Disaster-driven adaptation in the insurance market: the case of Hurricane Sandy

Hannah Hennighausen*

January 13, 2020

Click here for the latest version.

Abstract

Climate change and urbanization are escalating flood risk around the globe. Studying the factors that drive people to adapt to their changing risks aids policy makers in predicting future flooding costs and policy needs. This paper investigates the role of experienced risk in adaptation decisions. I exploit spatial variation in flooding to estimate the causal effect of Hurricane Sandy on people's perceived risks and decisions to insure against expected future flood damages. Hurricane Sandy's flooding boundaries had a large and long-lived effect. Since the storm, flood insurance demand in flooded areas has continuously increased relative to nearby areas that were not flooded. The estimated insurance response was driven by the purchase and retention of relatively cheaper policies located in the most flood-damaged areas, giving evidence that cost is a critical factor in people's adaptation decisions. Reconstructed flooding extents of six other recent events suggest that Hurricane Sandy's positive insurance response was the exception and not the rule.

*PhD student at the University of Graz; hannah.hennighausen@uni-graz.at

1 Introduction

Adaptation to weather extremes has been a prominent topic in recent years as climate change effects become increasingly inevitable and people continue to settle in vulnerable areas [1]. In the context of flooding, as the planet warms, sea level rise and increased evaporation mean that extreme flood events that historically happened only rarely are occurring more frequently [2]. Socioeconomic changes are amplifying the effects of climate change: by 2050, two-thirds of the world's population is expected to live in cities, many of which are located along coastlines, at rivers or both [3].

Flood insurance is an adaptation tool that will help buffer against the consequences of future floods [1]. By making more funds available more quickly, flood insurance enables a speedier recovery than simply relying on post-disaster aid [4]. Despite its benefits, only 30 percent of homeowners located in the flood riskiest areas in the United States are currently insured [5]. Understanding the factors that drive people's insurance purchase decisions aids policy makers in forming estimates about future floods' cost distributions and in making decisions about public investments in flood hazard mitigation.

This paper exploits spatial variation in flooding to study how direct experience with Hurricane Sandy's flooding extents influenced people's participation in the flood insurance market. After accounting for all other confounding factors that influence flood insurance demand (e.g. price, income, potential loss etc.), this paper's estimation of the insurance response equates to estimating Hurricane Sandy's impact on people's perceived risk of being flooded [6]. My findings indicate that people used the locations of Sandy's floodwaters to update their risk perceptions and inform their adaptation response. In a comparison of Hurricane Sandy against other major, recent flood events, I give evidence that Sandy's insurance response was the exception and not the rule.

Estimating the flood insurance response requires detailed, spatially-explicit and objective information about flooding extents and the number of insurance policies-in-force. I used the Federal Emergency Management Agency's (FEMA) recently-released universe of flood insurance policies spanning 2010 to 2018. In addition to a number of other useful characteristics, each policy is spatially identified to a U.S. census tract. I then overlaid Hurricane Sandy's flooding extents, also from FEMA, onto a map of census tracts to determine the policies located in tracts that were, or would be, flooded.

I investigated Sandy's causal impact through the lens of a difference-in-difference framework with leads and lags. Leads test for the existence of parallel pre-trends and lags give insights into the longevity of the risk mitigating behavior. My outcome variable is the log-transformed number of insurance policies-in-force in a given census tract in a given year. In the main specification, tracts that contained at least some flooding form the treatment group. Untreated tracts are those that are located in counties that received federal aid after Hurricane Sandy but were not flooded. My strategy's causal interpretation relies on the assumption that census tract and county-by-year fixed effects essentially randomize the flooding treatment across the study area.

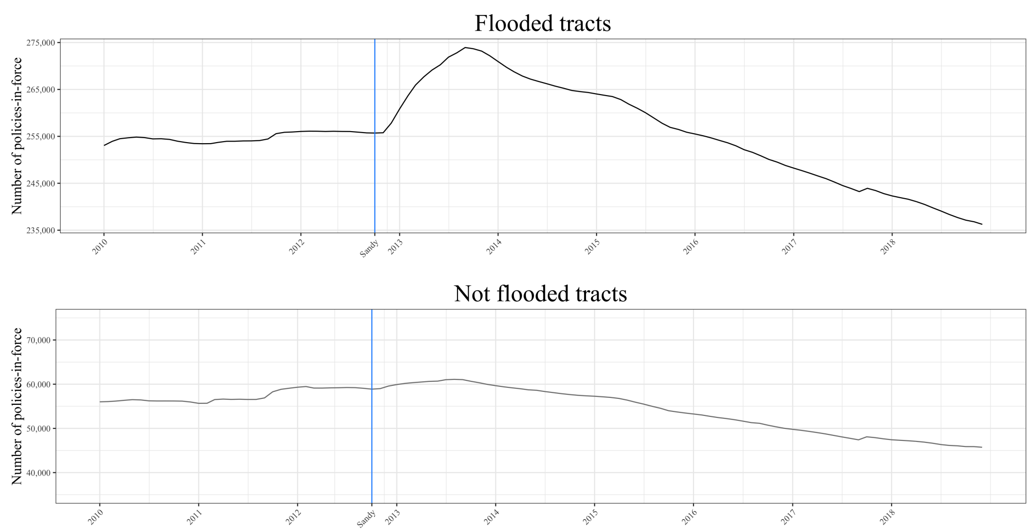


Figure 1

The regression results indicate that people's Hurricane Sandy experiences influenced their decisions to insure: Sandy caused an increase in the number of flood insurance policies-in-force in areas that were flooded compared to nearby areas that were not flooded. Figure 1 previews this result by plotting total insurance policies-in-force by month-year for the flooded and not flooded groups. The figure shows similar pre-Sandy trends for the two groups. Immediately after Sandy there is a sharp increase in policies-in-force for the flooded census tracts. Between 2014 and 2018, the number of policies-in-force falls by 25 precent in the flooded areas and by 35 percent in the not flooded areas[1]. This suggests that flooded areas had relatively better retention rates of existing policies in later years.

Three extensions to the main specification demonstrate the relevancy of heterogeneous treatment types and effects in this setting. I find that people used information about damage severity, and not only if they were flooded or not, in forming new expectations about future losses. Moreover, changes in risk perception were not confined to the boundaries of the flooding extents as areas that were "nearly missed" also increased their insurance demand post storm. Finally, flooded residents that had relatively cheaper insurance options purchased more policies after Sandy, while residents for whom the insurance options were costlier did not. While Hurricane Sandy may have induced changes in perceived risk for all flooded residents, only those for whom insurance was a relatively affordable possessed the agency to act on that risk perception change.

Several other papers have examined the impact of flood experience on insurance purchases [7] [8] [9]. For example, in a study of all U.S. communities from 1990-2007, Gallagher (2014) determined that insurance take-up rates spiked after flood events [6]. Kousky (2017) also estimated an increase in insurance take-up for U.S. counties hit by hurricanes between 2001 and 2010 [10]. In both cases, the effects were interpreted as temporary behavioral responses as relative insurance take-up rates rather quickly returned to baseline.

This paper advances the closely related literature in three important ways. First, the exceptional level of detail and objectivity in the storm and insurance data allowed me to identify flooded areas and insurance policy locations with far more precision than was previously possible, reducing potential bias in the coefficient estimates and allowing for more

[1]The reduction in flood insurance policies-in-force in the study area is on par with what's happening in the U.S. generally. Between 2010 and 2018, the number of policies-in-force in the U.S. decreased by eight percent. One possible reason is 2012/2014 legislation increasing premiums costs for policies that were previously subsidized. I explore this more in a separate project. Click here for slides.

robust causal inference. Second, for the first time, I demonstrated the relevancy of heterogeneous treatment types and effects within a single event, exposing how damage severity and the cost of insurance influence the adaptation response. Third, a critical difference between this paper's primary findings and those in the literature is that Sandy's behavioral response was not temporary, likely because of the storm's relative enormity and destructiveness. A major take-away for policy makers as they plan for future flooding is that different storms induce different adaptation responses.

This work also builds on a large literature documenting the influence of disaster experience on risk perceptions and risk mitigating behavior generally [11] [12]. The most prominent literature demonstrates that properties in risky areas tend to sell for a discount after the occurrence of a disaster event as people update their risk assessments [13] [14] [15]. Outside of property markets, Boustan et al (2012) documented the influence of disaster experience on migration decisions [16]. Additionally, Dessaint and Matray (2017) showed that managers that experience disasters alter their cash-holding behavior in an effort to reduce perceived financial risk [17].

Lastly, this research contributes to a more targeted literature chronicling Hurricane Sandy's adaptation response. Ortega and Taspinar (2018) showed that, after Hurricane Sandy, flood risky properties carried a price penalty and McCoy and Zhao (2018) determined that capital investment projects were more likely outside flood risky areas [18] [19]. Both studies' findings are consistent with the idea that residents changed how they viewed the possibility of future flood losses and made decisions after Hurricane Sandy that integrated their updated beliefs.

With the related literature in mind, this paper's general findings are intuitive: direct experience with Hurricane Sandy caused people to people to change their risk perceptions and adapt accordingly. I tested for external validity of the results by reconstructing the flooding extents from Hurricane Sandy and six other significant U.S. flood events using census tract locations of insurance claims. Through the same difference-in-difference framework I determined that statistically significant increases in insurance demand were detectable only when the flooding event was exceptionally severe. The exercise highlights two important points. If reconstructed flooding matches real flooding, then the Hurricane Sandy behavioral response was an outlier and not the norm. If reconstructed flooding doesn't match real flooding, then my results demonstrate the importance of precise, objective hazard data in estimating unbiased behavioral responses.

