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

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Abstract

This paper exploits spatial variation in flooding to estimate the causal effect of Hurricane Sandy on participation in the flood insurance market. Hurricane Sandy's flooding boundaries had a large and long-lived impact on people's insurance choices. Since the storm, the number of insurance policies-in-force in flooded areas has continuously increased relative to nearby areas that were not flooded. Extensions to the main specification show that damage intensity, proximity to the flooding and having little previous knowledge about flood risk all contributed to the marked insurance growth. Simulated flooding extents of six other recent flood events give evidence that Hurricane Sandy's insurance 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 the effects of climate change become progressively 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]. As a consumption-smoothing mechanism, flood insurance quickens recovery by making more funds available more quickly than federal disaster aid, which is often quite limited and slow to make its way to its recipients [4]. Information about the circumstances under which people purchase insurance helps policy makers plan for future flood damages and make decisions about local investments in flood hazard mitigation.

This paper exploits spatial variation in flooding to study people's participation in the flood insurance market in response to direct experience with Hurricane Sandy. Provided that people use all of the information they have in making decisions about whether to purchase insurance, my findings indicate that people learned about their flood risk from Hurricane Sandy's flooding boundaries. In a rough comparison of Hurricane Sandy against other major, recent flood events, I give evidence that Sandy's adaptation response was the exception and not the rule.

Estimating the insurance response requires detailed, spatially-explicit and objective information about flooding boundaries 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 [5]. 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 estimated the causal impact of Hurricane Sandy's flooding on insurance purchases in a difference-in-difference framework with leads and lags. Leads test for the existence of parallel trends and lags give insights into the longevity of the risk-reducing behavior. My outcome variable is the log-transformed number of insurance policies-in-force in a given census tract in a given year between 2010 and 2018. 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.

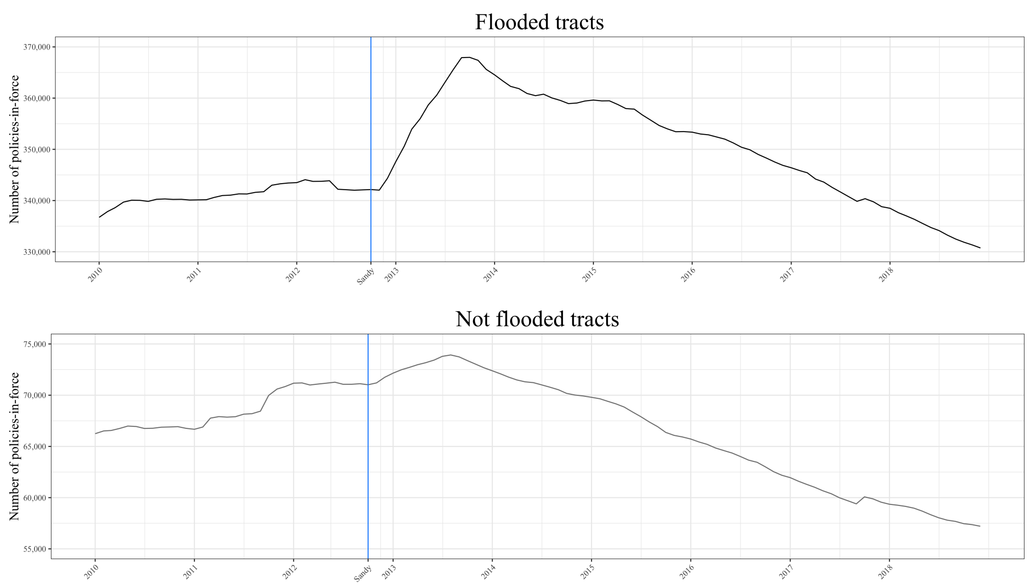


Figure 1

The regression results indicate that people used Hurricane Sandy's flooding boundaries to update their flood risk assessments: Sandy caused an increase in the number of 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 back to baseline in the flooded census tracts and far beyond baseline in census tracts that were not flooded[1]. This suggests that flooded areas had relatively better retention rates of existing policies in later years.

Extensions to the main specification paint a fuller picture of the Sandy effect. I find that people use information about damage intensity, and not only if they were flooded or not, in forming new expectations about future losses. Neighboring residents also increased their insurance, possibly because they saw themselves as being "nearly missed". Flooded residents that were exposed to pre-Sandy risk information did not update their expectations about future flood risk differently from comparable residents outside the flooding boundaries, while residents for whom the information was new did. Lastly, Sandy also caused a statistically significant increase in average coverage level per policy as well as total coverage in the flooded areas.

Several papers have examined the impact of flood events on insurance purchases [6] [7]. For example, in a study of all U.S. communities from 1990-2007, Gallagher (2014) found that insurance take-up rates spiked after flood events [8]. Kousky (2017) also estimated an increase in insurance take-up for U.S. counties hit by hurricanes between 2001 and 2010 [9]. In both cases, the effects were interpreted as temporary behavioral responses as 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 the locations of policies with far more precision than was previously possible, reducing potential bias in the coefficient estimates and allowing for more robust causal inference. Second, the richness of the data allowed me to demonstrate the relevancy of heterogeneous treatment effects in this setting. Third, a critical difference between this

[1] The general reduction in flood insurance policies-in-force in the study area is on par with what's happening in the United States generally. Between 2010 and 2018, the number of policies-in-force in the U.S. decreased by eight percent. Reasons cited for the decrease include changing premiums and increased reliance on federal disaster aid after flood events.

paper's primary findings and those in the literature is that the insurance wedge between flooded and not flooded census tracts 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, among other factors. A critical take-away for policy makers as they plan for future flooding is that different storms induce different adaptation responses.

