Climate Risk Perceptions and Demand for Flood Insurance

Abstract

We study how individuals' beliefs about climate change influence their adaptation behavior through the choice and level of flood insurance coverage. Using the heterogeneous impact of widening partisan polarization on climate change beliefs and exogenous flood insurance premium increases, we show that when more people are worried about global warming, higher the demand for flood insurance in areas where flood insurance is not mandatory. In areas where flood insurance is mandatory, higher the fraction of population who is worried about global warming, higher the propensity to carry voluntary contents coverage, and lower the likelihood of choosing the maximum deductible amount.

JEL Classification: D14, D81, D83, G11, G41

Keywords: global warming, adaptation, flood insurance, perceptions

1. Introduction

Flooding is the costliest natural disaster in the United States and the current estimates from the Federal Emergency Management Agency (FEMA) significantly underrepresent the 41 million households exposed to 1 in 100 year flood events (Wing et al., 2018; First Street Foundation, 2020).[1] Global warming can potentially increase future flood risks and lead to substantial economic losses (Solomon et al., 2007; Mousavi et al., 2011; Smith, 2020). Flood insurance is a form of effective adaptation measure that helps property owners minimize their losses and recover quickly (Billings et al., 2019), and a simple expected utility analysis shows that purchasing flood insurance is a rational and net positive benefit decision for people at most wealth levels. Despite the potential benefits, subsidized flood insurance premiums, and increasing flood risks, flood insurance take-up rate is less than 5% in areas where flood insurance is not mandated by federal law.[2]

At a time when the frequency and severity of floods are increasing in-part due to global warming (EASAC, 2018; Smith, 2020), homeowners who are not worried about global warming may assign a lower probability of flood damage to their homes. This would lead to a low flood insurance enrollment rate, reducing the homeowners' ability to cope with disasters and nation's ability to rebuild after a flood disaster.[3] In this paper, we examine how individuals' perceptions about global warming impact four flood insurance-related outcome variables: the demand for flood insurance, the amount of coverage, the choice of deductible, and the level of flood preparedness.

The National Flood Insurance Program (NFIP) sells the vast majority of the flood insurance policies in the United States. The NFIP provides up to $250,000 coverage for residential buildings and up to $100,000 coverage for contents. Under federal law, building coverage is required for all federally backed mortgages secured by structures that are located in Special

[1] For example, FEMA's maps show 0.3% of 600,000+ properties in Chicago are in the 100-year flood zone. But, First Street Foundation (2020) shows that about 13% of the properties are in the 100-year flood zone.

[2] Historically about one-in-four flood insurance claims come from these areas (NFIP Data).

[3] GAO (2008) and Horn and Webel (2019) detail the steps taken by the U.S. government and CIPR (2017) lists the steps taken by the industry toward increasing flood insurance market penetration.

Flood Hazard Areas (SFHAs)—areas that have a 1% probability of flooding in a given year. The content coverage, which covers personal belongings, is voluntary in SFHAs. Both building coverage and contents coverage are voluntary in areas outside the SFHAs (non-SFHA). The NFIP offers a few deductible choices for both the building and content coverage. The lowest deductible is \$1,000. Prior to April 1, 2015, maximum deductible allowed was \$5,000, and it was increased to \$10,000 after April 1, 2015

We obtain detailed data on flood insurance policies issued between 2009 and 2019 from the NFIP. We define flood insurance demand for a census tract-year as *Take-up Rate*, which is the proportion of homes in a census tract with active insurance policies in a given year. Our data on individuals' risk perception about global warming is from Yale Climate Opinion Maps.[4] We create three county-level climate risk perception measures from this survey data: the fraction of adults who are worried about global warming (*Worried*), the fraction of adults who believe global warming is happening (*Happening*), and the fraction of adults who believe global warming will harm them personally (*Personal*).

We start by analyzing link between climate risk perceptions and flood insurance using a simple regression framework with fixed effects for census tract and state-by-year, and a host of demographic characteristics. In Non-SFHA areas,[5] we find a strong positive monotonic relationship between the take-up rate and the fraction of population who is worried about global warming. Inside SFHAs, where only building coverage is mandatory, we find that the fraction of adults who are worried about global warming is positively related to the fraction of policies carrying voluntary contents coverage and negatively related to the choice of deductible for building coverage. We find similar results when using the other two climate risk perception variables as explanatory variables. This shows that individuals' climate risk perceptions influence their decision to take steps to protect themselves against potential losses from flooding disasters.

[4]We use the terms "global warming" and "climate change" interchangeably in this paper.

[5]We define a Non-SFHA census tract as a census tract where the fraction of SFHA policies is less than 5% of the total policies effective in 2011 in that census tract.

Even though the above fixed effects regressions control for census tract-level time-invariant unobservables and state-year specific shocks, the estimates could be biased by local time-varying factors. Therefore, we employ instrumental variable (IV) and difference-in-differences (DiD) methodologies to empirically identify the impact of climate risk perceptions on flood insurance demand. The IV strategy exploits the heterogeneous impact of widening partisan polarization on beliefs about global warming after the 2016 general election. In the United States, global warming has become one of the most politically polarizing issues (Dunlap and McCright, 2011; Hornsey et al., 2016), and the 2016 elections acted as a catalyst in widening this partisan divide (Brenan and Saad, 2018; Motta et al., 2019). According to Yale Climate Opinion Maps, in 2018, 91% of registered Democrats believed global warming is happening while only 52% of registered Republicans concurred. In 2016, these numbers were 84.7% and 57%, respectively. The Trump administration's messaging on global warming may have been a key factor in amplifying the polarization of climate risk perceptions. For example, President Trump called global warming a "hoax" and reversed several government actions to address global warming.[6]

Our instrument captures the heterogeneous receptiveness to Trump administration's messaging using county-level presidential election results. Specifically, we use the gain in county-level Republican candidate's vote share in the 2016 election compared to 2012, which is then multiplied by a dummy variable that equals 1 for years after 2016 ($Rep.\ Gain_{2016-2012} \times$ *After 2016*). This instrument captures the idea that individuals in counties where the 2016 Republican candidate gained significantly compared to 2012 are more likely to be exposed and be receptive to the Trump administration's messaging; thus are more likely to update their beliefs about risks posed by global warming. We obtain similar results when we use Republican vote share in general elections as our instrument[7].

[6] These include the announcement that the U.S. will withdraw from the 2015 Paris climate accord, the removal of climate change from the list of top U.S. national security threats, and the elimination of the terms "global warming" and "climate change" from U.S. government websites and lexicons (Brenan and Saad, 2018).

[7] Prior to 2017, we use 2012 Republican vote share, and after 2016, we used 2016 Republican vote share

We find that our instrument is strongly negatively correlated with all three climate risk perceptions variables. For our instrument to be valid, it also has to satisfy the exclusion restriction: the changes to voting behavior in a county should be uncorrelated with county-level shocks to the demand for flood insurance. To address this, we show that our instrument does not have any economically or statistically meaningful correlation with an array of county-level time-varying characteristics such as household income, age, education, etc.

One criticism of our instrument could be that it may be capturing changes in attitudes towards government intervention, and not necessarily the changes in beliefs about global warming. If flood insurance is seen as intrusive government behavior, there may be resistance to taking up flood insurance, particularly in areas where the Republican candidate gained vote share in 2016 elections. We address this concern by comparing health insurance take-up in areas where the Republicans gained and lost vote share. Health insurance is a contentious political topic, and if attitudes drive flood insurance take-up, then we should see a similar effect for health insurance take-up as well. However, we find no relationship between health insurance take-up and our instrument. Our robustness tests imply that the rising skepticism toward global warming captured by our instrument is not due to confounding factors, and it is unlikely that the error term contains common factors that impact both perceptions about climate risk and flood insurance demand.

The instrumental variable estimates are statistically and economically significant: in Non-SFHA areas, when there is a 10% increase in the fraction of people who believe global warming is happening, the flood insurance take-up rate increases by 39.33% (from 4.5% to 6.27%). In SFHA areas, a 10% increase in the fraction of adults who believe global warming is happening is associated with a 23.3% increase in the fraction of policies including voluntary content coverage (from 38.1% to 46.9%) and a 11.1% decrease in the fraction of policies opting the maximum allowed deductible (from 33.7% to 22.6%).

Our difference-in-differences strategy exploits a shock to flood insurance premium. Specifically, we test whether people who do not believe that global warming is happening are more likely to terminate flood insurance coverage following unanticipated increases in flood insurance premiums. The Biggert-Waters Flood Insurance Reform Act of 2012 (BW-2012) attempted to reform the NFIP by raising the flood insurance premiums to reflect the actual overall flood risk. This lead to an 18% increase in flood insurance premiums. As a result, homeowners who thought the premium increases were excessive would have been incentivized to terminate their flood insurance policies. However, in SFHAs (high-risk areas), where flood insurance is required under federal law, prepaying mortgages is the only way for these homeowners to terminate their floor insurance. We test whether the belief that global warming is making flooding more severe and frequent would act as a countervailing force and, therefore, the propensity to terminate flood insurance would vary depending on individuals beliefs about global warming.

To test the above hypothesis, we combine data from Zillow's Transaction and Assessment Dataset (ZTRAX), Moody's Analytics RMBS data, FEMA's National Flood Hazard Layer (NFHL), and public voter registration data in Florida to identify individual properties, their mortgage details, and party affiliation of household-head. We focus on Florida for this analysis because Florida voter registration data is publicly available. We find that SFHA-homeowners who live in areas with a lower fraction of adults who believe global warming is happening and Republican SFHA-homeowners are more likely to prepay their mortgages following the premium increases. We further show that our results are less likely to be driven by homeowners who prepay their mortgages due to refinancing, rather by the homeowners who are more likely to have the financial means to prepay their mortgages. Our results show that Republican-SFHA-homeowners whose mortgage outstanding is low and income is higher are more likely to prepay their mortgages post BW-2012. Republican voters are usually considered risk-averse (Kam and Simas, 2010; Hutton et al., 2014) and we would expect them to take-up flood insurance, especially in SFHA areas. This result suggests that climate risk perceptions of Republican voters takeover their risk-averse behavior.

Overall, our results show that individuals' perceptions about global warming significantly influence their decision to purchase flood insurance and the level of coverage they choose. These results suggest that people who do not believe global warming is happening are less likely to take the mitigative step of purchasing flood insurance. This would lead to significant loss of wealth if they are hit by a flood, and some of these losses would be borne by taxpayers in the form of disaster assistance. While ambitious mitigation measures, such as limiting greenhouse gas emissions, may soften the future impacts of global warming, we are quite a ways from implementing such measures that require consorted efforts from the global community. Purchasing flood insurance is an effective adaptation mechanism that individuals can undertake in the present. Flood insurance internalizes the costs of living in high flood risk areas and is a more effective and quicker route to address flood-related costs rather than relying on post-disaster assistance measures that typically cover less than 20% of the losses (CBO, 2019). Begley et al. (2020) document that about 46% of the disaster-relief loans are denied, and the denial rates are higher in areas with a larger share of minorities and sub-prime borrowers.

