (truncated at max. bid with adjustment)	$282.67	[$232.96, $352.56]	$637.75	[$406.48, $1,034.08]	$328.07	[$266.24, $407.38]

62 New York-based respondents and 104 Texas-based respondents reported living in a SFHA. 110 New York-based respondents and 185 Texas-based respondents reported being "somewhat concerned" or "very concerned" about flooding having a negative impact their communities.

Table A.11: Log-logistic response model results, Bishop-Heberlein random utility model

	All	**SFHA**	**Concerned**
Variable	(1)	(2)	(3)
Constant	4.189·	-4.70	5.604*
	(2.278)	(150.935)	(2.430)
Household income: < \$25,000 (ref. = \$100,001-\$250,000)	-1.099*	-4.219**	-1.428*
	(0.507)	(1.322)	(0.576)
Household income: \$25,001-\$50,000 (ref. = \$100,001-\$250,000)	-0.238	-3.102*	-0.312
	(0.456)	(1.281)	(0.514)
Household income: \$50,001-\$100,000 (ref. = \$100,001-\$250,000)	0.0523	2.236·	-0.304
	(0.421)	(1.227)	(0.477)
Household income: >\$250,000 (ref. = \$100,001-\$250,000)	-0.911	-2.169	-0.480
	(0.763)	(1.854)	(0.889)
Education: No high school (ref. = Associate's degree)	1.260	14.640	-0.138
	(1.156)	(150.893)	(1.306)
Education: Some high school (ref. = Associate's degree)	0.193	2.005*	0.014
	(0.500)	(0.913)	(0.572)
Education: High school diploma or equivalent (ref. = Associate's degree)	0.0630	0.771	0.180
	(0.331)	(0.580)	(0.381)
Education: Bachelor's degree (ref. = Associate's degree)	0.426	0.601	0.348
	(0.404)	(0.751)	(0.471)
Education: Postgraduate degree (ref. = Associate's degree)	0.399	1.944	0.022
	(0.509)	(1.304)	(0.536)
Ln(Vehicle Value)	-0.163	-0.301	-0.050
	(0.199)	(0.365)	(0.223)
In SFHA: Not sure (ref. = No)	-0.041	–	0.270
	(0.324)		(0.386)
In SFHA: Yes (ref. = No)	0.786**	–	1.069***
	(0.285)		(0.322)
VFD: Not sure (ref. = No)	0.275	0.988	0.339
	(0.638)	(1.517)	(0.866)
VFD: Yes, multiple times (ref. = No)	0.547	0.949	0.856*
	(0.372)	(0.615)	(0.407)
VFD: Yes, once (ref. = No)	0.311	0.984·	0.586·
	(0.287)	(0.517)	(0.325)
Vehicle type: Sedan (ref. = other)	1.272**	2.000**	1.696***
	(0.402)	(0.703)	(0.444)
Vehicle type: SUV (ref. = other)	1.028**	2.260**	1.287**
	(0.390)	(0.693)	(0.430)
Vehicle type: Van (ref. = other)	0.469	1.759	0.982
	(0.630)	(1.164)	(0.796)
State: Texas (ref. = New York)	-0.159	-0.100	0.088
	(0.277)	(0.528)	(0.331)
Concern: Not very concerned (ref. = Not concerned at all)	1.280·	12.352	–
	(0.745)	(150.883)	
Concern: Somewhat concerned (ref. = Not concerned at all)	2.029**	13.949	–
	(0.707)	(150.882)	
Concern: Very concerned (ref. = Not concerned at all)	2.602***	14.308	–
	(0.721)	(150.882)	
Bid amount	-1.158***	-1.171***	-1.327***
	(0.099)	(0.176)	(0.123)
Number of observations:	360	166	295
Log likelihood:	-359.73	-123.18	-279.93
AIC	767.47	290.36	601.86
BIC	860.73	358.82	679.29

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

A.3.1 Survey instrument text

Text of survey instrument available here.

URL = https://drive.google.com/file/d/1Y16E29HxoxX6Po20QbFl4mllqw6ZLQE9/view?usp=drive_link