Does Climate Change News Inform Flood Insurance Take-up?

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Abstract

Despite the rising flood risks exacerbated by climate change, the US's flood insurance take-up remains very low. This paper provides novel evidence on whether and how news coverage of climate change affects flood insurance decisions in the US. Our estimates provide robust evidence of an overall increase in the month-over-month growth rate in flood policies to the innovations in the news coverage (i.e., the unforeseen changes in coverage intensity), mainly driven by responses from the non-coastal counties. Sociodemographic heterogeneity in responses is also found. We also pay close attention to confirmation bias and find evidence that media bias instigates behavioral shifts along party lines.

Keywords: Flood Insurance, Climate Change, Media Bias, Confirmation Bias

JEL Codes: D12; D83; G52, Q54

1 Introduction

Floods are the most pervasive and expensive natural disaster in the US. 90% of all natural disasters involve flooding,[1] which has caused destruction to every state and almost every county resulting in colossal losses.[2] Between 2010 and 2018, the average annual loss from flooding was $17 billion.[3] The loss trend is rising as flood risks are exacerbated by a warming and complex climate (Tabari, 2020) coupled with more people and capital moving to flood-prone areas (Tellman et al., 2021). In 2020's climate, the average annual flood loss reaches about $32.1 billion (Wing et al., 2022).

Flood insurance is critical to flood risk management in the face of climate change. In the US, flood insurance has been primarily provided by the federal government through the National Flood Insurance Program (NFIP) since 1968. Despite being heavily subsidized and mandatory for many, the flood insurance take-up is persistently low. Even in high-risk communities, the uptake of flood insurance was only 48.3% in 2019 (Bradt et al., 2021). Over the past two decades, the billion-dollar flood-related events have plunged the NFIP heavily in debt and highlighted the importance of closing the protection gap, which eventually leads to reforms to NFIP to solve its insolvency and meet the rising climate risks sustainably.

The prospect of increased risk of flooding due to climate change also raises two questions: (1) How to effectively raise public awareness of climate risks? (2) How can climate change information elicit behavioral responses (take flood insurance and private flood mitigation)? This paper focuses on flood insurance and provides novel evidence that unforeseen increases in news coverage of climate change can nudge homeowners to purchase insurance to increase their resilience to floods.

The low flood insurance take-up in the US is primarily due to the misperception of risk (Wag-

[1] See FEMA Fact Sheets 2020.

[2] See Natural Resources Defense Council (NRDC) for details.

[3] This estimate is obtained from FEMA's testimony 2020.

ner, 2019).[4] For example, Bakkensen and Barrage (2021) find evidence that 40% of high-risk flood zone residents in Rhode Island have expressed "not at all" worried about flooding over the next ten years, and 60-70% underestimate their flood risks relative to the inundation models. Individuals have been shown to update their flood risk perceptions after disastrous floods or experiencing flood damages, which then translates into higher post-disaster flood insurance take-up (Browne and Hoyt, 2000; Gallagher, 2014; Atreya et al., 2015; Kousky, 2010, 2017). However, the high post-disaster insurance uptake is only temporary; homeowners tend to cancel policies after 2 to 4 non-loss years (Michel-Kerjan, 2010; Michel-Kerjan et al., 2011), suggesting a Bayesian learning process that allows forgetting or incomplete information about past floods (Gallagher, 2014). In contrast, Kousky (2017) argues that the increase in the post-disaster uptake is mainly due to recipients of federal disaster aid being required to purchase flood insurance. Some also find evidence of higher flood insurance take-up in socially connected (through the same media market Gallagher, 2014 or Facebook Hu, 2022; Xu and Box, 2022) but otherwise non-affected regions, suggesting an update of risk belief through social learning. Robinson et al. (2021) demonstrate that flood risk perception can also be raised using a combination of risk communication tools.

To understand the relationship between climate change and flood insurance take-up, Ratnadiwakara and Venugopal (2019) document that flood insurance demand increases with higher perceptions of global warming along extensive and intensive margins. Perceptions of climate change have also been found in other markets to affect market behaviors. For example, Baldauf et al. (2020) show that houses projected to be inundated sell at a discount only in neighborhoods where people believe in climate change. In a similar spirit, Barrage and Furst (2019) find that sea-level rise exposure affects new house investment negatively only in areas with high climate change beliefs. Nevertheless, the evidence provided by Ratnadiwakara and Venugopal (2019) dost not offer insights into dynamic learning about climate

[4] Wagner (2019) argues that adverse selection, public bailout, moral hazard, hassle costs, limited liability, and credit constraints have relatively small contributions to the low take-up.

change, updating beliefs, and changing behaviors accordingly.

The general public acquire information about climate change mainly through mass media (Carvalho, 2010; Schmidt et al., 2013) as lack of immediacy makes climate change beyond most people's life-world experiences (Moser, 2010). In recent decades, media discourse on climate change has become the central focus of research as it is a crucial influencer on public understanding and perception of the issue of climate change (Boykoff, 2008; Sampei and Aoyagi-Usui, 2009; Carvalho, 2010; Nerlich et al., 2010; Moser, 2014; Hart and Feldman, 2014; Ford and King, 2015).[5] For example, considerable research has demonstrated that thematic framing and journalistic norms in media coverage (e.g., Boykoff and Rajan, 2007; Hart and Feldman, 2014; Bolsen and Shapiro, 2017) and partisan media (e.g.,McCright and Dunlap, 2011; Feldman et al., 2017; Carmichael et al., 2017) can shape public attitudes toward climate change.

Research on the individual behavioral response to climate change news coverage is scarce. The study by Engle et al. (2020) is the only one we are aware of that links climate change news to firm-level response. They show that firms can use innovations in newspaper coverage of climate change and global warming dynamically to hedge against long-term climate risks. Our study expands this line of research and provides the first evidence on consumer response to the dynamic climate change news coverage from the insurance market.

We assemble a county-month panel of NFIP policy growth rate and average policy premiums for the contiguous US and a monthly time series of innovations in climate change and global warming news reporting for two national newspapers over six years from 2010 to 2015. We integrate NFIP data with disaster declaration data from FEMA, party affiliation, and

[5]Schmidt et al. (2013) provides an overview of media attention to climate change. A growing body of work has demonstrated that mass media information exposure can affect a wide range of attitudes and behaviors, including climate change. See DellaVigna and Kaplan (2007); Gerber et al. (2009); Enikolopov et al. (2011) on voting, FANG and PERESS (2009); ENGELBERG and PARSONS (2011); Peress (2014); Jiao et al. (2020) on financial market actions, Jensen and Oster (2009) on women's status in India, Simonov et al. (2020) Morrow et al. on compliance with recommendations during the Covid-19 pandemic.

sociodemographics, and geographic controls from the Census and other sources. Our baseline results suggest an overall positive influence of innovations in climate change news on month-over-month (MoM) growth in NFIP policies, which mainly manifests in non-coastal counties.