This paper informs the ongoing policy discussion on increasing flood insurance penetration, which is a longtime policy goal for the government (GAO, 2008). Increasing flood insurance penetration would help minimize the economic losses from future disasters, while also helping NFIP curtail its indebtedness.[8]. Recently, the NFIP has developed a "moonshot" goal of doubling the number of structures covered under its flood insurance program by 2023 (Horn and Webel, 2019) Therefore, from a policy-makers perspective, it is important to understand the factors that hamper flood insurance penetration. Our results can help policy-makers to narrow down the geographies and type of homeowners they should reach out to have the best impact.

This paper contributes to several strands of literature. We contribute to the literature on how individuals' beliefs impact their subjective probabilities of tail events. Research in psychology suggests that people generally overestimate the likelihood of tail events in their

[8]NFIP owed treasury $24.6 billion in January 2017

decision-making, which is consistent with probability weighting in prospect theory (Barberis and Huang, 2006; De Giorgi and Legg, 2012; Hu and Scott, 2007). However, subjective probability weights that individuals assign to tail events can vary based on their beliefs and risk preferences (Tversky and Kahneman, 1992; Barberis, 2013; Carman and Kooreman, 2014). These differences may affect participation in risk-mitigating efforts (Carman and Kooreman, 2014). We show that if people do not believe that global warming is happening, they may assign a low probability of flood damage to their homes, leading to a low flood insurance enrollment rate. Botzen et al. (2016) uses a survey of 1,000 New Yorkers and shows that political affiliation affects the perceived probability of suffering flood damage and implementation of flood protection measures. Baldauf et al. (2020) show that real estate prices reflect heterogeneity in climate risk perceptions.

This paper also contributes to the literature that examines how individuals form their perceptions about climate change. Marx et al. (2007) shows that perceptions of change in local climate may be subject to cognitive biases. Several papers have shown that when individuals analyze important issues such as climate change, they employ political and ideological filters (Hoffman, 2011; Howe and Leiserowitz, 2013; Dunlap et al., 2001). We complement this literature by providing evidence that party affiliation may bias judgments about global warming.

We also contribute to the small literature on determinants of flood insurance take-up. Browne and Hoyt (2000) and Blanchard-Boehm et al. (2001) study factors that impact flood insurance demand. Rees et al. (2008) show that insurance demand depends upon the perceived likelihood of loss and the size of the conditional loss. Gallagher (2014) has shown that flood insurance demand increases following a disaster. Davlasheridze and Miao (2019) show that public assistance following a disaster discourages flood insurance take-up. This paper, to our knowledge, is the first to document that climate risk perceptions impact flood insurance demand.

Finally, this paper also contributes to the growing literature in finance that studies how climate change impacts the financial decision-making process.[9] Goldsmith-Pinkham et al. (2020) and Painter (2019) study the effect of sea-level rise on yields of bonds issued by coastal municipalities. A survey of institutional investors by Krueger et al. (2020) shows that institutional investors consider climate risks as an important investment risk, but have just begun incorporating it into their investment processes. Engle et al. (2020) use climate change news innovations to construct mimicking portfolios capable of hedging against climate change risks. Kahn and Ouazad (2019) find that banks originate riskier conforming mortgages for sale to Fannie Mae or Freddie Mac. Lin et al. (2019) study how climate change influences investment decisions of electric utility companies. We add to this literature by showing how climate change risk perceptions influence the mitigative decision making of individuals.

2. Institutional Background

2.1 National Flood Insurance Program

The United States Congress created the National Flood Insurance Program (NFIP) in 1968 through the National Flood Insurance Act of 1968. Over 20,000 communities participate in the NFIP by complying with Federal Emergency Management Agency (FEMA) standards for building codes and floodplain management (FEMA 2007). These communities, that account for 98% of the US population, are eligible to purchase flood insurance from the NFIP.

2.1.1 Flood Zones and NFIP Policies

FEMA creates the Flood Insurance Rate Maps (FIRMs) which are used by the NFIP to determine flood insurance premiums. The NFIP participating communities are generally classified into Special Flood Hazard Areas (SFHAs) or Non-Special Flood Hazard Areas (Non-SFHAs). SFHAs are high risk areas that include coastal areas with a possibility of 3-foot breaking waves designated as Zone V, and non-coastal areas designated as Zone A.

[9] Hong et al. (2020) summarize some of the finance papers that study the effects of climate change.

Both zones V and A have a 1% or greater change of flooding within 100 years and a 26% chance of flooding within a 30-year mortgage period. Non-SFHAs are moderate to low risk areas that include zones B, C, X-shaded and X-unshaded. Zones B and X-shaded fall on the 500-year floodplains with 0.2% chance of flooding in a year. Zones C and X-unshaded have the least risk of flooding.

By law, homeowners of properties in SFHAs with mortgages issued by federally regulated or insured institutions are required to carry flood insurance. Homeowners of properties in Non-SFHAs can voluntarily purchase NFIP flood insurance and are eligible for Preferred Risk Policies (PRPs) that have lower premiums. The coverage is capped at $250,000 and $500,000 for residential and nonresidential buildings, respectively. NFIP flood insurance polices do not automatically cover homeowner's contents. A supplemental premium, however, can cover personal property damages up to $100,000. As of 2020, the minimum and maximum deductible amounts are $1,000 and $10,000, respectively.

2.1.2 Community Rating System (CRS) Program

The CRS program provides insurance premium discounts to communities that voluntarily engage in flood plain management activities (Roth Sr and Kunreuther, 1998). The CRS program recognizes 18 forms of community activities that are organized under four categories: (1) public information, (2) risk mapping and regulation, (3) flood damage reduction, and (4) public preparedness. Communities are ranked on a 10-point scale based on the activities they undertake. The maximum premium reduction SFHA communities can get is 45% and that for Non-SFHA communities is 10%.

2.1.3 The Biggert-Waters Flood Insurance Reform Act of 2012 (BW-2012)

In an attempt to increase the fiscal soundness of the NFIP, Congress passed the Biggert-Waters Flood Insurance Reform Act in July 2012. The primary objective of the Act was to make the flood insurance premium structure reflect the true risks and costs of flooding.

Pursuant to BW-2012, starting from January 2013, subsidized premiums were set to increase by 25 percent per year until the premium reached actuarially fair levels and grandfathering of risk ratings was to be eliminated.

However, in 2014, in response to outcries from homeowners who claimed that premium increases were not affordable, the U.S. Congress passed the Homeowner Flood Insurance Affordability Act that delayed the BW-2012 premium increases and restored grandfathering of properties into lower risk classes.

2.2 Private Flood Insurance Market

The private flood insurance market is very small and accounted for only 3.5% of residential policies in 2018 (Kousky et al. (2018)). The private market generally provides supplemental coverage exceeding the NFIP maximum or coverage for properties outside the standard purchase requirements for NFIP flood coverage (Dixon et al. 2007). Private flood insurance policies usually available at higher cost in the surplus-line market have become more available, especially for high-value homes. Recently, there is a push toward bundling flood insurance with home and other types of insurance coverage (CIPR, 2017).

3. Data

We combine data from several sources to construct three samples for our analysis. This section describes our data sources and the construction of our analytic samples.

3.1 Data Source

3.1.1 Flood Insurance and Disasters Data

FEMA NFIP Redacted Policies Data contains policy transactions from 2009 and it contains detailed information on all the policies sold by NFIP. The data set provides information such as the premium and fees charged, policy effective date, building coverage amount, contents coverage, flood zone, elevation difference from base flood elevation, construction year, whether the property was constructed after the flood insurance map became effective, census tract, zip code, etc. for each policy sold.

FEMA Disaster Declaration Data provides information on presidential disaster declarations at county-level. It includes the type of disaster (flood, hurricane, fire, etc) and types of disaster assistance programs that were initiated after the disaster.

3.1.2 Yale Climate Opinion Maps

The Yale Climate Opinion Maps are based on nationally representative surveys conducted by the Yale Program on Climate Change Communication and the Center for Climate Change Communication at George Mason University. These maps provide county-level estimates of the percentage of American adults who hold certain beliefs, risk perceptions and policy preferences regarding global warming (Howe et al., 2015). We focus on three statements in the survey: (i) Global warming is happening; (ii) Worried about global warming; (iii) Global warming will harm me personally. This survey data is available at county level for the years 2014, 2016, 2018, and 2019. We interpolate values for years 2015 and 2017 using years before and after. The survey also breaks down the answers by whether the respondent is a registered Democrat or a Republican.

3.1.3 Demographics Data

American Community Survey (ACS) is a nationwide U.S. Census Bureau survey that provides census tract level estimates of the characteristics. We use the 5-Year estimates for periods ending in 2009 through 2017. The variables extracted from the ACS include median household income, number of homes, total population, number of people with a college degree, number of white people, median age, health insurance coverage, etc. We use this data to control for demographic characteristics in analysis.

Zillow Home Value Index (ZHVI) , from zillow.com, is a monthly time series data that tracks monthly median home value at the zip code level. The ZHVI is constructed using the property-level 'Zestimates' provided by Zillow's proprietary home valuation model. The ZHVI incorporates home valuations on more than 100 million homes including new construction homes and homes that have not traded on the open market in many years (Bruce, 2014). ZHVI is smoothed, seasonally adjusted measure of the typical home value across a given region and housing type.[10]

County Presidential Election Returns from MIT Election Data and Science Lab (MEDSL) contains presidential election returns from 2000 to 2016 at the county-level.

3.1.4 Households and Mortgages

Zillow's Transaction and Assessment Dataset (ZTRAX) is compiled from public records and contains data on properties across more than 3,000 U.S. counties. It contains property and transaction details. Property-level data include number of bed rooms, bathroom, construction year, address, and GPS coordinates. Transaction details include data on sales price, type of the deed, names of buyers and sellers, mortgage amount, and lender name.

Moody's Analytics RMBS Data provides loan-level data at origination and monthly performance data for about 30 million mortgages underlying Non-Agency Residential Mortgage-Backed Securities. We observe information such as loan type (i.e., Fixed or ARM), interest rate, loan term, borrower's credit score, and loan to value ratio at origination. The performance data is updated monthly and contains information such as the loan status and outstanding loan balance. We merged monthly performance data with the Disaster Decla-

[10] Zillow's ZHVI calculation methodology can be found here: https://www.zillow.com/research/zhvi-methodology-2019-deep-26226/.

rations Summary to obtain our mortgage performance sample. The sample was restricted to mortgages, which financed purchase or refinancing of single-unit single-family homes with origination dates between 1993 and 2018 and a 30-year loan term.

FEMA's National Flood Hazard Layer (NFHL) is a publicly available geospatial database with flood hazard data. This file is used to identify the flood zone of individual addresses.

Voter Registration Data for the state of Florida was downloaded for years 2012-2016 from `flvoters.com`. This data provides names of registered voters, addresses, dates of birth, race, and political party affiliation.

3.2 Sample Construction

In this section, we explain the sample construction process used to create our three analytic samples using datasets described in the previous section.

Non-SFHA Census Tract-Year Panel is used to study the demand for flood insurance policies in Non-SFHA areas, where flood insurance is not mandatory. First, we use the NFIP Policy dataset to count the number of SFHA- and Non-SFHA- type flood insurance policies in each census tract for each year from 2009 to 2019. This data is then merged with ACS's yearly estimates on the number of houses and demographic characteristics for each census tract. Next, we add the Zillow's ZHVI data to get median house prices for each census tract. And finally, using the FEMA's Disaster Declaration dataset we identify whether a census tract experienced a flood related disaster in the previous three years.

