FLOOD INSURANCE MARKET PENETRATION IN GEORGIA BEFORE AND AFTER HURRICANE IRMA

by

MARY BLAIN GRIST

(Under the Direction of Craig Landry)

ABSTRACT

This paper aims to evaluate the effect that a significant natural disaster has on the take-up rates of flood insurance in a state typically considered low risk for hurricanes and tropical storms. In reviewing empirical literature, we analyze factors that contribute to the change in market penetration. We combine policies and claims data from the Federal Emergency Management Agency (FEMA) with demographic data and precipitation data to evaluate the change in policies and coverage in counties affected by Hurricane Irma before and after the event using the Difference-in-Differences regression method. We find significant effects on policies and coverage in counties affected after Hurricane Irma relative to those not directly affected. We consider this compelling evidence of short-run impacts that extreme weather events can have on areas that do not routinely experience disastrous storms. Finally, we highlight avenues for further research involving other contributing factors and additional natural disasters.

INDEX WORDS: Flood insurance, FEMA, NFIP, Difference-in-Difference, Hurricane

FLOOD INSURANCE MARKET PENETRATION IN GEORGIA BEFORE AND AFTER HURRICANE IRMA

by

MARY BLAIN GRIST

B.S., The University of Georgia, 2019

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2020

© 2020

Mary Blain Grist

All Rights Reserved

FLOOD INSURANCE MARKET PENETRATION IN GEORGIA BEFORE AND AFTER HURRICANE IRMA

by

MARY BLAIN GRIST

Major Professor: Craig Landry

Committee: Susana Ferreira
Gregory Colson

Electronic Version Approved:

Ron Walcott
Interim Dean of the Graduate School
The University of Georgia
May 2020

ACKNOWLEDGEMENTS

I would like to thank Mr. Reza Zarei for his kindness towards me, for patiently answering every stupid question I had, and for working tirelessly to ensure my success. One could not ask for a better friend and I know you will be an excellent professor! Thank you Dr. Landry for promptly answering all of my late night panic emails, for your constructive comments that always pushed me to by my best, and for your constant faith in me. Thank you Dr. Ferreira for your encouraging and positive attitude as well as your willingness to share your knowledge with me. Thank you Dr. Colson for being a great mentor/unlicensed therapist to me throughout my graduate career, for never letting me take myself too seriously, and for always celebrating even the smallest successes. Thank you to Julie and Brittany for being my grad school moms! Finally, thank you to my family and friends for putting up with the not so fun/very stressed version of me this semester and for your constant support. I could not have done this without all of you and I feel very grateful to be surrounded by such wonderful people!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

CHAPTER 1

INTRODUCTION

Floods account for the most lives lost and the most property damage of all natural disasters during the 20^{th} century (Perry, 2000). In the United States, floods caused $8 billion in damage on average per year from 1981-2011 (Ahmadiani, Ferreira et al. 2019). The impacts and costs of extreme weather events have been rising in the US and around the world partly due to an increase in the concentration of people and property in high-risk locations (Ahmadiani, Ferreira et al. 2019 and Walls, Magliocca et al. 2018). There are also more valuable properties located in harm's way (Pielke Jr and Downton 2000; Pielke Jr, Gratz et al. 2008; Bouwer 2011; Hallegatte, Green et al. 2013). It is estimated that 39 percent of the US population lives in coastal shoreline counties (NOAA 2013), which face threat of tropical and sub-tropical cyclones. Despite the major financial impacts floods have every year and a subsidized insurance rate structure, the National Flood Insurance Program (NFIP) suffers from low levels of market penetration (i.e. uptake).

There is increasing interest in alternative forms of flood risk management, such as provision of flood insurance, building community resilience to disasters, and investment in mitigation measures (such as maintaining green space and restoring wetlands). This is because investment in traditional structural flood control, like dikes and levees, have reached the limits of their practical application and often entail unintended consequences, including negative environmental impacts and induced development due to perceptions of protection (Kousky and Kunreuther 2010).

In most lines of insurance (home, auto, fire, life, etc.) premiums and losses claimed are almost continually in equilibrium (Michel-Kerjan 2010). This is because the value of loss-per-dollar of insurance does not vary significantly from year to year. Premiums are set so that the loss ratio[1] attains some target level producing a smooth time path of premiums (Jaffee and Russell 1997). Insuring for flood risk is a challenge to conventional insurance models because flooding events are low probability with fat tails at relatively extreme negative outcome levels; the probability of loss declines slowly relative to severity. In addition, as flood losses tend to cluster geographically, there is limited loss data available at any location and spatial correlation complicates diversification of risk pools. Unlike automobile accidents or property theft, flood risk is complicated by spatially correlated losses, and there are significant difficulties in estimating the probability and loss associated with extreme events. This makes setting capital reserves for extreme outcomes very difficult and costly to maintain (Ahmadiani, Ferreira et al. 2019). Losses are low or virtually nonexistent in some years and then very high in other years, so it is very hard to predict premiums needed to cover the damages and smooth capital reserves over time. Congress passed the Federal Flood Insurance Act of 1956 to test how economically feasible private sector insurance would be for flood insurance (Grossman 1958). Because of the high concentration and correlation of risks that are not independent, flood insurance was not an attractive line of business to insurers in the 1950's and 1960's (Michel-Kerjan 2010).

The National Flood Insurance Program (NFIP) was established in 1968 by the National Flood Insurance Act. This made flood insurance available to homeowners (FEMA 1 2019). The NFIP was divided into an emergency phase and a regular phase. In the emergency phase, flood

[1] Loss ratio is the losses an insurer occurs due to paying out claims as a percentage of the premiums they earn (Merriam-Webster 2020).

hazard maps were provided to residents who were allowed to purchase flood insurance at subsidized rates. A community is allowed to enter the regular phase once flood insurance rate maps[2] have been drawn, dividing the community into specific zones with probability of flooding determined for each zone, and the community has agreed to adopt more stringent mitigation efforts (Rejda 1998). The NFIP was designed as a voluntary partnership between the federal government and local communities (Michel-Kerjan 2010), with the purpose of mitigating flood risk at the community level and providing flood insurance for individual residences and businesses.