The paper proceeds as follows. The next section discusses the conceptual framework motivating the paper's hypotheses. Section three describes the background of the study and the data used in the analysis. Section four details the empirical strategy. Section five provides estimation results and section six concludes with a discussion of the findings in the broader policy context.

2 Conceptual Framework

Every day people are faced with with a multitude of risks. Their ability to sense and avoid harmful conditions through intuitive risk judgements is fundamental to their survival [20]. These risk judgements, typically called "risk perceptions", motivate people to privately mitigate their risks and avoid the consequences of risky events [21].

Perceived risk is equal to authorities' technical estimates of that risk plus subjective factors [22]. Direct experience with a risky event is often cited as the most influential subjective factor in forming risk perceptions [23]. In the case of low-probability, high-consequence risks like flooding, personal experience usually has a large, positive effect on risk perceptions as it offers people an illustration of the threat and demonstrates the potential for future consequences [24] [25].

Several studies have noted that direct experience with flooding does not always alter risk mitigating behavior [26] [27]. Bubeck et al (2012), for example, note that it is not the experience itself that drives mitigating behavior, but the severity of the experienced negative consequences: severe flood events cause changes in risk perceptions and mitigating behavior while more benign events do not [28]. Additionally, Wachinger et al (2013) write that even if people's risk perceptions do change, their mitigating behavior is mediated by their personal agency to act [29]. If the mitigating behavior is too costly, then they will not engage.

The following theoretical framework forms the basis of this paper's hypotheses. Through the von Neumann-Morgenstern expected utility framework I show how an increase in the perceived risk of flooding (from direct experience) also increases people's propensity to purchase flood insurance. I also motivate hypotheses surrounding heterogeneous treatment types and effects by demonstrating that people will cross the policy purchase threshold only if the change in risk perception is large enough relative to the cost of insurance.

2.1 Modeling the insurance decision

The risk-averse prospective buyer of a flood insurance contract maximizes her utility across two possible states of the world [30] [31]. In the flood-state she *perceives* that her home will be flooded and she will incur a net loss (total loss less disaster assistance) of L dollars with probability equal to $p \in (0, 1)$. In the no-flood-state she is not flooded and incurs no loss. If W dollars is her initial wealth, then her expected utility across the two states is equal to:

$$E(U) = (1 - p)U(W) + pU(W - L) \tag{1}$$

FEMA offers insurance policies with net flood insurance coverage (total coverage less the deductible) at a premium rate equal to $a \in (0, 1)$[2]. The prospective buyer must decide whether it is optimal for her to purchase an insurance policy. She does this by determining her optimal coverage level $C^* \in [0, \infty)$ that would be reimbursed to her in the flood-state. In exchange for flood loss reimbursement, the prospective buyer would pay a sure premium, P, in both states of the world. The dollar amount of the premium is a fraction of her chosen

[2]For example, in this study, the average premium rate inside the regulatory floodplain is 63 cents per 100 dollars of coverage. Outside the SFHA it is 18 cents per 100 dollars of coverage

insurance coverage: $P = aC$.

The prospective buyer determines her optimal coverage level by maximizing her expected utility with insurance across her two perceived states of the world:

$$\begin{aligned} \max_{C} \quad E(U) = (1-p)U(W-P) &+ pU(W-P-L+C) \\ \text{s.t.} \quad P &= aC \\ C &\geq 0 \end{aligned} \tag{2}$$

where $E[U]$ is increasing in coverage at a decreasing rate from risk aversion.

Her maximization problem is solved by substituting the premium cost constraint into the problem and deriving the Kuhn-Tucker conditions:

$$\frac{\mathrm{d}E(U)}{\mathrm{d}C} = -a(1-p)\frac{\mathrm{d}U(W-aC^*)}{\mathrm{d}C} + (1-a)p\frac{\mathrm{d}U(W-L+(1-a)C^*)}{\mathrm{d}C} \leq 0 \tag{3a}$$

$$C^*\frac{\mathrm{d}E(U)}{\mathrm{d}C} = 0 \tag{3b}$$

$$C^* \geq 0 \tag{3c}$$

The major hurdle the prospective buyer faces to crossing the policy purchase threshold is the value of a relative to p. For any level of risk perception, she will purchase an insurance policy only if the premium rate is low enough such that she is willing to pay to avoid being in the flood-state[3]. When this is not the case, her optimal coverage level is equal to zero and she will not purchase a policy:

$$\frac{a}{1-a} \geq \frac{p}{1-p}\frac{\frac{\mathrm{d}U(W-L)}{\mathrm{d}C}}{\frac{\mathrm{d}U(W)}{\mathrm{d}C}} \tag{4}$$

Imagine that Equation 4 is initially true and she doesn't carry flood insurance. Then imagine the prospective buyer is directly flooded by Hurricane Sandy. Her personal experience

[3]The statement rests on the assumption that the prospective buyer is risk averse. From risk aversion, $\frac{\mathrm{d}U(W-L)}{\mathrm{d}C} > \frac{\mathrm{d}U(W)}{\mathrm{d}C}$ so $\frac{\frac{\mathrm{d}U(W-L)}{\mathrm{d}C}}{\frac{\mathrm{d}U(W)}{\mathrm{d}C}} > 1$. If she were risk loving, p could be larger than a and still induce a no-insurance response.

with Sandy's storm surge causes her to increase her perceived probability of the flood-state occurring.

Equation 4 demonstrates that the prospective buyer's marginal rate of substitution of flood-state utility for no-flood-state utility is weighted by p. A sufficiently large increase in p relative to a would tip the scales such that she is willing to purchase insurance. In this case she would solve for her new optimal coverage level from Equation 3a held at equality. The key insight of the insurance decision model is that the prospective buyer, who initially did not hold a policy, will purchase one after she has been flooded *only if* her new perceived flood risk is now large enough relative to the premium rate she is required to pay.

In the remaining sections I test the hypothesis that Hurricane Sandy was severe enough to trigger changes in risk perception large enough to alter flood insurance purchasing behavior on average. Furthermore, I test if changes in insurance purchase behavior were largest where damage was most severe (heterogeneous, Sandy-induced changes in p) and for properties with relatively low premium rates (heterogenous, FEMA-provided a).

3 Background and Data

3.1 Hurricane Sandy

Hurricane Sandy made landfall in the United States on October 29, 2012. It was a category one hurricane with wind speeds of 80 miles per hour [32]. Sandy approached the East Coast at a perpendicular angle, coinciding with an exceptionally high tide from the full moon. The combined factors generated a colossal storm surge to make Sandy the second-costliest hurricane in United States history. Sandy affected 24 U.S. states, with Connecticut, New Jersey, New York and Rhode Island (CT-NJ-NY-RI) receiving the brunt of the storm's impact.

Hurricane Sandy had an enormous effect on residents and infrastructure. Across CT-

NJ-NY-RI, nearly 200,000 households applied for federal disaster assistance[4]. Facilities and services crucial to the well-being of residents (e.g. healthcare, transportation and telecommunications) were fully or partially shut-down during the storm, and in some cases, for long periods afterwards [33]. In sum, Hurricane Sandy highlighted significant vulnerabilities in certain geographical areas across the four states.

During Hurricane Sandy, the FEMA Modeling Task Force (MOTF) was deployed to the National Hurricane Center to determine the extent of the flooding using field-verified High Water Marks, Civil Air Patrol and NOAA imagery. The result is a spatially-explicit digital map of Hurricane Sandy's flooding extents in CT-NJ-NY-RI[5]. Across the four states, Hurricane Sandy caused 125 square miles of flooding in 37 counties.

FEMA's MOTF, in addition to simply identifying the flooding extents of Hurricane Sandy, also published information on the buildings impacted by Hurricane Sandy. The spatial layer contains points representing the locations of impacted buildings within Hurricane Sandy's flooding extents, as well as the extent of damage to each impacted building. Assessment of the building stock was based on information about water depth, debris estimates and site visits. FEMA sorted the 319,575 total impacted buildings into four categories: affected, minor damage, major damage and destroyed. Affected buildings (50 percent of total impacted buildings) generally sustained superficial damage. Buildings with minor (43 percent) or major (seven percent) damage or buildings that were destroyed (0.3 percent) sustained more severe external and/or internal damage, particularly from wind.

3.2 The National Flood Insurance Program

The National Flood Insurance Program (NFIP) is a federal program that enables property owners to purchase flood insurance as a protection against flood losses [34]. Prior to the NFIP's inception in 1968, federal actions related to flooding generally consisted of structural

[4]Information about federally-declared disasters is available here:
https://www.fema.gov/disasters

[5]Flooding and damage point information is available at:
https://content.femadata.com/MOTF/Hurricane_Sandy/

measures to control flooding and post-disaster assistance. Private insurance companies failed to be profitable because of the high concentration and correlation of flood risks and the prohibitively large costs in developing an actuarial rate structure that would adequately reflect properties' risks. Amidst increasing disaster relief costs, Congress passed the National Flood Insurance Act of 1968 with the following goals: (1) to better protect individuals against flood losses through insurance, (2) to reduce future flood damages through state and community floodplain management regulations, and (3) to reduce federal expenditures for disaster assistance and flood control. Nearly every flood insurance policy in the United States is sold through the NFIP[6] [5].

In addition to providing insurance and reducing flood damages through floodplain regulations, the NFIP identifies and maps floodplains. Mapping flood hazards creates risk awareness and forms a basis for compulsory purchase of flood insurance. The NFIP requires properties with a federally-backed mortgage located in the riskiest floodplain, the Special Flood Hazard Area (SFHA), to carry flood insurance. Currently, only 30 percent of homeowners in the SFHA are insured against flood damages [5]. In New York City, 55 percent of homeowners in the SFHA were insured just prior to Hurricane Sandy [35].