We label a census tract as *Non-SFHA Census Tract* if the number of SFHA-type policies is less than 5% of the total number of active policies in the tract in a given year. Census tracts with higher percentages of SFHA policies are excluded from this sample. Non-SFHA tracts with less than 30 policies and 100 houses in a given year are excluded from the sample to ensure that we not dealing with extremely small local populations. There are 16,375 census tract that fit our definition of Non-SFHA census tract. For each census tract-year, we define our main variable of interest, flood insurance demand—*Take-up Rate*—as the fraction of homes in the census tract with flood insurance policies.

SFHA Census Tract-Year Panel is used to study how SFHA-homeowners' decision to purchase content coverage and the choice of deductible are influenced by their beliefs about global warming. Note that SFHA-homeowners who have a mortgage from federally regulated or insured institutions are required by law to carry flood insurance. For this analysis we exclude zone V flood insurance policies (a small fraction of houses that face the risk of 3-feet breaking waves) and census tracts that have less than 10 SFHA-type policies. For each SFHA census tract-year, we calculate *Frac. Contents* as the fraction of SFHA policies that have content coverage and *Frac. Max. Deductible* as the fraction of SFHA policies that have maximum allowed building coverage deductible. This panel covers **(NUMBER)** SFHA houses from 18,642 census tracts.

Florida Loan-Month Panel is used to study whether people who are skeptical of global warming are more likely to terminate mandatory flood insurance coverage by prepaying their mortgages following unanticipated premium increases due to BW-2012. First, we merge Moody's Analytics RMBS Loan-Level data with ZTRAX data using zip code, loan origination date, loan amount, and lender's name. ZTRAX data includes the physical address, GPS coordinates of the address, and the buyer's name. Next, we use NFHL shapefiles to identify whether each underlying property is in an SFHA area. Finally, we merge the Florida voter registration data using the buyer's name and address to get their political affiliation. We exclude loans that were prepaid due to a sale and the sample is restricted to 30-year fixed-rate mortgages that financed purchases of primary residencies. In the resulting loan-month panel, we track the performance and status of 67,610 mortgages in Florida between 2005 to 2019. We are unable to extend the sample to other states since voter registration data is not easily obtainable for other states.

3.3 Descriptive Statistics

The summary statistics for the Non-SFHA Census Tract-Year panel in Table 1 Panel A show that the mean flood insurance cost per year for $100,000 coverage in the sample was $231 in 2016. There are 16,735 census tracts in the sample, distributed across the nation accounting for a population of 87 million people. Out of the 38 million homes in these census tracts 1.67 million homes ($\approx$ 4.46%) had flood insurance in 2016. The variable *Worried* shows that on average 57.4% of adults in a census tract believe that global warming is happening. *Happening* indicates that 69% of the adults are worried about global warming. *Personal* shows that 39.7% of adults think that global warming will impact them personally. Mean income in these census tracts is $76,102 and the mean house price is $270,986. Mean population in a census tract is 5,213 and each census tract contains about 2,242 homes.

Table 1 Panel B summarizes the SFHA Census Tract-Year panel used to analyze the link between climate risk perceptions, and content coverage and deductible choices. This sample consists of 18,642 census tracts that have at least 10 SFHA policies. 38.1% of the SFHA policies had contents coverage, but there is a large variation across tracts as indicated by a standard deviation of 23.5%. 33.7% of the SFHA policyholders picked the maximum deductible for their building coverage. The mean flood insurance cost per year for $100,000 coverage is $867.

Table 1 Panel C summarizes the Florida loan-month panel that we use to study borrower behavior after flood insurance premium increases in January 2013 due to BW-2012. The sample consists of 67,610 Florida loans. 18.2% of the mortgages are for homes in SFHAs and 32.9% of the borrowers are registered Republicans. The average credit score is 655 and the average loan-to-value ratio is 70. 26.5% of these mortgages were prepaid.

Figure 1 shows the geographic distribution of our main variable of interest—*Worried*: the fraction of adults in a census tract who are worried about global warming. The figure shows a large variation in peoples' perceptions about global warming within states.

4. Climate Risk Perception and Flood Insurance Demand

We start our empirical analysis by studying the impact of climate risk perceptions on flood insurance demand. We employ fixed effects regressions and instrumental variable regressions to understand the impact of climate risk perceptions on flood insurance take-up in non-SFHA areas, and content coverage and deductible choices in SFHA areas. We detail our empirical strategies in section 4.1 and present our results in section 4.2.

4.1 Empirical Strategies

4.1.1 Fixed Effects Regression

We start by running the following fixed effects regression specification to investigate the relationship between climate risk perceptions and flood insurance take-up and choice variables.

$$Y_{tcy} = \sum_{b} \beta_b \times b_{cy} + \boldsymbol{\beta X}_{tcy} + \mu_t + \mu_y + \epsilon_{tcy} \tag{1}$$

where subscripts t, c, and y represent the census tract, the county, and the year respectively. The dependent variable Y_{tcy} is one of the three flood insurance choice variables discussed in section 3.2: Take-up Rate, Frac. Contents and Frac. Max. Deductibles. The dummy variable b_{cy} represents the binned percentage of adults in county c and year y who are worried about global warming ($Worried \times 100$) where $b_{cy} \in$ (less than $Q1, Q1 - Q2, Q2 - Q3$, and greater than Q3). X_{tcy} is the set of controls for local time-varying factors such as census tract level median household income, median age, total population, the fraction of people with a college degree, number of homes, fraction of owner occupied homes, cost of flood insurance, house price, and dummy variables indicating whether the county c experienced any flood-related disasters in the previous 3 years. μ_t and μ_y represent census tract and year fixed effects respectively.

β_b captures the difference in the outcome variable Y_{tcy} in bin b relative to the omitted bin ($Worried \times 100 \in$ less than $Q1$). We expect β_b to increase in b when the outcome variable is flood insurance take-up or the fraction of SFHA policies with content coverage. β_b is expected to decrease in b when the outcome variable is the fraction of SFHA policies with maximum deductible.

4.1.2 Instrumental Variable Estimation

Identifying the impact of climate risk perceptions on the choice of flood insurance coverage is challenging due to omitted variables and measurement errors. The census tract and year fixed effects in the above specification (eq. 1) would absorb time-invariant unobservable factors and time-specific shocks. But unobservable factors such as awareness and level of flood risk, affordability and time-varying demographic and economic conditions could be correlated with food insurance demand and bias our estimates.[11] Further, our imprecise measure of climate risk perception could bias the coefficients downward. We address these concerns by estimating an instrumental variable specification that exploits the fact that public opinion on climate change is splintered sharply along party lines with widening polarization on the topic after the 2016 general election.

We argue that individuals in counties where the 2016 Republican presidential candidate gained significantly compared to 2012 are more likely to be exposed and be receptive to the current administration's messaging, and therefore are more likely to revise their perceptions on risks posed by global warming. We construct our instrument by multiplying the county-

[11] For example, Lindell and Hwang (2008), Kellens et al. (2011), and Mills et al. (2016) have shown that education and duration of residence correlate with risk preferences and perceptions.

level gain in the Republican candidate's vote share in 2016 compared to the same in 2012 by a dummy variable that equals to 1 for years after 2016. We denote our instrument as $\textit{Republican Gain}_{2016-2012} \times \textit{After 2016}$. Figure 2 shows the geographic distribution of our instrument. The color red represents counties with larger gains (henceforth referred to as "gained" areas) in 2016 by the Republican candidate, and the color blue represents the counties that saw a drop in Republican voter share in 2016 (henceforth referred to as "lost" areas).

Formally, we estimate the following 2-stage least squares IV regression model:

$$\begin{aligned} \textit{Worried}_{cy} &= \delta(\textit{Republican Gain}_{2016-2012} \times \textit{After 2016}) + \boldsymbol{b}\boldsymbol{X}_{tcy} + \mu_t + \mu_y + e_{tcy} \\ Y_{tcy} &= \gamma \widehat{\textit{Worried}}_{cy} + \boldsymbol{\beta}\boldsymbol{X}_{tcy} + \mu_t + \mu_y + \epsilon_{tcy} \end{aligned} \tag{2}$$

where subscripts t, c, and y represent the census tract, county, and year respectively. *Perception* represents one of our three climate risk perceptions measures, namely *Happening*, *Worried* and *Personal*.

Relevance of the Instrument: To show that the instrument is relevant, we run the following variant of the first stage of equation 2.

$$\textit{log(Worried)}_{cy} \times 100 = \sum_z \beta_z \times z_c \times \textit{After 2016} + \boldsymbol{b}\boldsymbol{X}_{tcy} + \mu_t + \mu_y + e_{tcy}$$

z_c is a dummy variable that indicates the binned gain *(gain* $\in$ *(less than 0%, 0-5%, greater than 10%))* of the Republican candidate in the 2016 election compared to 2012 in a county. Subscript c represents the county. Coefficients β_z capture the difference in the county-level perception on global warming post 2016 compared to pre 2016 for each bin z relative to the omitted bin, less than 0% Republican gain. The results of this estimation are reported in Table 2 and it shows that there is a strong negative relationship between the instrument and the climate risk perceptions. In areas where the Republican candidate gained more than 10% of the vote share, the fraction of adults who are worried about global warming dropped by about 2.2% after the election, relative to the counties where Republican gain is less than 0%.

4.2 Empirical Results

4.2.1 Flood Insurance Take-up in Non-SFHA Areas

We start our analysis by investigating the link between climate risk perceptions and flood insurance take-up rates in Non-SFHA areas using the Non-SFHA Census Tract-Year panel.

Fixed-Effects Estimation: In Table 3 we run the specification 1 with the dependent variable is *log(take-up rate)*. Column (1) does not control for any demographics and Columns (2) includes the full set of control variables. Results suggest that flood insurance take-up rate is higher in areas where more people are worried about climate change. The flood insurance take-up rate in the highest perception quartile is about 4% higher compared to the lowest quartile. This effect is economically significant given the mean take-up of 4.5% in non-SFHA areas.

IV Estimation: We present the results of the second stage of our IV estimation in Table 4. The conditional F-statistic for all regressions are well above the critical value of 8.96 (see Table I in Stock and Watson (2002)) suggesting that our instrument is not weak. The estimates in column (2) imply a one standard deviation increase in the *Worried* would increase the flood insurance take-up by 19.8% from current levels. That is, the mean take-up rate would increase from 4.5% to 5.4%. We find a similar impact for the other two measures of climate risk perceptions. This shows that individuals' perceptions about climate risk influence their decision to take adaptive measures against flooding risks.

4.2.2 Content Coverage Take-up and Choice of Deductible in SFHA

Next, we investigate how beliefs about global warming influence coverage decisions made by people who live in high flood risk areas (SFHAs). Given properties backed by mortgages in SFHAs are required to carry flood insurance, we test the propensity of these homeowners to purchase content insurance and to choose the maximum deductible.

