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

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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 decisions to insure against future flood damages. Hurricane Sandy's flooding boundaries had a large and long-lived impact. 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, implying that cost was a critical factor in people's adaptation decisions. Simulated flooding extents of six other recent events give evidence that Hurricane Sandy's adaptation response was the exception and not the rule.

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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 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, mandates, expectations about disaster aid etc.), estimating the insurance response equates to estimating Hurricane Sandy's impact on people's perceived flood risk[1] [6]. Provided that people use all of the information they have in making decisions about whether to purchase insurance, my findings indicate that people used information about where Sandy flooded to update their flood risk perceptions and inform their adaptation

[1]The risk perception to flood insurance purchase mechanism is noisy and imperfect. For example, people could have updated their risk perceptions and, instead of buying insurance, moved belongings from basements to higher levels. For this reason, my estimates should be interpreted as a lower bound on post-Sandy differences in risk perception if only people inside the flooding extents increased their non-insurance risk-reducing behaviors. My estimates should be interpreted as an upper bound if only those outside the flooding extents increased their non-insurance risk-reducing behaviors.

response[2]. In a rough 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 flooding's 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 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 adaptive 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.

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

[2]The availability heuristic is an alternative explanation for my findings that doesn't require that people learned from their Sandy experience. Under the availability heuristic, people prioritize ease and quickness in decision-making by ignoring part of the information they have. For example, people may only use their Sandy experience to make decisions because that is the information they can most easily recall. Given that the change in risk perceptions does not appear to be temporary, I lean away from the availability heuristic explanation for the behavioral change.

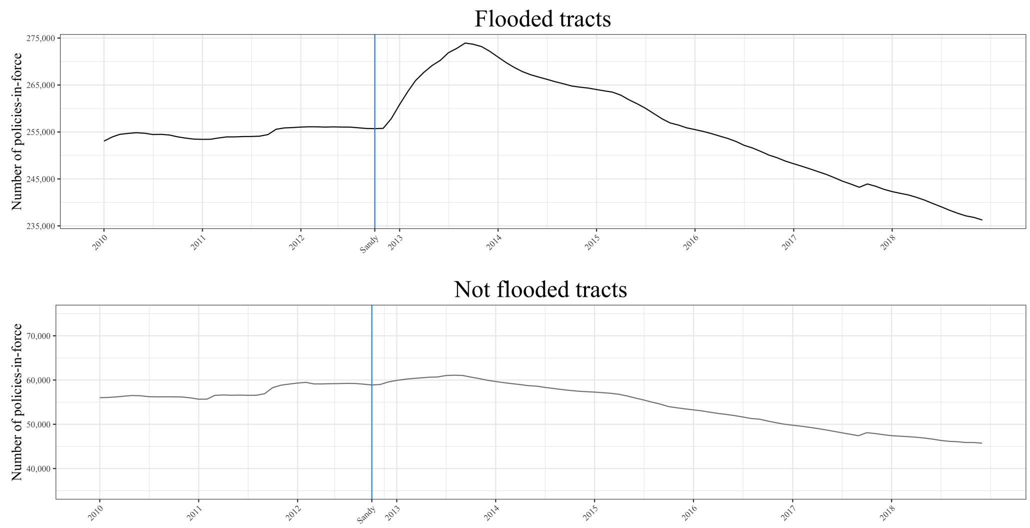


Figure 1

census tracts. Between 2014 and 2018, the number of policies-in-force falls by 25% in the flooded areas and by 35% in the not flooded areas[3]. This suggests that flooded areas had relatively better retention rates of existing policies in later years.

Extensions to the main specification demonstrate the relevancy of heterogeneous treatment 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, flooded residents that had relatively more affordable insurance options increased their insurance demand, while residents for whom the insurance options were costlier did not. While Hurricane Sandy likely induced changes in perceived flood risk for all residents, only those for whom insurance was a relatively affordable endeavor were able to act on that risk perception change.

Several other papers have also 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)

[3]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.

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 robust causal inference. Second, for the first time, I demonstrated the relevancy of heterogeneous treatment effects within a single event, exposing how damage intensity and the cost of adaptation influenced the adaptation response. Third, a critical difference between this paper's primary findings and those in the literature is that the insurance wedge between flooded and not flooded areas grew after the initial spike, rather than returning to baseline. In this paper, the behavioral response was not temporary, likely because of Sandy's relative enormity and destructiveness. A critical 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 demonstrating the influence of information about environmental risk on risk perceptions and risk-reducing behavior [11] [12]. In the context of information about risk coming from experiences with risky events, the most prominent literature documents that properties in flood-risky areas tend to sell for a discount after flood events [13] [14]. Non-flooding risk-reducing responses in the property market have also been documented for wildfires, earthquakes and volcanoes [15] [16]. Outside of property markets, Dessaint and Matray (2017) show that managers that experience disasters increase their cash holdings in an effort to reduce their perceived financial risk [17].

Lastly, this research contributes to a more targeted literature documenting 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. To test for external validity, I simulated the flooding extents from Hurricane Sandy and six other significant U.S. flood events using census tract locations of insurance claims. Again in a difference-in-difference framework, I found that that the Hurricane Sandy simulated flooding extents, like the objective flooding extents, estimated an increase in insurance policies-in-force. For the six other floods, I estimated either no post-flood change or a relative decrease in insurance policies-in-force. The exercise highlights two important points. If simulated flooding matches real flooding, then the Hurricane Sandy response was an outlier, not the norm. If simulated 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 describes the background of the study and the data used in the analysis. Section three discusses the empirical strategy. Section four provides estimation results and section five concludes with a discussion of the findings in the broader policy context.

2 Background and Data

2.1 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 [20]. Sandy approached the East Coast at a perpendicular angle, coinciding with a spring high tide that was higher than normal because of a full moon. The combined factors generated a monstrous 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 [21]. 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[6]. 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.

[4]For information about federally-declared disasters, see here:
https://www.fema.gov/disasters

[5]Flooding information is available at:
https://www.arcgis.com/home/item.html?id=3a5c59699d86453a89f590171a10e9b5

[6]Information about the damage locations appears to have been unfortunately taken off the web in the last few months. Email me if you would like me to send you the shapefile.

2.2 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 [22]. Prior to the NFIP's inception in 1968, federal actions related to flooding generally consisted of structural 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[7] [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 [23].

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 suffi-

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

cient 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[22].