Insurance premium costs vary across properties and reflect structures' flood hazard, exposure and vulnerability. Premiums are highest for buildings with high base flood elevations, buildings with basements and buildings constructed with materials that have low resistance to water damage. The NFIP subsidizes the insurance premiums of SFHA buildings built prior to the release of the community's first floodplain map, reasoning that these pre-FIRM (Flood Insurance Rate Map) buildings were built by individuals who did not have sufficient knowledge about flood hazards to make informed decisions. Currently, approximately 20 percent of all NFIP policies are subsidized because of their pre-FIRM status inside the SFHA[34].

In 2012, the U.S. Congress passed the Biggert Waters Flood Insurance Reform Act as a

[6]In 2018, 3.5 to 4.5 percent of residential insurance policies came from private insurers.

way to phase out subsidization of insurance premiums and make the NFIP more financially stable [36]. The NFIP was originally designed to be a self-sustaining program that paid claims with premiums. Recently, however, major hurricanes like Hurricane Sandy forced the NFIP to borrow funds from the U.S. Treasury. To improve the sustainability of the NFIP in the future, Biggert-Waters (and its modifier, the Homeowner Flood Insurance Affordability Act of 2014 - HFIAA) intended to better the financial position of the NFIP by having actuarially-based flood insurance rates for all policies [37]. Beginning in 2013, premium rates increased by 5 to 25 percent per year for pre-FIRM properties inside the SFHA.

3.3 Data

The present analysis relies on a national database of nearly fifty million individual flood insurance policies[7]. Each policy was effective sometime between 2010 and 2018. Policies are spatially identified to census tracts with the average census tract in my sample containing nearly 1,800 housing units. I subsetted the policies database to the nine percent of total policies that are associated with census tracts in CT-NJ-NY-RI. I further restricted the sample to policies attached to residential properties located in counties that received federal aid after Hurricane Sandy. This was done to improve the comparability of the treatment and control groups: if any lingering omitted variables change smoothly over space, then limiting the study area would reduce any resulting bias in the estimates. Figure 2 depicts the census tracts analyzed in this study.

The data contain a number of helpful characteristics describing each policy. The effective and termination date of each policy is listed, allowing me to view "snapshots" of the number of insurance policies-in-force on any given day[8] The data also provide the date a policy on the property first began. With that information, I can deduce the numbers of new, existing and dropout policies in each year. From 2010 to 2018, the largest number of new policies

[7]Policy information is available at:
https://www.fema.gov/media-library/assets/documents/180376

[8]Most policies are effective for 365 days because the Standard Flood Insurance Policy contract is for one year only.

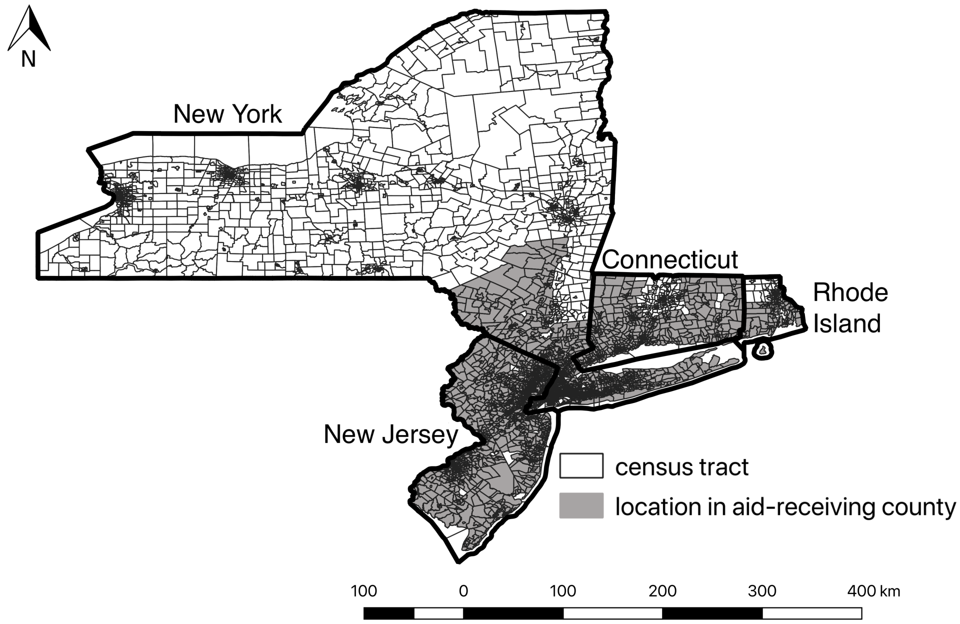


Figure 2

began in 2013 and the largest number of dropouts occurred in 2014.

The present study's outcome variable is the log-transformed number of insurance policies-in-force in a given census tract. I recorded the number of policies-in-force in each census tract on October 25th in each year from 2010 to 2018[9]. By choosing this date in particular, I am able to compare insurance counts in the years surrounding Hurricane Sandy to insurance counts *just prior* to Hurricane Sandy, whose incident period began on October 26th, 2012. For estimability reasons, I balanced the sample on calendar year such that every census tract contains at least one policy in each year. Adding one to the outcome variable to avoid losing observations with a value of zero yields the same conclusions.

[9]The average flooded census tract tends to have a greater number of flood insurance policies than the average census tract that was not flooded, likely reflecting relative baseline risks. For this reason, it is debatable whether comparing the two groups' (within census tract) percent changes in insurance policies effectively represents changes in risk perception. For example, a 50 percent increase in a census tract with 100 policies would yield 50 additional policies while a 50 percent increase in a census tract with 10 policies would yield only 5 additional policies. On the other hand, comparing census tracts with policy counts would not reflect the fact that some census tracts are wholly contained by risky floodplains while other census tracts contain little flood risky land. In light of this debate, I tested the robustness of this paper's conclusions using subsamples of census tracts with similar numbers of policies-in-force (e.g. restricting the sample to census tracts with 10 policies or fewer). Conclusions are robust.

My key variables of interest are a series of indicator variables that describe if a census tract experienced at least some flooding. I merged the panel of census tract-by-year policies-in-force with information related to Hurricane Sandy flooding extents, also by census tract. Thirty-one percent of census tracts in the sample were flooded. The median census tract was 20 percent flooded. Ten percent of census tracts were majorly damaged, seven percent experienced only minor damage and five percent were affected. Figure 3 presents the locations of the flooded, damaged and affected census tracts[10].

I accounted for potential confounders with the insurance data itself as well as information from the Census Bureau, Federal Housing Finance Agency and FEMA. The insurance data describe whether the buildings attached to policies are pre-FIRM and located in the SFHA as well as each policy's premium cost, coverage and deductible levels. This information is helpful in controlling for subsidized policies' premium rate increases due to recent legislation. In constructing the sample, I also dropped all policies attached to structures with construction dates after the start of the study period to account for differential construction trends across groups. Finally, to isolate the effect of people's perceived risks on insurance demand, I matched each census tract-year observation to median income estimates from the Census Bureau, house price index estimates from the Federal Housing Finance Agency and flood risk map change information from FEMA[11][12][13]. The final panel contains 39,321 observations: 4,369 census tracts across nine years.

[10]Curiously, FEMA did not identify damaged buildings within some of the flooding extents, particularly in New Jersey. I'm unsure if this is because they were not badly-enough damaged or because the area was simply not studies. All conclusions about the impact of damage severity on insurance purchases are robust to removing these census tracts from the sample.

[11]Median income information is available at:
https://www.census.gov/programs-surveys/acs. Median incomes are five year estimates.

[12]House Price Index information is available at:
https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx.

[13]Flood risk map change information is available at:
https://www.fema.gov/national-flood-hazard-layer-nfhl

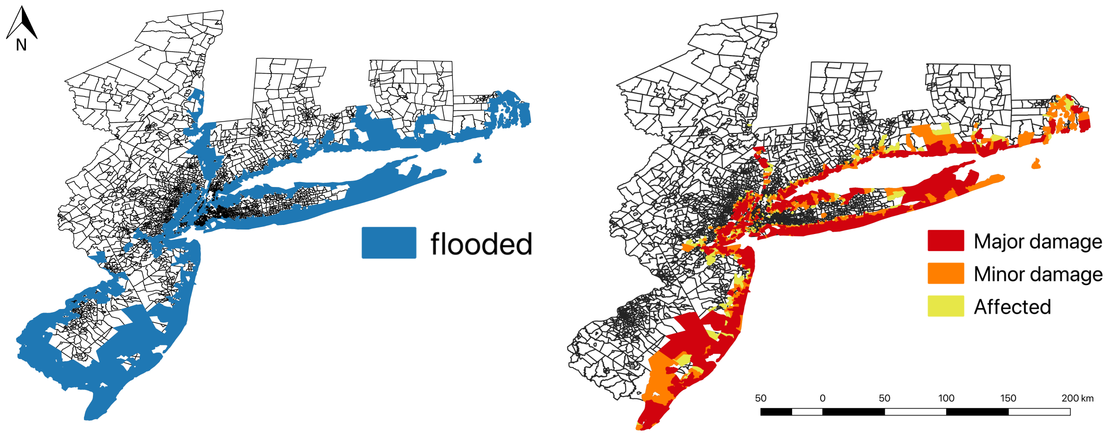


Figure 3

4 Empirical Strategy

My empirical strategy leverages variation in flooding across the study area to causally identify Hurricane Sandy's impact on insurance purchase decisions. The strategy is based on the idea that census tracts that were not flooded serve as a valid counterfactual to census tracts that were flooded, after accounting for all time-invariant and -varying confounders.

Equation 5 estimates the impact of flooding on insurance demand:

$$y_{it} = \sum_{\tau=2010,\tau\neq 2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{\text{flooded}} + \gamma \boldsymbol{X}_{it} + \mu_{Cft} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{5}$$

The unit of observation is a census tract calendar year. The dependent variable, y_{it}, measures the log-transformed number of policies-in-force for census tract i in year t.