Given the concern about the partisan coverage and political polarization in public attitude toward climate change (e.g., McCright and Dunlap, 2011; Dunlap et al., 2016), we pay close attention to if and how media bias instigates behavioral shifts along party lines. Specifically, we test for two forms of *confirmation bias*. First, if there exists selective exposure and attention (Frimer et al., 2017) over news outlets by partisanship, i.e., if information from the politically aligned newspaper is preferred and elicits large responses. Second, if people selectively process choice-consistent information more efficiently (Talluri et al., 2018), i.e., if homeowners tend to interpret climate change news that supports their existing decision and reinforces their decisions. Our choice of the two newspaper outlets, the New York Times (NYT) and the Wall Street Journal (WSJ), differ in the political slant of their coverage and the partisan composition of their audiences, with WSJ being more conservative in news coverage (Gentzkow and Shapiro, 2010) and having more conservative audiences (Gentzkow and Shapiro, 2011). Our results show that the MoM growth rate in NFIP policies for Republican and Democrat counties increases with innovations in climate change news regardless of the news outlets as long as innovations reflect the rising climate risks, suggesting the choice-consistent confirmation among the insured. We also provide evidence that Republican counties discount NYT news in flood insurance decision-making, which is consistent with the finding of Carmichael et al. (2017) that Republicans tend to reject opposing information about climate change from liberal media.

We further investigate the heterogeneity in response to news innovation by sociodemographics, as the American public's attitude toward climate change and global warming are also related to gender, race, age, education, and income (McCright and Dunlap, 2011; Egan and Mullin, 2016). Our analyses yield mixed results; while counties with above-median household income have a larger MoM growth rate of PIF, counties with above-median house value and above-median female population appear to have lower growth rates.

The remainder of the paper is organized as follows. Section 2 provides institutional details relevant for understanding flood insurance in the US. Section 3 presents hypotheses and the empirical framework. Section 4 describes the data collection and cleaning process. Section 5 presents and discusses the main findings, 6 concludes.

2 Flood Insurance in the United States

In the United States, standard home insurance policies do not cover flooding damages, but floods account for over 90% of natural disasters and cause more damage than wildfires, tornadoes, and earthquakes combined (Wagner, 2019).

Private flood insurers provided flood insurance between 1895 and 1927 but retreated from the market after the devastating 1927 Mississippi River flood (Knowles and Kunreuther, 2014). Flood insurance had become unavailable to U.S. homeowners for four decades since.

To reduce flood damage and protect homeowners, the National Flood Insurance Program (NFIP) was finally successfully established in 1968 by Congress and has been the dominant insurer for flooding since its inception.

The NFIP is based on a voluntary partnership between the federal government and the local communities. The Federal Emergency Management Agency (FEMA) will provide federally backed flood insurance to homeowners in a participating community if that community joins the program and regulates development in their mapped floodplains to at least the minimum NFIP criteria. Homeowners of 1-4 family dwellings[6] can purchase up to $250,000

[6] FEMA defines dwelling as a building designed for use as a residence for no more than 4 families or a single-family unit in building under a condominium form of ownership. https://www.fema.gov/flood-insurance/terminology-index

and \$100,000 of building and content coverage, respectively. Residential buildings with 5 or more units have a maximum of \$500,000 and \$100,000 in building and content coverage.[7] Building coverage and content coverage are purchased separately.

Overseen by FEMA housed within the Department of Homeland Security (DHS)[8], NFIP underwrites over 5.1 million (about 90-95% of) residential flood policies in over 22,100 communities and provides \$1.25 trillion of content and building coverage today (Kousky, 2018).[9]

FEMA is also responsible for identifying and mapping community-level flood risks. A Flood Insurance Rate Map (FIRM) is the most common map, and most participating communities have it. A Flood Insurance Rate Map (FIRM) is an official map of a community that shows the high-risk, moderate-to-low-risk, and undetermined-risk zones. High-risk zones are the Special Flood Hazard Areas (SFHAs), or the 1 percent annual chance floodplains (100-year floodplains). The moderate-to-low risks are known as the non-SFHAs. Depending on the risk from wave action, areas in the SFHAs are categorized into A zones and V zones which are also at risk from wave action (usually coastal areas). Homeowners in the SFHAs with mortgages from federally-backed or federally-regulated lenders must purchase flood insurance. The mandatory purchase requirement is implemented by lenders instead of FEMA; yet, the implementation has been proved challenging.[10] As of 2019, insurance take-up in SFHAs was only 48.3% in 2019, and 2.2% in non-SFHA where purchase is voluntary (Bradt et al., 2021).

NFIP premium base rates are based on FIRM zones and whether a building was built pre-FIRM or post-FIRM, and are adjusted for other factors such as whether the house has a basement and its elevation rating.[11] 80% of all NFIP policies pay full-risk premiums and

[7] This information is obtained from FEMA website.

[8] The program was originally administered by the Federal Insurance Administration (FIA) which was in the Department of Housing and Urban Development (HUD).

[9] Also see FEMA NFIP Fact Sheet.

[10] https://sgp.fas.org/crs/homesec/R44593.pdf

[11] Please see FEMA rate table, 2021 for more details.

20%, mainly pre-FIRM properties, pay subsidized rates.[12] According to Government Accountability Office (GAO), as of 2010, the average annual subsidized premium was $1,121, representing 40-45% of the full-risk price.[13] In July 2012, Congress passed the Biggert-Waters Flood Insurance Reform Act of 2012 (BW-12) to eliminate subsidized rates on certain properties and put all pre-FIRM properties on a gliding path (a maximum of 25% annual increase) to full-risk rates beginning in 2013, which lead to public outcry. In March 2014, Congress passed the Homeowner Flood Insurance Affordability Act (HFIAA), which slowed the phase-out pace for most primary residences with a minimum and maximum annual phaseout rates of 5%-18%. As of 2019, the average annual NFIP flood insurance cost was $700.[14]

A new NFIP policy typically takes 30 days from purchase to become effective.[15] FEMA's Standard Flood Insurance Policy (SFIP) for residential buildings is a single-peril policy and has a one-year policy term. All policies expire at 12:01 am on the last day of the effective term, but policyholders remain covered for 30 days after the expiration date. NFIP must issue a renewal notice 45 days before the policy's expiration date by first-class mail to all parties listed on the policy, including policyholders, agents, and lenders, and a final notice on the expiration date.[16] To renew without a lapse in coverage, insurers must receive the premium within 30 days after expiration. Hence, homeowners decide whether to purchase or renew flood insurance every policy year.

3 Hypotheses and Empirical Model

This section presents the hypotheses and empirical approach we employ to analyze changes in aggregate demand for flood insurance along the extensive margin with changes in newspaper

[12] See FEMA.

[13] See GAO: Flood Insurance: Public Policy Goals Provide a Framework for Reform, GAO-11-670T.

[14] The estimate is from FEMA Historical Flood Risk and Costs.

[15] There are 3 exceptions. Please see NFIP Flood Insurance Manual for details.