The private market faces challenges that the NFIP strives to correct. Losses are a certainty in some areas, and flood losses can be catastrophic. Consumers are often not willing to pay premiums high enough to cover the expected losses, and insurers are unable to pool those insured with different degrees of exposure to flood losses because lower risk will typically not purchase the pooled rate coverage (Anderson 1974). The NFIP is responsible for developing flood maps, establishing deductibles/coverage-limit menus, and setting insurance premiums. They also establish rules to determine subsidized premiums for certain existing buildings (primarily structures built before Flood Insurance Rate Maps were drawn) (Michel-Kerjan 2010). The objectives of the NFIP are to make flood insurance available at reasonable premiums; use risk-based rates in order to incentivize people to bear the cost of living in the floodplain; create widespread community and individual participation; and ensure the premiums and fees are adequate to cover claims and program expenses (Ahmadiani, Ferreira et al. 2019). These objectives often work at cross purposes.

---

[2] The official map of a community on which the Federal Emergency Management Agency (FEMA) has delineated both special hazard areas and risk premium zones applicable to the community (FEMA 3 2019)

Today, the NFIP struggles with outdated flood-risk maps, lack of motivation by residents to invest in risk protective measures, repetitive losses for some properties, and low insurance penetration/retention. The NFIP is designed to be financially self-supporting, but it cannot financially handle catastrophes by itself as rates are only formulated to cover the average loss year (Wetmore, Bernstein et al. 2006). Hurricanes Katrina in 2005, Hurricane Sandy in 2012, and Hurricane Harvey in 2017 demonstrated premiums collected by the NFIP were insufficient for the program to provide claim payments after large disasters by itself (Atreya, Ferreira, Michel-Kerjan 2015; FEMA 2018). In 2017, losses from Hurricanes Harvey, Irma, and Maria forced the NFIP to borrow $11.9 billion from the US Treasury (FEMA 2018). The main source of NFIP revenues beyond premiums is the $30 policy fee paid by all flood policyholders. Browne and Hoyt (2000) find that the premiums of NFIP policies in Florida stayed virtually the same before and after the 7 major hurricanes of 2004 and 2005. This is because the NFIP sets its rates nationally instead of in response to local episodes. Because of this policy and other shortcomings, the NFIP is not charging adequate premiums for high-risk contracts, which creates more financial distress. The NFIP's pricing strategy of basing rates on historical average loss year also does not account for fat tails in the loss distribution and does not allow for anticipation of changes in future conditions, such as changes in land development or changes in weather patterns (Michel-Kerjan and Kousky 2010). The source of a major loss of revenue for the NFIP is payments made to insurers participating in the Write-Your-Own Program, where participating property and casualty insurance companies are allowed to write and service the Standard Flood Insurance Policy in their own names (FEMA 5 2019). More than one-third of the premiums collected by the NFIP goes to the insurers participating in the Write-Your-Own program (and nearly all NFIP flood policies are issued through the Write-Your-Own Program) (Michel-Kerjan 2010).

Due to low market penetration of flood insurance, the Flood Disaster Protection Act of 1973 regulated mortgage lenders to require flood insurance for the purchase of property acquired or developed areas identified as high-risk for flooding known as Special Flood Hazard Areas (SFHA)[3]. Even with this new requirement, insurance adoption rates still remained shockingly low in SFHAs. Dixon et al. (2006) estimate 60% market penetration in SFHAs in the South and West. Empirical estimates of high-risk SFHAs in the coastal zone find only 50% market penetration (Landry and Jahan-Parvar 2011). These estimates coupled with an estimate of 1/3 of policies in force outside of these SFHAs lead us to believe overall market penetration is low (Dixon et al. 2006; Kousky and Kunreuther 2010). The NFIP implemented mandatory purchase requirements (MPR), flood-risk disclosure, and aggressive marketing to increase participation (Ahmadiani et. al.2019). Despite these heroic efforts, around 70 percent of the NFIP's policies are still located in just five states: Florida, Texas, Louisiana, California, and New Jersey (Michel-Kerjan and Kousky 2010).

Our objective is to determine how occurrences of hurricanes in areas that are rarely hit (presumably "safe havens") affect flood insurance take-up rates. To accomplish this, we review and synthesize literature on flood insurance and the factors affecting take-up rates. Then we use FEMA's policy data combined with demographic data and precipitation data to examine the change in number of policies per county in Georgia using the Difference-in-Differences

[3] The land area covered by the floodwaters of the base flood where NFIP's floodplain management regulations must be enforced. Area where the mandatory purchase of flood insurance is required. Includes Zones, A, AO, AH, A1-30, AE, A99, AR, AR/A1-30, AR/AE, AR/AO, AR/AH, AR/A, VO, V1-30, and V (FEMA 4 2019).

regression method. For this analysis we hone in on years 2015-2019 because we are looking at Hurricane Irma's (2017) effect in Georgia. Section 2 reviews relevant literature, section 3 provides an overview of our datasets, section 4 presents our methods, section 5 reveals our results, section 6 offers discussion of our results, and section 7 concludes our findings.

CHAPTER 2

LITERATURE

There is a fairly extensive literature on flood insurance uptake, particularly in the United States. The exact reasons people do not buy flood insurance are unclear but possible explanations include: little to no past experience with floods, misperceptions of the likelihood of flooding (including the "Gambler's Fallacy"), reliance on disaster aid (known as "Charity Hazard"), and misperceptions related to the impacts of flooding events (including the "availability heuristic, in which effects of past flooding events wear off as time passes).