This work builds on a large literature demonstrating the influence of information about environmental risk on risk-reducing behavior generally [10] [11]. 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, decreasing the financial risk these homebuyers face [12] [13]. Non-flooding risk-reducing responses in the property market have been documented for wildfires, earthquakes and volcanoes [14] [15]. Outside of property markets, Dessaint and Matray (2017) show that managers respond to experienced disasters by increasing their cash holdings, leaving them inefficiently liquid [16].

Lastly, this research contributes to a more targeted literature documenting the adaptation response to Hurricane Sandy in particular. Ortega and Taspinar (2018) show that, after Hurricane Sandy, flood risky properties carried a price penalty and McCoy and Zhao (2018) determine that capital investment projects were more likely outside flood risky areas [17] [18]. 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 these updated risk perceptions.

With the related literature in mind, this paper's general findings are intuitive: direct experience with Hurricane Sandy caused people to update their expectations about future losses. 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 context 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 [19]. Sandy approached the East Coast at a perpendicular angle and coincided with a spring high tide that was higher than normal because of a full moon. The combined factors generated a monstrous storm surge and wind damage to make Sandy the fourth-costliest hurricane in United States history. It 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 disaster assistance [20]. Facilities and services crucial to the well-being of residents (such as 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 [22]. The result is a spatially-explicit digital map of Hurricane Sandy's flooding extents in CT-NJ-NY-RI. 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's flooding. The spatial layer contains points representing the location of an impacted building within Hurricane Sandy's flooding extents, as well as the extent of damage to each impacted building. Assessment of the building stock was done using a combination of aerial imagery and inundation-based damage assessment. 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.

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 [23]. 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 flood-properties' risks. Amidst increasing disaster relief costs and flood losses, 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.

In addition to providing insurance and reducing flood damages through floodplain management regulations, the NFIP identifies and maps floodplains. Mapping flood hazards creates risk awareness of the flood hazards 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. Insurance premium costs vary across properties and reflect a structure's flood risk. Premiums are highest for buildings located in the SFHA, buildings with basements and buildings with high base flood elevations. The U.S. government subsidizes the insurance premiums of 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. They also subsidize the policies on properties that have been newly mapped into riskier flood zones. Currently, approximately 20 percent of all NFIP policies are subsidized.

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 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. In 2014, pre-FIRM primary residences began to see rate increases of maximum 18 percent per year.

2.3 Data

The present analysis relies on a national database of nearly fifty million individual flood insurance policies [5]. Each policy was effective sometime between 2010 and 2018. Policies are spatially identified to a census tract 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 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 changed smoothly over space, then limiting the study area would reduce any resulting bias in the estimates.

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. 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. 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 as well as each policy's premium cost. This information is helpful in controlling for premium rate increases to subsidized properties. Another source of bias could be increased construction in the SFHA between 2010 and 2018: as the number of buildings in the SFHA increases, additional insurance take-up is driven by the obligation to purchase and not necessarily learning. In my sample, I dropped all policies attached to properties with construction dates after the start of the study period.

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. 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 impacts, also by census tract [22]. Thirty-one percent of census tracts in the sample were flooded. The median census tract was 20 percent flooded. Twenty-one percent of census tracts were damaged and seven percent were affected. The final panel contains 41,967 observations: 4,663 census tracts across 9 years. Figure 2 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 the effect of Hurricane Sandy on insurance demand. 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:

$$y_{it} = \sum_{\tau=2010, \tau\neq 2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{flood} + \gamma P_{it} + \zeta C_{it} + \theta D_{it} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{1}$$