In 2012, the U.S. Congress passed the Biggert Waters Flood Insurance Reform Act as a way to phase out subsidization of insurance premiums and make the NFIP more financially stable [24]. 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) intended to better the financial position of the NFIP by having actuarially-based flood insurance rates for all policies [25]. Beginning in 2013, premium rates increased by 25 percent per year for pre-FIRM repetitive-loss properties and non-primary residences located inside the SFHA. In 2015, pre-FIRM primary residences inside the SFHA also began to see rate increases of 5-18 percent per year.

2.3 Data

The present analysis relies on a national database of nearly fifty million individual flood insurance policies[8]. 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 subset 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.

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

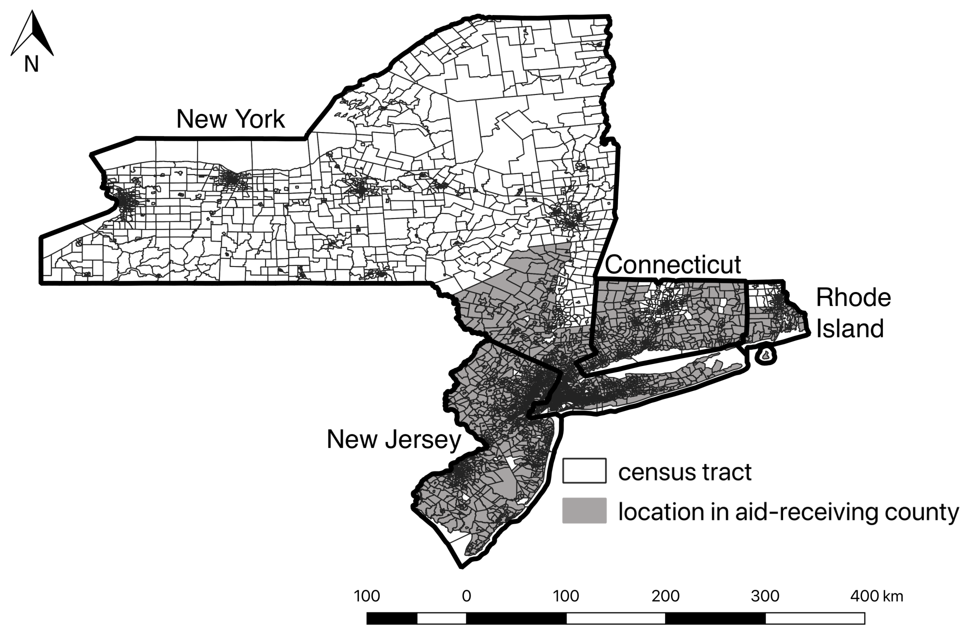


Figure 2

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

The data also describe whether the building attached to a policy is 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 increases in premiums for subsidized policies. Another source of bias could be differential construction trends across flood zones between 2010 and 2018: estimated differences in insurance purchase behavior could be driven by differences in the number of new structures subject to compulsory purchase mandates rather than differences in risk perceptions and learning. In my sample, I dropped all policies attached to structures with construction dates after the start of the study period.

[9]Most policies are effective for 365 days because the Standard Flood Insurance Policy contract is for one year only. The data also provide the date a policy on the property first began.

The present study's primary outcome variable is the log-transformed yearly number of insurance policies-in-force in a given census tract. I recorded the number of insurance policies-in-force in each census tract on October 25th for the years 2010-2018[10]. 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. Finally, 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.

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. The final panel contains 39,321 observations: 4,369 census tracts across 9 years. Figure 3 presents the locations of the flooded, damaged and affected census tracts.

3 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 1 estimates the impact of flooding on the number of policies-in-force:

[10] While, generally speaking, flooded census tracts tended to have more policies-in-force just prior to Hurricane Sandy, potentially reflecting their relatively greater flood risk, this paper's conclusions are robust to subsamples of census tracts with similar numbers of policies-in-force (e.g. restricting to census tracts with 10 policies-in-force).

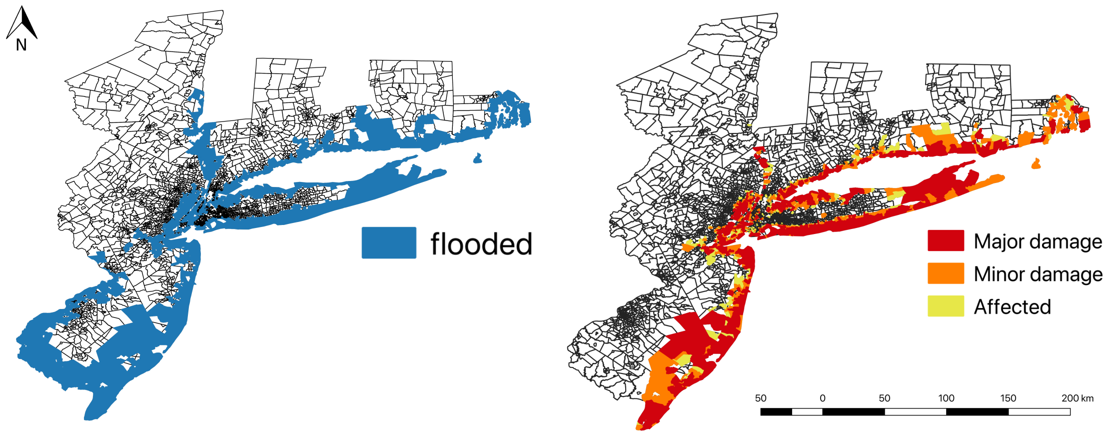


Figure 3

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

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^{flood}. 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^{flood} 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[11] Second,

[11]Kahn-Lang & Lang (2018) note that pre-treatment parallel pre-trends are neither necessary nor sufficient to establish difference-in-difference validity [26]. Deryugina (2016) argues that nonparallel pre-trends would not invalidate a hurricane shock's exogeneity [27]. It would still be possible to estimate a hurricane's causal

the post-Sandy year-treatment indicators allow transitional patterns, which can give insights about the longevity of adaptive behaviors, to play out without imposing restrictions on trend. In sum, this paper's empirical strategy seeks to minimize misspecification and maximize transparency of the research design.

Identification of the Sandy effect

This paper's main goal is to estimate how being flooded by Hurricane Sandy changed people's flood risk perceptions and decisions to participate in the flood insurance market. Equation 1'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.

One threat to the parallel trends assumption is recent legislation increasing premiums for policy-holders with subsidized insurance costs. Ninety percent of pre-FIRM buildings inside the SFHA are located in areas that were flooded by Sandy. Because the demand for insurance decreases as the cost of premiums rise, not controlling for the 2012/2014 legislation would result in underestimation of the Sandy effect [7] [12]. Equation 1 controls for the change in legislation with three variables represented 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.

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.

[12] 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.