The key variables of interest are $\mathbf{1}[t=\tau]$ and W_i^{flooded}. Their product tracks flooded census tracts before and after Hurricane Sandy. $\mathbf{1}[t=\tau]$ is equal to one if the observation occurs in year τ and W_i^{flooded} is equal to one if the observation's census tract was flooded. The coefficient of interest, β_τ, measures any systematic differences in policies-in-force between the treated and untreated census tracts. The effect in 2012 is normalized to zero by excluding $\mathbf{1}[t=2012]$ from the regression. To adjust for potential correlations in the error term, ϵ_{it}, standard errors are clustered at the county level.

Estimating leads and lags has two advantages over a classical difference-in-difference set-up with a single post indicator. First, the pre-Sandy year-treatment indicators provide important evidence about this study's key identifying assumption: flooded and not flooded census tracts would have had parallel trends had Hurricane Sandy not occurred[14] Second, the post-Sandy year-treatment indicators allow transitional patterns, which can give insights about the dynamics and longevity of adaptive behaviors, to play out without imposing trend assumptions. In sum, this paper's empirical strategy seeks to minimize misspecification and maximize transparency of the research design [40].

Identification of the Sandy effect

Equation 5's estimates can be interpreted causally if, in the absence of Sandy, insurance trends for flooded and not flooded census tracts would have moved in parallel. Causality is threatened if any non-Sandy factors influencing insurance demand affected the flooded and not flooded areas differently, sending the two groups on distinct insurance trend trajectories. I accounted for non-Sandy factors that influence insurance demand in the following ways:

Premium rates – Increasing premium rates (a) for policy-holders with subsidized insurance costs is a threat to the parallel trends assumption. As ninety percent of subsidized policies are attached to properties located inside Sandy's flooding extents, not controlling for their recent premium rate increases could result in underestimation of the Sandy effect [7] [15]. Equation 5 controls for the effect of Biggert-Waters/HFIAA with three variables represented

[14] Kahn-Lang & Lang (2018) note that pre-treatment parallel pre-trends are neither necessary nor sufficient to establish difference-in-difference validity [38]. Deryugina (2016) argues that nonparallel pre-trends would not invalidate a hurricane shock's exogeneity [39]. It would still be possible to estimate a hurricane's causal effect as long as nothing else changed between the treatment and control group after the hurricane but not because of the hurricane. In this paper, potential confounders include post-Sandy changes in insurance premiums, flood risk maps and flood risk mitigation efforts. I account for the first two with census-tract specific variables, as described in the next section. With respect to flood risk mitigation efforts, while I cannot totally rule out the idea that they caused some bias on Equation 1's point estimates, I hope that inclusion of county-by-year fixed effects, which assume that yearly changes in mitigation efforts are correlated by proximity and political boundary, alleviate some concerns.

[15] Estimating Equation 1 without the legislation controls shows that this is indeed the case. Without the legislation variables, the yearly indicators are underestimated by 0.1-2 percent in each year.

by $\boldsymbol{X}_{it}$. They are (1) the log-transformed average premium for pre-FIRM, SFHA buildings' policies in census tract i in year t, estimated separately from (2) the log-transformed average coverage level for pre-FIRM, SFHA buildings' policies and (3) the log-transformed average deductible choice for pre-FIRM, SFHA buildings' policies. For the premium, coverage and deductible variables I added one to avoid losing observations with the log transformation.

Flood risk map changes – Of the 4,369 census tracts in this study, nine percent overlap a FIRM panel that was updated during the study period[16]. If structures inside the flooding extents were mapped into the SFHA, where flood insurance is mandated, then the estimated coefficients on the year-treatment indicators would be upward biased. The opposite is true if structures outside the flooding extents were mapped into the SFHA[17]. With the panel-update information, I generated an indicator variable equal to one if census tract i is located in a FIRM panel that changed in year t. The map-change indicator was then interacted with community and treatment indicators to generate a variable that accounts for map-change impacts specific to each community's flooded and not flooded areas. The strategy's underlying assumption is that, within each community and treatment assignment, all census tracts would have gained or lost SFHA area. The map-change variable is represented by μ_{Cft} in Equation 5.

In addition to the observed confounders, a rich set of fixed effects non-parametrically control for unobserved characteristics that may also explain insurance demand. County-by-year fixed effects, ψ_{ct}, capture county-specific yearly factors. These include expectations surrounding post-disaster aid and flood risk mitigation efforts [41]. Census tract fixed effects, π_i, absorb unchanging differences in flood insurance demand between census tracts like the number of structures in flood risky areas and political beliefs [7] [42]. Inclusion of the fixed effects means that the coefficients on the year-treatment indicators are being driven by over-time and within census-tract variation in insurance policies-in-force, tempered by general

[16]FEMA flood risk maps are composed of *FIRM panels*. Each FIRM panel is approximately the same size as a census tract.

[17]Estimating Equation 1 without map-change fixed effects underestimates the year-treatment indicators by 0.5-2 percent in each year.

insurance demand movements specific to each county.

Isolating changes in perceived risk

This paper's aim is to isolate Hurricane Sandy's causal impact on insurance demand resulting from changes in people's risk perceptions. Equation 4 demonstrates that initial wealth and potential losses also affect insurance demand[18]. In the case that Sandy caused either of these factors to change differentially for the flooded group compared to the not flooded group, Sandy's estimated impact on risk perceptions would be biased. I accounted for potential confounders in the following ways:

Wealth levels – If Hurricane Sandy caused wealth levels (here proxied as income levels) to decrease in the flooded area, then omitting the variable may result in an ambiguously signed bias in Sandy's risk perception effect[19]. I account for changing wealth by including a variable equal to the log transformed median income for census tract i in year t. The median income variable is also represented by $\boldsymbol{X}_{it}$.

Potential losses – As the value of the potential loss decreases, for example, from decreasing home prices, so does the demand for flood insurance. Ortega and Taspinar (2018) give evidence that direct flooding by Hurricane Sandy caused decreases in the value of the housing stock. For this reason, I account for changing housing values by including a variable equal to the log transformed housing price index (hpi) for census tract i in year t. The hpi variable is also represented by $\boldsymbol{X}_{it}$.

Next I investigated heterogeneous adaptation responses attributable to differences in damage severity as well as differences in the cost of insurance from differences in flood risk zones. Their specifications are described below.

[18]Risk preferences also affect insurance demand. For example, if the flooded group became more risk averse after Hurricane Sandy, they would demand more insurance regardless of changes in risk perceptions. As risk aversion is unobservable, I put this point to the side for now. Testing risk aversion parameters before and after disaster events is a fruitful area for future research.

[19]Insurance cover is a normal good if risk aversion increases or is constant with wealth and an inferior good if risk aversion decreases with wealth. While either case is possible, we typically expect wealth to increase a person's willingness to bear risk. This makes insurance coverage an inferior good meaning a decrease in wealth would cause an increase in insurance coverage demanded.

Damage differences

Did differences in damage severity drive differences in the insurance response? Equation 6 captures non-linear variation in treatment outcomes based on damage levels:

$$y_{it} = \sum_{\tau=2010,\tau\neq 2012}^{2018} \rho_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{\text{major damage}} + \sum_{\tau=2010,\tau\neq 2012}^{2018} \delta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{\text{minor damage}} + \sum_{\tau=2010,\tau\neq 2012}^{2018} \alpha_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{\text{affected}} + \gamma \boldsymbol{X}_{it} + \mu_{itCf} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{6}$$

Like Equation 5, the unit of observation is a census tract calendar year and the dependent variable measures the log-transformed number of insurance policies-in-force for census tract i in year t. The indicator variable $W_i^{\text{major damage}}$ equals one if a census tract contained at least one majorly damaged or destroyed building. $W_i^{\text{minor damage}}$ equals one if a census tract contained at least one building with minor damage and no buildings that were destroyed or sustained major damage. Finally, W_i^{affected} equals one if a census tract contained at least one affected building and no damaged buildings. The control group is census tracts not containing any damaged or affected buildings[20].

Near-misses

Did Hurricane Sandy affect insurance purchases places that were "nearly missed"? If geographical areas share similar flood hazards, then Hurricane Sandy may have caused residents in neighboring "dry" census tracts to also re-evaluate their future flood risk. Equation 7 tests the hypothesis that changes in risk perception were not confined to areas that were directly flooded but instead spilled over into neighboring tracts:

[20]Curiously, Figure 3 shows flooded census tracts without damaged or affected buildings. It's possible that wind damage was less in the areas that do not overlap and buildings' damage levels were more difficult to detect from aerial images. Removing census tracts that were flooded but do not contain damaged or affected buildings from the sample does not impact Equation 2's conclusions.

$$y_{it} = \sum_{\tau=2010,\tau\neq 2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{\text{flooded}} + \sum_{\tau=2010,\tau\neq 2012}^{2018} \alpha_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{\text{neighbor}} + \gamma \boldsymbol{X}_{it} + \mu_{itCf} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{7}$$

Here, I build on Equation 5 by adding an additional treatment definition: neighbor. The indicator variable W_i^{neighbor} equals 1 if census tract i was not flooded but shares a border with a flooded census tract. Figure 4 depicts the locations of the spillover census tracts.