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

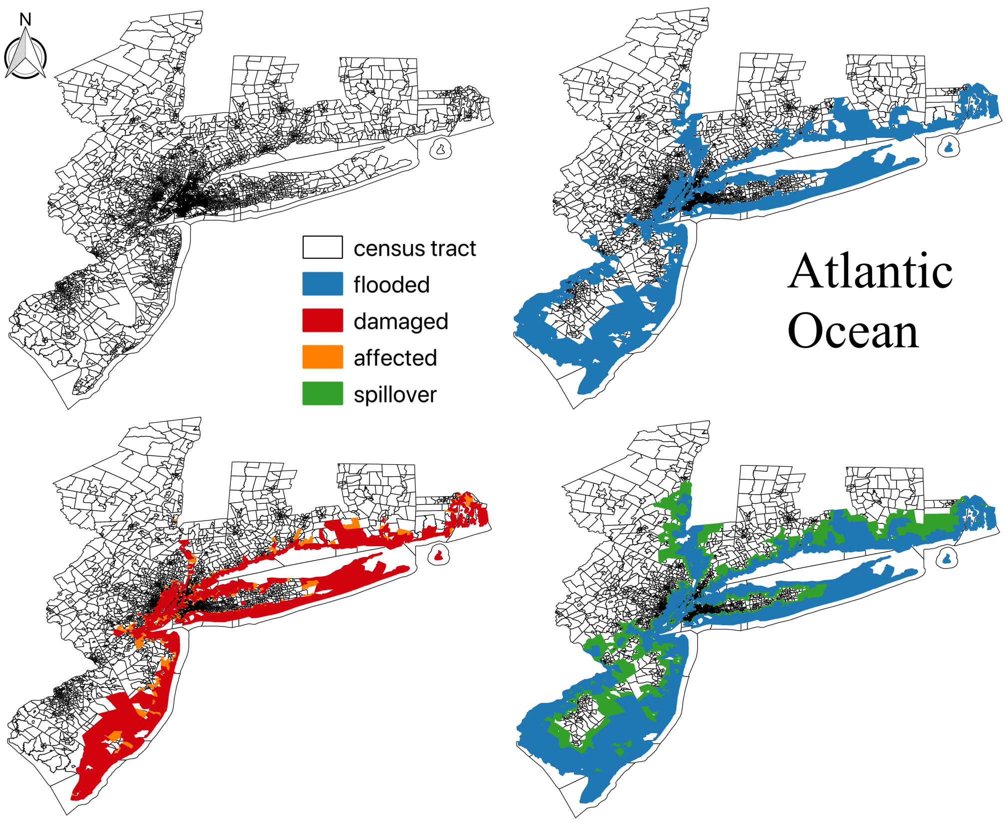

N
census tract
flooded
damaged
affected
spillover
Atlantic
Ocean

Figure 2

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.

Equation 1 can be interpreted causally if, in the absence of Sandy, insurance trends for treated and untreated census tracts would have moved in parallel. The largest threat to the parallel trends assumption is recent legislation increasing premiums for policy-holders with subsidized insurance costs. As older, pre-FIRM buildings tend to be located in areas that were flooded and, theoretically, demand for insurance decreases as the cost of premiums rise, not controlling for the legislation would result in underestimation of the Sandy effect [6] [2]. Equation 1 controls for the change in legislation with three variables. P_{it} is the log-transformed average premium for pre-FIRM buildings' policies, and is estimated separately from C_{it}, the log-transformed average coverage level for pre-FIRM buildings' policies and D_{it} the log-transformed average deductible choice for pre-FIRM buildings' policies. For the premium, coverage and deductible variables I add one to avoid losing observations (census tracts without pre-FIRM policies) with the log transformation.

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 economic conditions and expectations surrounding post-disaster aid [26]. Census tract fixed effects, π_i, absorb unchanging census tract attributes, like population, underlying flood risk and political beliefs [27]. Inclusion of the fixed effects means that the coefficients on the treatment-time indicators are being driven by variation over time and within census tract. 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 main advantages over a classical difference-in-difference

[2] Estimating Equation 1 without the legislation controls shows that this is indeed the case. Without the legislation variables, the yearly indicators are underestimated by 0.1-0.5 percent in each year.

set-up with a single post indicator. First, the post-Sandy yearly indicators allow transitional patterns, which can give insights about the longevity of risk-reducing behaviors, to play out without imposing any restrictions on trend. Second, the pre-Sandy yearly indicators allow for full flexibility of pre-trends, providing important evidence about difference-in-difference's key identifying assumption that treated and untreated units would have had parallel trends had Hurricane Sandy not occurred. In sum, my empirical approach is driven by the data, aimed at minimizing misspecification and maximizing transparency of the research design.

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

Does insurance demand depend on damage intensity or simply the incidence of flooding? Figure 2 shows that census tracts close to the coast tended to be more damaged by Hurricane Sandy than census tracts far from the coast. Equation (2) and captures non-linear differences in treatment outcomes based on damage levels:

$$y_{it} = \sum_{\tau=2010,\tau\neq 2012}^{2018} \delta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{damaged} + \sum_{\tau=2010,\tau\neq 2012}^{2018} \alpha_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{affected} + \gamma P_{it} + \zeta C_{it} + \theta D_{it} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{2}$$

Like Equation 1, the unit of observation is a census tract calendar year and the dependent variable measures (the log of) the number of insurance policies-in-force for census tract i in year t. The indicator variable $W_i^{damaged}$ equals one if a census tract contained at least one damaged building. $W_i^{affected}$ equals one if a census tract contained at least one affected building and no damaged buildings. Affected buildings are those that were only superficially damaged by Hurricane Sandy. The control group is census tracts not containing any damaged or affected buildings.

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

$$y_{it} = \sum_{\tau=2010,\tau\neq 2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{flooded} + \sum_{\tau=2010,\tau\neq 2012}^{2018} \nu_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{neighbor} + \gamma P_{it} + \zeta C_{it} + \theta D_{it} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{3}$$

Here, I built 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 2 depicts the locations of the spillover census tracts.