A second threat to the parallel trends assumption is post-Sandy updates in flood risk maps. If structures inside the flooding extents were mapped into the SFHA after Hurricane Sandy, 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[13]. Of the 4,369 census tracts in this study, nine percent overlap a FIRM panel that was updated after Hurricane Sandy[14]. 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 or between Hurricane Sandy and year t[15]. 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_{itCf} in Equation 1.

In addition to the observed confounders, a rich set of fixed effects non-parametrically control for unobserved characteristics that may explain insurance demand. County-by-year fixed effects, ψ_{ct}, capture county-specific yearly factors. These include changes in county-level economic conditions, expectations surrounding post-disaster aid and flood risk mitigation efforts[16] [28]. 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[17] and political beliefs [7] [29]. 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 insurance demand movements specific to

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

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

[15] Census tracts that underwent map changes are depicted graphically in the Appendix.

[16] Flood risk mitigation efforts are often undertaken at the community-level and not the county-level. Replacing the county-by-year fixed effects with community-by-year fixed effects do not change my conclusions. Their results are presented graphically in the Appendix.

[17] Recall that all structures with construction dates after the begin of the study period were removed from the sample.

each county.

I estimated four variants of Equation 1 as described below. In all specifications, identification of the key variables of interest requires that they are uncorrelated to idiosyncratic shocks to insurance demand, conditional on the control variables.

Differences in damage levels

Did insurance demand depend on damage severity or simply the incidence of flooding? Equation (2) captures non-linear differences in treatment outcomes based on damage levels:

$$
\begin{aligned}
y_{it} = & \sum_{\tau=2010,\tau\neq 2012}^{2018} \rho_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{majordamage} + \sum_{\tau=2010,\tau\neq 2012}^{2018} \delta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{minordamage} + \\
& \sum_{\tau=2010,\tau\neq 2012}^{2018} \alpha_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{affected} + \gamma \boldsymbol{X}_{it} + \mu_{itCf} + \pi_i + \psi_{ct} + \epsilon_{it}
\end{aligned} \tag{2}
$$

Like Equation 1, 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 $W_i^{majordamage}$ equals one if a census tract contained at least one majorly damaged or destroyed building. $W_i^{minordamage}$ 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[18].

Spatial spillovers

Did Hurricane Sandy affect insurance purchases in places that were "nearly missed"? If geographical areas share similar flood hazards, then Hurricane Sandy may have caused resi-

[18]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.

dents in neighboring "dry" census tracts to also re-evaluate their future flood risk. Equation 3 estimates spillover effects:

$$
\begin{aligned}
y_{it} = & \sum_{\tau=2010,\tau\neq 2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{flooded} + \sum_{\tau=2010,\tau\neq 2012}^{2018} \nu_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{neighbor} + \\
& \gamma \boldsymbol{X}_{it} + \mu_{itCf} + \pi_i + \psi_{ct} + \epsilon_{it}
\end{aligned} \tag{3}
$$

Here, I build on Equation 1 by adding an additional treatment definition: neighbor. The indicator variable $W_i^{neighbor}$ equals one 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.

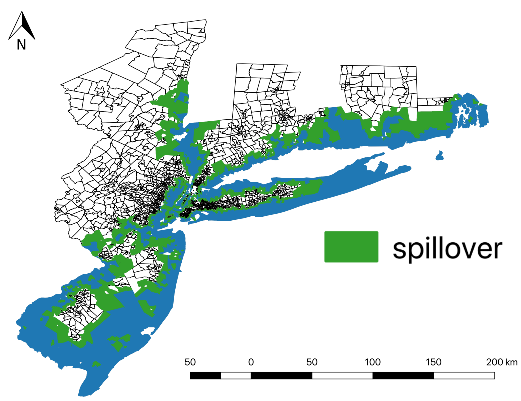


Figure 4

Differences across flood zones

Did adaptation responses differ across flood zones? Two mechanisms could have induced heterogeneous treatment effects across flood zones. The first concerns affordability. Because flood insurance premiums, in theory, reflect relative flood risk, flood insurance is more expensive inside the SFHA compared to outside the SFHA. The second mechanism concerns differences in pre-Sandy knowledge about flood risk. Inside the SFHA, flood insurance is compulsory and mortgage lenders must inform homebuyers of the property's flood risk. Policyholders inside the SFHA likely had flood risk information prior to Hurricane Sandy, while flooding may have come as a surprise to policy holders outside the SFHA.

I looked for differences in insurance responses across flood zones by splitting the initial policy sample into two subsamples and re-estimating Equation 1 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, insurance purchase rates are calculated with policies outside the SFHA. I kept flooding and damage intensity constant 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[19]. In each subsample, there are 2,348 census tracts across all four states. Forty-eight percent of census tracts in the subsamples were flooded by Hurricane Sandy.

The intensive margin

Did Hurricane Sandy have an impact on policy coverage choices? The previous specifications estimate insurance demand changes at the extensive margin. Here I focus on the intensive margin. Equation 4 estimates the impact of Hurricane Sandy on average coverage per policy:

$$\phi_{it} = \sum_{\tau=2010,\tau\neq 2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{flood} + \chi\, N_{it} + \mu_{itCf} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{4}$$

ϕ_{it} is the average coverage level of policies in census tract i in year t. Like Equation 1, W_i^{flood} equals one if census tract i was flooded and $\mathbf{1}[t=\tau]$ tracks the years before and after Hurricane Sandy. N_{it} is the log-transformed number of pre-FIRM policies in census tract i in year t. The variable replaces Equation 1's pre-FIRM premium, coverage and deductible variables as a way to account for changes in premium costs from recent legislation. μ_{itCf} still controls for community- and treatment group-specific changes in flood risk maps. π_i and ψ_{ct} take care of time-invariant and time-varying insurance demand differences between census tracts and ϵ_{it} is the error term.

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

4 Results

Figure 5 plots the year-treatment coefficients from Equation 1. The coefficients are interpreted as the percentage difference 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.

The results reveal that Hurricane Sandy had a notable impact on the flood insurance market. In the first year after Sandy, there was an 11 percent increase in the number of policies-in-force in the flooded census tracts compared 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 consistent with the related literature: Gallagher (2014) found a nine percent increase in insurance take-up rates across all flood events from 1990 to 2007. 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 growth.

The estimated insurance response was efficient at the individual level if the welfare change from spending money on insurance was equal to the welfare change from the incremental increase in perceived risk. From a social planner's perspective, the insurance response was welfare-increasing if post-Sandy perceived risk reflects real risk. 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[20].