Perception of risks influenced by natural hazard events affect the decision to buy flood insurance (Atreya, Ferreira et al. 2015). Atreya, Ferreira et al. 2015 find that flood insurance purchase decisions are highly dependent on prior year disaster losses. NFIP policy take-up rates correlate positively with prior flood experience, local hazard proximity conditions, and education levels (Zahran, Weiler et al. 2009). People also have a difficult time evaluating the probabilities of unlikely events (Ahmadiani, Ferreira et al. 2019). Historically, Georgia has had very few hurricanes relative to its East Coast neighbors, and most of the state is not particularly prone to flooding, so this could account for why flood insurance market penetration is so low. According to NOAA (2019), only 7 percent of hurricanes that make landfall in the East Coast every year hit Georgia; forty percent hit Florida and 16 percent hit North Carolina. Since 1851, 32 hurricanes have made directs hit on Georgia, while Florida has had 126 (40%) and North Carolina has had 51 (16%) (NOAA 2019). According to FEMA, the majority of Georgia counties have experienced fewer than 10 natural disasters in the last 50 years and no counties have experienced more than 15. Florida counties experienced 20-30 natural disasters within the same time period (FEMA 1 2020). Based on these statistics, one could argue Georgia is a “safe haven.” According to Christopher Ingraham of The Washington Post, Georgia is the least disaster-prone state in the South and stands out as a state where disaster declarations are relatively rare compared to its neighboring states such as Alabama, Florida, South Carolina, and North Carolina. Since a disaster declaration has to be declared by the governor in multiple counties of a state and approved by the president, one could argue a disaster declaration is as much a political phenomenon as it is a natural one. Either Georgia has milder weather and fewer natural disasters than its neighboring states, or the perception in Georgia of what constitutes a major disaster is more relaxed leading people to believe it is a “safe haven”(Ingraham 2015).

Petrolia et al (2013) found that the likelihood of holding flood insurance increased with previous flood event experience, while Browne and Hoyt (2000) find that the number of flood insurance policies sold during a certain period is positively correlated with flood losses during the previous period. Therefore, increasing public knowledge of flood damage may be an effective means to increase flood insurance market penetration.

According to Kunreuther and Michel-Kerjan (2010) there is evidence of a “Gambler’s Fallacy” where people believe the odds of another flood occurring in the same area decline after a recent flood. Because of this fallacy, people do not purchase flood insurance or may let their flood insurance lapse after a loss. People are agnostic about the relationship between past flood damage and demand for flood insurance (Kunreuther and Michel-Kerjan 2010). Even when residents know they might be at risk, they can underestimate their risk or disregard it. This is known as “probability neglect” and is also discussed in Sunstein (2002) and Zeckhauser and Sunstein (2010).

Charity hazard is the tendency of an individual at risk not to purchase insurance or other risk financing because they expect or rely on charity from others (friends, community, non-profits, or the government) (Browne and Hoyt 2000). The individual underinsures in anticipation of post-disaster aid (Kaplow 1991; Raschky and Weck-Hannemann 2007). These individuals may perceive disaster aid as a government responsibility and thus have a lower likelihood of engaging in flood mitigation activities including purchasing insurance (Botzen, Aerts et al. 2009). This is also known as Samaritan's Dilemma where people feel the government will always help them in the aftermath of a disaster, so they do not need to purchase insurance (Browne and Hoyt 2000).

Take-up rates for flood insurance often increase right after a disaster event, but they typically decline subsequently (Ahmadiani, Ferreira et al. 2019). Following seven major hurricanes hitting the Gulf Coast in 2004 and 2005, there was a significant jump in the number of flood insurance policies written (Michel-Kerjan 2010). Flood events temporarily increase the purchase of flood insurance but the effects fade after about 3 years (Atreya, Ferreira, Michel-Kerjan 2015). Many banks require proof of flood-insurance-coverage when the original mortgage is issued, but they do not check to see if policies are renewed. On average, flood insurance policies lapse after only 2 to 4 years regardless of whether policyholders live in Special Flood Hazard Areas (Michel-Kerjan 2010). A possible solution to low insurance penetration and retention would be to add multiyear flood insurance contracts (Michel-Kerjan 2010). Petrolia, Landry et al. (2013) find that the effects of past flood events are significant among non-SFHA respondents but not among SFHA respondents. This could be because people in the SFHA know their flood risks already regardless if a particular flooding event occurs, or they are required to hold flood insurance.

Other factors affecting take-up rates for flood insurance include income, premium rates, education, age, race, risk preferences, coastal vs. inland counties, and available substitutes. Since insurance is viewed as a normal good, higher income households are more likely to purchase flood insurance (Atreya, Ferreira, Michel-Kerjan 2015), but the wealthiest households may also choose to self-insure (Landry and Jahan-Parvar 2011). Positive income effects are small for NFIP participation but larger for coverage level (Ahmadiani, Ferreira et al. 2019). In other words, income has little to do with market penetration of flood insurance, but greater effect for the level of coverage for the insured (possibly due to greater asset value). Kunreuther et al. (1978) and Browne and Hoyt (2000) find a positive relationship between income and purchasing insurance and a negative relationship between price and purchasing insurance. Higher income individuals are more likely to purchase insurance and additionally purchase greater amounts of insurance than lower income individuals (Browne and Hoyt 2000).

Empirical research indicates that premiums have a limited effect on the likelihood of holding insurance (Kriesel and Landry 2004; Dixon, Amelung et al. 2006; Atreya, Ferreira et al. 2015). The amount of coverage is reflected in small price elasticities (Landry and Jahan-Parvar 2011). Identifying a pure price effect can be difficult because premiums are highly correlated with risk factors and chosen deductible amount (National Academies of Sciences, Engineering, and Medicine 2015). Kriesel and Landry (2004) find participation responsiveness to price to be inelastic. Insurance choice studies for homeowners' policies and automobile insurance have found that people prefer low-deductible policies even when they are not financially rational. This could be because homeowners might not be aware that higher deductible flood insurance is offered, and also some customers forced to buy flood insurance by lenders will get claims payments more often with a low deductible policy (Eldred 1980; Cutler and Zeckhauser 2004;

Sydnor 2006). Lowering premiums further contributes to the strain and unsustainable financial structure of the NFIP.