Risk communication in flood zones

Did purchase rates depend on prior knowledge about flood risk? Pre-Sandy communication about flood hazards likely differed for residents across flood zones. By law, mortgage lenders must inform buyers of SFHA properties about their flood risk. Moreover, most buildings inside the SFHA are required to carry flood insurance, though the reality is far from perfect compliance[3]. Outside the SFHA, these mandates do not exist.

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

[3]Nationally, market penetration inside the SFHA is approximately 30 percent. Twenty percent of NYC buildings flooded by Hurricane Sandy carried flood insurance.

SFHA during the entire study period[4].. 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:

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

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. π_i and ψ_{ct} take care of time-invariant and time-varying fixed effects and ϵ_{it} is the error term.

4 Results

Figure 3a plots the treatment-year coefficients from Equation 1. The coefficients are interpreted as the percent change in flood insurance policies-in-force 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

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

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 a twelve 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 33 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. While 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 and socially efficient if post-Sandy perceived risk reflects real risk.

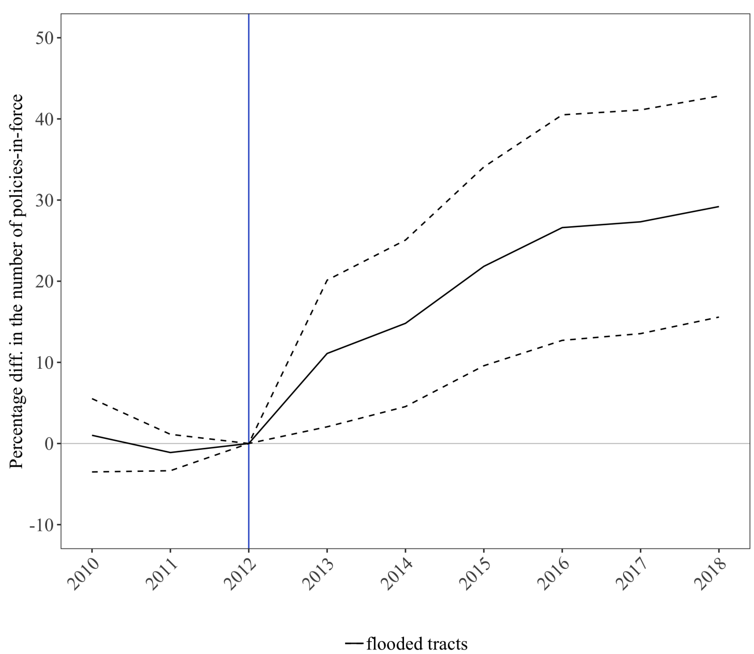


Figure 3

Figure 4 provides evidence that Equation 1's estimated growth in the number of insurance 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.