Figure 6 provides evidence that Equation 1's estimated growth in the number of insur-

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

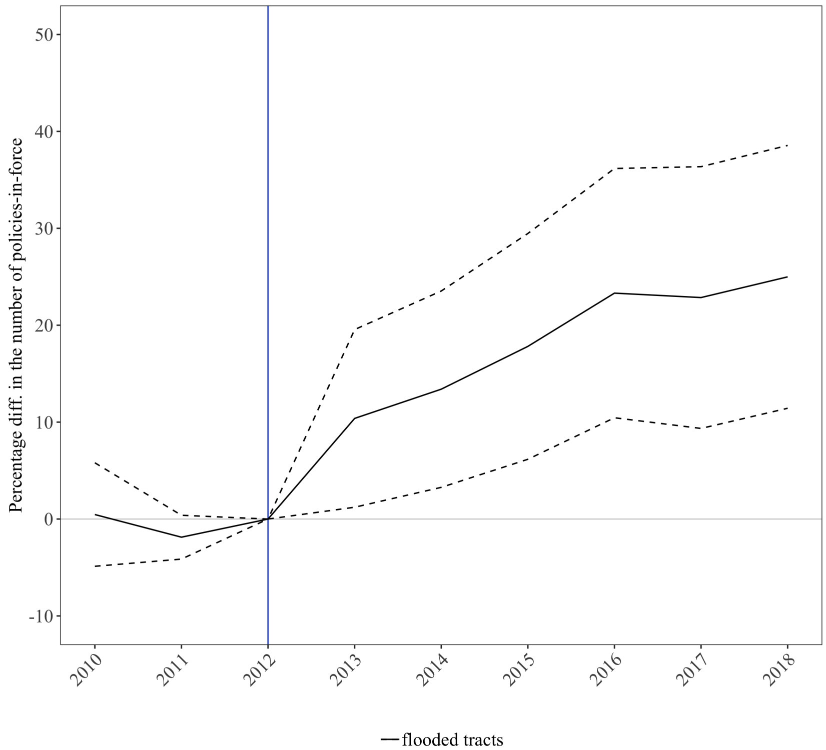


Figure 5

ance policies-in-force is initially being driven by relatively more new policies purchased and later by relatively more policies retained. Figure 4 plots the average new policy rate minus the average dropout rate for treated and untreated census tracts. When the estimates are positive, the new policy rate outweighs the dropout rate and the total number of insurance policies-in-force increases. When the estimates are negative, the opposite is true. In the year after Sandy, the average new policy rate was higher than the dropout rate for the flooded census tracts and, to a lesser degree, the census tracts that were not flooded. Both groups saw increases in the number of insurance policies-in-force, though the effect was stronger for the treated census tracts. Starting in 2014, the dropout rate outweighed the new policy rate. Both groups saw decreases in the number of insurance policies-in-force, but the effect was less pronounced for the flooded census tracts.

In all of the present study's regression estimates, the point estimates for the log-transformed average premium for pre-FIRM buildings' policies, the log-transformed average coverage level

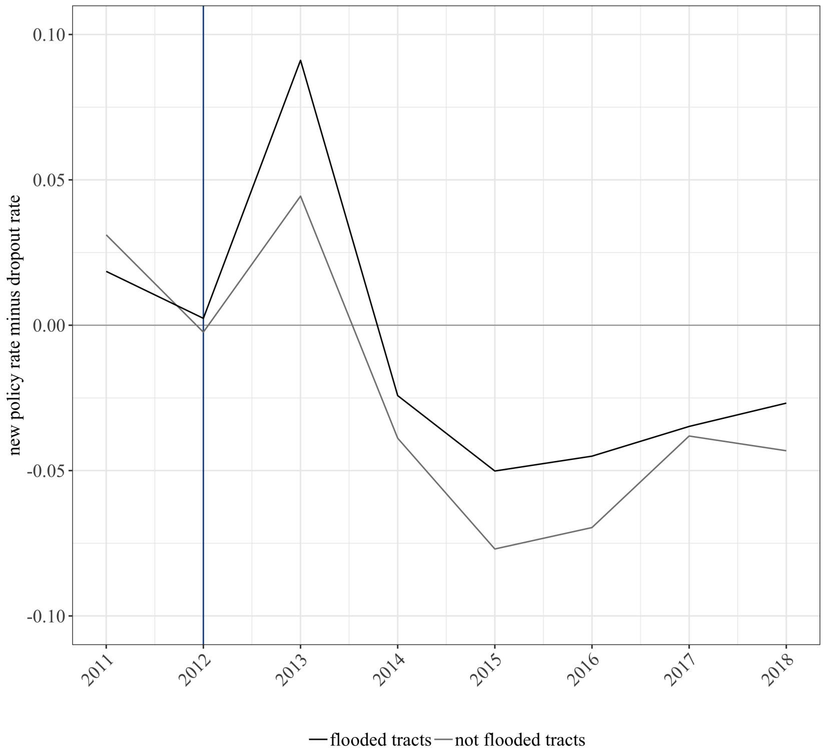


Figure 6

for pre-FIRM buildings' policies and the log-transformed average deductible level for pre-FIRM buildings' policies remain consistent, economically intuitive and statistically significant. The coefficient on premiums is negative, ranging from -0.03 to -0.05. Its sign indicates that increasing premiums on pre-FIRM buildings are associated with fewer policies-in-force, after controlling for choice of coverage and deductible. Average coverage and deductible are positively correlated with policies-in-force with point estimates ranging from 0.03 to 0.07.

Differences in damage levels

I also considered treatment differences across damage levels. Figure 7 plots Equation 2's treatment-year coefficients and their 95 percent confidence intervals. The results show that treatment severity mattered: census tracts that contained majorly damaged or destroyed buildings underwent the largest increases in the number of insurance policies-in-force compared to census tracts that sustained minor damage and affected census tracts. In the year