Fixed-Effects Estimation: Figure **??** plots the β coefficients from equation 1 when the fraction of SFHA policies with contents coverage (Panel A) and the fraction of SFHA policies with maximum deductible (Panel B) are used as the dependent variables. The binned *Happening* is the explanatory climate risk perception in these figures. As expected, the figures shows that fraction of policies with contents coverage and maximum deductible are, respectively, positively and negatively correlated with *Happening*. Table 5 shows the same result in regression form with the continuous climate risk perception variables and a full set of control variables.

IV Estimation: Table 6 reports the second-stage IV estimates with the fraction of SFHA policies with contents coverage as the dependent variable. As expected, we see a positive and significant impact of beliefs about global warming on fraction of SFHA policies with content insurance. A 10% increase in the fraction of adults in a county who believe that global warming is happening is associated with a 23.3% increase (from 0.381 to 0.47) in the fraction of SFHA policies with contents coverage. This effect is economically large given the average content insurance take-up rate is 38.1%. Our alternate measures of climate risk perceptions—*Worried* and *Personal*—also show a similar impact.

Table 7 reports second-stage IV estimates for the regression that examines the relationship between climate risk perceptions and the fraction of SHFA policies in a census tract with maximum deductible. We find that a 10% increase in the fraction of adults in a county who believe that global warming is happening is associated with a 11.1% decrease (from

0.337 to 0.226) in the probability of selecting the maximum allowed deductible.

The results in sections 4.2.1 and 4.2.2 taken together clearly show that individuals' perceptions about global warming strongly influence their flood insurance purchase decisions and thereby their ability to cope with flooding disasters.

One concern about the instrument is the possibility that our instrument may be capturing changes in attitude towards government intervention, and not changes to climate risk perceptions. Republicans are known to resist such intrusive behavior (Henderson and Hillygus, 2011). If flood insurance is seen as intrusive government behavior, then there are may be resistance to taking up flood insurance, particularly in areas with Republican gains. We address this concern by comparing health insurance take-up in gained and lost areas. Health insurance has been a contentious political topic and if the differences in flood insurance take-up are driven by attitudes towards government intervention, we should see a similar effect on health insurance take-up as well. However, in Figure 3, we find no such difference in the health insurance take-up between gained and lost areas.

5. Climate Risk Perception and Flood Insurance Termination

In this section we provide evidence to support the results in section 4.2. We show that people who believe global warming is happening are less likely to terminate mandatory flood insurance by prepaying their mortgages after a sudden premium increase. But, skeptics are more likely payoff their mortgages to terminate the insurance after a premium increase.

5.1 Flood Insurance Premium Shocks as a Source of Identification

The Biggert-Waters Flood Insurance Reform Act passed in July 2012 forced insurance premiums to increase from January 2013 onward. To show the impact of this act on premiums, we run the below regression separately for SFHA and non-SFHA areas, and plot β_y (premium increase) in Figure 4. Subscripts i and y represent policy and year respectively.

$$log(\text{premium})_{iy} = \sum_{y} \beta_y \times y + \mu_i + \epsilon_{iy} \tag{3}$$

Results suggest that premiums increased by 20% during the period 2013-2015 as a result of BW-2012. Such sharp premium increases could make flood insurance unaffordable for some homeowners (HFIAA, 2014) and incentivize them to terminate their policies. SFHA-zone homeowners are mandated by law to carry flood insurance. So, the only way SFHA homeowners with a mortgage can terminate their flood insurance is by prepaying the mortgage. Given that SFHA homeowners face higher flood risks, we hypothesize that their propensity to terminate flood insurance by prepaying mortgages will be influenced by their beliefs on global warming. Homeowners who believe global warming is making flooding more severe and frequent would be less likely to terminate their coverage compared to homeowners who do not believe global warming is happening.

Using the Florida Loan-Month panel discussed in section 3.2, we run the following difference-in-differences specification to test the above hypothesis:

$$Prepaid_{im} = \sum_{b} \beta_b \times b \times SFHA \times Post + \mu_i + \mu_{ty} + \epsilon_{im} \tag{4}$$

where subscripts i,m,t, and y represent the loan, month, census tract and the year respectively. $Prepaid_{im}$ is a dummy variable that takes the value one if loan i was prepaid in month m. *SFHA* indicates whether the underlying property is located inside a SFHA area and *Post* indicates if the month m is after July 2012. μ_i and μ_{ty} represent loan fixed-effects and census tract-year fixed effects respectively. The dummy variable b represents the binned percentage of adults in who believe global warming is happening ($Happening \times 100$) where $b_{cy} \in (< 60, 60 - 65, 65 - 70, 70 - 75, > 75)$. β_b captures the difference in the propensity to prepay SFHA-mortgages after 2012 in bin b relative to Non-SFHA mortgages areas in bin b compared to the omitted bin (< 60). We expect β_b to decrease in b.

Extending the logic of equation 4, we can argue that SFHA-zone homeowners in counties that are more skeptical of global warming are more likely to terminate their insurance by prepaying their mortgages. To test his conjuncture we run the following regression:

$$Prepaid_{im} = \sum_{y} \beta_y \times y \times SFHA \times Skeptic\,County + \mu_i + \epsilon_{im} \tag{5}$$

where y is a dummy variable indicating the year and *Skeptic County* is a dummy variable that indicates counties where *Happening* is below 70%.[12] We expect the β_y to be positive and significant, especially when $y > 2012$.

Thus far we have used the county-level perception variable (*Happening*) for our analysis. Political affiliation is considered to be a strong determinant of an individual's beliefs about global warming (Dunlap et al., 2001). Therefore, we run equation 5 after replacing *Skeptic County* with *Republican*, a dummy variable that takes the value one if the borrower is a registered Republican. β_y would capture the difference in propensity to prepay SFHA-mortgages by Republicans in year y relative to the non-Republicans. We expect the β_y to be positive and significant when $y > 2012$.

5.2 Propensity to Prepay Mortgages After Premium Increase

Figure 5 plots β_b coefficients from equation 4. As expected, we observe a negative monotonic relationship between climate risk perceptions and propensity to prepay. The estimates suggest that a 10% drop in the fraction of adults who believe that global warming is happening is associated with a 2.2% increase in mortgage prepayment in SFHA areas, relative to non-SFHA areas after the premium increase. This is a 8.32% increase from the unconditional prepayment of 26.5%.

The Figure 6 plots β_y estimates from specification 5. The plot clearly shows a spike in prepayment behavior of skeptic counties after 2012 compared to non-skeptic counties. This

[12] We follow Baldauf et al. (2020) for categorizing counties.

implies that SFHA-zone homeowners who are skeptical of global warming are more likely to prepay their mortgages to terminate their flood insurance after passage of BW-2012.

Figure 7 investigates the impact of party affiliation on prepayment. The plot indicates that Republican borrowers in SFHAs are more likely to prepay their mortgages in response to BW-2012 flood insurance premium increases. This result suggests that climate risk perceptions influence republican voters away from carrying flood insurance, even though these voters are more likely to buy insurance to reduce their level of risk exposure (Kam and Simas, 2010; Hutton et al., 2014). Taken together these results suggest that individuals' perceptions about global warming strongly influence their decision to carry flood insurance, even among those who face a high risk of flooding.

We examine the heterogeneity of this result in the Table 8. We expect that the homeowners who have a lower outstanding mortgage balance and homeowners who live in high-income areas would be better positioned to terminate their flood insurance policies by prepaying their mortgages. To test this hypothesis, we run the following regression separately for loan-months with outstanding mortgage balance less than \$100,000 (column (1)), for loan-months with outstanding mortgage balance greater than \$100,000 (column (2)), for homeowners who live in areas where median income is less than \$50,000 (column (3)), and for homeowners who live in areas where median income is greater than \$50,000 (column 4).

$$Prepaid_{im} = \alpha + \beta_1 \times Post \times Republican \times SFHA + \beta_2 \boldsymbol{X} + \mu_i + \epsilon_{im} \tag{6}$$

where i is the loan, m is the month, *Post* is a dummy variable that takes the value one for periods after 2012, and the dummy variables *Republican* and *SFHA* indicate the homeowners political affiliation and the flood zone respectively.

Columns (1) and (2) in Table 8 show that homeowners with lower outstanding mortgage balances are more likely to prepay compared to homeowners with higher outstanding mortgage balances. Columns (3) and (4) show that homeowners with higher income are more likely to prepay their mortgages in the post period compared to homeowners with lower income. The statistically significant coefficients of *Republican* $\times$ *Post* suggest that political affiliation which influences an individual's climate risk perception plays an important role is the decision to prepay mortgages, except when the homeowner's income is below 50,000. Further the *Republican* $\times$ $SFHA$ $\times$ *Post* coefficient in column (4) suggests that wealthier individuals who are in SFHA zones prepay their mortgages when they are sceptical about global warming. These results attempt to shed light on heterogeneous response of individuals to carrying flood insurance.

6. Additional Results

6.1 Flood Preparedness

In this section, we study how climate risk perceptions influence level of preparedness in a community and thus the amount of discounts homeowners can get on their flood insurance premiums. For this exercise we focus on owner-occupied 'zone-A' policies (homes built after flood maps became effective) in coastal states (from Texas to Maine). We use the Community Rating System (CRS) discount as our main measure of flood preparedness. CRS discounts range from 5% up to 45% and are based on the level of floodplain management activities undertaken by the community.

We regress the $log(1 + CRS\ Discount)$ on *log(Happening)* and control for an array of underlying structure related and census tract level demographic characteristics along with state and year fixed effects. Table 9 reports the results of this regression. The estimates show that a 1% increase in the fraction of adults in a county who believe global warming is happening is associated with a 0.125% increase in CRS discount for homeowners.

6.2 Content Coverage Take-up and Choice of Deductible in SFHA: Variation by Party Affiliation

This section provides additional support to our findings in section 4.2.2 by running a similar analysis using individual level data from Florida voter records. We use party affiliation as a proxy for climate risk perceptions and run the below regression to test whether Republican homeowners in SFHA areas are less likely to purchase contents coverage and more likely to choose the maximum deductible amount.

$$Y_{iytz} = \beta \times Republican_i + \boldsymbol{\delta X} + \mu_{tz} + \mu_y + \epsilon_{iytz} \tag{7}$$

where subscripts i,y,t, and z represent the policy, year, census tract, and the flood zone. Y is a dummy that could either indicate whether the policy includes contents coverage, or whether the maximum deductible was chosen. *Republican* is a binary variable that indicates if the homeowner is a registered Republican. μ_{tz} and μ_y are census tract-flood zone fixed effects and year fixed-effects respectively.

Results of the estimation are reported in Table 10. Republican homeowners in SFHA areas are less likely to have contents coverage and more likely to choose the maximum deductible.

7. Conclusion

Many households who are exposed to flood risk in the United States are not covered by flood insurance. This insurance gap undermines the nation's ability to cope with disasters and would delay recovery. Given the availability of flood insurance premium subsidies and the increasing in frequency and severity of floods and hurricanes, it is puzzling why flood insurance enrollment is low.

In this paper we document that public perception regarding global warming influences both the decision to purchase flood insurance (extensive margin) and the amount of coverage homeowners choose (intensive margin). We employ two empirical strategies: 1) we exploit the with widening polarization across political party lines around climate change after the 2016 general election to study the link between individuals' climate risk perceptions and their decisions to purchase flood insurance, and 2) we use a regulation that led to increase in flood insurance premium structure to study how individuals' climate risk perceptions influence their decision to terminate flood insurance coverage.