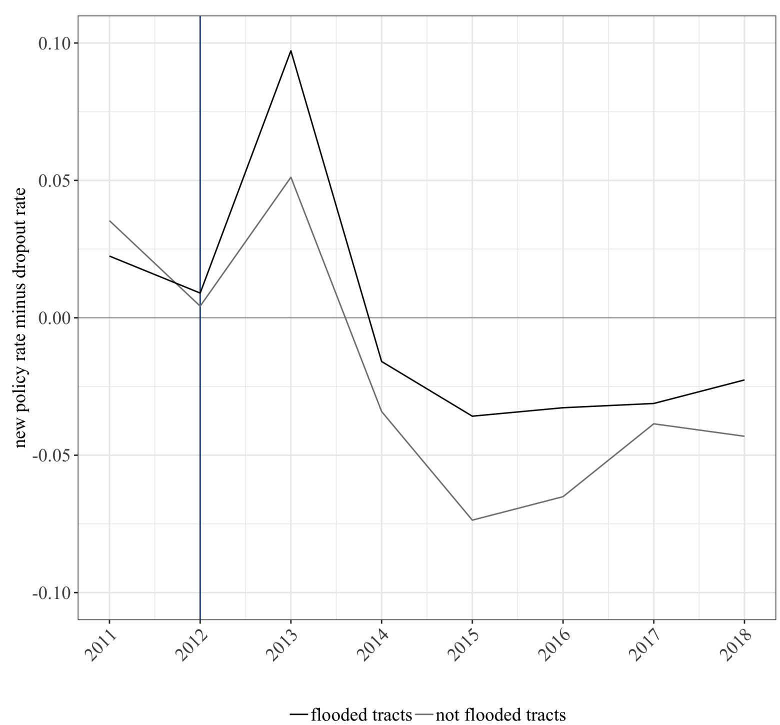


Figure 4

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

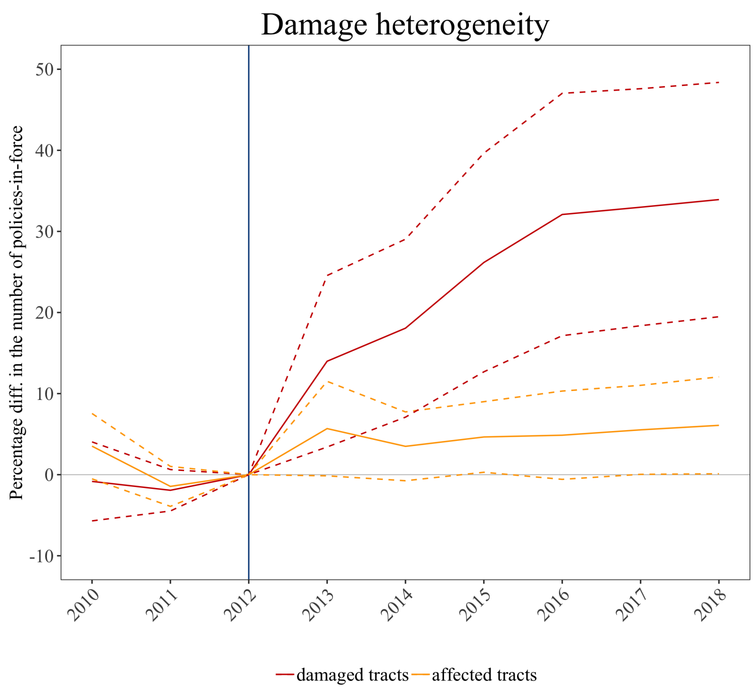


Figure 5

I also considered treatment heterogeneity across damage levels. Figure 5 plots Equation 2's treatment-year coefficients and their 95 percent confidence intervals. The results show that treatment intensity mattered: damaged census tracts underwent far greater increases in the number of insurance policies-in-force than affected census tracts. In the year immediately after Hurricane Sandy, relative insurance increased by approximately 16 percent in the damaged census tracts. In the succeeding years, the upward trend continued, reaching 39 percent in 2018. In the affected group, the estimates are also statistically distinguishable from zero beginning in 2013. There, the initial percentage increase in policies-in-force is just under half that of the damaged group at six percent. Unlike the damaged group, there is no subsequent relative growth in policies between 2014 and 2018 for the affected group. Additionally, the difference in the number of policies-in-force between the damaged and affected groups is statistically significant from 2014 onwards[5].

Spatial spillovers

Next I examined areas that were "nearly missed" by Hurricane Sandy. Figure 6 gives evidence that residents in neighboring census tracts also updated their expectations about future flood risk differently from the control group. In those areas, there was an initial five percent increase in the number of insurance policies-in-force in 2013. From 2014 onwards, the point estimates hover between four and six percent and are always statistically different from zero at the ten percent level. The finding suggests that close proximity to the flooding was an important determinant in encouraging people to purchase insurance after Sandy.

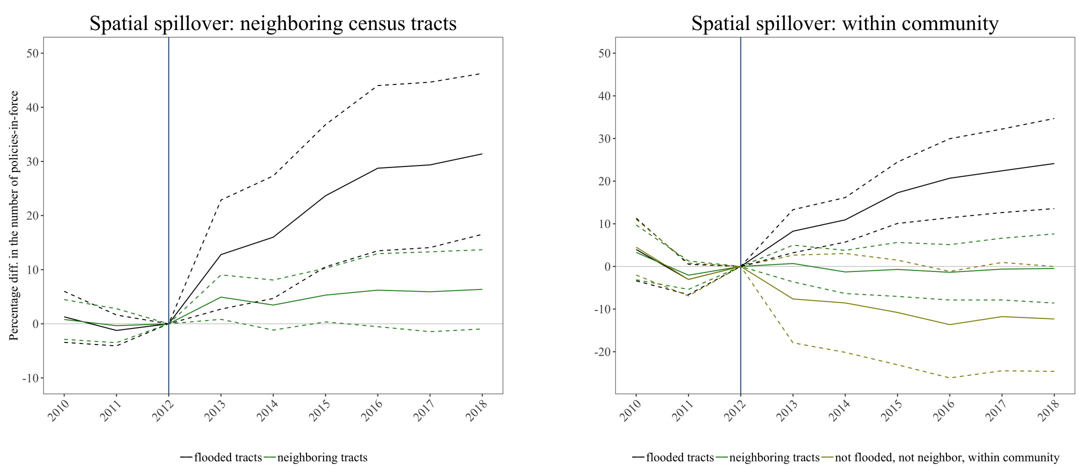


Figure 6

[5]My conclusions are robust to a number of strategies concerning damage and flooding definition. The robustness exercises exploit variation in the percentage area of each census tract that was flooded and the percentage of housing units that were damaged or affected.

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 6 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. Taken together, the two spillover findings suggest that proximity to the flooding boundary encouraged insurance purchases. Those closest to the flooding boundaries may have seen themselves as "nearly missed". Hurricane Sandy's flooding extents had a positive effect on their risk beliefs relative to all non-flooded, non-neighboring census tracts. 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 (notably neighboring census tracts compared to the control tracts), the spillover exercise highlights the importance of thoughtful reference group selection before settling on conclusions. Difference-in-difference estimates on the treatment group are biased in the presence of spillovers in the control gorup. In the case of flood risk, a positively uncontaminated control group is difficult to argue. 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 future iterations of this project I plan to test whether non-spatial information diffusion channels cause changes in risk perceptions and insurance market participation as well as the pattern and extent of spatial diffusion.

Figure 7 shows that pre-Sandy risk communication 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.