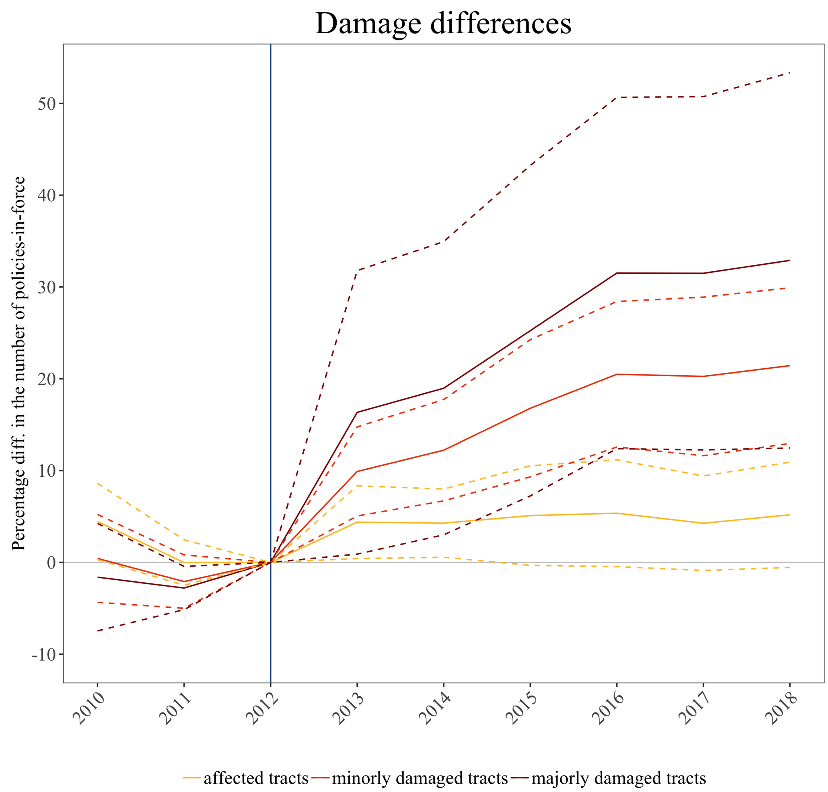


Figure 7

immediately after Hurricane Sandy, relative insurance increased by nearly 20 percent in the most damaged census tracts. In the succeeding years, the upward trend continued, reaching 39 percent in 2018. In every year after Sandy, the increase 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. For the affected group, the estimates are statistically distinguishable from zero only in the two years after Hurricane Sandy. Additionally, the difference in the number of policies-in-force between the three damage groups is statistically significant in nearly every year and combination.

Spatial spillovers

Next I examined areas that were "nearly missed" by Hurricane Sandy. Figure 8 gives evidence that residents in neighboring census tracts did not update their expectations about future flood risk differently from the control group in a statistically significant way. In those areas, there was an initial five percent increase in the number of insurance policies-in-force in 2013 only statistically significant at the ten percent level. From 2014 onwards, the point estimates hover between four and six percent and are never statistically different from zero at the ten percent level. The finding suggests that close proximity to the flooding was not a statistically important determinant in encouraging people to purchase insurance after Sandy.

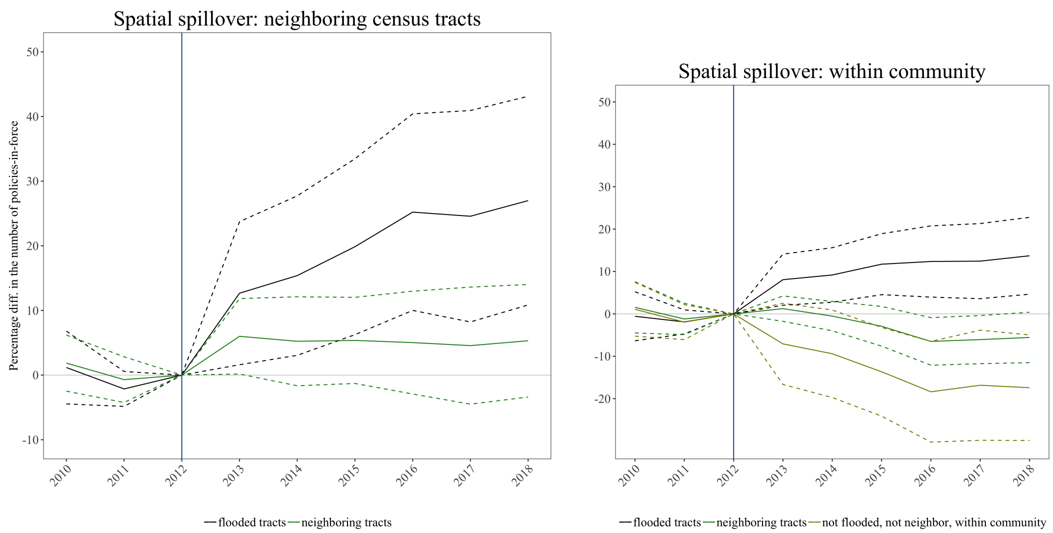


Figure 8

In a second specification I tested for within community spillover effects. In the United States, flood risk policy and initiatives are often carried out at the community level. For example, community floodplain managers may organize informational campaigns or make flood risk maps available at the local library. Here, a second spillover treatment group consists of non-neighboring dry census tracts located in flooded communities. My hypothesis is based on the idea that people that were not flooded but live in flooded communities received more flood risk information post-Sandy than people that do not live in flooded communities.

Figure 8's right panel shows that, relative to communities that were not flooded, Sandy caused a decrease in the number of insurance policies-in-force for the new within-community spillover group. The effect persists over the entire study period and statistical significance oscillates between the five and ten percent levels. My finding gives evidence that farther from the flooding boundaries but within the same community, people may have seen themselves as "rightfully missed", relative to census tracts in communities that were not flooded.

Given the odd spatial pattern estimated in the second specification, the spillover exercise highlights the importance of thoughtful reference group selection before settling on conclusions. Notably, some of the increase in policies-in-force in the flooded areas can be attributed to a relative decrease in areas far from the flooding boundary but within the same community when these census tracts are included in the control group. This makes clear that difference-in-difference estimates on any treatment group are biased in the presence of spillovers in the control group. In the case of flood risk, however, it is difficult to argue a totally uncontaminated control group. In today's world, information about flood events likely diffuses not only over space but through other networks like online newspapers and social media as well. In a follow-up project, I plan to test whether non-spatial information diffusion channels caused changes in risk perceptions and insurance market participation. For this project, I plan to continue to explore the pattern and extent of risk information from Sandy over space in an effort to get a better handle on the control group.

Differences across flood zones

Figure 9 shows that risk zones mattered. 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, policy counts increased after Hurricane Sandy.

There are several possible explanations for the difference in post-Sandy insurance trends. First, because flood insurance is mandatory inside the SFHA, it could be that there was no possibility for additional market penetration: all buildings inside the SFHA 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.