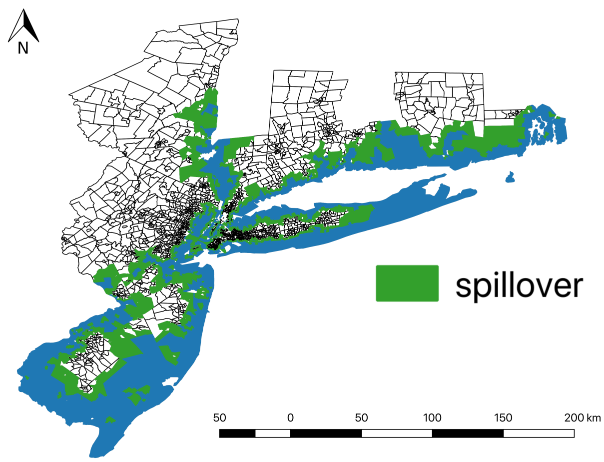


Figure 4

Flood risk zones

Was the strength of the insurance response sensitive to location in a particular flood risk zone?

Flood risk zones come from relative riskiness in the floodplain. As FEMA designed flood insurance premium rates to reflect relative riskiness, one of the major differences between flood risk zones is the cost of purchasing a policy. In CT-NJ-NY-RI, the average premium rate inside the SFHA is four times the average premium rate outside the SFHA. Recall from Equation 4 that the prospective buyer of an insurance policy will only purchase if their perceived risk of being flooded is large relative to the premium rate they pay. Then all else equal, a lower insurance cost threshold, for example in the case of properties outside the SFHA, would lead to larger Sandy-induced changes in insurance demand.

I leveraged (non-random) variation in premium rates across the study area to better understand the role that insurance cost played in influencing people's insurance purchase decisions after Hurricane Sandy. I split the initial policy sample into two subsamples and re-estimated Equation 5 on each. In the first subsample, the outcome variable is the number of SFHA insurance policies in a given census tract. In the second subsample, the outcome variable is calculated with policies outside the SFHA. I retained consistency in flooding and damage severity across the two subsamples by restricting the analysis to census tracts that contained both policies inside and outside the SFHA during the entire study period[21]. In each subsample, there are 2,010 census tracts across all four states. Forty-six percent of census tracts in the subsamples were flooded by Hurricane Sandy.

Note that insurance costs may not be the only fundamental difference between flood risk zones. For example, if people outside the SFHA are more risk averse, then differences in risk preferences would also drive differences in estimated impacts. The relevancy of other fundamental differences to my conclusions is discussed in the results section below.

5 Results

Figure 5 plots the year-treatment coefficients from Equation 5. The coefficients are interpreted as the difference in percentage changes in flood insurance demand between flooded and not flooded census tracts relative to the day before Hurricane Sandy. The dashed lines indicate the 95 percent confidence intervals and show whether the point estimates are statistically different from zero. Prior to 2012, logged insurance counts for the flooded and not-flooded census tracts were statistically indistinguishable from each other providing evidence that, contingent on the controls and fixed effects, the untreated census tracts serve as a valid counterfactual to the treated census tracts.

Hurricane Sandy's flooding extents had a notable impact on people's decisions to insure.

[21] Conclusions remain the same even if I do not restrict the analysis to census tracts that contain both policies inside and outside the SFHA.

In the first year after Sandy, there was an 11 percent increase in the number of policies-in-force in the flooded census tracts relative to census tracts that were not flooded. Between 2012 and 2018, policies-in-force grew at an average of three percent per year in the treated group, topping out at 28 percent. The initial spike is approximately in line with the related literature: Gallagher (2014) estimated an average nine percent increase in insurance take-up rates across all flood events from 1990 to 2007 [6]. Our conclusions, however, deviate in the subsequent years: where Gallagher estimated a steady decline to baseline after the initial take-up, I estimated statistically significant, relative growth.

The persistency of the Sandy effect in the insurance market is consistent with Ortega and Taspinar's (2018) finding in the New York City housing market [18]. They demonstrated that after an initial drop in sales prices after the storm, damaged properties continued to hold a statistically significant price penalty through 2017. Taking the two findings together gives strong evidence that Hurricane Sandy's flooding extents induced learning, changing perceived flood risks in a more permanent fashion than would be expected under heuristics.

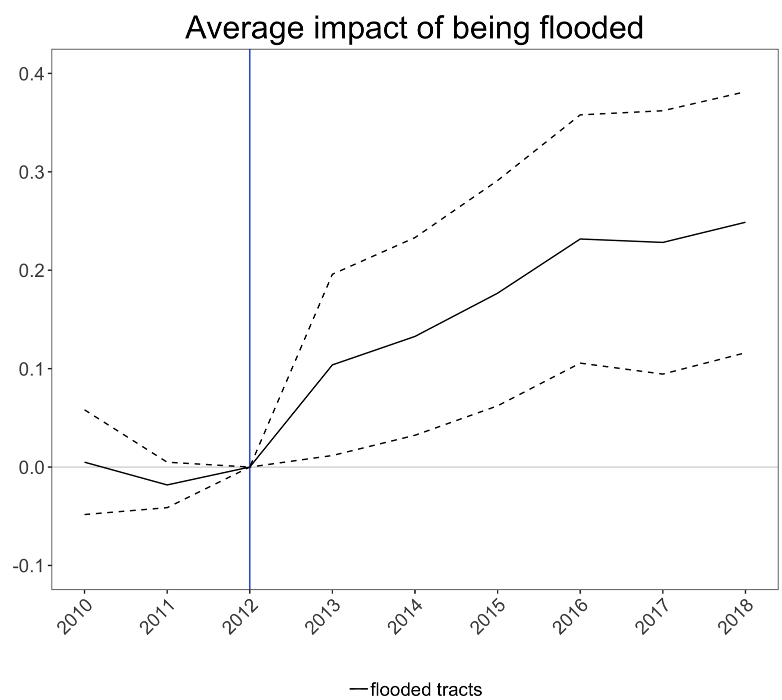


Figure 5

Damage differences

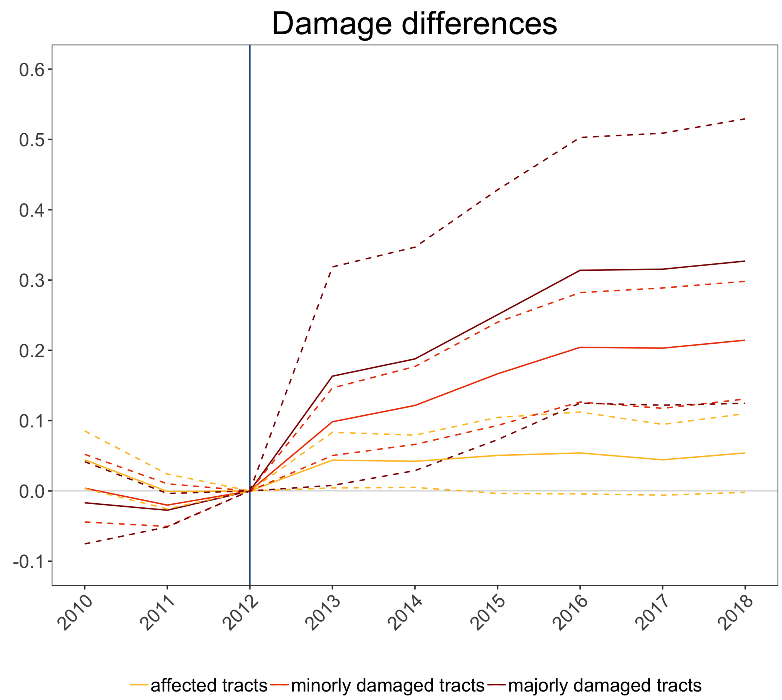


Figure 6

I also considered treatment differences based on damage levels. Bubeck et al. (2012) noted that, across flood events, estimated differences in risk mitigating outcomes is often driven by differences in the severity of the consequences [28]. Figure 6 (from Equation 6) demonstrates that the same logic holds true also within a single flood event. The increase in policies-in-force in the most damaged census tracts was approximately twice that of the census tracts that sustained minor damage and at least four times that of the census tracts containing only affected buildings. The differences in the number of policies-in-force between the three damage groups are statistically significant in nearly every year and combination.

To my knowledge, this paper is the first to show that adaptation responses within a single flood event are not uniform. The finding implies that people form their risk perceptions using rather detailed disaster experience information from their immediate geographical surroundings. In the case that local experience reflects real risk, these heterogeneous adaptation responses were welfare improving. In the case that Sandy's damage distribution doesn't reflect the average future storm, the response is maladaptive [43].

Near-misses

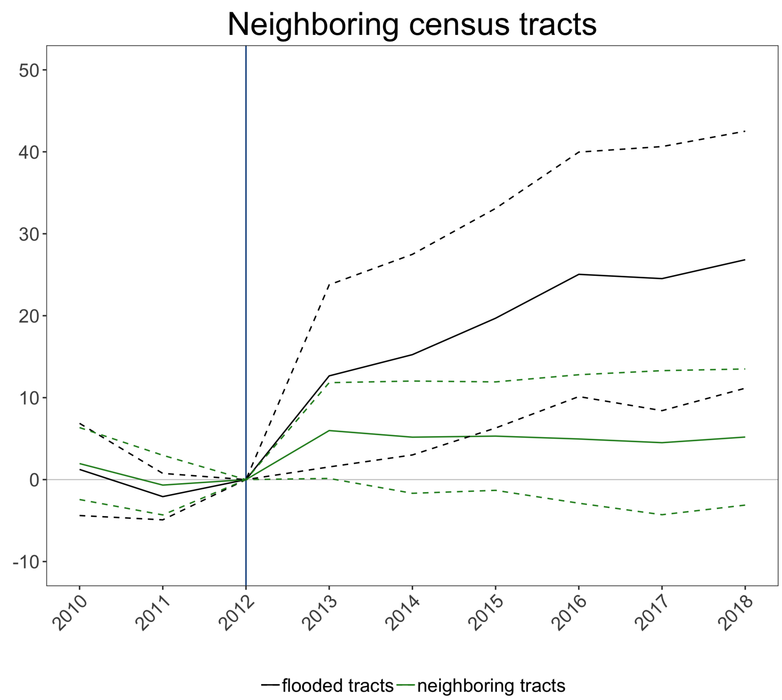


Figure 7

Next I examined areas that were "nearly missed" by Hurricane Sandy. Figure 7 gives evidence that residents in neighboring census tracts also updated their expectations about future flood risk. In 2013, near-miss areas underwent a six percent relative increase in policies-in-force, statistically significant at the 5 percent level. In the years after, the estimated coefficients are fairly stable but with less precision.

