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. Understanding how people adapt to changes in their perceived flood risk helps predict future costs to flooding. Using spatial variation in flooding, I provide causal estimates of direct experience with Hurricane Sandy's flooding on participation in the flood insurance market. Hurricane Sandy had a large impact on people's insurance choices. Since the storm, the number of insurance policies-in-force in flooded areas has continuously increased relative to 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

This paper studies the responsiveness of perceived financial risk to direct experience with a major weather event. Specifically, I exploited spatial variation in flooding to test the impact of Hurricane Sandy on the affected population's participation in the flood insurance market. Estimating insurance market responses sheds light on people's changing expectations about future flood damages through their willingness to pay to avoid future shocks. With climate change and urbanization escalating flood risk around the globe, information about disaster-driven, private adaptation responses is important for predicting future flood damages and public adaptation needs.

Climate change is altering the intensity, probability and timing of floods [1] [2]. As the planet warms up, sea level rise and increased evaporation mean that extreme weather events that historically happened only rarely will occur more frequently [3][4]. Socioeconomic changes are amplifying the effects of climate change [5]. 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 [6]. Urbanization not only puts more human assets in the way of floods, but also increases non-permeable surfaces creating additional flooding issues [7].

Adaptation will help buffer against the consequences of future floods [8]. Used to reduce the damages associated with a hazard of a given size and probability, effective adaptation often requires a mix of strategies. Physical flood protection measures, like dikes and levees, and nature-based solutions, like wetlands, serve to reduce populations' exposure to the hazard. These protection measures, however, do not eliminate risk completely. The remaining risk is called residual risk and describes the amount of risk after structural and non-structural protection measures have been implemented.

Insurance is a common solution for financing residual risk. It is a consumption-smoothing mechanism used to reduce peoples' vulnerability to excessive losses that threaten their living conditions. Flood insurance payouts hasten 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 [9]. In the case of Hurricane Katrina, households with flood insurance were 37 percent more likely to be rebuilt [10].

The setting for this paper is the United States flood insurance market in the years before and after Hurricane Sandy. Sandy is the fourth costliest hurricane in U.S. history. Its path crossed eight countries and 24 U.S. counties, causing 70 billion dollars in damage and at least 233 deaths deaths [11]. Sandy caused particularly high damages to the U.S. states New Jersey and New York, and, to a lesser extent, Rhode Island and Connecticut [12] This study estimates Sandy's insurance market impact in Connecticut, New Jersey, New York and Rhode Island (CT-NJ-NY-RI). Most flood insurance policies in the United States are provided through the National Flood Insurance Program, an entity under the Federal Emergency Management Agency.

This paper's estimation strategy relies on two main data sources. First, I used the recently-released universe of insurance policies spanning 2010 to 2018 [13]. 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 onto a map of census tracts to determine the policies located in tracts that were, or would be, flooded. Flooding extents were determined by the FEMA Modeling Task Force, constructed from field-verified High Water Marks, Civil Air Patrol and NOAA imagery [14].

I estimated the causal impact of Hurricane Sandy's flooding on insurance purchases in an event study framework. 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 CT-NJ-NY-RI 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 flooding experience across the study area.

Extensions to the main specification paint a fuller picture of the Sandy effect. First, I made use of variation in the locations of damaged and affected buildings to test whether insurance demand is sensitive to the level of damage a census tract sustained. Second, I checked for the presence of spillover effects in tracts that were not flooded but border flooded tracts. Third, I explored whether pre-Sandy risk communication mattered by splitting the initial policy sample into two groups: inside and outside the regulatory floodplain. Lastly, I evaluated the impact of Hurricane Sandy on average coverage level per policy, the intensive measure of flood insurance demand.