[16] For further details, please see NFIP Manual.

coverage of climate change and global warming (CC) news.

3.1 Flood Insurance Decision Making

We start by defining our outcome of interest, the month-over-month (MoM) growth rate in policies-in-force (PIF). Common choices of response variable in flood insurance studies include take-up rates and the logarithm of PIF. However, as we are tracking changes in active policies at high frequency, a more reasonable candidate would be the growth rate.

There is no standard definition of PIF (Bradt et al., 2021). We quantify policies being "in force" in a given month m if they remain in effect at the end of that month. We count the number of PIF by county-month (c, m) and approximate the MoM growth rate as follows:

$$\text{MoM PIF}_{c,m} = \Delta log(PIF_{c,m}) := log(PIF_{c,m}) - log(PIF_{c,m-1}) \tag{1}$$

If a policy is in force for two consecutive months $m-1$ and m, it does not cause changes to the monthly growth rate of PIF. Policies that propel changes in the MoM growth rate are new policies that became effective or policies that were terminated in month m. Due to the 30-day waiting period, a new policy that takes effect in month m must be purchased no later than the first day of that month, except February. Hence we assume that the decision to purchase a new policy is made in month $m-1$.

For a policy to cease to be effective, it is either expired or cancelled. As mentioned in section 2, insurers must send a renewal notice for payment 45 days before a policy's expiration date and a final notice on the expiration date. The decision not to renew can be made anytime, we assume it was made between the renewal date and expiration date. Although an NFIP policy can be terminated mid-term or full-term by cancellation or full-term by nullification, it cannot be done as easily as a home policy and must provide a valid reason outlined by FEMA. The cancellation effective date varies by valid cancellation reasons but usually differs from the requested date. For simplicity, we assume if a policy ceased to be effective in month m either due to expiration or cancellation, the decision was made in month $m-1$.

Each month, homeowners decide to purchase, renew or terminate a policy, with outcomes observed after the 30-day waiting period (i.e., next month). We rely on previous research to underpin factors that affect demand for flood insurance. The literature has established that demand for flood insurance is affected by the price of flood insurance, flood zone, coastal location, past flood experiences, income, age, education level, race, and subjective flood risk perception (e.g.,Browne and Hoyt, 2000; Atreya et al., 2015; Brody et al., 2016; Bradt et al., 2021). Subjective risk perception has been shown to be updated after the realization of local floods (Gallagher, 2014; Atreya et al., 2015; Kousky, 2018) and learning from floods experienced by social peers (Gallagher, 2014; Hu, 2022; Xu and Box, 2022).

As mentioned in section 1, mass media is where most people obtain climate-related information, and traditional news reporting remains the dominant platform (Chinn et al., 2020). Media coverage has also played an important role in shifting public attitude about climate change, with the frequency of coverage matters more than the contents (Brulle et al., 2012). Repeated coverage makes climate change more salient; however, individuals might get used to the "new normal" of the issue as Moore et al. (2019) show that people tend to normalize the extreme weather events caused by climate change and underrate the risks of climate change, known as the "boiling frog" effect. If that is the case, an unexpected increase in news coverage might again highlight the rising climate risks to the public. Acknowledging the "boiling frog" phenomenon, we hypothesize that innovations in climate change news coverage (i.e., the unpredicted changes in the proportion of news articles on these topics) in national newspapers act like the boiling water to make people jump and edge them to take insurance.

3.2 Baseline

Aggregating observed policies to county level, we test the hypothesis that MoM growth in PIF increases with CC news innovations by the following fixed effects model:

$$MoM\ PIF_{c,m+1} = \alpha_c + \beta * Innovation_m + \boldsymbol{X^1_{c,m}}'\boldsymbol{\gamma} + \boldsymbol{X^2_{c,y}}'\boldsymbol{\delta} + \theta_y + \lambda_{s,m} + \varepsilon_{c,m}, \tag{2}$$

where c represents county, m indicates month, and y the year. *Innovations* are unexpected changes in CC news coverage. $\boldsymbol{X^1}$ is a set of observable factors that vary by county-month, including the average of policy premium and flood-related events in the past 6 months. $\boldsymbol{X^2}$ is a set of socioeconomic and household characteristics of county c that varies by year. Year fixed effects θ_y control for national random shocks (e.g., NFIP reforms) that could affect demand for flood insurance. State-by-month fixed effects $\lambda_{s,m}$ capture the unobserved state specific time shocks (e.g., state regulations). α_c indicates county fixed effect, which absorbs time-invariant county-level heterogeneity (e.g., flood zone, coastal location).[17]

β is the coefficient of interest. It is the estimate of the news innovation on the MoM growth in PIF. With the "boiling water" assumption, an unpredicted change in news coverage calls attention to rising climate risks and increases homeowners' beliefs about climate-triggered flood risks hence flood insurance demand; the model predicts $\beta > 0$.

Flood insurance uptake is higher in coastal communities, likely due to storm surges and tidal flooding risks (Bradt et al., 2021). According to Landry and Turner (2020), most coastal residents expect worse coastal storms and hazards in the future. Hence, it is plausible that people in coastal regions are less sensitive and reactive to CC news than non-coastal residents, given their already higher risk perceptions. On the contrary, although inland flooding creates a massive threat to properties across the US, this risk is overlooked by most inland residents. For this reason, we estimate equation (2) separately for coastal and

[17]We also used a more restrictive specification with county-specific time trend.

non-coastal counties and expect $\beta_{Coastal} < \beta_{non\text{-}Coastal}$. On the other hand, since mandatory purchase requirement applies to some properties in SFHAs, we might same news coverage on climate change have less effect on the extensive margin flood insurance demand in SFHAs. For this reason, we also estimate equation (2) separately for SFHA and Non-SFHA policies across counties and expect a higher PIF growth to news innovations for voluntary purchases, i.e., $\beta_{SFHA} < \beta_{non\text{-}SFHA}$.

3.3 Confirmation Bias

In the section, we pay attention to whether political ideology shapes how individuals interpret partisan media coverage of climate change and affects their flood insurance decisions in return.

Previous studies have found that climate change news coverage in the US is politicized and polarized; more conservative news outlets tend to have a more suspicious mind about climate change and spread doubt about the reality of climate change among their largely conservative audiences (McCright and Dunlap, 2011; Feldman et al., 2017; Carmichael et al., 2017).[18] Over the years, news coverage on climate change has become increasingly politicized and polarized in major US newspapers (Chinn et al., 2020), paralleled by heightened partisan polarization in the American public's views of climate change and global warming (McCright and Dunlap, 2011; Dunlap et al., 2016), with Democrats more likely than Republicans to believe anthropogenic climate change and support policies to address it (Chinn et al., 2020). In addition, Carmichael et al. (2017) find that partisan media strengthens the views of like-minded audiences, and Republicans tend to reject opposing information about climate change from liberal media. These findings demonstrate what psychology and cognitive science call "confirmation bias", that is, people tend to seek or intercept information that is in line with

[18] It has long been established that news outlets in the US differ in the political slant of their coverage and audience's partisan composition (Gentzkow and Shapiro, 2010, 2011; Groseclose and Milyo, 2005).

their pre-existing beliefs (Nickerson, 1997).