The finding supports previous results showing that close proximity to disaster events is an important determinant in encouraging risk mitigating behavior. For example, Gallagher (2012) estimated a statistically significant increase in insurance policies-in-force in non-flooded communities close to communities that were flooded [6]. Taking our two findings together - where I estimate a smaller scale spillover effect and he a larger scale spillover effect, the overall conclusion appears to be that people who are not directly hit by flooding events also update their risk perceptions.

Spillover channels are important for policy makers designing public risk mitigation efforts. For example, even those not directly hit by flooding may pass through a ”window of opportunity” where they become more responsive to flood safety information. Spillover channels are also important for economic researchers in choosing a control group and interpreting results. Exploring non-spatial spillover channels, for example from previous experience or relating to the type of flood risk, is a fruitful area for future research.

Flood risk zones

Figure 8 gives evidence that residents with access to lower premium rates also had larger insurance responses. Inside the SFHA and across the entire study period, there is no statistically significant difference in the number of policies-in-force between census tracts that were flooded and those that were not. Outside the SFHA, relative policy counts increased after Hurricane Sandy.

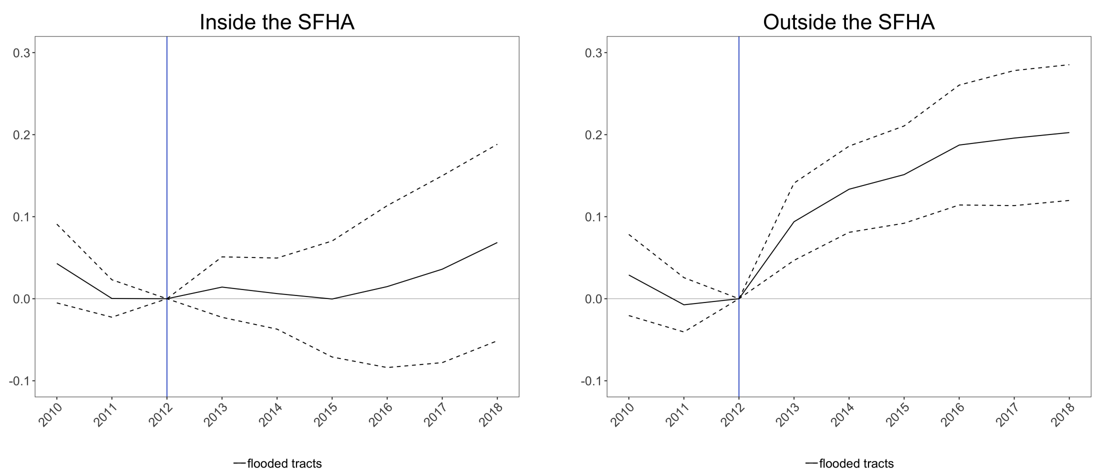


Figure 8

No estimated change in insurance response could also mean that Sandy caused flooded and not flooded residents to both change their risk perceptions, but equally. Figure 9 suggests that this is not the case. Save for a small bump, inside the SFHA, the number of policies-in-force decreased for both groups from 2012 onward. Outside the SFHA, policies-in-force increased in flooded areas and remained relatively steady in areas that were not flooded.

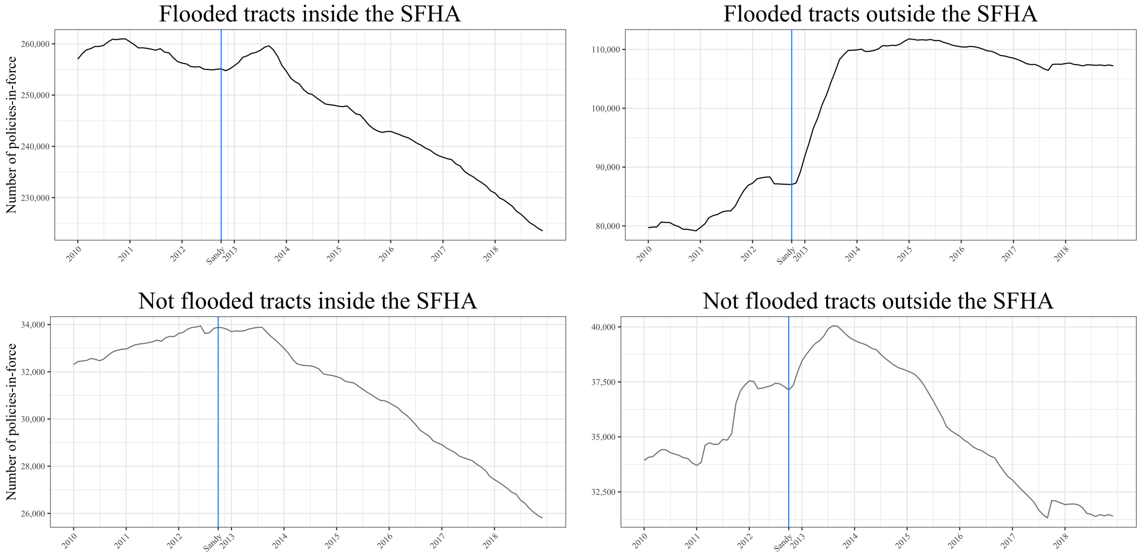


Figure 9

Anecdotal evidence also points to the fact that many people who were flooded by Hurricane Sandy did not purchase insurance afterwards for affordability reasons. In a special report by "The City", journalists uncovered that many New York City residents in high risk flood zones continued to view flood insurance as prohibitively expensive after Hurricane Sandy [44]. Meanwhile, in Canarsie, Brooklyn, where there were no properties located inside the SFHA, flood insurance policies increased six-fold.

It is important to note that a causal interpretation of insurance cost on adaptation responses is inhibited by the non-random assignment of premium rates. There are other fundamental differences between residents inside and outside the SFHA that may explain the two groups' differential adaptation responses.

The first explanation concerns learning. Mortgage lenders are mandated to inform SFHA residents of their location in a flood risky area when they purchase a property. Outside the SFHA there is so such mandate. The lack of insurance response inside the SFHA may be because the flooding extents simply confirmed the flooded residents' priors about their risk levels. Outside the SFHA, residents were new learners, increased their perceived risks and purchased more insurance. Recent research on property markets, however, gives evidence that SFHA residents do in fact update their risk perceptions after flooding events. For example, Atreya and Ferreira (2015) showed that direct flooding caused property prices both inside and outside the SFHA to drop [14].

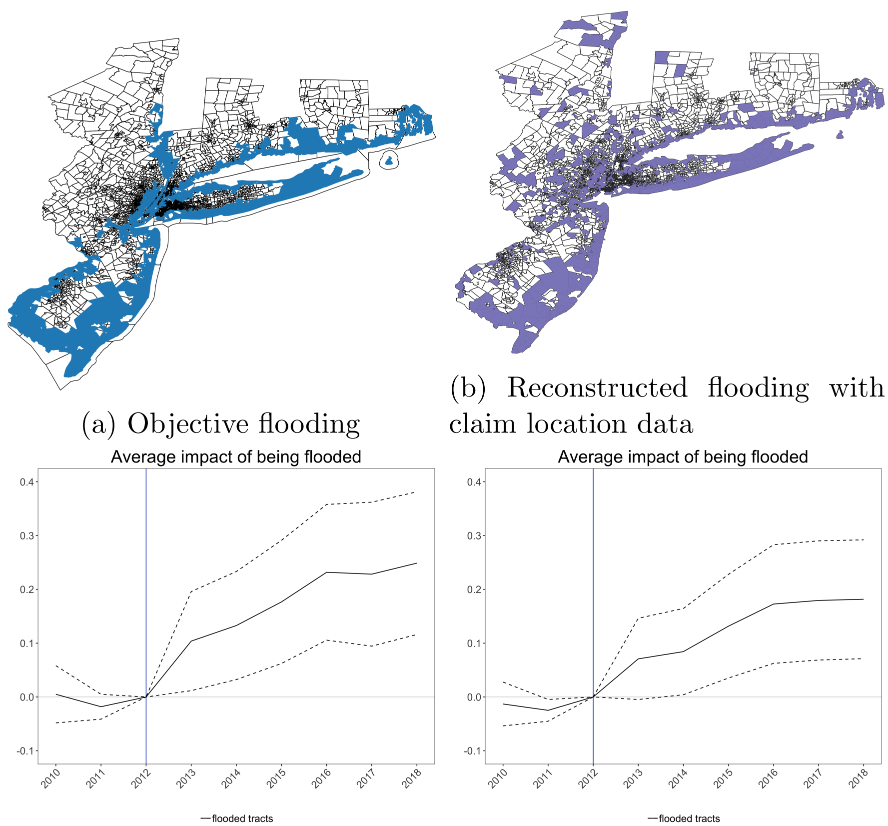
A second explanation concerns risk preferences. If people who choose to settle inside the SFHA also tend to be less risk averse, then Sandy may have induced a much smaller increase in risk perception than that for residents outside the SFHA. In this case, the two groups' differential insurance responses are not the result of differences in insurance costs but differences in changed risk perceptions driven by differences in risk preferences. Estimating risk aversion across disaster risk zones is a fruitful area for future research.