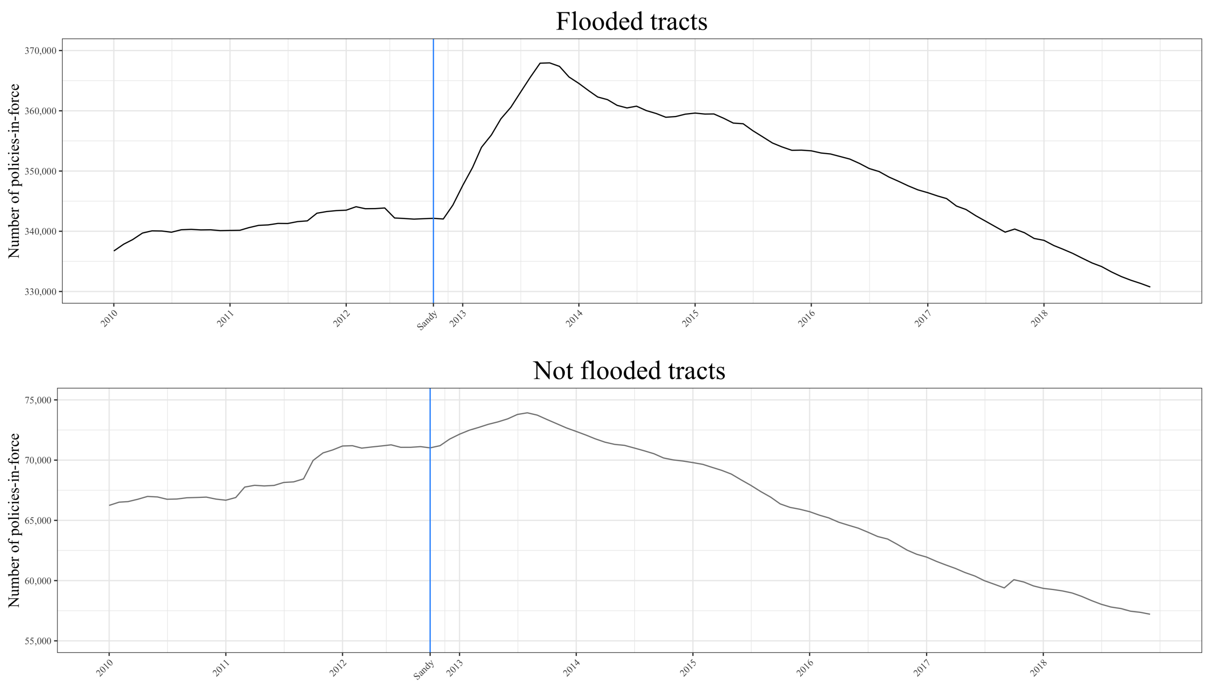

Figure 1

Hurricane Sandy caused an increase in the number of insurance policies-in-force in areas that were flooded compared to those that were not flooded. Figure 1 previews this result by plotting total insurance policies-in-force by month 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. This suggests that flooded areas had relatively better retention rates of existing policies in later years. The estimated insurance response was efficient 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.

The level of damage sustained mattered for the adaptation response. The magnitude of the estimated increase in policies-in-force is nearly three times as large for census tracts that contained damaged buildings compared to census tracts that contained only "affected" buildings. In contrast to some of the previous literature, 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.

Census tracts that did not flood but border flooded tracts also underwent an increase in the number of insurance policies-in-force. The finding suggests that proximity to the flooding was an important determinant in whether people purchased insurance after Sandy. One behavioral explanation for the result is that residents in neighboring census tracts saw themselves as being "nearly missed" by the flooding extents and adapted accordingly.

Residents inside the regulatory floodplain did not respond in the insurance market while residents outside the regulatory floodplain did, indicating the influence of pre-Sandy risk information. Outside the regulatory floodplain there are no mandatory disclosure laws, nor obligations to purchase flood insurance. Inside the regulatory floodplain, lenders must inform their clients of their property's location in a flood risky area and flood insurance is required on properties with a federally-backed mortgage (though compliance is far from perfect). Flooded residents that received pre-Sandy flood risk information did not update their expectations about future flood risk differently from comparable residents outside the flooding extents. Residents for whom the information was new did update their expectations differently.

Lastly, Sandy also caused a statistically significant increase in average coverage level per policy. For the median policy, the increase is equal to $16,800 in coverage dollars.

Swapping out average coverage level per policy for total coverage dollars (a measure of both the intensive and extensive margins), Hurricane Sandy induced a relative increase in coverage equal to nearly two million dollars for the median census tract.

This paper contributes to a broad literature demonstrating the influence information about environmental risk has on risk-reducing behavior. Ferris and Newburn (2017) estimated that flash-flood alert messages decreased the number of cars on the road and the percentage of car accidents [15]. Beatty et al (2018) used scanner data to show that the threat of a hurricane causes people to purchase more bottled water [16]. Ward and Beatty (2015) found that people spend less time doing vigorous activities outside on days with bad air quality alerts and Dessaint and Matray (2017) show that natural disasters cause managers to inefficiently increase corporate cash holdings as their perceived liquidity is threatened [17] [18]. Additionally, a large literature provides evidence that first-hand experience with disaster risk is often priced into property prices, decreasing the financial risk homeowners in risky areas face [19].