In our context, the effect of confirmation bias may surface in 2 forms. First, it manifests in the form of selective exposure and attention; individuals tend to selectively expose themselves to belief-confirming information and ignore or give little attention to belief-conflicting information Frimer et al. (2017). Second, it can also manifest as selectively processing choice-consistent information more efficiently Talluri et al. (2018).

To investigate whether there is evidence that flood insurance decisions are affected by confirmation bias depicted by their political ideology, we start with the following specification at the county level:

$$\begin{aligned} MoM\ PIF_{c,\,m+1} = \alpha_c + \beta_a * Innovation\,Aligned_{c,\,m} + \beta_{na} * Innovation\,Non\text{-}Aligned_{c,\,m} \\ + \boldsymbol{X^1_{c,\,m}}'\boldsymbol{\gamma} + \boldsymbol{X^2_{c,\,y}}'\boldsymbol{\delta} + \theta_y + \lambda_{s,\,m} + \varepsilon_{c,\,m}, \end{aligned} \tag{3}$$

where *Innovation Aligned* represents CC news innovations from politically aligned (i.e., same political slant) newspapers. *Innovation Non-Aligned* indications innovations from the newspaper of opposite partisan slant. For example, innovations from "Republican-leaning" news outlets are aligned with Republican counties and non-aligned with Democratic counties, whereas innovations from "Democrat-leaning" news outlets are aligned with Democratic counties and non-aligned with Republican counties.

Under selective exposure and attention, little attention will be given to the opposing frame when presented with news from both political media frames; hence, we expect β_{na} to be statically insignificant.

However, given that those who do not participate in the flood insurance market are not observable in the NFIP dataset, the choice-consistent information selection would suggest that as long as the information conveyed in the news acknowledge the rising climate risks and their impacts, the insured will respond positively to the information. In this case, we would expect both β_a and β_{na} to be positive, and $\beta_a > \beta_{na}$.

To further analyze whether Republican audiences are more likely to reject opposing information about CC from liberal media (Carmichael et al., 2017), we re-estimate Equation 3 by interacting innovations with county partisanship. If there is evidence that Republicans reject or have a negative attitude towards Democrat-leaning news media, we expect $\beta_{na} < 0$ for Republican counties.

3.4 Sociodemographic Heterogeneity

In addition to partisanship, researchers have shown that gender, race, age, education, and income also predict attitudes towards climate change and global warming(McCright and Dunlap, 2011; Egan and Mullin, 2016). For example, McCright and Dunlap (2011) show that while females and whites are more likely to report beliefs consistent with scientific consensus, it is females and non-whites who show greater concerns about global warming; people with higher income or higher educational attainment are more likely to believe in global warming but less likely to concern about the issue. Hence, we explore whether and how heterogeneity in climate attitudes born by sociodemographic factors manifests into flood insurance decisions by interacting sociodemographic characteristics with CC news innovation in equations (2) and (3).

4 Data

The analysis in this paper relies on data assembled from various sources. Below, we outline the structure of these datasets and the construction of our variables of interest.

4.1 Climate Change and Global Warming News

To track media coverage of climate change and global warming, we focus on two national newspaper, the New York Times (NYT) and the Wall Street Journal (WSJ). As mentioned in section 1, NYT and WSJ differ in the political slant of their coverage and the partisan composition of their audiences, with WSJ being more conservative in news coverage and having more conservative audiences (Gentzkow and Shapiro, 2011).

4.1.1 The New York Times Climate Change News Index

Global News Index and Extracted Features Repository (GNI) serves as our data source for obtaining news articles published in the NYT from Jan 1, 2009, to Dec 31, 2015. We used the Bulk LexisNexis portion of the GNI exclusively and employed keyword query method to gather news articles that contain "climate change" or "global warming" in their titles.[19] The keyword query we used specifies that the two words in quotation marks can only be at most one word apart from one another so that titles that contain phrases such as "climate is changing" and "changing climate" will also be extracted. In order to measure the coverage intensity of climate change and global warming, we also downloaded all news articles from the NYT that were available on GNI during the sample period. After removing apparent duplication, we counted articles to year-month level for both the full dataset and the climate-related dataset. We construct the NYT CC new index as monthly coverage intensity by dividing the number of news articles that contain the keywords in their titles in month m by the total number of news in month m.

$$\text{CC Intensity}_m = \frac{\#\text{ of titles containing climate change or global warming}_m}{\text{total }\#\text{ of articles}_m} \tag{4}$$

[19] Ideally, we should have filtered through headlines as evidence has shown that media audiences pay attention to salient news in an information-rich environment (Falkinger, 2008). Giving the data available to us does not provide a means to identify headlines or front-page articles; filtering through titles became the second-best option.

In terms of data quality, we compared our NYT dataset with the NYT dataset also extracted from GNI by Althaus et al. (2021). The authors show an average of 1.4% of total weekly coverage in climate change or global warming topics from 1977 to 2019, with a 4% weekly coverage in 2019. Our dataset shows a comparable average of 1.6% weekly coverage from 2009 to 2015 (Fig. 1).[20]

4.1.2 The Wall Street Journal Climate Change News Index

GNI's WSJ Corpus comprises only historical articles from 1945 to 2006. Consequently, we use the WSJ CC index from Engle et al. (2020). The authors first construct their climate change vocabulary (CCV) from a corpus of 74 authoritative documents, including 19 climate change white papers and 55 climate change glossaries. The "term frequency-inverse document frequency" (TF-IDF) method is then used to quantify the intensity of climate change news coverage in the WSJ by comparing news contents with CCV.[21] According to the authors, their WSJ CC news index associates increased climate change reporting with news about elevated climate risk.

There are two reasons why we opt for the straightforward measure of NYT coverage intensity. Firstly, we do not have access to the actual article contents due to data limitations, making it impossible to implement the TF-IDF method. Secondly, Althaus et al. (2021) find little added value from using more extensive items on top of the combination of either "climate change" or "global warming" in terms of climate change communication. Therefore, we settle on two keywords and the simple article frequency count.

[20] 2012 is a leap year with 366 days; other years in our sample period (2019-2015) all have 365 days each. As a result, there are 2556 days in total in the sample. The NYT dataset (without keyword query) contains news articles from each of the 2556 days. We also extracted daily news articles from the Washington Post (WP) initially. However, the WP dataset contains only news from 375 days throughout the 7-year sample period. Hence, we did not proceed with the WP dataset.

[21] Rare terms in a given news article and common terms that appear in most news articles will have low TF and low IDF scores, respectively, which result in low TF-IDF scores. Terms with high frequency in a given article but with an overall low frequency among all articles will have high TF-IDF scores.