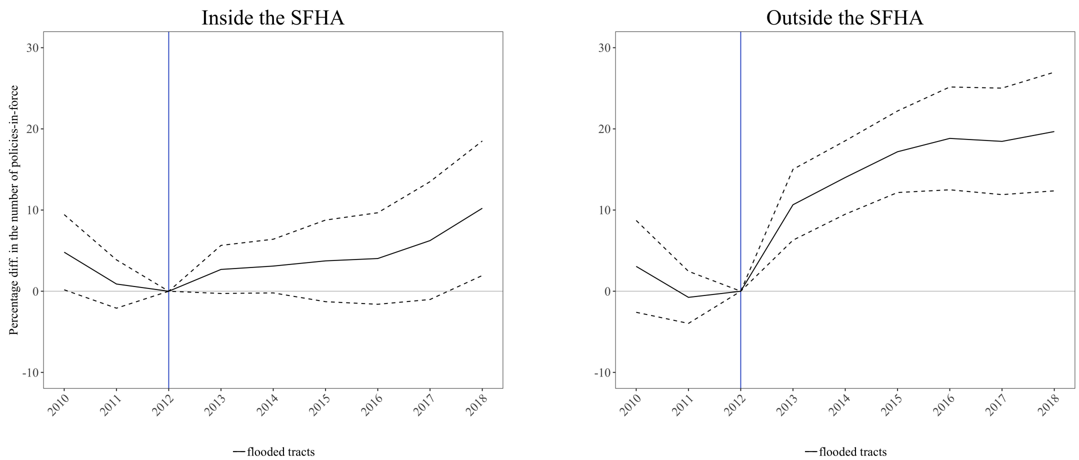


Figure 7

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.

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

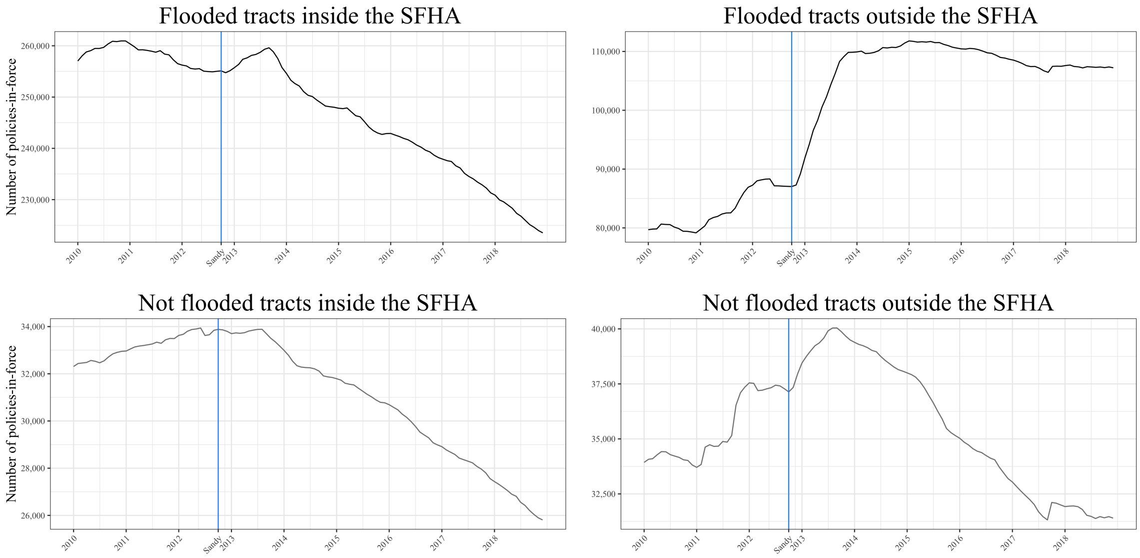


Figure 8

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.

Figure 8 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. The rule does not apply to homeowners outside the SFHA.

The intensive margin

Figure 9 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.