Several papers have examined the impact of flood events on insurance purchases specifically [20] [21]. For example, in a study of all U.S. communities from 1990-2007, Gallagher (2014) found that insurance take-up rates spiked after a flood event and then slowly returned to baseline [22]. Kousky (2017) also estimated an increase and subsequent decrease in insurance take-up for U.S. counties hit by hurricanes between 2001 and 2010 [23]. This paper advances the extant literature in several important ways. First, the exceptional level of detail in the storm and insurance data allowed me to identify flooded areas and the locations of policies with much more precision than was previously possible, reducing potential bias in the estimates. The detailed data also allowed me to consider heterogeneous treatment effects that were previously not testable. Second, the setting reflects worrying, current trends in the U.S. flood insurance market. Between 2010 and 2018, the number of policies-in-force in the United States fell by eight percent after decades of increase. Understanding the insurance impact of a storm in the current context is important for formulating modern risk policy.

Finally, an important difference between this 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 my findings, flooded residents haven't forgotten about the storm yet. Differences in conclusions highlight the important role that context plays in predicting behavioral responses to risk.

Lastly, this research also contributes to a more targeted literature documenting the adaptation response to Hurricane Sandy in particular. Ortega and Taspinar (2018) showed that New York City properties inside the regulatory floodplain carried a price penalty after Hurricane Sandy [24]. McCoy and Zhao (2018) determined that capital investment projects on homes not damaged by Sandy (but in close proximity to damage) were more likely outside the regulatory floodplain compared to inside the regulatory floodplain [25]. Both studies' findings are consistent with the idea that residents changed how they viewed the possibility of future flood losses and made decisions after Sandy that integrated these updated risk perceptions.

With the related literature in mind, this paper's findings are intuitive: direct experience with a risky event 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 an event study 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 [26]. 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 (C-NJ-NY-RI) receiving the brunt of the storm's impact.

Hurricane Sandy had an enormous effect on residents and infrastructure. Across C-NJ-NY-RI, nearly 200,000 households applied for disaster assistance [27]. 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 [28]. 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 [14]. The result is a spatially-explicit digital map of Hurricane Sandy's flooding extents in C-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 [29]. 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 (cite). 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 (cite). 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% 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 [30]. 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 [31]. 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 [13]. 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 the 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. However, 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 a change in flood risk perception. 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 [14]. 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.