4.2 Climate Change News Innovations

As explained in section 3, we assume that innovation of news coverage is the "boiling water" that makes people jump. Engle et al. (2020) measure innovations from a first-order autoregressive (AR1) model. Innovations are the residuals of the AR (1) model. We follow the same procedure to construct NYT CC news innovations by estimating the simple linear AR (1) model below:

$$\text{CC Intensity}_m = \alpha + \rho \text{CC Intensity}_{m-1} + \varepsilon_m, \tag{5}$$

where ρ estimates how predictable the coverage intensity of CC news in each month is by the previous month. ε_m is innovation residual, which is the part of CC Intensity$_m$ that its lagged value cannot predict; hence, it brings new information to the evolution of coverage intensity.

Fig. 2 shows the time series of NYT and WSJ climate change news indices and innovations. Note that NYT indices are one order of magnitude smaller than WSJ indices, which we believe is mainly due to our restriction on using only articles with specified keywords in their titles. For the magnitudes of innovations to be interpretable and comparable across news outlets, we scale NYT indices by 10,000 and WSJ by 1,000.

4.3 Flood Insurance Policy

We obtain data on flood insurance policies purchased through the NFIP from FEMA's Open Data Initiative.[22] NFIP policies issued since 2009 is available on OpenFEMA. There is a substantial discrepancy between number of policies in 2009 and later years; consequently, in the main analysis we focus on five years of cross-county single-family residential NFIP policies in the contiguous US prior to the 2016 Atlantic hurricane season: January 1, 2010,

[22]NFIP policies were downloaded via FEMA's read-only Application Programming Interface (API) based access at OpenFEMA Dataset: FIMA NFIP Redacted Policies - v1 in June 2021.

to December 31, 2015.

The initial sample downloaded contains 33,976,088 individual NFIP policies issued from 2009 to 2015. We restrict the sample to single-family residences in the contiguous US. The maximum allowable building and content coverage for single-family dwellings are \$250,000 and \$100,000. Policies with building and content coverage exceeding their maximum allowable amounts are excluded. Policies with total coverage less than or equal to zero are also removed. NFIP policy data contains refunds; hence policies with negative total premium are dropped. Following Bradt et al. (2021), we also leave out policies whose premiums do not align with FEMA's rate schedule by trimming policies with less than the first and greater than the ninety-ninth percentile of all premiums issued in the same year. The screening process reduces the sample size to 27,712,009. Further details are available in Appendix A.

As defined in section 3, we quantify policies being "in force" in a given month m if they take effect before the first day of month $m+1$ and terminate after the last day of month m. For each county-month, we aggregate PIFs and take the average premiums of PIFs. After calculating MoM growth in PIFs, we drop observations in 2009, which results in 216,432 county-month observations from January 2010 to December 2015.

In light of the potential disparities in designated flood zones mentioned in section 3.2, we also count SFHA and non-SFHA PIFs for each county-month and compute MoM growth as well as the average premiums. Policies in zones "A" and "V" are in SFHAs.

4.4 Flood Experience, Coastal and Sociodemographic Variables

To capture prior flood experiences, we count each county's previous exposure to flooding, measured as the total number of flooded-related federal disaster declarations in the past six months.[23]

Acknowledging counties direct adjacent to oceans bear more risk from coastal hazards, we use NOAA's shoreline counties as another control for coastal risk.[24]

Finally, we incorporate county-based majority political partisanship, measured by the 2012 presidential election result sourced from MIT Election Data and Science Lab,[25] as well as a set of sociodemographic and household characteristics from the American Community Survey (ACS) 5-Year Data for each county-year in our sample. From the ACS, we use the median household income, median house value, the percentage of households with a mortgage, the percentage of population that is non-white, the percentage of population that is under 35, the percentage of population with a college degree or higher, the percentage of population that is female, and total population.

Assembling all of the county-level data listed above results in a final count of 216,360 observations from 2010 to 2015, with 3005 counties.

Table 1 lists the definitions of the dependent variable and the explanatory variables as well as their frequency of measurement. Table 2 provides the summary statistics of these variables.

5 Empirical Results

5.1 Baseline

Baseline estimates of NYT and WSJ innovations are in Table 4, Panels A (NYT) and B (WSJ). Note that although some studies document that while NYT is more likely to accept

[23]The source for flooded-related federal disaster declarations is OpenFEMA Dataset: Disaster Declarations Summaries - v2.

[24]Data is downloaded from Decadal Demographic Trends for US Coastal Shoreline Counties

[25]County Presidential Election Returns 2000-2020

anthropogenic climate change and call for action, WSJ is less likely to discuss the impacts and threats posed by climate change, to frame climate change in terms of adverse economic effects but more likely to highlight the negative economic consequences of taking actions (Feldman et al., 2017), the WSJ CC news index constructed by Engle et al. (2020) associates increased climate change reporting with news about elevated climate risk.

Column 1 reports estimates based on the whole sample. Both panels indicate PIF growth rate increases with CC news innovations; a unit increase in NYT CC news innovation increases PIF MoM growth rates by 0.007 percentage points (ppts), while a unit increase in WSJ CC news innovation increases PIF growth rates by 0.0331 ppts. As mentioned above, NYT innovations are one order of magnitude smaller than WSJ innovations by construction. Hence, caution should be taken when comparing their effect sizes. If we are willing to assume that every one out of ten news CC articles will contain "global warming" or "climate change" in its title, the effect sizes would be within the same order of magnitude.

As we move to columns 2-5, we restrict to the subsample of non-coastal counties, coastal counties, SFHA policies, and non-SFHA policies. Table 3 summarizes raw PIFs by subsample. Overall about 1205 NFIP policies are in force each month at the county level, but with significant disparities between coastal (7390 PIFs) and non-coastal counties (352 PIFs). Average PIF in coastal counties is almost 21 times larger than in non-coastal counties, partially due to the dense population residing in coastal areas. Hence we also present the take-up rate, which is the number of policies divided by housing units. Coastal counties' overall county-month take-up rate is 7.51%, compared to 1.06% in non-coastal counties. With these raw comparisons, our model will predict a larger response to CC innovations for non-coastal counties. Comparing columns 2-5 in Panels A and B of Table 4, it is clear that responses to CC innovations are mainly from the non-coastal counties and non-SFHA policies, as expected.

It is also clear from the baseline estimation that the MoM growth of PIF decreases with premium (though not statistically significant in most specifications) and increases with flood-related presidential disaster declarations (PDDs) in the past half-year. On average, one more PDD in the past six months increases the MoM growth by 0.263 ppts. The effect of past PDDs is most prominent for the voluntary segment of the NFIP, i.e., non-SFHA policies (0.568 ppts), and not statistically different from zero for SFHA policies, consistent with previous literature (Petrolia et al., 2013).

5.2 Confirmation Bias

We now proceed to estimate Equation (3). Estimation results are presented in Table 4, Panel C. Consistent across columns, results show that the MoM growth rate increases with aligned and non-aligned innovations; differences in effect sizes are not statistically different from zero. With the presumption that both series of innovations associate news reports on rising climate risks, our results provide at least some support for the choice-consistent selection mechanism.