Our results show that individuals' opinions on global warming can help explain that their decision to purchase flood insurance, amount of coverage chosen, and level of flood preparedness. In high flood risk zones where insurance is mandatory, people who do not believe global warming is happening are less likely to carry content insurance and more likely to prepay their loan in response to premium increases. Overall, our results indicate that individuals' perceptions about global warming influences their decision to take adaptive measures against flooding disasters. Such climate change skepticism may act as a barrier for effective climate change adaptation. Our results can help policy-makers to narrow down the geographies they should reach out in order to effectively increase the flood insurance penetration.

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Figure 1: Percentage of Adults Who are Worried About Global Warming

This map shows the percentage of adults who are worried about global warming by county-level. This map is based on data obtained from 2018 Yale Climate Opinion Maps.

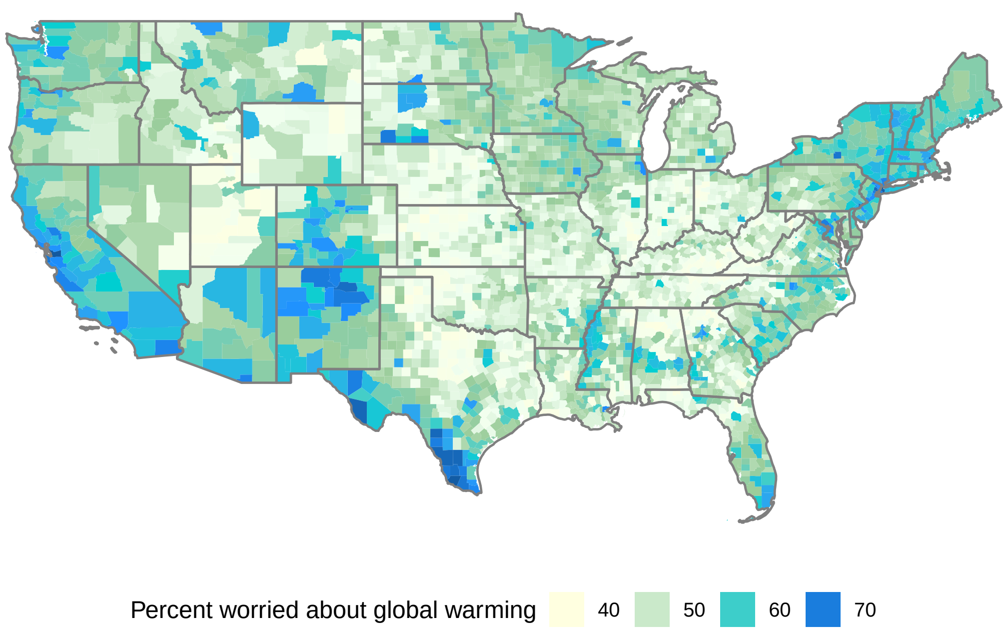

Figure 2: Republican Presidential Candidate's Gain in 2016

This figure shows the geographical distribution of our instrument. The instrument is the county-level gain in the Republican candidate's vote share in 2016 presidential election compared to that in 2012 election multiplied by a dummy variable that equals to 1 for years after 2016. The redder a county, the higher vote share gain by the Republican candidate in 2016 compared to 2012.

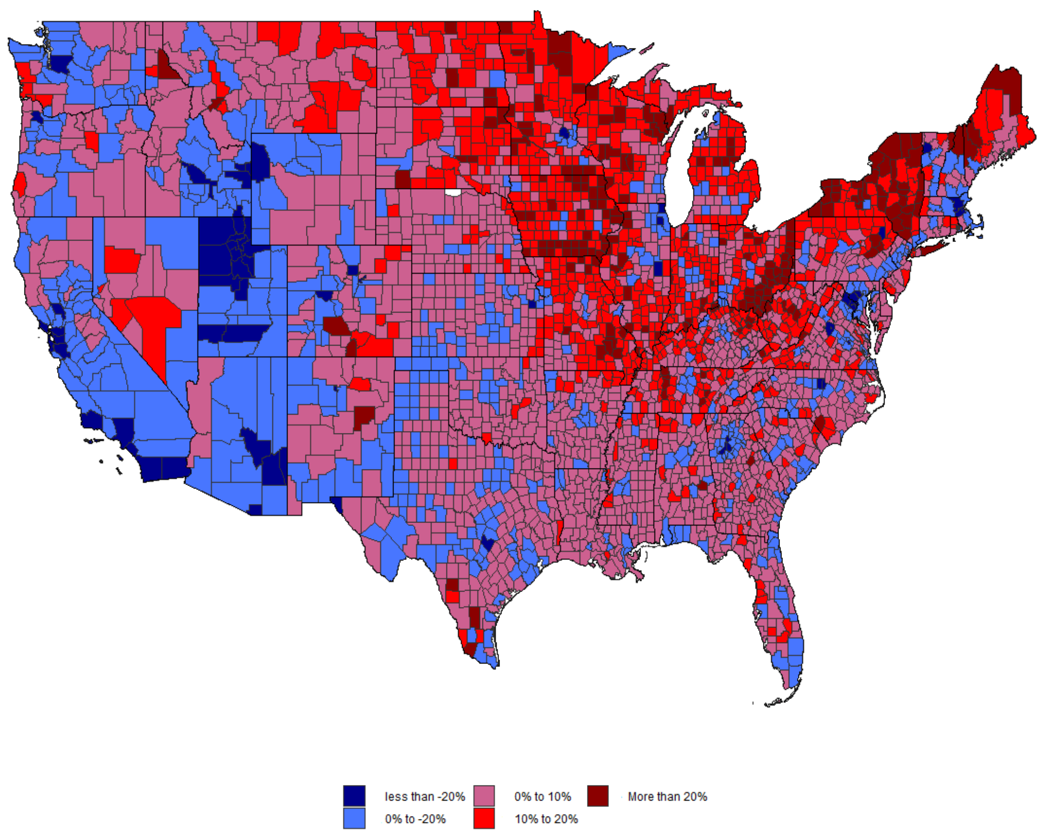

Figure 3: Health Insurance Take-up and Republican Presidential Candidate's Gain in 2016

This figure compares the health insurance take-up rates in counties with where the Republican candidate gained vote share to the counties where the candidate lost vote share. The figure below plots the estimates of β_y and 95% confidence intervals of the following estimation. Black color represents the counties where the Republican candidate gained vote share and gray color represents the counties where Republican lost vote share in 2016 compared to 2012.

$$log(Health\ Insurance\ Take\text{-}up)_{ty} = \sum_y \beta_y \times y + \mu_t + \epsilon_{ty}$$

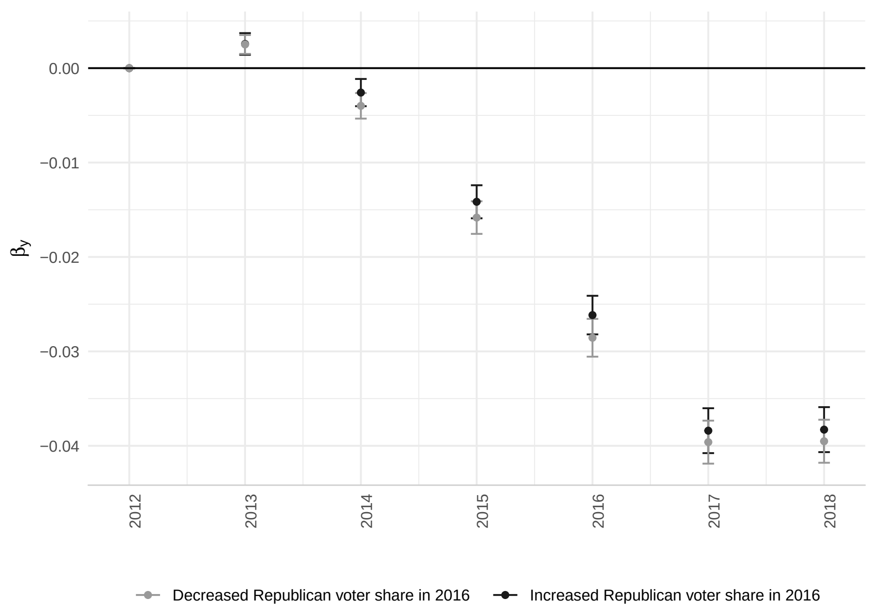

Figure 4: Premium Increases Due to the Biggert-Waters Flood Insurance Reform Act of 2012

This figure plots the estimates of β_y and the corresponding 95% confidence intervals of the following estimation using a policy-year panel. We identified unique properties by matching on a number of characteristics. The subscripts i and y represent the policy and the year respectively. The dummy variable y represents the year. The coefficient β_y captures the difference in the premium in year y relative to the year 2010. Black dots represent policies in SFHA areas and gray dots represent the policies outside the SFHA areas.

$$log(premium)_{iy} = \sum_y \beta_y \times y + \mu_i + \epsilon_{iy}$$

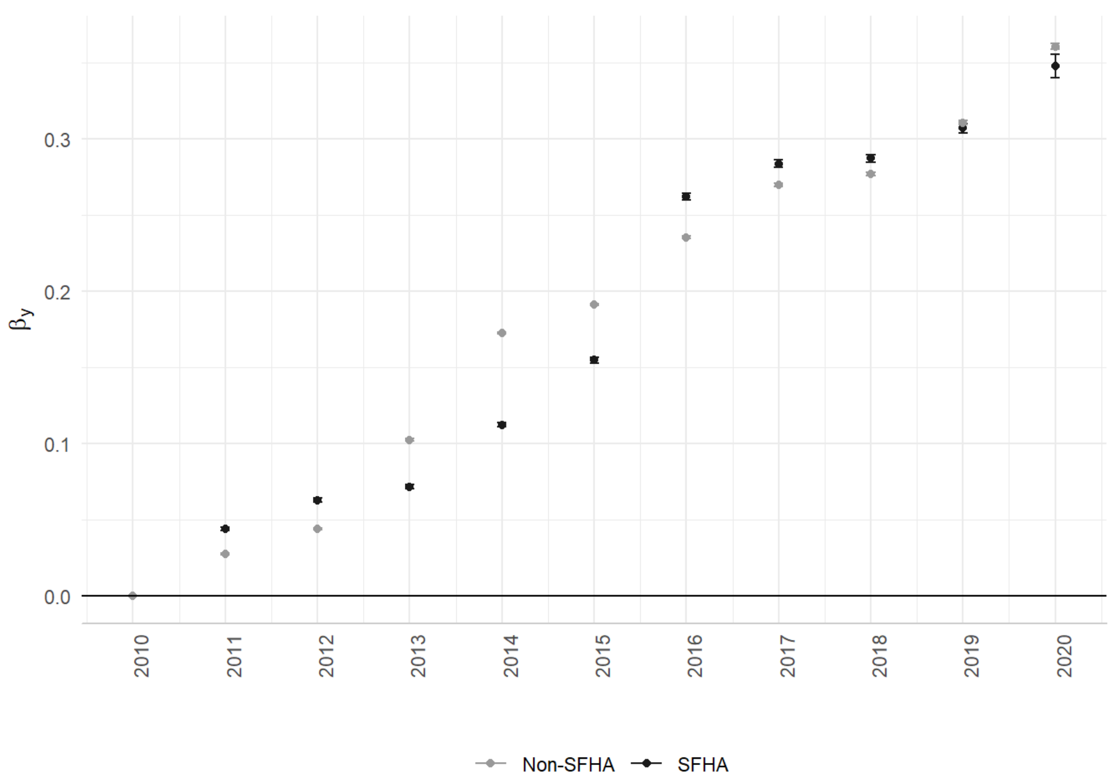

Figure 5: Climate Risk Perceptions and Mortgage Prepayment in SFHA

This figure plots the estimates of β_b in the following estimation using a loan-month panel. Subscripts i,m,t, and y represent the loan, month, census tract and the year respectively. *Prepaid* is a dummy variable that takes the value one if the loan i was prepaid in month m. *SFHA* is a dummy variable that indicates if the underlying property is located inside the SFHA and *Post* indicates if the month m is after year 2012. μ_i and μ_{ty} represent loan fixed-effects and census tract-year fixed effects respectively. The dummy variable b represents the binned percentage of adults in who believe global warming is happening ($Happening \times 100$) where $b_{cy} \in (< 60, 60 - 65, 65 - 70, 70 - 75, > 75)$

$$Prepaid_{im} = \sum_{b} \beta_b \times b \times SFHA \times Post + \mu_i + \mu_{ty} + \epsilon_{im}$$