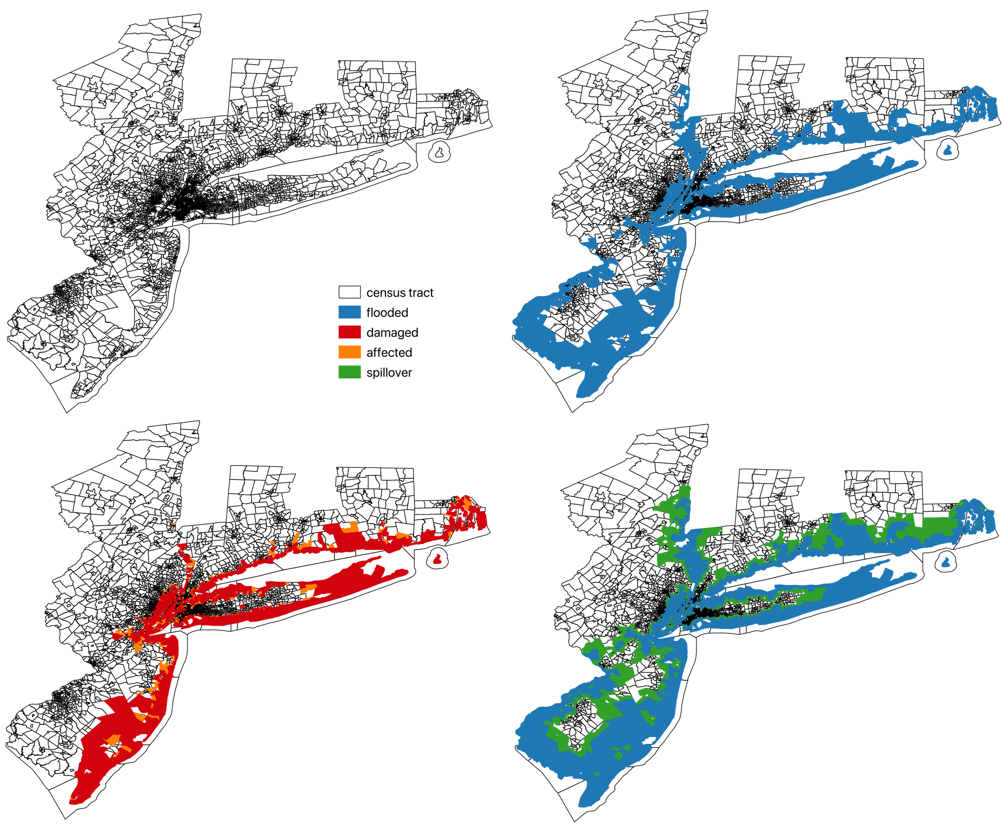

Figure 2

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 in an event study framework:

$$y_{it} = \sum_{\tau=2010,\tau\neq2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{flood} + \gamma P_{it} + \zeta C_{it} + \theta D_{it} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{1}$$

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 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. Equation 1 controls for the change in legislation with three variables. P_{it} is (the log of) the average premium for pre-FIRM buildings' policies, and is estimated separately from C_{it}, (the log of) the average coverage level for pre-FIRM buildings' policies and D_{it} (the log of) the 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 [32]. Census tract fixed effects, π_i, absorb unchanging census tract attributes, like population, underlying flood risk and political beliefs [33]. 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.

The event study strategy has two main advantages over a standard difference-in-difference 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.

Heterogeneity 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:

$$y_{it} = \sum_{\tau=2010,\tau\neq2012}^{2018} \beta_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{flooded} + \sum_{\tau=2010,\tau\neq2012}^{2018} \nu_\tau \cdot \mathbf{1}[t=\tau] \cdot W_i^{neighbor} + \gamma P_{it} + \zeta C_{it} + \theta D_{it} + \pi_i + \psi_{ct} + \epsilon_{it} \tag{3}$$

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

Do 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. 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 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. 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 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.

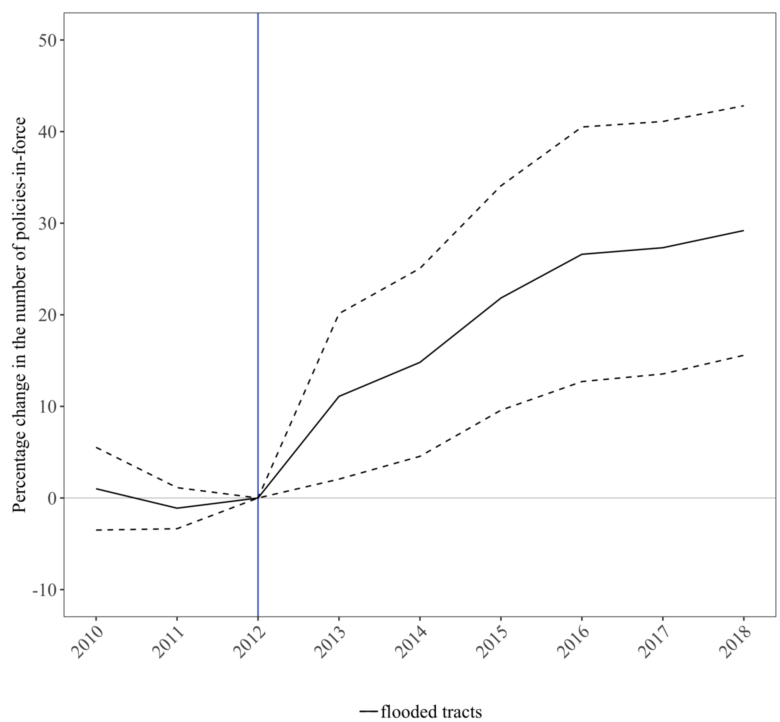

Figure 3

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.