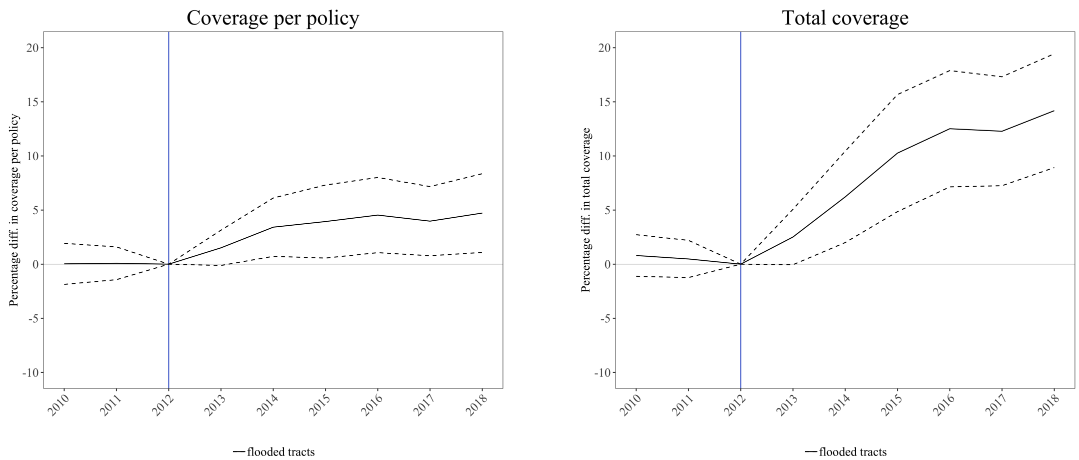


Figure 9

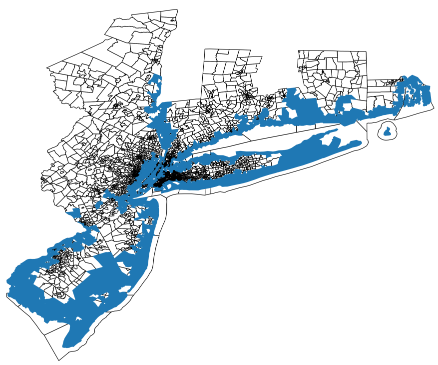
Hurricane Sandy encouraged a relative increase in insurance in the flooded areas at both the intensive and extensive margins. It follows then that overall coverage dollars in the flooded areas also increased. I estimated the effect precisely by swapping the log transformed coverage per policy outcome 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. In 2018, the relative coverage growth was equal to nearly two million dollars for the median census tract.

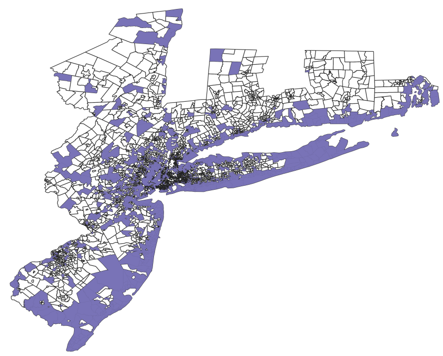
External validity

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 [19]. 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 [28]. 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[6].