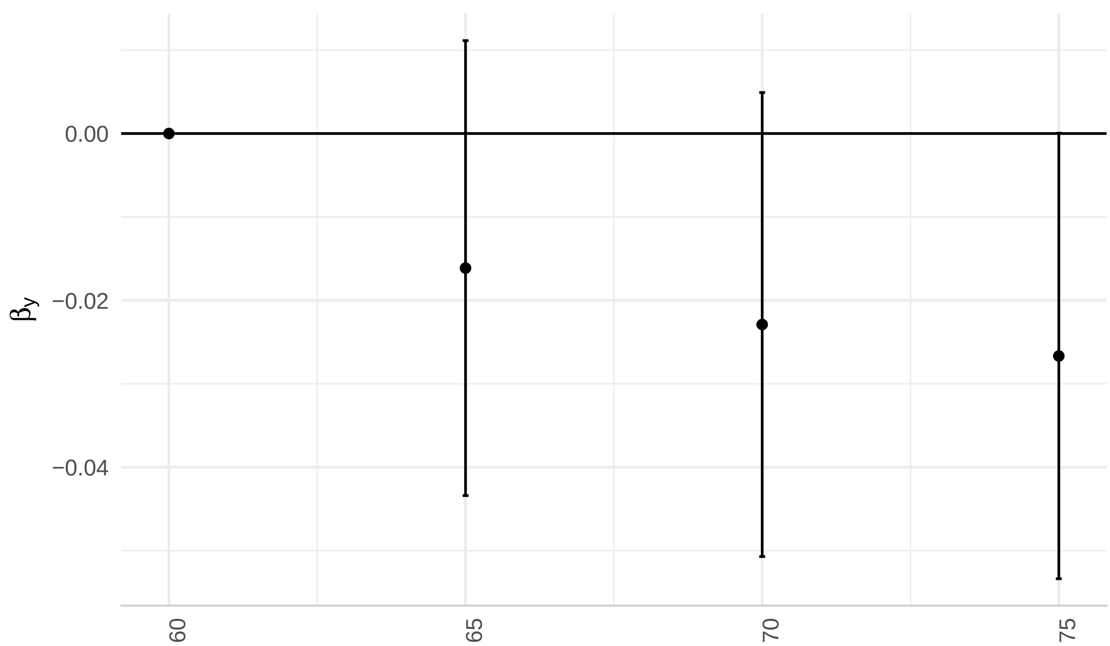

Figure 6: Climate Risk Perceptions and Mortgage Prepayment in SFHA: Skeptical Counties

This figure plots the estimates of β_y in the following estimation using a loan-month panel. Subscripts i,m,t, and y represent the loan, month, census tract and the year respectively. *Prepaid* is a dummy variable that takes the value one if the loan i was prepaid in month m. *SFHA* is a dummy variable that indicates if the underlying property is located inside the SFHA and *Skeptic County* takes the value of one if the fraction of believers in the county is less than 70%. μ_i and μ_{ty} represent loan fixed-effects and census tract-year fixed effects respectively. The dummy variable y represents the year

$$Prepaid_{im} = \sum_y \beta_y \times y \times SFHA \times \text{Skeptic County} + \mu_i + \epsilon_{im}$$

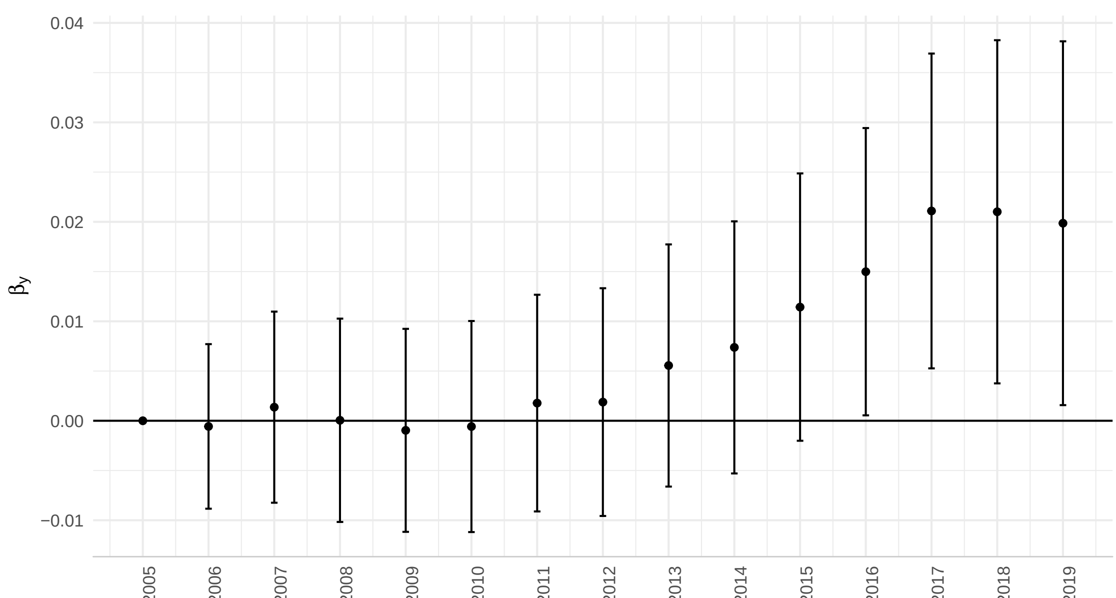

Figure 7: Mortgage Prepayment in SFHA and Political Affiliation

This figure plots the estimates of β_y in the following estimation using a loan-month panel. Subscripts i,m,t, and y represent the loan, month, census tract and the year respectively. *Prepaid* is a dummy variable that takes the value one if the loan i was prepaid in month m. *SFHA* is a dummy variable that indicates if the underlying property is located inside the SFHA and *Republican* takes the value of one if the borrower is a registered Republican. μ_i and μ_{ty} represent loan fixed-effects and census tract-year fixed effects respectively. The dummy variable y represents the year

$$Prepaid_{im} = \sum_y \beta_y \times y \times SFHA \times \text{Republican} + \mu_i + \epsilon_{im}$$

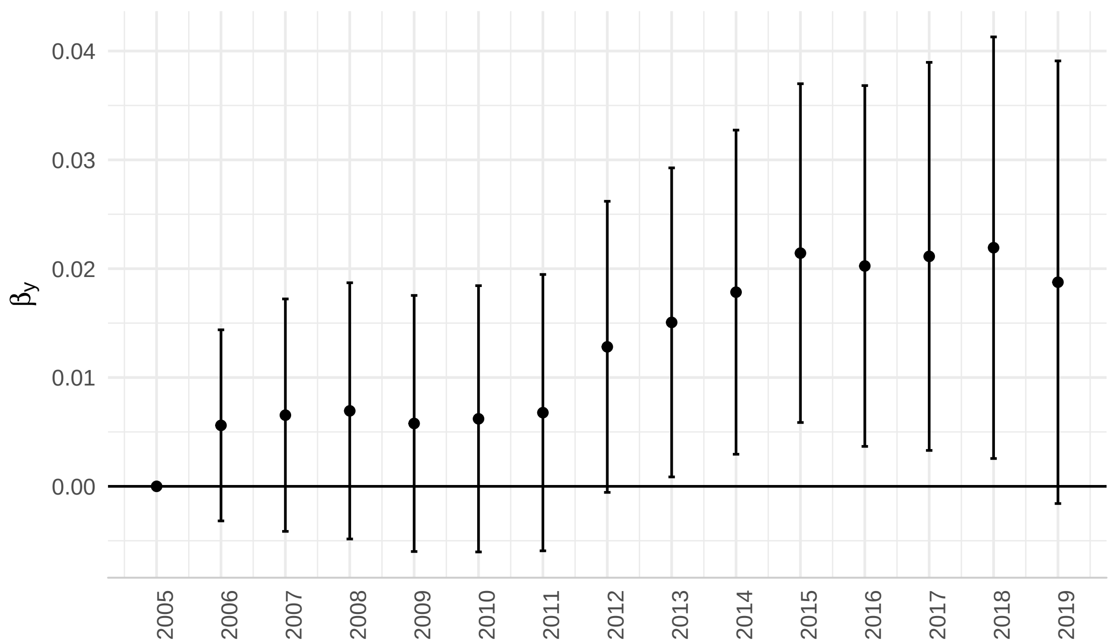

Table 1: Summary Statistics

This table shows sample means and standard deviations of key variables of the samples used in our analysis. Panel A presents the descriptive statistics for variables in non-SFHA census tract-year sample for year 2016. This sample is restricted to 16,735 census tracts with less than 5% SFHA insurance policies and at least 30 flood insurance policies in each year from 2009 to 2018. Panel B presents descriptive statistics for the year 2016 from the SFHA Census Tract-Year panel, which tracks the fraction of SFHA policies in a census tract with contents coverage and maximum deductible. This sample contains 18,642 census tract that contain at least 10 SFHA type policy. Panel C presents the descriptive statistics for 67,610 mortgages that were successfully matched with ZTRAX data and Florida's voter registration data.