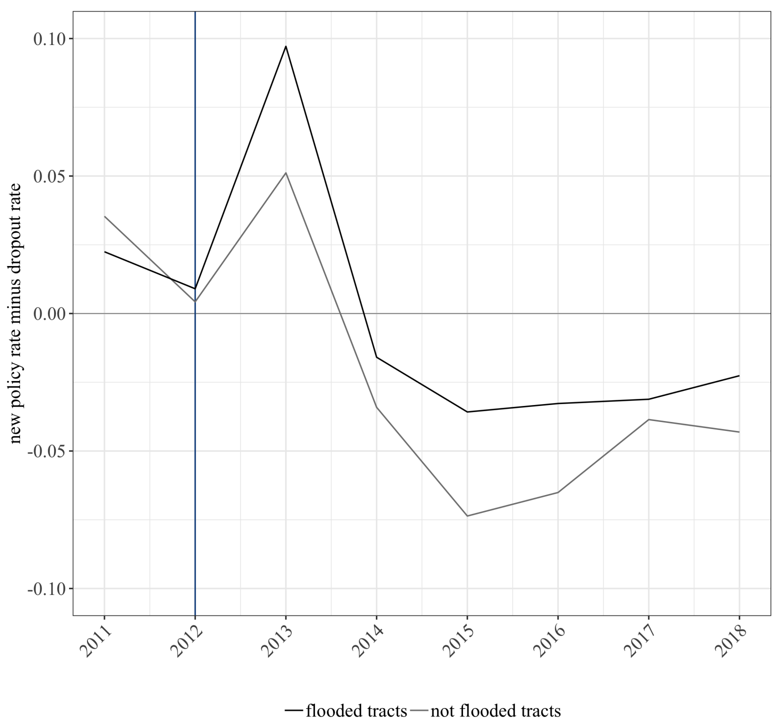

Figure 4

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.

Heterogeneity in damage levels

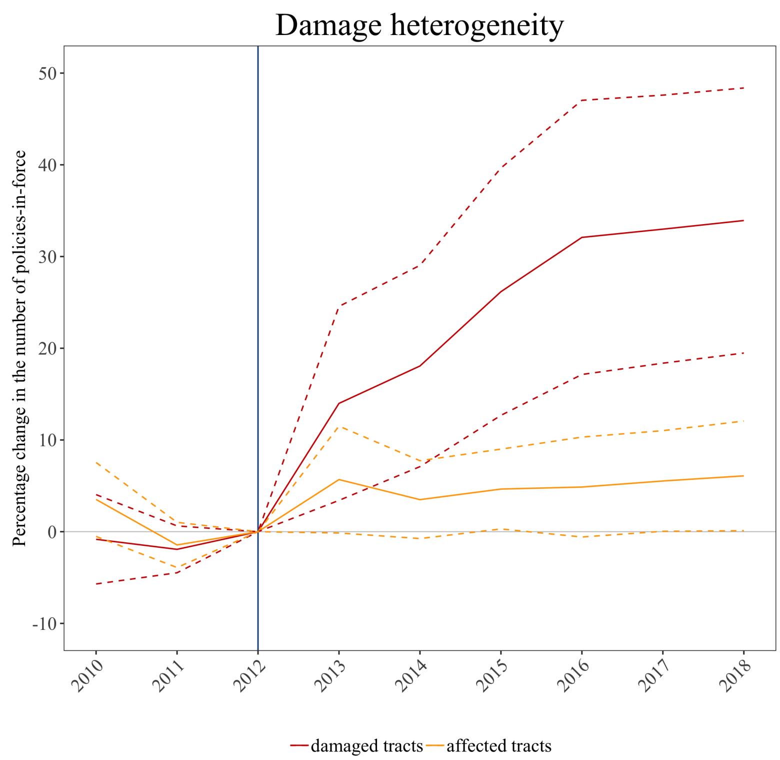

Figure 5

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.

My conclusions are robust to a number of strategies concerning treatment heterogeneity 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. Their regression estimates are presented graphically in the Appendix.

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.

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, the spillover treatment group consists of 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 different types of post-Sandy risk information 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 spillover group. The effect