Demographic factors can have significant effects on who buys flood insurance and are important for targeting future markets. Atreya, Ferreira et al. (2015) find level of education and age have a significant effect on the number of policies in a county. While the level of formal education and households purchasing flood insurance are positively correlated, education about the need for flood insurance has a dwindling effect. A greater level of education positively correlates with the probability of purchasing flood insurance, but this effect is heterogenous across time (Ahmadiani, Ferreira et al. 2019). Half of the residents living in floodplains do not have flood insurance, possibly because they do not know they live in a flood-prone area (Michel-Kerjan 2010). At age 65, risk aversion rises and so does the demand for flood insurance (Atreya, Ferreira et al. 2015).

Atreya, Ferreira et al. (2015) tested race as an explanatory variable affecting flood insurance demand and found there is much variation across race and ethnic groups in the ways they perceive and deal with natural hazard risks. They found African Americans purchase more flood insurance than the white population. Atreya, Ferreira et al. (2015) suggest that it might be important to target flood risk awareness by race or age to improve market penetration. Evidence supporting this theory can be found stemming from the U.S. Federal Emergency Management Agency's (FEMA) large-scale information campaign called "Cover America" (launched in 1995); this risk awareness campaign resulted in a significant increase in the enrollment in the program (Michel-Kerjan 2010).

Population naturally affects the uptake of flood insurance policies in an area; therefore, it is important to control for population per county when conducting our analysis. Coastal counties with higher populations tend to have the largest number of flood insurance policies per land area (Michel-Kerjan 2010). Kriesel and Landry (2004) find that only half of eligible properties in coastal areas participate in the NFIP. A 2006 RAND report found that about 49 percent of the properties in SFHAs purchase flood insurance and only 1 percent outside of SFHAs purchase insurance (Dixon et al., 2006).

According to Finkelstein and McGarry (2006), there is evidence that persons who are more risk averse are more likely to purchase insurance. Those with an internal locus of control are also more likely to buy flood insurance because they are more likely to perceive responsibility for their own losses. These people (internals) believe they are in control of their surrounding environment and are therefore willing to adopt behavior that exhibits control over the implications of environment outcomes, such as buying flood insurance. Externally oriented people believe they are powerless to influence their environment and are therefore more likely to refrain from buying flood insurance (Baumann and Sims 1978).

Among those within the SFHA, the lack of adequate demand for flood insurance can be explained by the existence of substitutes such as disaster relief (Raschky and Weck-Hannemann 2007; Botzen, Aerts et al. 2009; Raschky, Schwarze et al. 2013). According to Lewis and Nickerson (1989), underinvestment in loss mitigation and insurance is a consequence of disaster relief provided by the government creating limited liability for those affected by flooding events. Atreya, Ferreira et al. (2015) found no evidence that insurance purchase and mitigation efforts are substitutes, while Landry, Turner, and Petrolia (2020) find that optimistic expectations of disaster relief can reduce market penetration by anywhere from 1.5% to 23%. The latter paper employs instrumental variables to control for endogeneity of expectations of disaster assistance.

Knowing who buys flood insurance can help the NFIP target more of the market in the future. As previously stated, Atreya, Ferreira et al. (2015) found a positive association between individuals who are educated, over the age of 45, and African American and the likelihood of purchasing flood insurance. The data from Ahmadiani, Ferreira et al. (2019) suggests that borrowing costs can crowd out flood insurance coverage for households with low risk that are outside the 100-year flood plain. Non-SFHA households without a mortgage are more likely to have flood insurance compared with non-SFHA with a mortgage. Deductible choice varies with flood zone where more homeowners in the riskiest areas choose a higher deductible. In Florida, on average, 70 percent of the policyholders buy the maximum limit of contents coverage if they have also purchased the maximum limit of building coverage. Those inside SFHAs are more likely to choose the highest deductible offered (Michel-Kerjan and Kousky 2010). Mortgaged households in the SFHA are 73.7 percent more likely to hold flood insurance relative to non-SFHA non-mortgaged households. This is because the mandatory purchase provisions stipulated under federal law have had a significant impact on individual household participation in NFIP (Petrolia, Landry et al. 2013).

It is important for us to consider demographic factors as well as to be aware of the psychological reasons people do not purchase flood insurance when conducting our analysis. These factors help to paint a more comprehensive picture of how the occurrence of hurricanes in rarely hit areas affect flood insurance take-up rates.

CHAPTER 3

DATA

Our flood insurance policy data comes from FEMA's website. These data were obtained from the National Flood Insurance Program (NFIP) through OpenFEMA (FEMA 2 2019) and includes more than 47 million policy records for transactions during the past 10 years. Specifically, we will be looking at the policy data from the years 2015-2018 to analyze changes in policies and coverage levels before and after Hurricane Irma (2017) in counties affected and unaffected by the hurricane. To ensure robustness of results, we utilized several control variables such as: housing units, population, average precipitation, median household income, and average persons per household. We obtained the demographic data through the US Census Data website (USCB 2020), precipitation data through the PRISM climate group (PRISM 2020), and the regions from the Georgia Department of Economic Development (GDED 2020).

Table 1 represents summary statistics for Georgia's total-policy-count-per-county, total-coverage-per-county (in millions of dollars), average-precipitation-per-year (in inches), housing units, population, policies-per-capita and per-household, coverage-per-capita and per-household, and our quasi-experimental, interaction variables associated with the DID framework (Irma did1-3). Years 2015 and 2016 represent the pre-Irma era while years 2017 and 2018 represent post-Irma. There is a very small decrease in mean total number of enforced policies of 0.32 % from pre-Irma to post-Irma and mean total-coverage-enforced-per-county increases by about 5.26%. The mean of precipitation in inches is slightly higher in the post-Irma era, while mean housing units and mean population remain virtually unchanged. The mean of Irma_did1 indicates that about 4.4% of all counties in Georgia were significantly affected by Hurricane Irma and received individual assistance (IA) from FEMA (Irma ia), the mean of irma did 2 indicates 9.4% of counties in Georgia are adjacent to the IA counties affected, and the mean of irma did3 indicates that counties significantly affected and those adjacent equate to about 13.8% of all counties in Georgia. We see virtually no change in average policies or coverage per capita or per household from 2015-2017. These summary statistics indicate we will not see dramatic changes in policies or coverage from 2015-2018.