Panel A: Non-SFHA Census Tract-Year Panel in 2016

	Mean	**St. Dev.**	**Pctl(25)**	**Median**	**Pctl(75)**	**N**
Flood Insurance						
Policies take-up	0.045	0.062	0.016	0.026	0.047	16,735
Policies take-up (Pop.)	0.020	0.031	0.007	0.012	0.021	16,735
Cost of flood insurance	231	190	139	182	232	16,671
Climate Risk Perception						
Happening	0.696	0.058	0.655	0.698	0.742	16,735
Worried	0.574	0.068	0.523	0.574	0.625	16,735
Personal	0.397	0.053	0.355	0.389	0.438	16,735
Demographics						
Household income	76,102	35,205	51,958	67,108	91,174	16,735
Median age	41	8	35	40	45	16,735
Fraction of white pop.	0.775	0.211	0.694	0.843	0.930	16,735
Frac. of college edu. pop.	0.202	0.056	0.166	0.204	0.240	16,735
Total population	5,213	2,588	3,570	4,801	6,334	16,735
Number of homes	2,242	999	1,598	2,097	2,702	16,735
Frac. of owner occ. homes	0.677	0.191	0.563	0.717	0.824	16,735
Median house age	53	165	28	38	50	16,735
House price	270,986	379,707	122,354	176,270	285,152	13,907

Panel B: SFHA Census Tract-Year Panel in 2016

	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)	N
Flood Insurance						
Policies with contents coverage	0.381	0.235	0.186	0.345	0.555	18,642
Policies with maximum deductible	0.337	0.204	0.175	0.308	0.474	18,642
Cost of flood insurance	867	592	384	886	1,240	18,642
Climate Risk Perception						
Happening	0.692	0.060	0.647	0.693	0.736	18,642
Worried	0.568	0.069	0.517	0.561	0.621	18,642
Personal	0.392	0.053	0.350	0.382	0.427	18,642
Demographics						
Household income	69,870	29,901	50,092	63,064	82,431	18,642
House price	243,953	343,146	116,343	164,115	256,341	15,007
Total population	4,768	2,386	3,208	4,442	5,919	18,642
Number of homes	2,118	983	1,479	1,985	2,585	18,642
Median house age	48	119	30	40	51	18,642
Median age	41	8	36	41	45	18,642
Fraction of white pop.	0.781	0.222	0.699	0.861	0.942	18,642
Frac. of college edu. pop.	0.203	0.055	0.168	0.205	0.239	18,642
Frac. of owner occ. homes	0.666	0.192	0.552	0.708	0.814	18,642

Panel C: Florida Loans Matched with ZTRAX and Voter Registration Data

	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)	N
Mortgage Characteristics						
Prepaid	0.265	0.441	0.000	0.000	1.000	67,610
Property inside SFHA	0.182	0.386	0.000	0.000	0.000	67,610
Loan-to-value ratio	70	24	62	79	80	67,513
Credit score	655	66	611	653	699	65,820
Loan balance	191,860	164,596	99,729	152,636	223,864	67,603
Loan origination	2005.4	1.445	2005	2006	2006	67,610
Climate Risk Perception						
Happening	0.712	0.041	0.687	0.696	0.750	67,610
Worried	0.579	0.054	0.537	0.572	0.648	67,610
Personal	0.411	0.054	0.371	0.399	0.453	67,610
Demographics						
Registered Republican	0.329	0.470	0.000	0.000	1.000	37,103

Table 2: Republican Gain and Climate Risk Perceptions (First Stage)

This table reports the results of the regressions (equation 2) that examine the link between Republican gain in 2016 and climate risk perceptions. The dependent variable in columns (1) and (2) is *Worried*, and the dependent variable in columns (3) and (4) is *Happening* and *Personal*, respectively. Panel A uses the non-SFHA sample, and Panel B SFHA sample. Control variables are supressed in Panel B. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Non-SFHA Sample

	Worried (1)	Worried (2)	Happening (3)	Personal (4)
Worried in 0 to 5* After 2016	-1.427***	-1.387***	-1.208***	-0.905***
	(0.039)	(0.041)	(0.043)	(0.032)
Worried in 5 to 10* After 2016	-1.534***	-1.645***	-1.425***	-0.813***
	(0.047)	(0.055)	(0.057)	(0.041)
Worried gt 10 * After 2016	-2.177***	-2.167***	-1.927***	-1.192***
	(0.053)	(0.058)	(0.059)	(0.045)
log(median_hh_income)		-0.105	-0.001	-0.087
		(0.083)	(0.078)	(0.064)
log(median_age)		0.044	-0.011	-0.05
		(0.194)	(0.182)	(0.144)
log(white_frac)		-0.204**	-0.165**	-0.046
		(0.087)	(0.079)	(0.069)
log(college_frac)		-0.421***	-0.334***	-0.246***
		(0.078)	(0.073)	(0.059)
log(total_population)		-0.292	-0.2	-0.259*
		(0.192)	(0.185)	(0.147)
log(no_of_homes)		-0.142	-0.441*	-0.874***
		(0.270)	(0.251)	(0.211)
log(owner_frac)		-0.458***	-0.317***	-0.261***
		(0.121)	(0.116)	(0.099)
log(lr_cost)		-0.048	-0.057*	-0.017
		(0.037)	(0.035)	(0.027)
log(median_house_age)		0.023*	0.026**	0.030***
		(0.013)	(0.013)	(0.011)
log(house_price)		0.828***	0.859***	0.124
		(0.138)	(0.130)	(0.106)
disaster_1		0.101***	0.149***	0.055***
		(0.020)	(0.018)	(0.013)
disaster_2		0.060***	0.103***	0.151***
		(0.022)	(0.020)	(0.015)
disaster_3		-0.216***	-0.195***	-0.052***
		(0.022)	(0.019)	(0.015)
Census Tract FE	✓	✓	✓	✓
State *Year FE	✓	✓	✓	✓
Observations	116,802	100,265	100,265	100,265
Adjusted R2	0.96	0.962	0.963	0.973

Panel B: Non-SFHA Sample

	Worried (1)	Worried (2)	Happening (3)	Personal (4)
Worried in 0 to 5* After 2016	-1.463***	-1.424***	-1.357***	-1.075***
	(0.035)	(0.038)	(0.042)	(0.029)
Worried in 5 to 10* After 2016	-1.502***	-1.625***	-1.427***	-0.896***
	(0.042)	(0.050)	(0.052)	(0.037)
Worried gt 10 * After 2016	-2.187***	-2.146***	-1.881***	-1.164***
	(0.050)	(0.056)	(0.058)	(0.042)
Controls	✗	✓	✓	✓
Census Tract FE	✓	✓	✓	✓
State *Year FE	✓	✓	✓	✓
Observations	116,802	100,265	100,265	100,265
Adjusted R2	0.96	0.962	0.963	0.973

Table 3: Climate Risk Perceptions and Flood Insurance Take-up (OLS)

This table reports the results of the regressions (equation 1) that examine the link between climate risk perception and flood insurance demand in Non-SFHA areas. The dependent variable is *Take-up Rate*, which is the fraction of homes in a Non-SFHA census tract t in county c and in year y that have flood insurance. The Column (1) does not include any controls except for the fixed effects and Column (2) includes the full set of controls. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Q1-Q2	0.005	0.005
	(0.003)	(0.003)
Q2-Q3	0.009**	0.013***
	(0.004)	(0.004)
gt Q3	0.039***	0.042***
	(0.005)	(0.005)
log(median_hh_income)		0.014
		(0.009)
log(median_age)		-0.001
		(0.018)
log(white_frac)		0.017
		(0.012)
log(college_frac)		-0.019***
		(0.007)
log(total_population)		0.067***
		(0.019)
log(no_of_homes)		-0.353***
		(0.027)
log(owner_frac)		0.040***
		(0.016)
log(lr_cost)		0.013***
		(0.005)
log(median_house_age)		0.001
		(0.002)
log(house_price)		-0.034**
		(0.013)
disaster_1		0.018***
		(0.002)
disaster_2		0.022***
		(0.002)
disaster_3		0.019***
		(0.002)
Census Tract FE		
State * Year FE		
Observations	116,986	100,422
Adjusted R2	0.976	0.976

Table 4: Climate Risk Perceptions and Flood Insurance Take-up (IV Estimation)

This table reports the results of the 2^{nd} stage regression of the IV regression model (equation 2) that examines the relationship between climate risk perceptions and *Take-up* in Non-SFHA areas. Column (1) does not include controls. Columns (2) through (4) employ full set of control. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Take-up Rate			
	(1)	(2)	(3)	(4)
worried	0.045***	0.033***		
	(0.002)	(0.002)		
climatechangereal			0.034***	
			(0.002)	
personal				0.036***
				(0.002)
log(median_hh_income)		0.01	0.007	0.005
		(0.010)	(0.010)	(0.009)
log(median_age)		0.01	0.01	0.015
		(0.020)	(0.020)	(0.019)
log(white_frac)		0.024*	0.022*	0.021*
		(0.013)	(0.012)	(0.012)
log(college_frac)		-0.016*	-0.019**	-0.016**
		(0.008)	(0.008)	(0.008)
log(total_population)		0.074***	0.068***	0.089***
		(0.021)	(0.021)	(0.020)
log(no_of_homes)		-0.348***	-0.335***	-0.319***
		(0.030)	(0.030)	(0.030)
log(owner_frac)		0.069***	0.067***	0.053***
		(0.017)	(0.017)	(0.016)
log(lr_cost)		-0.003	-0.002	-0.002
		(0.005)	(0.005)	(0.005)
log(median_house_age)		-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.002)
log(house_price)		0.040***	0.024**	0.018
		-0.012	-0.011	-0.011
disaster_1		0.025***	0.021***	0.024***
		-0.001	-0.001	-0.001
disaster_2		0.026***	0.021***	0.026***
		-0.002	-0.002	-0.002
disaster_3		0.028***	0.023***	0.030***
		-0.002	-0.002	-0.002
Census tract FE				
State * Year FE				
Cond. F. Stat	779.42	131.33	110.83	95.25
Observations	116,802	100,265	100,265	100,265
Adjusted R2	0.975	0.975	0.975	0.976

Table 5: Climate Risk Perceptions, Contents Coverage and Choice of Deductible in SFHA Areas (OLS)

This table reports the results of the regressions (equation 1) that examine the effect of climate risk perceptions on the fraction of SFHA policies in a census tract with contents coverage (columns (1)-(3)) and maximum deductible (columns (4)-(6)). We report the estimation of equation 1 replacing dummy variables with continuous measures of climate risk perceptions. The sample used for these regressions is the SFHA-Census Tract Panel. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Content coverage		Maximum deductible	
	(1)	(2)	(3)	(4)
worriedcat1. Q1-Q2	0.014*	0.011	-0.016*	-0.021**
	(0.008)	(0.008)	(0.008)	(0.009)
worriedcat2. Q2-Q3	0.016*	0.016*	-0.031***	-0.040***
	(0.009)	(0.009)	(0.009)	(0.010)
worriedcat3. gt Q3	0.023**	0.026**	-0.038***	-0.054***
	(0.011)	(0.012)	(0.012)	(0.013)
log(median_hh_income)		-0.017		0.036**
		(0.014)		(0.016)
log(median_age)		-0.007		0.032
		(0.031)		(0.039)
log(white_frac)		0.006		0.016
		(0.017)		(0.020)
log(college_frac)		0.002		0.015
		(0.013)		(0.015)
log(total_population)		-0.032		-0.04
		(0.030)		(0.037)
log(no_of_homes)		0.067		0.035
		(0.044)		(0.053)
log(owner_frac)		-0.002		-0.018
		(0.025)		(0.026)
log(hr_cost)		-0.134***		0.076***
		(0.011)		(0.015)
log(median_house_age)		-0.004		0.009*
		(0.004)		(0.005)
log(house_price)		-0.021		0.076***
		(0.018)		(0.024)
disaster_1		0.003		-0.005
		(0.004)		(0.004)
disaster_2		0.008**		-0.005
		(0.004)		(0.004)
disaster_3		0.010***		-0.014***
		(0.004)		(0.004)
Census tract FE				
State * Year FE				
Observations	128,153	107,139	128,153	107,139
Adjusted R2	0.929	0.933	0.887	0.892