A final explanation concerns mandatory purchase requirements inside the SFHA. It could be that there was no possibility for additional market penetration inside the SFHA: all buildings were already insured when Hurricane Sandy hit. I find no evidence to support this hypothesis. Across the flooded area, the insurance take-up rate inside the SFHA was 34 percent immediately prior to Sandy. Moreover, I reach the same conclusions when removing census tracts with high insurance take-up from the sample.

Testing for external validity

This paper's findings are intuitive: direct experience with flooding caused people to update their expectations about future flood-related losses. Hurricane Sandy, however, is a unique case. It was one of the most damaging hurricanes ever to make landfall in the United States. Nearly 600,000 housing units were impacted and as long as five years after the storm some residents were still rebuilding [32]. Moreover, Hurricane Sandy hit an area of the country that doesn't have extensive experience with major hurricanes. As a result, the storm served as a wake-up call for many and exposed vulnerabilities in the region.

Because of Hurricane Sandy's unique context and before making generalizations about updated risk perceptions, I was keen to test the external validity of my findings. Unfortunately detailed and objective flooding extent information like that provided by the MOTF for Sandy is rarely available because of high development costs. Instead, I reconstructed flooding extents from Hurricane Sandy and six other historical U.S. flood events using census tract locations of insurance claims. Each significant flood event had 1,500 or more paid losses, occurred sometime between 2012 and 2016 and affected at least ten counties[22]. Treatment groups are composed of census tracts with at least one insurance claim attached to a given event. Census tracts that did not have claims but are located in counties that received federal aid form the control groups[23].



(a) Objective flooding

(b) Reconstructed flooding with claim location data

Figure 10

First, I tested the legitimacy of the reconstructed flooding extents strategy by applying it to Hurricane Sandy. Figure 10 compares Sandy's objective flooding extents to its reconstructed flooding extents. Generally speaking, the objective and reconstructed flooding

[22]Information about significant flood events can be found here:
https://www.fema.gov/significant-flood-events

[23]For some of the states, some of the control group census tracts may have been hit by another historic flood during the study period. If you're curious, I may have already accounted for this in the latest version

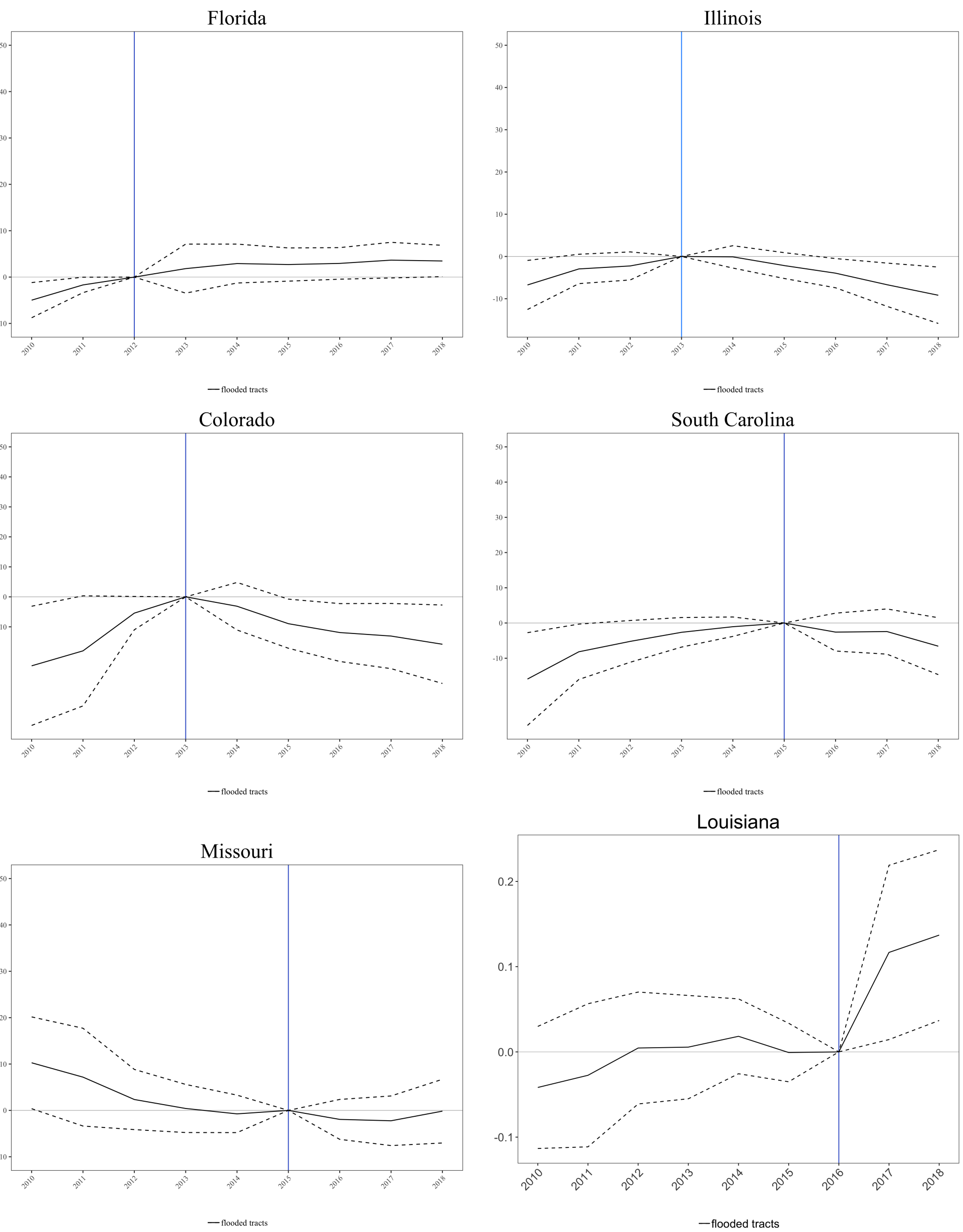
extents match well[24]. For each treatment group definition, two-thirds of the flooded census tracts were also flooded in the treatment group definitions from the objective flooding extents. Figure 10 also compares the regression results for the two treatment group definitions estimated separately on Specification 5. The magnitude and certainly the direction of the post-Sandy effect for the simulated flooding extents is close to that in the model with objective flooding extents. This suggests that, at least in the case of Hurricane Sandy, using claims data to simulate flooding extents is a reasonable strategy.

Next I reconstructed flooding extents for six other historic flood events across the United States. They include flooding from hurricanes (Florida, South Carolina) and riverine flooding (Illinois, Colorado, Missouri, Louisiana), slower-onset (Illinois, Missouri) and flash flooding (Colorado, Louisiana). Some of these floods hit areas that are commonly flooded (Florida, Louisiana) and other floods hit areas where large flood-scale flooding is rare (Colorado). Hurricane Sandy's total insurance payouts were at least four times as large as those generated by the other floods.

Figure 11 gives evidence that the magnitude of Hurricane Sandy's insurance response was an outlier and not the norm. Only one other event saw a statistically significant increase in the number of insurance policies-in-force for the (reconstructed) flooded census tracts. The 2016 Louisiana event, like Sandy, was particularly large, paying out 800 million dollars in victim assistance. The finding supports Bubeck et al's (2012) conclusion that, on average, people change their risk mitigating behavior in response to only the severest of events.

The strategy of reconstructing flooding extents with insurance claim information is limited by two assumptions. I assume that, one, flooding occurred in census tracts with claims and, two, flooding did not occur in census tracts without claims. The second assumption is more difficult to fulfill. If structures have different resiliencies to flood damage, then its possible some of the untreated census tracts were indeed flooded, but no claims were filed. In

[24]Insurance claims not being filed in census tracts with objective flooding is understandable: perhaps they simply had no insurance prior to Hurricane Sandy. A more puzzling phenomena are the census tracts with claims outside the flooding extents.



Florida
flooded tracts
Illinois
flooded tracts
Colorado
flooded tracts
South Carolina
flooded tracts
Missouri
flooded tracts
Louisiana
flooded tracts

Figure 11

the case that an area has heterogeneous insurance take-up within the flooding extents, again, flooded census tracts without insurance policies could have been erroneously assigned to the control group. Given the uncertainties in my findings that these assumptions produce, the flooding simulation exercise also highlights the the importance of precise, objective hazard data in estimating unbiased behavioral responses.

6 Conclusion

This paper provides evidence that Hurricane Sandy caused flooded residents to reassess their perceived risk of future flooding. In the year after the storm, the number of flood insurance policies-in-force in flooded census tracts increased by 11 percent relative to census tracts that were not flooded. In contrast to previous findings, the policies wedge between the treated and untreated groups continued to grow in the succeeding years, suggesting that flooded residents haven't "forgotten" about the storm, but rather experienced a form of more permanent learning. Extensions to the main specification showed that more severe damage is associated with larger insurance demand increases, near-miss census tracts close to the flooding also responded positively to the risk signal and insurance costs probably mattered for eliciting an adaptation response.

My findings are encouraging but insufficient in the larger picture. Encouraging because people who were flooded, and are presumably at a larger flood risk generally, had a stronger response to Hurricane Sandy than people that were not flooded. Their participation in the insurance market means that more policy holders will be exposed to, for example, incentives for damage mitigation than would have otherwise been the case. It also means that the public burden of post-disaster aid may be somewhat alleviated in future years.

Sandy's insurance response, however, has elements of being maladaptive[45]. In the case that Hurricane Sandy's flooding extents don't wholly reflect real risk, then households that were not flooded would be left relatively exposed to future events. Moreover, in some areas insurance may be a second-best response to increases in real flood risk. Social welfare may be higher had people simply moved out of the flood risky areas after Sandy. This is the motivation behind the few FEMA home buy-outs being carried out in CT-NJ-NY-RI.