Table 1

Summary Statistics

	2015	2016	2017	2018
num_policy	590.1635	583.7044	571.6918	598.4403
	(2645.429)	(2654.319)	(2562.301)	(2844.928)
total_cove~n	126	126	125	135
	(5.99e+08)	(6.04e+08)	(5.89e+08)	(6.70e+08)
precipitat~h	57.0823	42.3215	52.1062	64.6770
	(9.9966)	(7.9098)	(5.6948)	(8.7620)
hunits	26394.67	26638.6	26923.85	27208.21
	(55905.06)	(56601.86)	(57450.18)	(58176.64)
population	64032.14	64809.83	65490.91	66160.22
	(138061.5)	(140406.4)	(142115.9)	(143496.1)
policy_cap~a	0.0074	0.0073	0.0071	0.0072

	(0.0231)	(0.0227)	(0.0223)	(0.0233)
policy_hh	0.0164	0.0161	0.0157	0.0159
	(0.0524)	(0.0518)	(0.0507)	(0.0525)
cov_capita	1468.673	1469.136	1446.265	1518.085
	(5280.871)	(5261.447)	(5220.312)	(5601.737)
cov_hh	3273.545	3267.416	3217.607	3354.783
	(12015.85)	(11980.8)	(11848.49)	(12578.68)
irma_did1	0	0	0.04403	0.04403
	(0)	(0)	(0.2058)	(0.2058)
irma_did2	0	0	0.09434	0.09434
	(0)	(0)	(0.2932)	(0.2932)
irma_did3	0	0	0.13836	0.13836
	(0)	(0)	(0.2464)	(0.2464)

Standard deviation in parentheses

Figures 1 and 2 give us a more comprehensive view of the change in number of policies in Georgia 6 months before and after Hurricane Irma. We were able to create a scale for the number of policies in each county to show roughly how many policies were active in each county. These figures only take into account the total number of policies-per-county and if that county was affected by the hurricane. We do not take demographic data, rainfall, elevation, etc. into account so we do not get a full picture of the effect Hurricane Irma has on the number of policies in each county.

Figure 2 was converted from FEMA's disaster declaration maps in GIS to show 3 categories of assistance. Each county was placed into Public Assistance (Categories A and B -

least severe), Public Assistance (Categories A-G – most severe), or Individual Assistance and Public Assistance (Categories A-G). Categories C-G are more serious. Category A is debris removal, B is emergency protective measures, C is roads and bridges, D is water control facilities, E is public buildings and contents, F is public utilities, and G is parks, recreational, and other facilities. We used these maps to show severity of the hurricane based on the level of assistance needed in each county.

For the comparison of before and after Hurricane Irma, in Figures 1 and 2, we see a reduction in overall policies after the hurricane. The policy count went from 52,441 to 47,042 for an overall reduction of 5,399 policies. Chatham County had the biggest drop in number of policies going from 18,124 to 13,630 for a total loss of 4,494 policies. Since Chatham County is located along Georgia's East coast and was hit severely by Hurricane Irma, we would expect an increase in flood insurance take-up, but we have not taken into account factors such as population, rainfall, elevation, etc. that we will take into account in our regression. Bryan county has the second largest drop in policies after Irma with a reduction of 722. This county somehow avoided most of the blow from Irma and has less than 10 flooding events (FEMA 2 2020) from 1996-2016 which could account for why there would be a drop in flood insurance policies.