Table 6: Climate Risk Perceptions and Contents Coverage in SFHA Areas (IV Estimation)

This table reports the results of the 2^{nd} stage regression of the IV regression model (equation 2) that examines the relationship between climate risk perceptions and the Fraction of policies with content coverage in SFHA tracts. Column (1) does not include controls. Columns (2) through (4) employ full set of control. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Frac. Contents			
	(1)	(2)	(3)	(4)
worried	0.041***	0.046***		
	(0.005)	(0.005)		
climatechangereal			0.046***	
			(0.005)	
personal				0.056***
				(0.006)
log(median_hh_income)		-0.01	-0.012	-0.008
		(0.015)	(0.015)	(0.015)
log(median_age)		-0.023	-0.019	-0.04
		(0.034)	(0.034)	(0.033)
log(white_frac)		0.002	-0.001	-0.002
		(0.019)	(0.019)	(0.018)
log(college_frac)		0.01	0.007	0.003
		(0.014)	(0.014)	(0.014)
log(total_population)		-0.090***	-0.102***	-0.090***
		(0.032)	(0.032)	(0.031)
log(no_of_homes)		0.125***	0.148***	0.161***
		(0.046)	(0.046)	(0.046)
log(owner_frac)		0.055**	0.051*	0.049*
		(0.026)	(0.026)	(0.026)
log(lr_cost)		-0.151***	-0.145***	-0.141***
		(0.011)	(0.011)	(0.011)
log(median_house_age)		-0.009**	-0.009**	-0.009**
		(0.004)	(0.004)	(0.004)
log(house_price)		(0.022)	-0.030*	-0.066***
		-0.016	-0.016	-0.017
disaster_1		(0.001)	(0.003)	0.002
		-0.003	-0.003	-0.003
disaster_2		(0.001)	-0.007*	0.002
		-0.003	-0.003	-0.003
disaster_3		0.005*	0.000	0.009***
		-0.003	-0.003	-0.003
Census tract FE				
State * Year FE				
Cond. F. Stat	893.53	122.23	129.79	120.06
Observations	127,891	106,925	106,925	106,925
Adjusted R2	0.865	0.872	0.872	0.874

Table 7: Climate Risk Perceptions and Choice of Deductible in SFHA areas (IV Estimation)

This table reports the results of the 2^{nd} stage regression of the IV regression model (equation 2) that examines the relationship between climate risk perceptions and Fraction of policies with maximum deductible in SFHA areas. Column (1) does not include controls. Columns (2) through (4) employ full set of control. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Frac. Max. Deductible			
	(1)	(2)	(3)	(4)
worried	-0.004	-0.021***		
	(0.004)	(0.004)		
climatechangereal			-0.021***	
			(0.004)	
personal				-0.026***
				(0.005)
log(median_hh_income)		0.018	0.019	0.017
		(0.017)	(0.017)	(0.017)
log(median_age)		0.081**	0.079**	0.089**
		(0.040)	(0.040)	(0.040)
log(white_frac)		0.036	0.037*	0.037*
		(0.022)	(0.022)	(0.022)
log(college_frac)		0.02	0.021	0.023
		(0.016)	(0.016)	(0.016)
log(total_population)		0.085**	0.090**	0.084**
		(0.038)	(0.038)	(0.038)
log(no_of_homes)		-0.019	-0.03	-0.036
		(0.055)	(0.055)	(0.055)
log(owner_frac)		-0.069**	-0.067**	-0.066**
		(0.027)	(0.027)	(0.027)
log(lr_cost)		0.079***	0.076***	0.075***
		(0.016)	(0.016)	(0.016)
log(median_house_age)		0.006	0.006	0.007
		(0.005)	(0.005)	(0.005)
log(house_price)		0.171***	0.174***	0.191***
		-0.022	-0.022	-0.023
disaster_1		0.004	0.005	0.002
		-0.003	-0.003	-0.003
disaster_2		0.023***	0.026***	0.022***
		-0.003	-0.004	-0.003
disaster_3		0.013***	0.015***	0.011***
		-0.003	-0.003	-0.003
Census tract FE				
State * Year FE				
Cond. F. Stat	893.53	122.23	129.79	120.06
Observations	127,891	106,925	106,925	106,925
Adjusted R2	0.845	0.849	0.849	0.85

Table 8: Heterogeneity in Mortgage Prepayment After Biggert-Waters Act

This table reports the results of the regression (equation 6) that examines the relationship between political affiliation and propensity to prepay after the Biggert-Waters Act of 2012. We run the regression separately on four sub-samples of the Florida-Loan Month panel: mortgage balance below $100,000, mortgage balance above $100,000, household income below $50,000, and household income above $50,000. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Mortgage $<$ 100k	Mortgage $\geq$ 100k	Income $<$ 50k	Income $\geq$ 50k
	(1)	(2)	(3)	(4)
Republican×SFHA×Post	0.006	0.001	0.001	0.019**
	(0.005)	(0.001)	(0.006)	(0.008)
SFHA×Post	0.002	-0.0001	-0.004	-0.002
	(0.002)	(0.001)	(0.004)	(0.004)
Republican×Post	0.003*	0.002***	0.005	0.007***
	(0.002)	(0.000)	(0.003)	(0.002)
Loan Age	0.0002***	0.0001***	0.0001***	0.00003
	(0.000)	(0.000)	(0.000)	(0.000)
log(Loan Balance)	-0.011***	-0.005***	-0.020***	-0.027***
	(0.001)	(0.001)	(0.001)	(0.001)
Loan FE	✓	✓	✓	✓
Observations	946,152	2,392,791	987,354	2,271,060
Adjusted R^2	0.961	0.093	0.741	0.823

Table 9: Climate Risk Perceptions and Flood Preparedness

This table reports the results of the regressions that examine the relationship between our measures of climate risk perception and $log(1 + CRS\ Discount)$. We restrict our sample to policies issued by NFIP in "A" flood zones for years 2016 through 2018 in coastal states (Texas to Maine). Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$log(1 + CRS\ Discount)$			
	(1)	(2)	(3)	(4)
log(Happening)	0.218***	0.125***		
	(0.018)	(0.019)		
log(Worried)			0.064***	
			(0.013)	
log(Personal)				0.056***
				(0.011)
log(Household income)	-0.030***	-0.006	-0.006	-0.005
	-0.005	(0.004)	(0.004)	(0.004)
log(Median age)	0.046***	0.023***	0.021***	0.025***
	-0.009	(0.008)	(0.007)	(0.007)
log(House price)	0.015***	0.004	0.005*	0.004
	-0.003	(0.003)	(0.003)	(0.003)
Base flood elevation	-0.00003***	-0.00001***	-0.00001***	-0.00001***
	0	0.000	0.000	0.000
Number of Floors	-0.021***	-0.011***	-0.011***	-0.011***
	-0.001	(0.001)	(0.001)	(0.001)
Elevation difference	0.00000***	0.00000***	0.00000***	0.00000***
	0	0.000	0.000	0.000
log(Cost of Flood Insurance)	-0.031***	-0.023***	-0.023***	-0.023***
	-0.002	(0.001)	(0.001)	(0.001)
Fraction of white pop.	0.023**	-0.001	-0.004	-0.004
	-0.009	(0.009)	(0.009)	(0.009)
Frac. College Degree	-0.047	-0.013	-0.014	-0.008
	-0.029	(0.025)	(0.026)	(0.026)
Frac. of owner occ. homes	0.015*	0.004	0.006	0.004
	-0.008	(0.007)	(0.007)	(0.007)
State FE	✗	✓	✓	✓
Observations	3,929,925	3,929,925	3,929,925	3,929,925
Adjusted R^2	0.224	0.425	0.422	0.423

Table 10: Content Coverage, Choice of Deductible in SFHA and Party Affiliation

This table reports the results of the regressions that examine the relationship between the party affiliation and flood insurance coverage using individual level data. Sample is restricted to only SFHA policies in the Florida-Loan Month panel and the column (1) uses the dummy variable *Contents covered* to indicate if the homeowner has contents coverage as the dependent variable. Column (2) uses the dummy variable *Maximum deductible* as the dependent variable. Standard errors are clustered at census tract level and reported in parentheses below coefficient estimates. We use *,**, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Contents covered (1)	Maximum deductible (2)
Republican	-0.024**	0.019**
	(0.010)	(0.009)
White	0.004	-0.007
	(0.015)	(0.014)
Base flood elevation	0.002	-0.003**
	(0.002)	(0.001)
log(Homeowner's age)	0.047**	-0.021
	(0.023)	(0.019)
log(Age of the house)	-0.01	0.016
	(0.014)	(0.014)
log(Building coverage)	-0.037*	0.035*
	(0.020)	(0.019)
log(Value of the house)	0.039***	-0.009
	(0.010)	(0.011)
log(Time since purchase)	0.027***	-0.049***
	(0.004)	(0.004)
Primary residence	0.015	-0.001
	(0.013)	(0.012)
Owner occupied	0.022	0.027
	(0.048)	(0.035)
Post FIRM construction	0.032*	-0.061***
	(0.019)	(0.020)
log(No of stories)	-0.01	0.025
	(0.018)	(0.019)
Elevation difference	-0.00002	0.0001
	(0.000)	(0.000)
log(Cost of flood insurance)	-0.130***	0.067***
	(0.015)	(0.015)
log(Lot size)	-0.003	0.005
	(0.008)	(0.009)
Bedrooms	-0.004	0.002
	(0.006)	(0.006)
Census tract × Flood zone FE	✓	✓
Year FE	✓	✓
Observations	11,013	11,013
Adjusted R^2	0.207	0.198

A Appendix: Expected Utility of Insurance Purchase

Consider a household who has an initial wealth of w with an expected flood loss of λ with a probability p. Assuming an insurance premium of c and a utility function U the household will purchase flood insurance if:

$$U(w-c) - p \times U(w-\lambda) + (1-p) \times U(w) > 0 \tag{8}$$

To determine the baseline excess utility of purchasing flood insurance, we assume the following:

1. $U(w) = log(w)$; The Constant Relative Risk Aversion (CRRA) utility with a risk aversion parameter of 1
2. $w = \$75,000$; The mean wealth of a U.S. household
3. $\lambda = \$39,850$; The mean flood insurance claim outside SFHA from 2012 to 2018
4. $p = 0.014$; The fraction of policies with claims outside the SFHA from 2012 to 2018
5. $c = \$470$; The mean flood insurance premium

Substituting these values in equation (9) we get a higher utility for purchasing flood insurance compared to not purchasing flood insurance.

The figures below shows how the excess utility of purchasing flood insurance $(U(w-c) - p \times U(w-\lambda) + (1-p) \times U(w))$ vary based on different parameter values. The figures shows that the excess utility from purchasing flood insurance is higher when the wealth is lower, probability estimate of a flood is higher, and the expected losses are higher.