Table 5 provides further evidence on how political ideology shapes the interpretation of partisan news coverage by re-estimating Equation (3) with county's partisanship interacted with aligned and non-aligned innovations. Results indicate that Republican counties tend to respond more to news on elevated climate risks from Republic-leaning news media and relatively less Democrat-leaning news media, supporting the observation by Carmichael et al. (2017) as mentioned in section 3.3.

The comparison between Democrat and Republican responses to WSJ innovations shows that not only Democrat counties respond to WSJ coverage but also react more than Republican counties. This finding contracts the observation by Carmichael et al. (2017) that *"Democrats are significantly more concerned about climate change when coverage of the issue increases in the NYT but are not affected by coverage in the WSJ"*.

5.3 Sociodemographic Heterogeneity

The above analysis show some evidence of heterogeneity in response to CC news coverage for political ideology. Next, we explore possible disparities born by sociodemographic characteristics. Table 6 presents the results for some relevant characteristics; counties with a higher than median female population or higher than median house values have a relatively smaller increase in their MoM growth of PIFs to CC news innovations, while counties with higher than median household income respond more to innovations.

6 Conclusion

This paper presents novel evidence on how unexpected changes in the news coverage (i.e., innovations) of climate change can be used to increase flood insurance demand on an extensive margin, highlighting the interaction between political ideology and partisan coverage. Our results shed light on how to communicate with the public about climate change effectively and utilize news coverage dynamically to insurance the rising climate risks.

Consistent across all model specifications, innovations in CC news increase the average MoM growth rate of PIF. The effect is mainly manifested in non-coastal counties, where inland flooding poses a massive threat. While both parties respond positively to news coverage on climate change, the effect size is larger for Democratic counties. In addition, there is evidence that Republicans are not as responsive as Democrats when the news is from the media that lean more to the opposite side of the political spectrum.

Our study shed light on how to utilize news coverage of climate change dynamically to encourage flood insurance take-up in the face of climate risks and provides the incentive to close the belief gap in climate change instilled by political ideology to close the resulted response gap.

Our analysis provides several exciting directions for future research. First, it would be interesting to distinguish between positive and negative news on climate change. One would expect negative reporting on climate change spread doubt and dissuade people from taking mitigations. For example, housing media sentiment has been shown by Soo (2015) to have significant predictive power of future housing prices. More research is needed to explore the content, sentiment, and tone of media coverage of climate change on individuals' risk mitigations. Our analysis focus on traditional print media. Since social networks, such as Facebook, Twitter, and Instagram, are where breaking news and media hypes spread Roese (2018). A natural and exciting extension to the current work is investigating how the public's decision on disaster insurance or mitigation reacts to social media's coverage of climate change and global warming over time.

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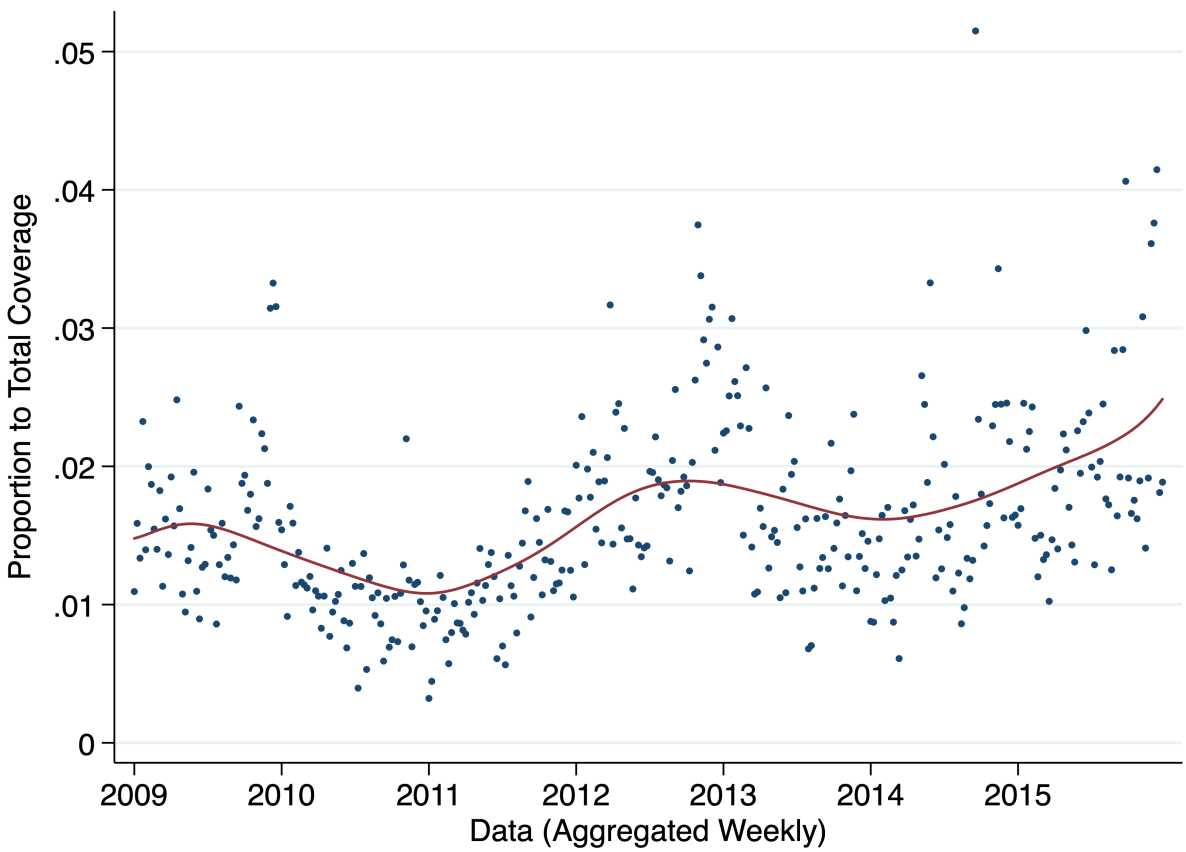
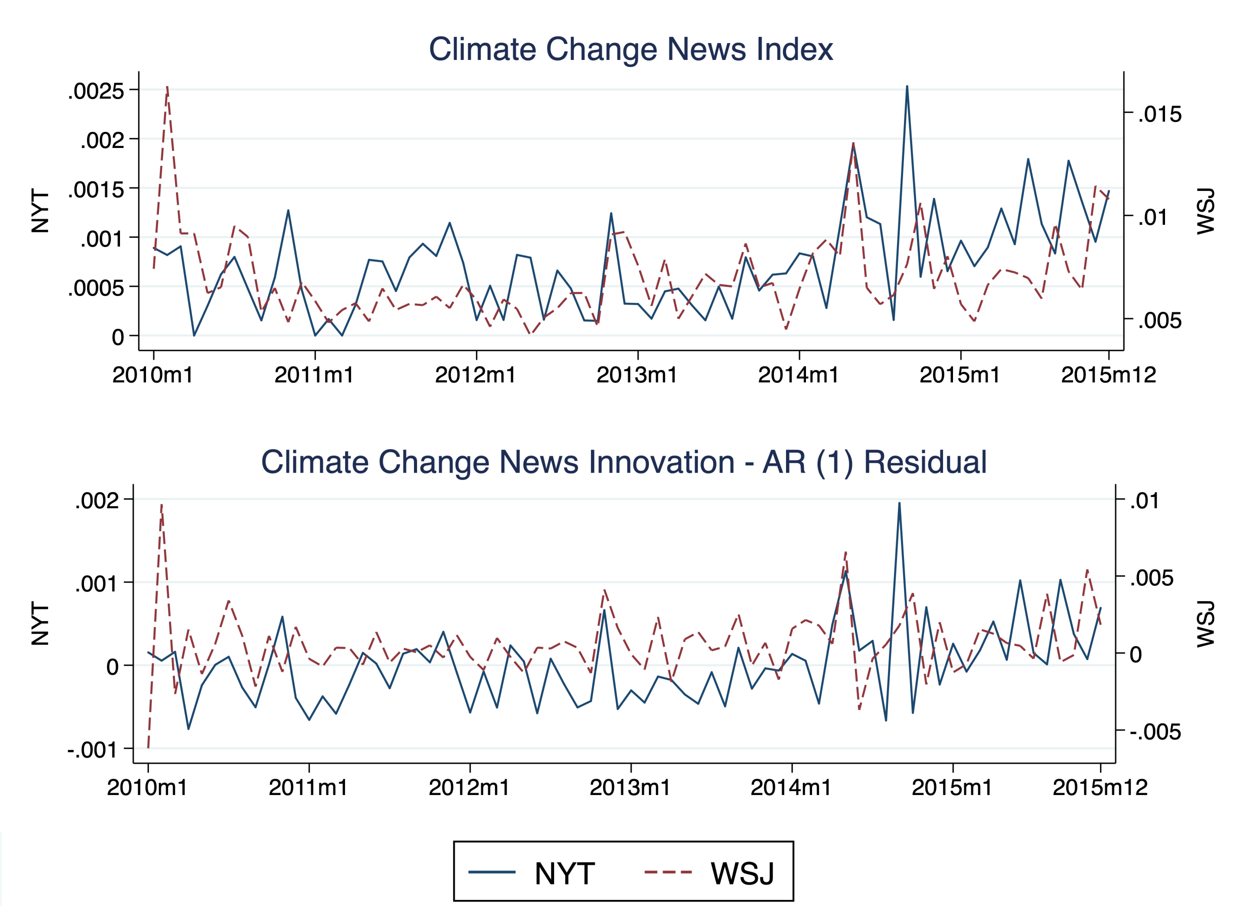
Figures