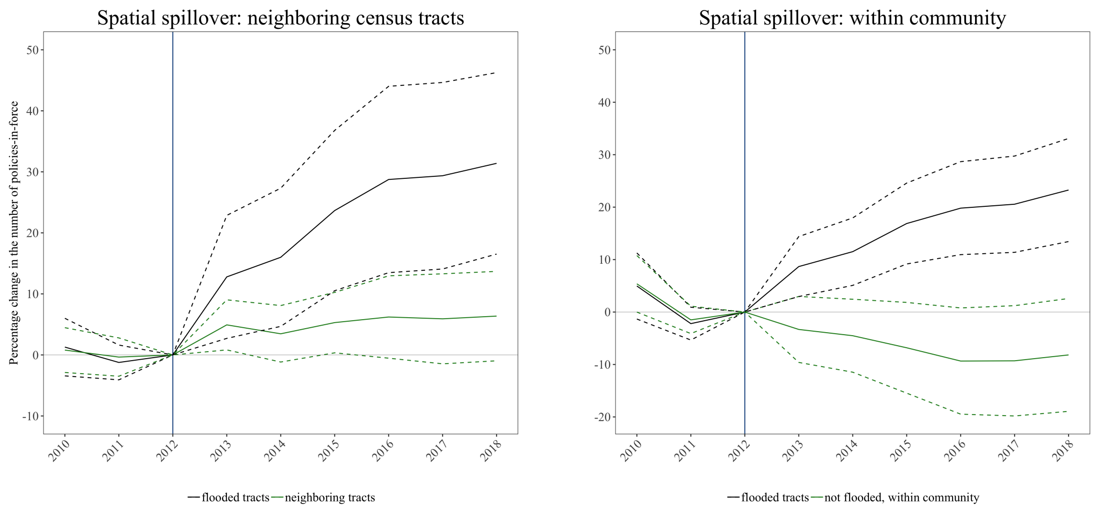

Figure 6

persists over the entire study period and is statistically different from zero at the 10 percent level. Taken together, the two spillover findings suggest that proximity to the flooding boundary encouraged insurance purchases, but only to a point. 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. Farther from the flooding boundaries but within the same community, people may have seen themselves as "rightfully missed". Despite being exposed to the same risk information, the storm's flooding extents has caused them to believe that they are safe.

Risk communication in flood zones

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.

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

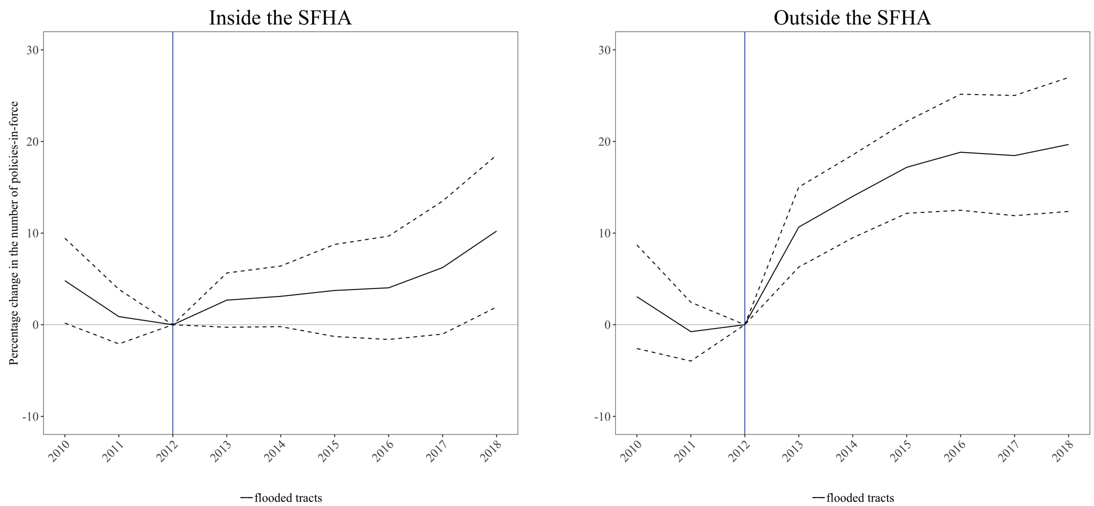

Figure 7

flooded area, the insurance take-up rate inside the SFHA was 34 percent immediately prior to Sandy. Moreover, Figure 2 in Appendix shows that I reach the same conclusions when removing census tracts with high insurance take-up from the sample.