Moreover, Sandy's adaptation response came at a huge cost and reflects market failures in the National Flood Insurance Program. Nearly 1.5 billion dollars in federal aid was granted to affected households in CT-NJ-NY-RI. Had the 20,000 households that purchased insurance after Sandy been insured prior to Sandy, FEMA could have saved 160 million dollars in relief money[25]. One potential future research avenue concerns other, non-disaster means means to encourage insurance purchases. Discerning their efficacy, particularly with respect to insurance affordability, would yield benefits in designing future campaigns that elicit the same type of response as a disaster event. A second potential research topic deals with the tradeoff between individual-level adaptation and community hazard mitigation. The public good nature of hazard mitigation may elicit behavioral responses that shift the distribution of flooding costs to the public away from the individual. Understanding the extent to which this happens could help policy makers in deciding on insurance legislation, and, in particular, mandates in flood risky areas.

[25]Each individual or household receiving disaster aid after Hurricane Sandy received approximately 8,000 dollars.

References

[1] B. Jongman, “Effective adaptation to rising flood risk,” *Nature Communications*, vol. 9, no. 1, p. 1986, 2018.

[2] S. Rahmstorf, “Rising hazard of storm-surge flooding,” *Proceedings of the National Academy of Sciences*, vol. 114, p. 11806, 11 2017.

[3] “2018 revision of world urbanization prospects,” tech. rep., United Nations: Department of Economic and Social Affairs, 2018.

[4] C. Kousky, “The role of natural disaster insurance in recovery and risk reduction,” *Annual Review of Resource Economics*, vol. 11, no. 1, pp. 399–418, 2019.

[5] C. Kousky, H. Kunreuther, B. Lingle, and L. Shabman, “The emerging private residential flood insurance market in the united states,” *Wharton Risk Management and Decisions Processes Center: Policy Brief*, 2018.

[6] J. Gallagher, “Learning about an infrequent event: Evidence from flood insurance take-up in the united states,” *American Economic Journal: Applied Economics*, vol. 6, no. 3, pp. 206–233, 2014.

[7] M. J. Browne and R. E. Hoyt, “The demand for flood insurance: Empirical evidence,” *Journal of Risk and Uncertainty*, vol. 20, no. 3, pp. 291–306, 2000.

[8] K. Carolyn, “Understanding the demand for flood insurance,” *Natural Hazards Review*, vol. 12, no. 2, pp. 96–110, 2011.

[9] A. Royal and M. Walls, “Flood risk perceptions and insurance choice: Do decisions in the floodplain reflect overoptimism?,” *Risk Analysis*, vol. 39, pp. 1088–1104, 2019/11/28 2019.

[10] C. Kousky, "Disasters as learning experiences or disasters as policy opportunities? examining flood insurance purchases after hurricanes," *Risk Analysis*, vol. 37, no. 3, pp. 517–530, 2017.

[11] J. S. Ferris and D. A. Newburn, "Wireless alerts for extreme weather and the impact on hazard mitigating behavior," *Journal of Environmental Economics and Management*, vol. 82, pp. 239–255, 2017.

[12] T. K. M. Beatty, J. P. Shimshack, and R. J. Volpe, "Disaster preparedness and disaster response: Evidence from sales of emergency supplies before and after hurricanes," *Journal of the Association of Environmental and Resource Economists*, vol. 6, no. 4, pp. 633–668, 2019.

[13] S. J. McCoy and R. P. Walsh, "Wildfire risk, salience & housing demand," *Journal of Environmental Economics and Management*, vol. 91, pp. 203–228, 2018.

[14] A. Atreya and S. Ferreira, "Seeing is believing? evidence from property prices in inundated areas," *Risk Analysis*, vol. 35, no. 5, pp. 828–848, 2015.

[15] C. Kousky, "Learning from extreme events: Risk perceptions after the flood," *Land Economics*, vol. 86, no. 3, pp. 395–422, 2010.

[16] L. P. Boustan, M. E. Kahn, and P. W. Rhode, "Moving to higher ground: Migration response to natural disasters in the early twentieth century," vol. 102, no. 3, pp. 238–244, 2012.

[17] O. Dessaint and A. Matray, "Do managers overreact to salient risks? evidence from hurricane strikes," *Journal of Financial Economics*, vol. 126, no. 1, pp. 97–121, 2017.

[18] F. Ortega and S. Taşpınar, "Rising sea levels and sinking property values: Hurricane sandy and new york's housing market," *Journal of Urban Economics*, vol. 106, pp. 81–100, 2018.

[19] S. J. McCoy and X. Zhao, "A city under water: A geospatial analysis of storm damage, changing risk perceptions, and investment in residential housing," *Journal of the Association of Environmental and Resource Economists*, vol. 5, no. 2, pp. 301–330, 2018.

[20] P. Slovic, "Perception of risk," *Science*, vol. 236, p. 280, 04 1987.

[21] W. K. Viscusi, "Insurance and catastrophes: The changing role of the liability system," *The Geneva Papers on Risk and Insurance Theory*, vol. 20, no. 2, pp. 177–184, 1995.

[22] L. Sjöberg, "Factors in risk perception," *Risk Analysis*, vol. 20, pp. 1–12, 2019/12/27 2000.

[23] N. Weinstein, "Effects of personal experience on self-protective behavior," *Psychological Bulletin*, vol. 105, no. 1, pp. 31–50, 1989.

[24] P. Slovic, B. Fischhoff, and S. Lichtenstein, "Why study risk perception?," *Risk Analysis*, vol. 2, pp. 83–93, 2019/12/28 1982.

[25] M. Siegrist and H. Gutscher, "Natural hazards and motivation for mitigation behavior: People cannot predict the affect evoked by a severe flood," *Risk Analysis*, vol. 28, pp. 771–778, 2019/12/27 2008.

[26] K. Takao, T. Motoyoshi, T. Sato, T. Fukuzondo, K. Seo, and S. Ikeda, "Factors determining residents'preparedness for floods in modern megalopolises: the case of the tokai flood disaster in japan," *Journal of Risk Research*, vol. 7, pp. 775–787, 11 2004.

[27] R. Zaalberg, C. Midden, A. Meijnders, and T. McCalley, "Prevention, adaptation, and threat denial: Flooding experiences in the netherlands," *Risk Analysis*, vol. 29, pp. 1759–1778, 2019/12/27 2009.

[28] P. Bubeck, W. J. W. Botzen, and J. C. J. H. Aerts, "A review of risk perceptions and other factors that influence flood mitigation behavior," *Risk Analysis*, vol. 32, pp. 1481–1495, 2019/12/27 2012.

[29] G. Wachinger, O. Renn, C. Begg, and C. Kuhlicke, "The risk perception paradox—implications for governance and communication of natural hazards," *Risk Analysis*, vol. 33, pp. 1049–1065, 2019/12/27 2013.

[30] J. von Neumann, O. Morgenstern, and A. Rubinstein, *Theory of Games and Economic Behavior*. Princeton University Press, 1944.

[31] R. Rees and A. Wambach, "The microeconomics of insurance, foundations and trends in microeconomics," vol. 4, no. 1-2, pp. 1–163, 2008.

[32] E. S. Blake, T. B. Kimberlain, R. J. Berg, J. P. Cangialosi, and J. L. B. II, "Tropical cyclone report hurricane sandy," tech. rep., National Hurricane Center, 2013.

[33] "Chapter 1: Sandy and its impacts," tech. rep., New York City Government, 2014.

[34] C. R. Service, "Introduction to the national flood insurance program (nfip)," *Policy Brief*, 2019.

[35] L. Dixon, N. Clancy, B. Bender, A. Kofner, D. Manheim, and L. Zakaras, "Flood insurance in new york city following hurricane sandy," *RAND*, 2013.

[36] R. O. King, "The national flood insurance program status and remaining issues for congress," tech. rep., Congressional Research Service, 2013.

[37] "Homeowner flood insurance affordability act," tech. rep., Federal Emergency Management Agency, 2014.

[38] A. Kahn-Lang and K. Lang, "The promise and pitfalls of differences-in-differences: Reflections on '16 and pregant' and other applications," *NBER Working Paper Series*, 2018.

[39] T. Deryugina, "The fiscal cost of hurricanes: Disaster aid veruss social insurance," *American Economic Journal: Economic Policy*, vol. 9, no. 3, pp. 168–198, 2017.

[40] Y. Liao and Y. Pannassie, "How hurricanes sweep up housing markets: Evidence from florida," *Working Paper*, 2019.

[41] C. Kousky, E. O. Michel-Kerjan, and P. A. Raschky, "Does federal disaster assistance crowd out flood insurance?," *Journal of Environmental Economics and Management*, vol. 87, pp. 150 – 164, 2018.

[42] W. J. W. Botzen, E. Michel-Kerjan, H. Kunreuther, H. de Moel, and J. C. J. H. Aerts, "Political affiliation affects adaptation to climate risks: Evidence from new york city," *Climatic Change*, vol. 138, pp. 353–360, Sep 2016.

[43] S. E. Anderson, R. R. Bart, M. C. Kennedy, A. J. MacDonald, M. A. Moritz, A. J. Plantinga, C. L. Tague, and M. Wibbenmeyer, "The dangers of disaster-driven responses to climate change," *Nature Climate Change*, vol. 8, no. 8, pp. 651–653, 2018.

[44] A. Choi, C. Chung, C. Michel, and G. B. Smith, "Flirting with disaster: Flood zones still uninsured years after sandy," 2019.

[45] S. E. Anderson, R. R. Bart, M. C. Kennedy, A. J. MacDonald, M. A. Moritz, A. J. Plantinga, C. L. Tague, and M. Wibbenmeyer, "The dangers of disaster-driven responses to climate change," *Nature Climate Change*, vol. 8, no. 8, pp. 651–653, 2018.