Figure 1: The New York Times's Weekly Climate Change Coverage



Notes: This figure provides a graphical illustration of the percentage of weekly news articles in the NYT that mentions climate change or global warming in either contents or titles. For this graph, we use the keyword query to extract articles that have the specified keywords in their titles or contents.

Figure 2: Climate Change News Index and Innovation



Notes: This figure plots the time series of climate change news index and innovation for the NYT and WSJ. The NYT time series are from the authors' calculation. The WSJ time series are from (20).

Tables

Table 1: Variable Definition

Variables	Frequency	Definition
Policy-in-Force (PIF)	County-Month	Being "in force" in a given month if being active at the end of that month
PIF MoM	County-Month	Month-over-month net growth rate of total PIF
Premium	County-Month	Mean of policy premiums in US dollars
PDD6m	County-Month	Sum of flood-related federal disaster declarations in past 6 months
NYT CC news Index	Month	Fraction of articles with "climate change" or "global warming" in their titles
WSJ CC news Index	Month	Fraction of WSJ dedicated to climate change related tops
CC news Innovation	Month	Residual of a linear AR (1) model
Coastal	County	1 if it is one of NOAA's coastal shoreline counties
Republican	County	1 if republican has a larger share of the presidential vote than democrat in 2014
Log Population	County-Year	Log of population
Log Income	County-Year	Log of median household income
Log House Value	County-Year	Log of median owner-occupied units value
% Mortgage	County-Year	% of housing units with a mortgage
% Non-White	County-Year	% of non-white population
% Below 35	County-Year	% of population under 35 years of age
% College and Above	County-Year	% of population with college degree or higher
% Female	County-Year	% of female

Table 2: Summary Statistics

	Mean	SD	Min	Max
PIF	1204.77	8077.87	0	264,702
PIF MoM (%)	0.06	5.57	-160.94	207.94
Premium ($100)	5.66	1.90	0.00	26.48
PDD6m	0.19	0.50	0.00	5.00
NYT CC News Index (*100,000)	7.16	4.90	0.00	25.33
NYT CC News Innovation	-1.02	46.74	-76.72	195.16
WSJ CC News Index (*10,000)	69.73	20.79	41.82	162.62
WSJ CC News Innovation	-0.88	23.97	-37.24	110.62
Coastal	0.12	0.33	0.00	1.00
Republican	0.77	0.42	0.00	1.00
Log Population	10.36	1.40	5.48	16.12
Log Median Income	10.88	0.25	10.02	12.09
Log Median House Value	11.68	0.46	10.30	13.82
% Mortgage	55.21	12.05	0.00	91.40
% Non-White	15.99	16.03	0.00	89.80
% Below 35	43.77	5.94	12.60	78.30
% College and Above	33.26	7.50	12.55	68.76
% Female	50.06	2.28	26.80	62.60
Observations	216,360			

Table 3: Raw PIF - By Group

	(1) Total County	(2) Non-Coastal County	(3) Coastal County	(4) Non-SFHA	(5) SFHA
PIF	1204.77	352.25	7390.20	565.58	669.50
Take-up Rate (%)	1.84	1.06	7.51	-	-
Total Housing Units (1000)	43.50	30.56	137.38	-	-
Population (1000)	102.41	71.37	327.65	-	-
Observations	216,360	190,152	26,208	214,056	208,512
# of Counties	3,005	2,641	364		

Notes: The Take-up rate is calculated as PIF divided by total housing unit. For SFHA and Non-SFHA, we do not have information on total housing in these designated zones.