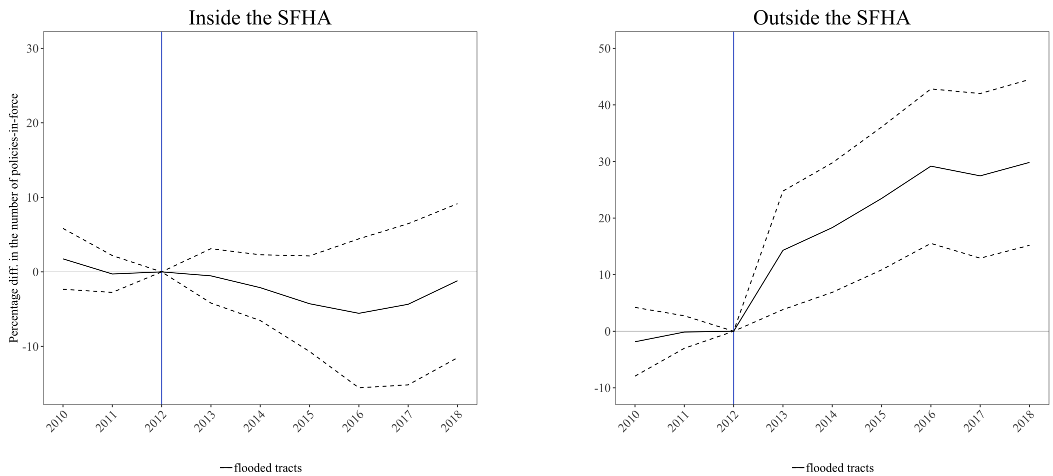


Figure 9

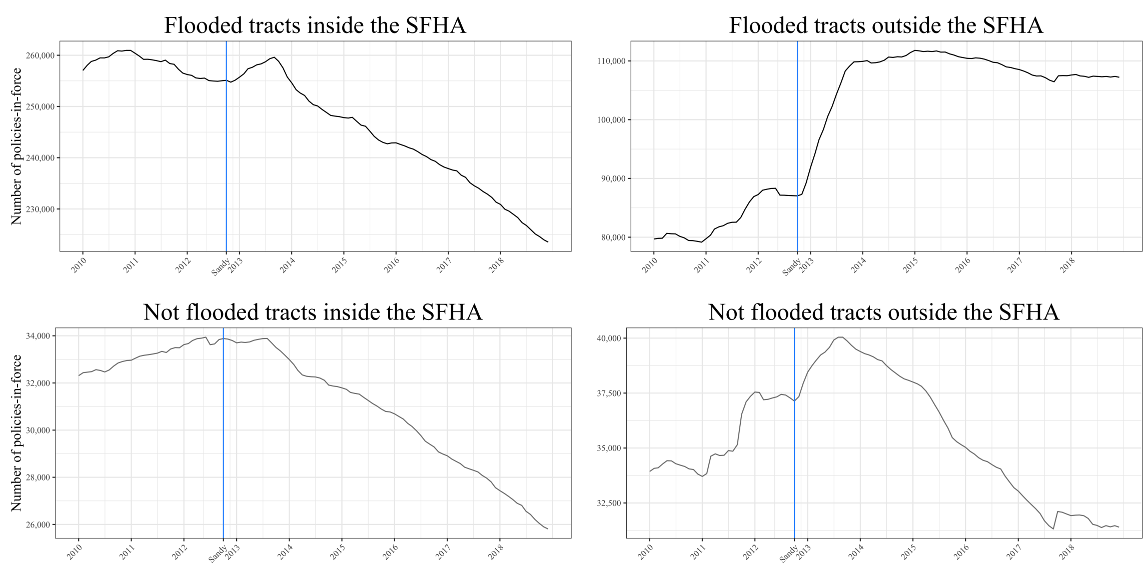


Figure 10

A second explanation for the difference in post-Sandy insurance take-up trends concerns learning. Prior to Sandy, SFHA residents were probably more knowledgable about their flood risk than non-SFHA residents. The hurricane provided additional flood hazard information to both groups. Outside the SFHA, flooded residents were new learners, updated their expectations about future flood losses differently from not flooded residents and adapted accordingly. There was no insurance response to Sandy inside the SFHA, suggesting that the flooding extents simply confirmed the flooded residents' priors about their flood risk.

A third explanation for the heterogeneous treatment effects concerns affordability. Because flood insurance premiums, in theory, reflect relative flood risk, flood insurance is more expensive inside the SFHA compared to outside the SFHA. Inside Sandy's flooding extents, the median policy inside the SFHA has a premium cost nearly three times that of the median policy outside the SFHA. As a result, it may be that SFHA homeowners did in fact update their perceived flood risks but could simply not afford to purchase insurance. This has important implications for adaptation potentials based on affordability and the possibilities of government intervention. A future, important topic of research is heterogeneous adaptation responses based on differences in adaptation affordability.

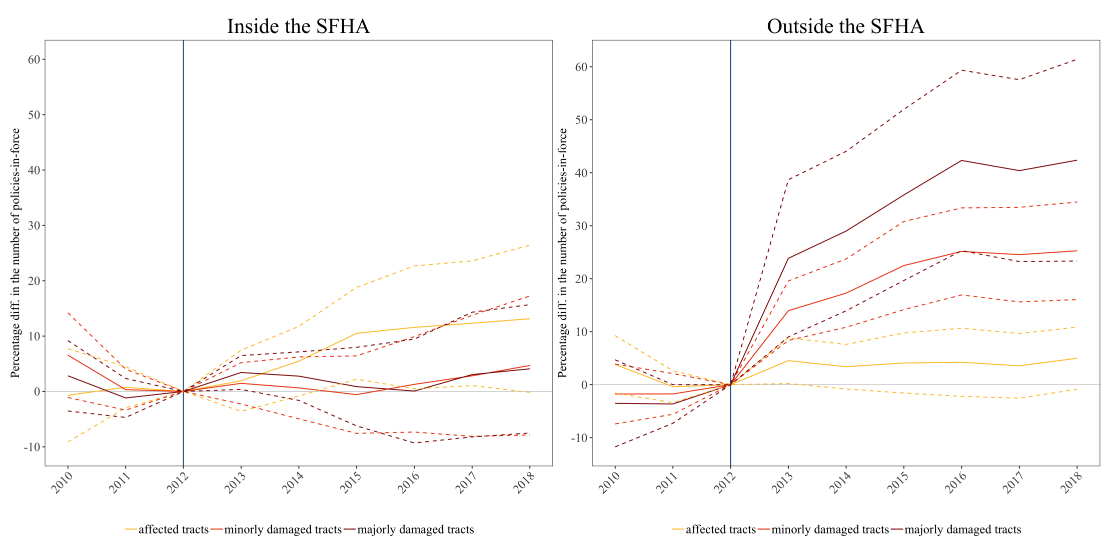


Figure 11

Figure 10 provides additional evidence of heterogeneous treatment effects by plotting the number of insurance policies-in-force inside and outside the SFHA for the flooded and not flooded groups. Immediately after Sandy and within the flooding extents there is small bump in insurance policies-in-force inside the SFHA but a much larger bump and policy retention rate outside the SFHA. The result is surprising given that SFHA homeowners that received federal disaster assistance from Sandy are required to maintain flood insurance to be eligible for disaster assistance from future storms. For those that received disaster aid, either they do not expect to need disaster aid in the future or they are simply not able to afford it today.