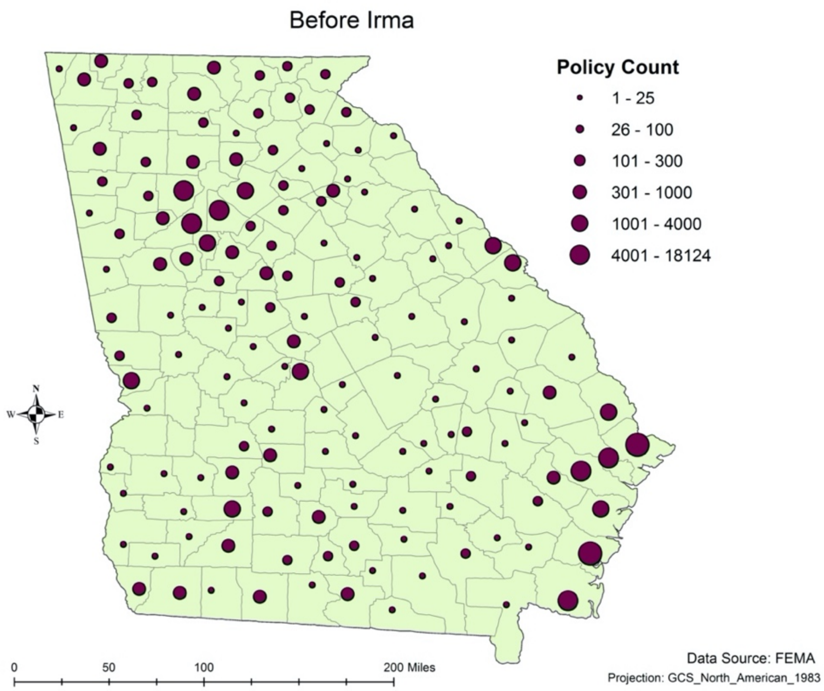

Figure 1

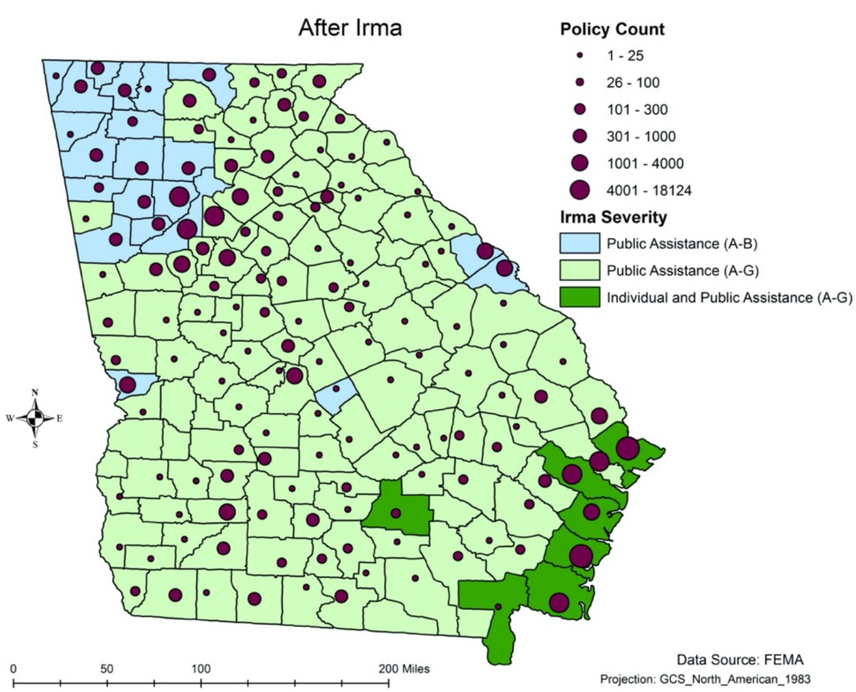

Figure 2

CHAPTER 4

METHODS

For our regression, we used the Difference-in-Differences method through OLS to compare the total-policies-in-force and total-flood-insurance-coverage before and after Hurricane Irma in counties affected and unaffected by the hurricane. Our base model regression is:

$$Y = \beta_0 + \beta_1 irma + \beta_2 irma\ treatment + \beta_3 irma\ did + \beta_4 precipitation\ inch + \beta_5 lag\ precip + \beta_6 \ln(inc) + \beta_7 \text{counties} + \varepsilon_t$$

Y represents either policies per capita, policies per household, coverage per capita, or coverage per household. To create the policies dependent variables, we divide total number of policies per county by total population per county and total households per county. For coverage, we dived total coverage per county by total population per county and total households per county. A dummy variable (Irma) indicates the time when the treatment started in 2017. Years 2015 and 2016 have a value of 0 and years 2017 and 2018 have a value of 1. Irma treatment represents counties affected by one of our 3 treatment definitions: Irma ia (treatment definition 1), Irma spill (treatment definition 2), and Irma ias (treatment definition 3). Irma ia represents those counties with significant enough damage from Hurricane Irma to warrant a FEMA IA grant. To warrant FEMA IA grant, there must be significant damage to categories A-G in a county which includes debris removal, roads and bridges, water control facilities, etc. IA counites receive a 1 and all other counties receive a 0. Irma spill is another dummy treatment variable representing those counties adjacent to IA counties. This treatment variable attempts to account for spillover effects and account for counties that may have experienced damage but are not required to purchase flood insurance after receiving aid. Those receiving individual assistance from FEMA must purchase and maintain flood insurance coverage on their property as long as the flood damaged building exists. They must also inform the new owner of the flood insurance mandate (FEMA 2017); failure to comply will result in no future IA payments. Irma ias combines counties receiving individual assistance with their adjacent counties. Irma did is a dummy interaction term between time and treatment. Our standard errors are clustered by treatment at the county level, which is also our panel level cross-sectional variable (counties). We also included various demographic control variables. Precipitation inch is average inches of precipitation per year per county, lag precip is the average inches of precipitation in each county 1 year before, and linc represents the natural log of household income.

In our appendix we account for additional demographic variables to test for robustness. Lphh represents the natural log of average persons per household. The total population variables divide the total population per county into different age groups: less than 19, 20-39, 40-59, and above 60. Percent female is total females divided by total population per county.

Region is a dummy variable combining all counties in Georgia into 1 of 12 regions. Figure 3 depicts the different regions of Georgia as defined by the Georgia Department of Economic Development (GDED 2020). Our standard errors are clustered by treatment at the county level, which is also our panel level cross-sectional variable. We included the regions dummy in our appendix to pick up unobserved cross-sectional factors.

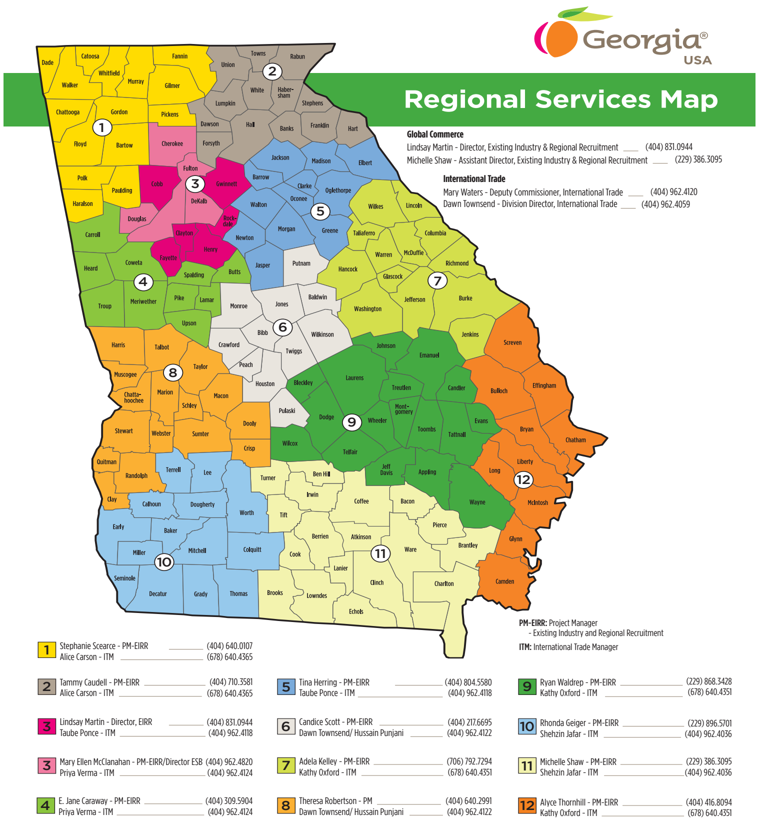

Figure 3

To assess the parallel trends assumption and to give a better visual of the change in policies using the Difference-in-Differences method, we created a two-line plot for Irma ia (Figures 4-7). In the appendix, we also include plots for Irma spill and Irma ias (Figures 8-15). These figures depict the average policies/coverage per capita and per household per year for our treatment and control groups. We are mainly focused on the changes observed before 2017 and after 2017 (when Irma occurred).