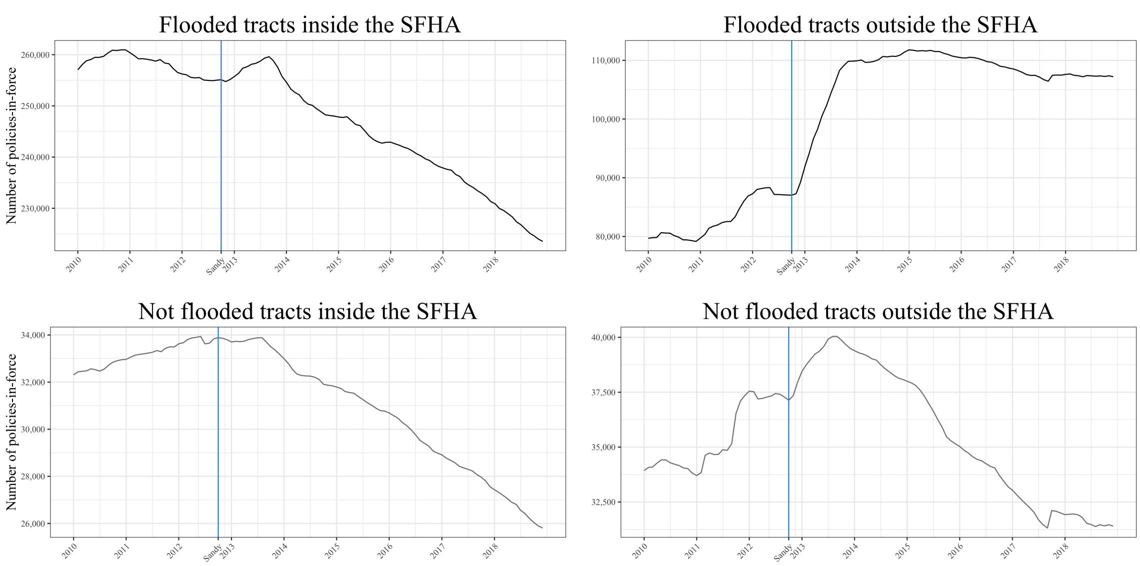

Figure 8

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.

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.

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.

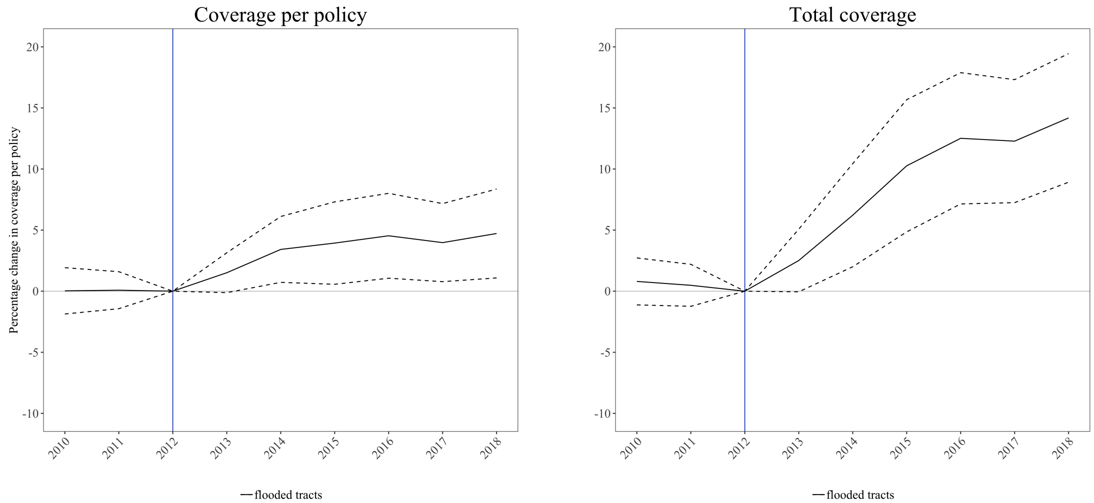

Figure 9

In 2018, the relative coverage growth is 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. Many people chose not to evacuate because all but one European weather model predicted the storm would turn and travel out to sea instead of striking the coastline [26]. Nearly 600,000 housing units were impacted and as long as five years after the storm some residents were still rebuilding. 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 how expensive it is to develop. Instead, I simulated flooding extents from Hurricane Sandy and seven other significant U.S. flood events using census tract locations of insurance claims. Each significant flood event had 1,500 or more paid losses and occurred sometime between 2012 and 2016 [34]. Treatment groups are made up 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.

First, I tested the legitimacy of the simulated flooding extents strategy by applying it to Hurricane Sandy. Figure 10 presents the point estimates and 95 percent confidence intervals from Sandy's simulated flooding extents applied to Specification 1. The magnitude and direction of the post-Sandy effect is close to that in the model with objective flooding extents, indicating 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 events across the United States. They include flooding from hurricanes (Florida), riverine flooding (Illinois, Colorado, South Carolina, Missouri, Louisiana) and flash flooding (Colorado). Some of these floods hit areas that are commonly flooded (Florida, for example) and other floods hit areas where large flooding events are rare (Colorado). Hurricane Sandy's total insurance payouts were at least four times as large as those generated by the other floods.