Finally, Figure 11 gives evidence that the overall insurance response estimated in the main specification was driven by the insurance response of policies outside the SFHA and inside the more severely damaged census tracts. This suggests that changes in flood risk perception induce an adaptation response only if the adaptation option is relatively affordable.

The intensive margin

Figure 12 shows that Sandy caused a modest increase in average coverage level per policy in the flooded census tracts. Prior to Sandy, the difference in average coverage levels between the treated and untreated groups is statistically indistinguishable from zero. After Sandy, flooded census tracts saw a statistically significant increase in coverage by approximately six percent. For the median census tract's policy, the point estimate translates to approximately $16,800 in coverage dollars.

Hurricane Sandy encouraged a relative increase in insurance in the flooded areas at both the intensive and extensive margins. It follows then that overall coverage dollars in the flooded areas also increased. I estimated the effect precisely by swapping the log transformed coverage per policy outcome variable for log transformed total coverage dollars in census tract i in year t. Figure 9 shows that Sandy induced a 5 percent increase in total coverage dollars in the year after the flood. Between 2014 and 2018, the wedge in total coverage dollars between flooded and not flooded census tracts continued to increase by 2.5 percent per year.

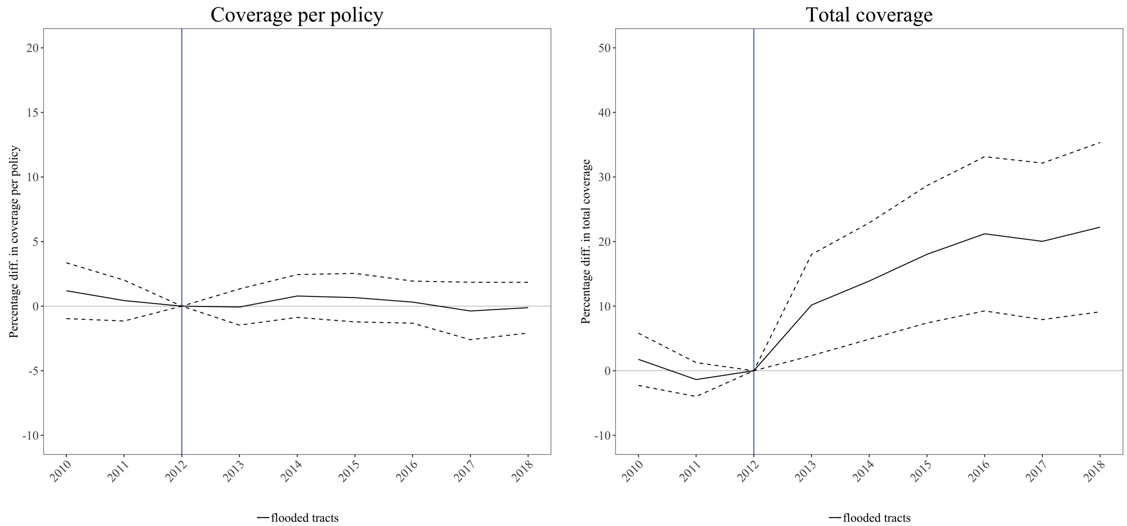


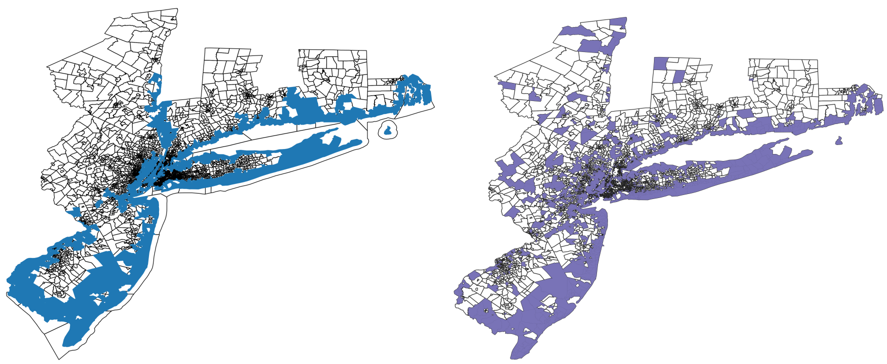
Figure 12

In 2018, the relative coverage growth was equal to nearly two million dollars for the median census tract.

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 [20]. 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 simulated 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[21]. 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[22].



(a) Objective flooding (b) Simulated flooding with claims

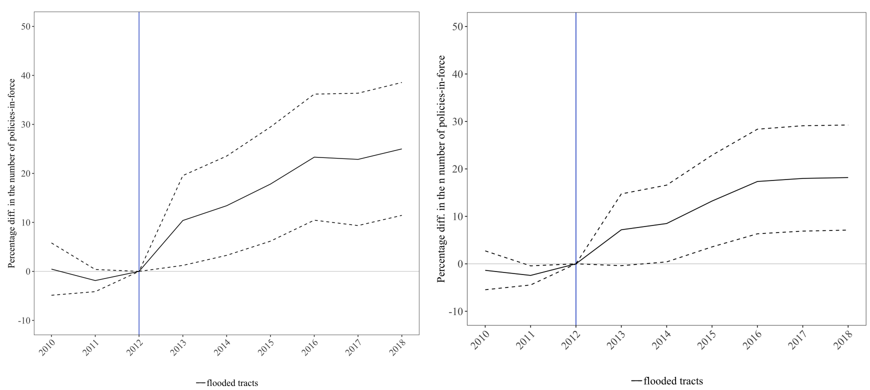


Figure 13

First, I tested the legitimacy of the simulated flooding extents strategy by applying it to Hurricane Sandy. Figure 13 compares Sandy's objective flooding extents to its simulated flooding extents. Generally speaking, the objective and simulated flooding extents match well[23]. For each treatment group definition, 2/3 of the flooded census tracts were also flooded in the other treatment group definition. Figure 13 also compares the regression results for

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

[22]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

[23]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.

the two treatment group definitions estimated separately on Specification 1. 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 legitimate strategy.

Next I simulated 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 14 gives evidence that the magnitude of Hurricane Sandy's insurance response was an outlier and not the norm. No events saw a statistically significant increase in the number of insurance policies-in-force for the (simulated) flooded census tracts. In the case of Colorado and Illinois, there was a statistically significant negative insurance response, giving evidence that experience with flooding discouraged insurance purchases.