Table 4: Regression Results

Panel A: NYT	ALL (1)	non-Coastal (2)	Coastal (3)	Non-SFHA (4)	SFHA (5)
Innovation	0.00700*	0.00746*	0.00414	0.00303	0.0112**
	(0.00314)	(0.00354)	(0.00375)	(0.00437)	(0.00346)
Premium ($100)	-0.0678	-0.0551	-0.405**	-0.184*	-0.0522
	(0.0414)	(0.0428)	(0.126)	(0.0862)	(0.0287)
PDD6m	0.263***	0.278***	0.137***	0.568***	-0.0124
	(0.0298)	(0.0351)	(0.0218)	(0.0430)	(0.0252)
AR2	0.00724	0.00751	0.00931	0.00830	0.00235
Panel B: WSJ	(1)	(2)	(3)	(4)	(5)
Innovation	0.0331***	0.0365***	0.00685	0.0454***	0.0121*
	(0.00697)	(0.00791)	(0.00551)	(0.00862)	(0.00600)
Premium ($100)	-0.0662	-0.0537	-0.403**	-0.176*	-0.0521
	(0.0415)	(0.0428)	(0.126)	(0.0860)	(0.0287)
PDD6m	0.263***	0.279***	0.139***	0.568***	-0.0111
	(0.0299)	(0.0351)	(0.0219)	(0.0431)	(0.0252)
AR2	0.00738	0.00767	0.00931	0.00847	0.00232
Panel C: Confirmation Bias	(1)	(2)	(3)	(4)	(5)
Aligned	0.0130**	0.0139**	0.00284	0.0182**	0.0102*
	(0.00421)	(0.00501)	(0.00435)	(0.00555)	(0.00400)
Non-aligned	0.0121***	0.0133***	0.00584	0.00921*	0.0103**
	(0.00334)	(0.00372)	(0.00342)	(0.00464)	(0.00356)
Premium ($100)	-0.0670	-0.0544	-0.403**	-0.180*	-0.0520
	(0.0414)	(0.0428)	(0.126)	(0.0861)	(0.0287)
PDD6m	0.262***	0.278***	0.137***	0.567***	-0.0124
	(0.0298)	(0.0351)	(0.0218)	(0.0430)	(0.0252)
AR2	0.00731	0.00759	0.00932	0.00836	0.00236
County FE	Yes	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Y	0.0568	0.0629	0.0134	0.195	-0.0783
N	212,619	186,508	26,111	207,456	203,232

Clustered Standard errors in parentheses. *p<.05; **p<.01; ***p<.001

Table 5: Confirmation Bias - By Partisanship

	ALL (1)	non-Coastal (2)	Coastal (3)	Non-SFHA (4)	SFHA (5)
Aligned	-0.000470	-0.00308	0.00188	-0.00240	0.0113*
	(0.00363)	(0.00452)	(0.00485)	(0.00579)	(0.00464)
Non-Aligned	0.0518***	0.0670***	0.00621	0.0663***	0.0136
	(0.0128)	(0.0172)	(0.00680)	(0.0165)	(0.0108)
Republican × Aligned	0.0267**	0.0310**	0.00396	0.0416***	-0.00277
	(0.00888)	(0.00988)	(0.00912)	(0.0114)	(0.00837)
Republican × Non-Aligned	-0.0460***	-0.0607***	-0.000775	-0.0665***	-0.00342
	(0.0134)	(0.0177)	(0.00878)	(0.0172)	(0.0114)
Premium ($100)	-0.0661	-0.0536	-0.403**	-0.176*	-0.0520
	(0.0414)	(0.0428)	(0.126)	(0.0860)	(0.0287)
PDD6m	0.263***	0.279***	0.137***	0.569***	-0.0121
	(0.0299)	(0.0352)	(0.0218)	(0.0431)	(0.0252)
AR2	0.00740	0.00770	0.00925	0.00847	0.00235
County FE	Yes	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Y	0.0568	0.0629	0.0134	0.195	-0.0783
N	212,619	186,508	26,111	207,456	203,232

Clustered Standard errors in parentheses. *p<.05; **p<.01; ***p<.001

Table 6: Sociodemograpgic Heterogeneity

Panel A: NYT	ALL (1)	non-Coastal (2)	Coastal (3)	Non-SFHA (4)	SFHA (5)
Innovation	0.0108*	0.0115*	0.00776	0.00323	0.0155***
	(0.00419)	(0.00462)	(0.00649)	(0.00594)	(0.00439)
High Female × Innovation	-0.00798	-0.00873	-0.00628	-0.000417	-0.00895
	(0.00454)	(0.00512)	(0.00587)	(0.00642)	(0.00503)
Innovation	0.000266	0.000331	0.00856	-0.00313	0.00792
	(0.00435)	(0.00467)	(0.00806)	(0.00604)	(0.00509)
High Median Income × Innovation	0.0130**	0.0146**	-0.00594	0.0118	0.00636
	(0.00465)	(0.00517)	(0.00760)	(0.00656)	(0.00513)
Innovation	0.0115*	0.0128*	0.00715	0.00937	0.00982
	(0.00472)	(0.00498)	(0.00906)	(0.00656)	(0.00511)
High Median House Value × Innovation	-0.00891	-0.0115*	-0.00351	-0.0123	0.00271
	(0.00468)	(0.00507)	(0.00877)	(0.00663)	(0.00514)
Panel B: WSJ	(1)	(2)	(3)	(4)	(5)
Innovation	0.0499***	0.0545***	0.00794	0.0729***	0.0118
	(0.0108)	(0.0120)	(0.00968)	(0.0136)	(0.00835)
High Female × Innovation	-0.0347**	-0.0383**	-0.00189	-0.0565***	0.000688
	(0.0128)	(0.0144)	(0.0107)	(0.0160)	(0.0109)
Innovation	0.0205*	0.0227*	-0.00631	0.0334**	0.0112
	(0.00990)	(0.0106)	(0.0122)	(0.0126)	(0.00936)
High Median Income × Innovation	0.0263*	0.0313*	0.0181	0.0248	0.00183
	(0.0130)	(0.0148)	(0.0132)	(0.0159)	(0.0107)
Innovation	0.0465***	0.0497***	-0.0172	0.0664***	0.0222*
	(0.0127)	(0.0132)	(0.0148)	(0.0154)	(0.00985)
High Median House Value × Innovation	-0.0267*	-0.0290*	0.0290	-0.0412*	-0.0200
	(0.0136)	(0.0145)	(0.0154)	(0.0168)	(0.0111)
County FE	Yes	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Y	0.0568	0.0629	0.0134	0.195	-0.0783
N	212,619	186,508	26,111	207,456	203,232

Clustered Standard errors in parentheses. *p<.05; **p<.01; ***p<.001

A Data Cleaning

Table A1: Summary of Sample Selection

Reasons for exclusion	# Dropped	# Remained
(Initial NFIP individual policy sample, 2009-2015)	NA	33,976,088
Under construction		33,926,511
House of worship		33,900,326
Small business building		33,689,012
Agricultural structure		33,681,354
Non-single-family residence with more than 1 policies		28,689,524
County FIPS with fewer than 5 digits		28,632,748
Building coverage > \$25,000		28,632,369
Contents coverage > \$10,000		28,632,340
Total coverage = 0		28,632,297
Total premium < 0		28,632,257
States other than the Lower 48		28,286,513
Premium less than 1^{st} or greater than 99^{th} percentile of all premiums in the effective year		27,712,009