The remaining subfigures in Figure 10 give evidence that 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 [35]. For example, populations used to flooding may not internalize additional events and consider their situation more risky [36]. In other cases, populations that trust disaster aid will fully subsidize

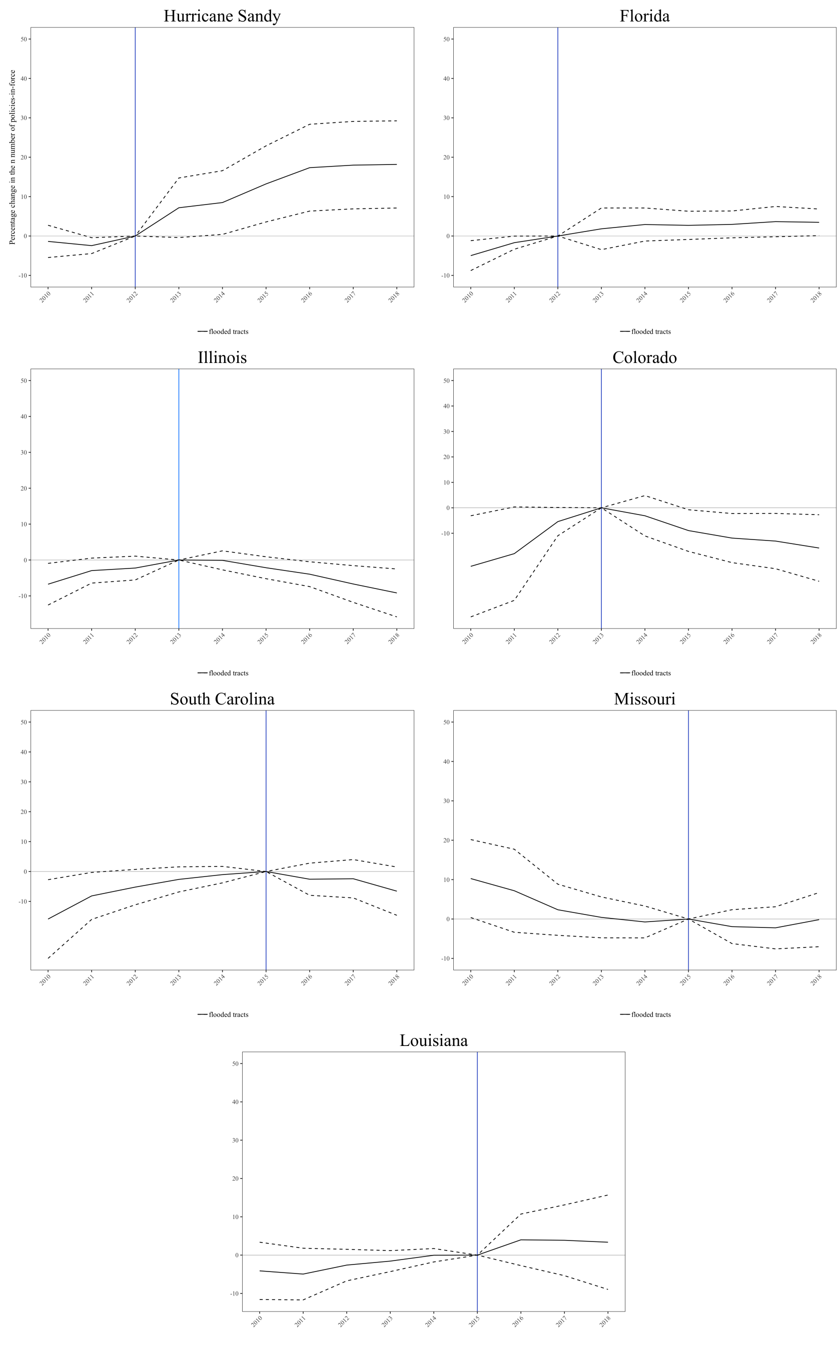
Hurricane Sandy
Florida
Illinois
Colorado
South Carolina
Missouri
Louisiana
Percentage change in the n number of policies-in-force
flooded tracts

Figure 10

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 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. 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.

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 some 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.

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 [37]. 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 RI-NJ-NY-CT. 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.

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