The external validity exercise highlights the fact that adaptation decisions by individuals depend on their context. Risk perception is made up of a complex combination of innate biases and experience, i.e. cultural-, socio-political- and emotional factors [30]. For example, populations used to flooding may not internalize additional events and consider their situation more risky [31]. In other cases, populations that trust disaster aid will fully subsidize their flood losses may believe that they aren't at financial risk. An area for future research is to investigate the impact of various factors influencing risk perception (e.g. familiar vs. new, uncertainty, the dread factor, catastrophic vs. chronic, control vs. no control, etc.) on individual adaptation responses to natural hazards for a more precise understanding of future damages.

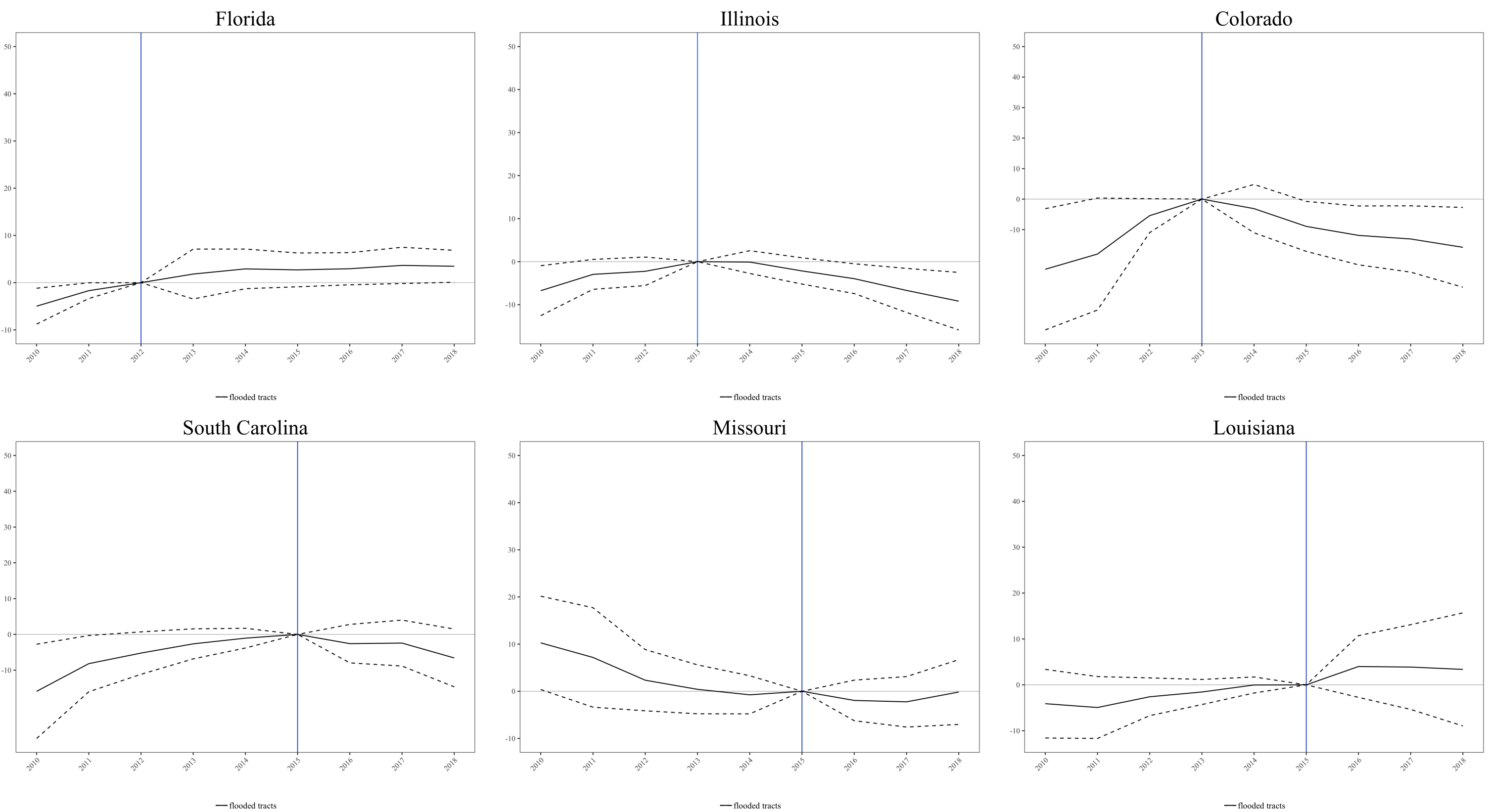

Florida
Illinois
Colorado
South Carolina
Missouri
Louisiana
flooded tracts
flooded tracts
flooded tracts
flooded tracts
flooded tracts
flooded tracts

Figure 14

The strategy of simulating 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 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.

5 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 13 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. Extensions to the main specification showed that larger damage levels are associated with greater insurance increases, "near-miss" census tracts close to the flooding also responded positively to the risk signal, it mattered if a resident had previously been exposed to flood risk information and insurance increased in flooded census tracts also at the intensive margin.

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[32]. If Hurricane Sandy's flooding extents don't fully 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, since Hurricane Sandy, the number of total insurance policies has fallen by six percent in the CT-NJ-NY-RI. Low insurance take-up rates limit insurance's ability to support resiliency. In preliminary flood risk maps that incorporate information from Sandy, only two out of ten New York City properties in high risk zones are currently insured [33]. Flooded neighborhoods with the lowest current insurance take-up rates (between ten and twenty percent) also have the lowest median incomes, demonstrating the importance of wealth in combating vulnerability to natural hazards.

Finally, Sandy's adaptation response came at a huge cost. Nearly 1.5 billion dollars in federal aid was granted to affected households in CT-NJ-NY-RI. 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.

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] 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.

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

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

[16] R. L. Bernknopf, D. S. Brookshire, and M. A. Thayer, "Earthquake and volcano hazard notices: An economic evaluation of changes in risk perceptions," *Journal of Environmental Economics and Management*, vol. 18, no. 1, pp. 35–49, 1990.

[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. Taṣpınar, "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] 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.

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

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

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

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

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

[26] 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.

[27] 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.

[28] 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.

[29] 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.

[30] O. Renn, "Risk governance. coping with uncertainty in a complex world," *Earthscan*, 2008.

[31] M. Manex, M. Carmona, D. Haro, and S. Hanger, "Chapter three: Risk perception," tech. rep., IIASA, 2016.

[32] 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.

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