[6]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





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

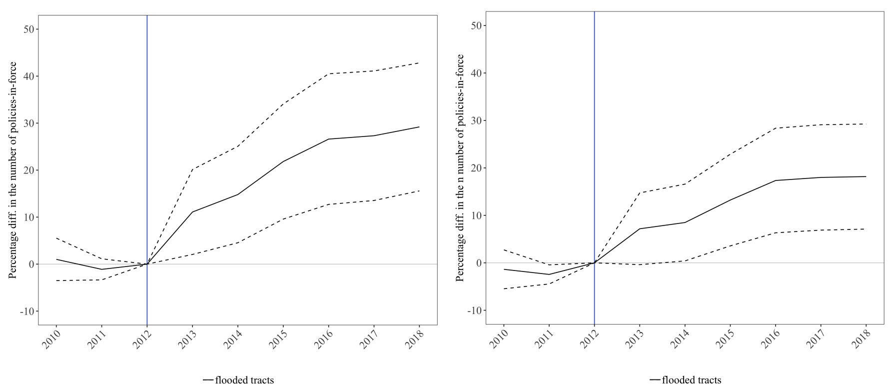


Figure 10

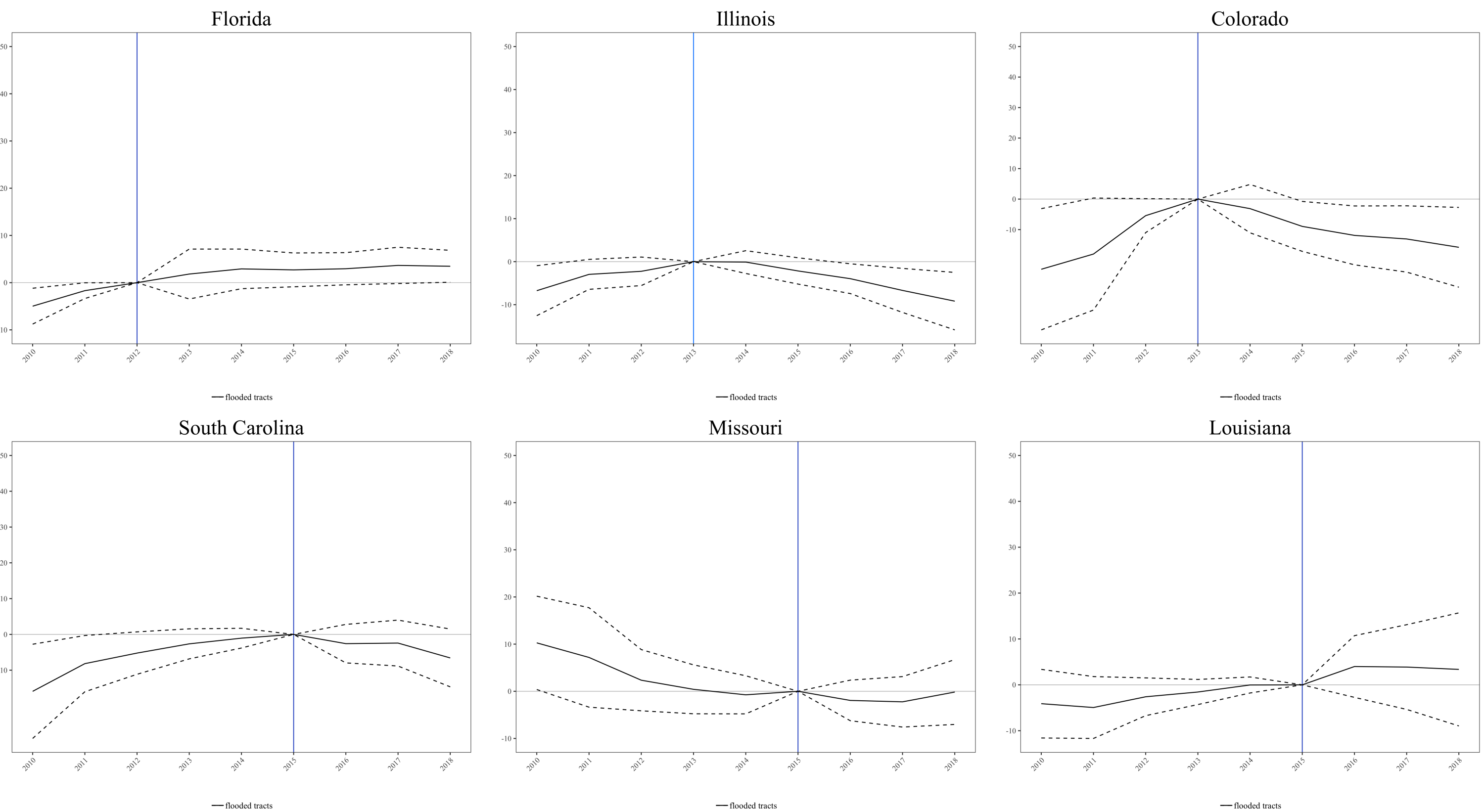

Florida
Illinois
Colorado
South Carolina
Missouri
Louisiana
flooded tracts

Figure 11

First, I tested the legitimacy of the simulated flooding extents strategy by applying it to Hurricane Sandy. Figure 10 compares Sandy's objective flooding extents to its simulated flooding extents. Generally speaking, the objective and simulated flooding extents match well[7]. For each treatment group definition, 2/3 of the flooded census tracts were also flooded in the other treatment group definition. Figure 10 also compares the regression results for 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 11 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 [29]. For example, populations used to flooding may not internalize additional events and consider their situa-

[7]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.

tion more risky [30]. 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.

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.

Limitations

The demand for flood insurance is influenced by structure vulnerability, the likelihood of being directly flooded, insurance mandates, in addition to a host of other factors. If any one of these factors systematically changed the treated or control groups' risk assessments after Sandy, but not because of Sandy, the coefficients estimated in Equations 1-5 may be biased. Potential confounding processes are detailed below. For them to have made an impact, the confounders must also not have been covered by the county-by-year fixed effects included in the regressions.

Owners of structures located in the SFHA that sustained damage equal to more than fifty percent of the market value of the home were required to elevate their structures after Sandy. For a hazard of a given size, elevation makes flooding less likely. If the structure's owner internalizes the post-elevation flood risk, their willingness to enter and stay in the insurance market may decrease, making the estimated effect a lower bound after controlling for premium costs. The number of structures that were expected to be elevated after Hurricane Sandy is not insignificant. For example, in Long Island, a borough of New York City, 3,000 homes were substantially damaged by the storm[8]. Removing elevated properties from the dataset and estimating the subsample on Specification 1 indeed yields higher point estimates.

Second, public flood mitigation projects, like constructing flood walls and sand dunes, may discourage insurance purchases for some areas. After Sandy, there was large push to protect the coastal communities from future events. While a few, smaller mitigation projects are already complete, the biggest projects with the largest risk-reducing impact, like the "big U" in New York City, are still in the planning phase. If already-implemented public flood mitigation projects caused flooded residents to decrease their perceived flood risk, then the estimated impact of Sandy is a lower bound.

Lastly, post-Sandy changes in the regulatory floodplain could have influenced flood risk perception. If structures inside the flooding extents were mapped into the SFHA after Hurricane Sandy, where flood insurance is mandated, then my estimates would represent the upper bound. Similarly, if structures outside the flooding extents were mapped into the SFHA, my estimates would represent the upper bound. Of the 46 counties in the study, half generated new floodplain maps after 2012. Most new maps came into effect between 2016 and 2018, meaning their influence could have contributed to the increasing wedge in policies-in-force between the flooded and not flooded areas. As of right now, I am not sure to what extent the boundaries of the floodplains changed with the new maps. Ideally, I would use earlier and later floodplain maps to generate a control variable equal to a census tract's SFHA percentage in a given year.

[8]Because elevating homes is often prohibitively expensive even after subsidies, an important future research topic concerns the impact of elevation mandates on migration and neighborhood demographics.

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.

Since Hurricane Sandy, however, 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 [31]. 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.

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] “Fima nfip redacted policy data set,” 2019.

[6] 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.

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

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

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

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

[15] 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.

[16] 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.

[17] 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.

[18] 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.

[19] 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.

[20] “Disasters,” 2019.

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

[22] "Hurricane sandy impact analysis-fema motf," 2013.

[23] "Introduction to the national flood insurance program (nfip)," tech. rep., Congressional Research Service, 2019.

[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] 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.

[27] 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.

[28] "Significant flood events," 2019.

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

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

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