In figures 4 and 5, we see an increase in average number of policies per year in the treatment group after 2017 while the control group's policies remain constant across all years. Policies per capita and per household remain virtually unchanged in the treatment group from

2015-2017. In figures 6 and 7, coverage is constant across all years for the control group and constant from 2015-2017 for our treatment group. We see an increase in coverage per capita and coverage per household after 2017 implying counties warranting FEMA IA grant status increased their coverage after Hurricane Irma.

Figures 8-11 represent counties adjacent to IA counties as their treatment group to account for spillover effects. In Figures 8 and 9, we see a decrease in policies per capita and per household from 2016-2017 and an increase after 2017 in the treatment group. The control group stays fairly constant over all years but there is a slight decrease from 2016-2017 and a slight increase from 2017-2018. Similar effects are observed when looking at Figures 10 and 11 for coverage per capita and per household.

Figures 12-15 combine IA counties and those adjacent into the treatment group. The control group remains virtually unchanged in policies and coverage per capita and per household from 2015-2019. There is an increase in policies and coverage in the treatment group after Irma (2017).

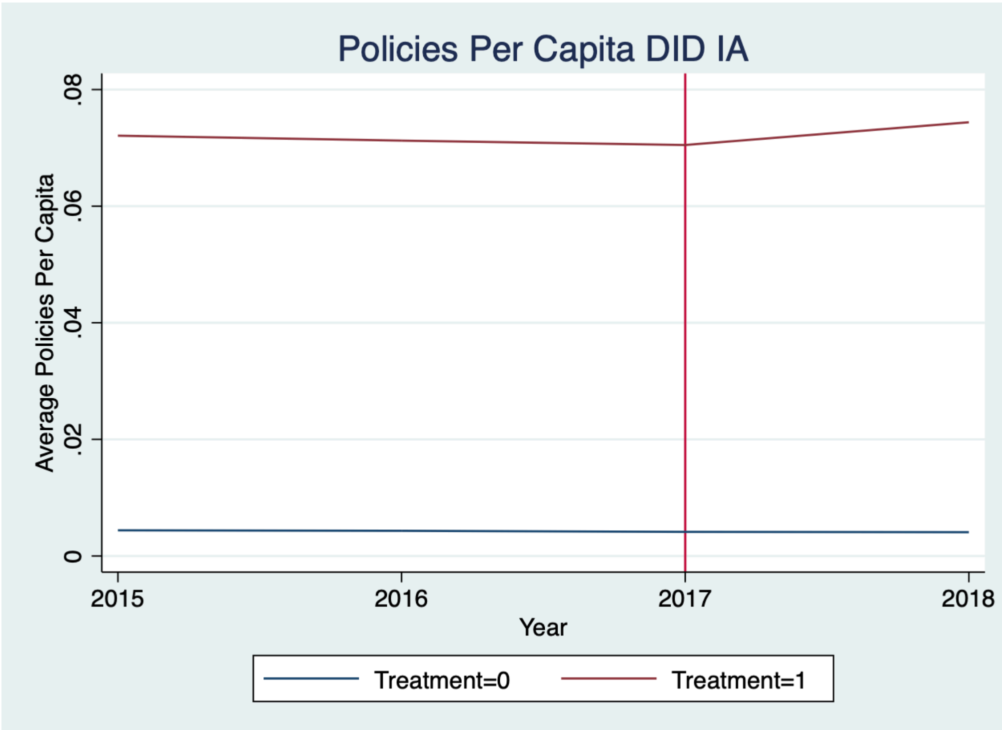

Figure 4

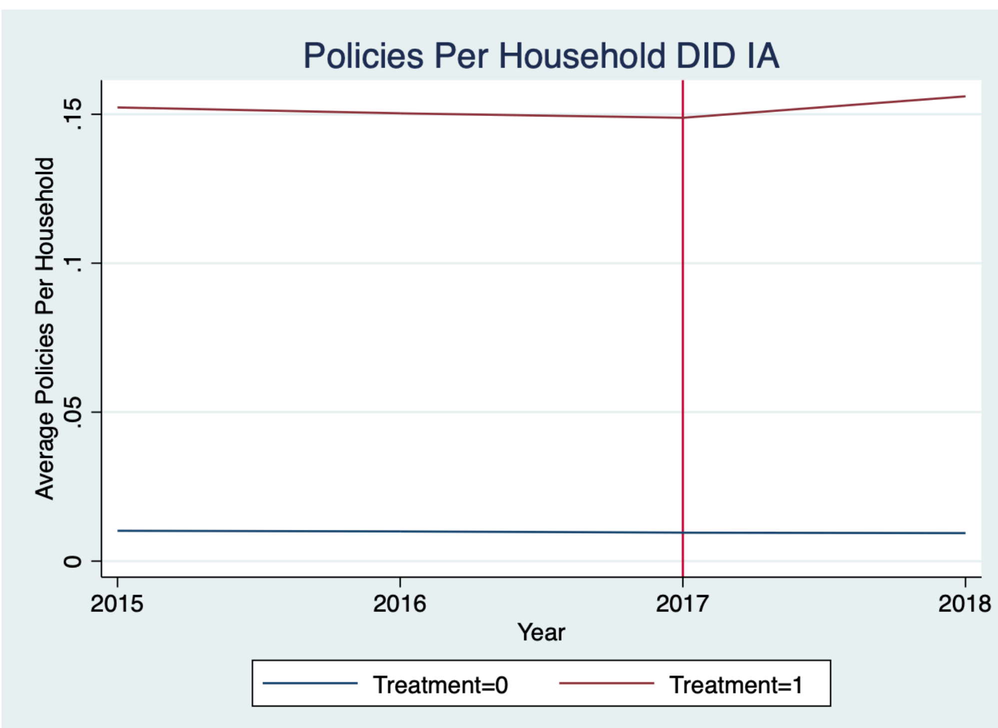

Figure 5

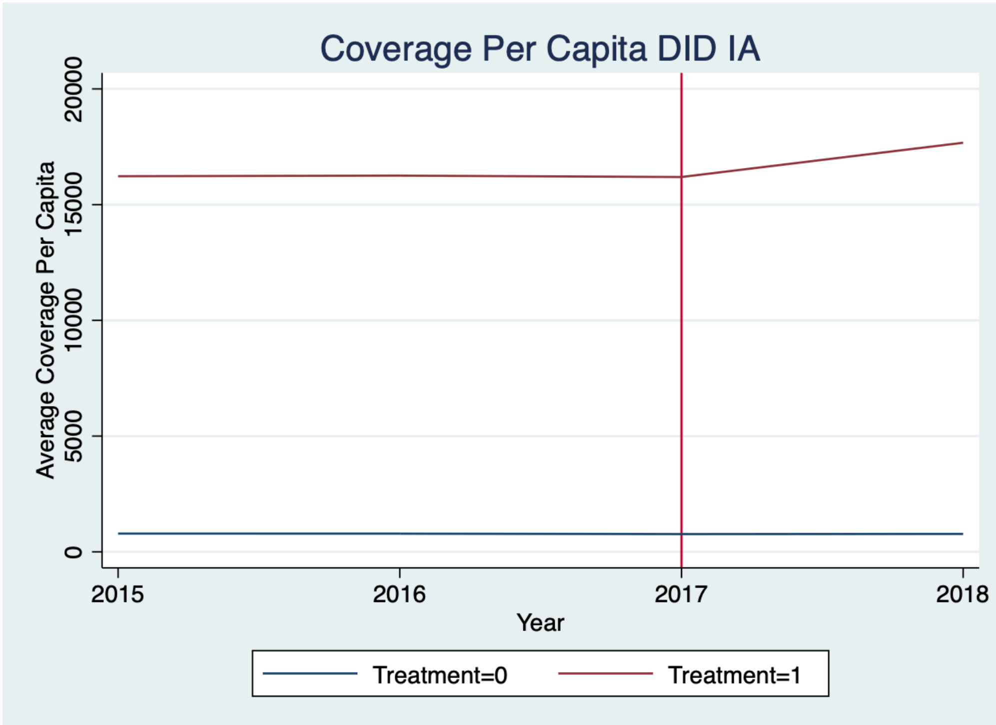

Figure 6

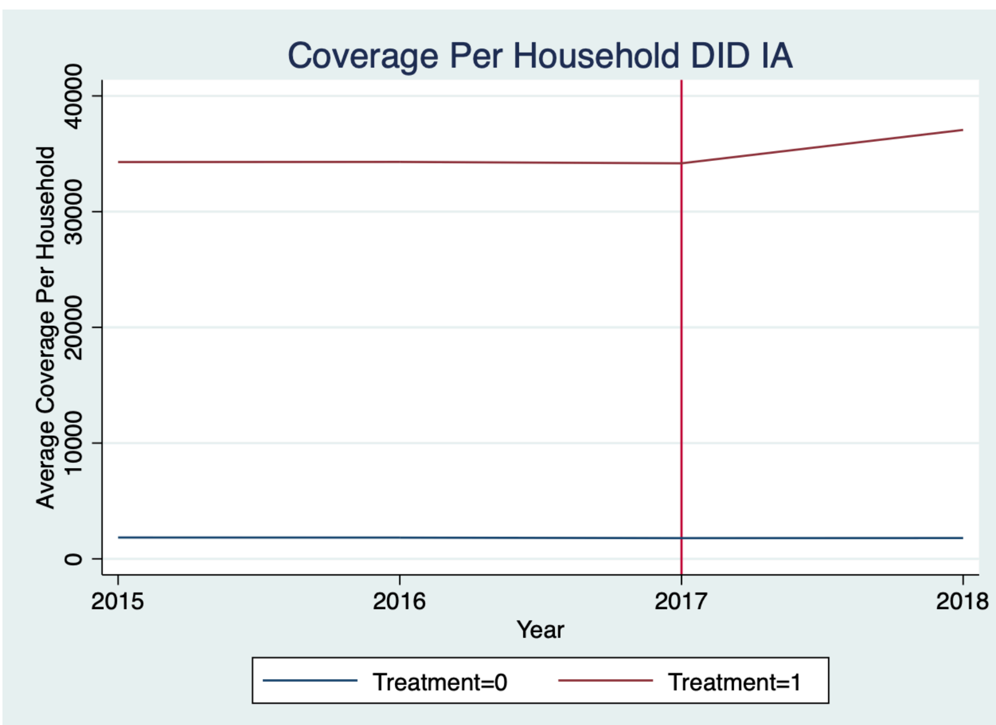

Figure 7

CHAPTER 5

RESULTS

Looking at the results, Table 2 presents NFIP polices and coverage per-capita and per-household using the difference-in-differences method. Our treatment variable Irma ia represents counties receiving individual assistance. We used average precipitation, 1 year lag in average precipitation, and the natural log of household income as control variables in our model. Across all specifications, the IRMA time effect for the control group is negative and only significant at the 5% level for a type 1 error for policies per capita. The Irma ia coefficient is positive and not statistically significant across the board. Irma did1 is our difference in difference variable describing the difference between the change in the treatment group and the change in the control group as time crosses from pre- to post- Irma. Focusing on the DID estimate, we find the Georgia counties that received FEMA IA assistance in the wake of Irma (Irma ia) had 0.0011 more policies per capita and 0.0018 more policies per household (both effects statistically significant at the 1% for a Type I error). Looking at columns 3 and 4, we observe NFIP Coverage per capita and per household. Irma did1 shows that treated counties had \$715.96 more coverage per capita and \$1,385.82 more coverage per household with both effects statistically significant at the 1% for a Type 1 error. We do not observe significant effects from our control variables: precipitation, lag precipitation, and natural log of precipitation.

Table 3 depicts policies and coverage per capita and per household using Irma spill as the treatment variable. We hope to observe any spillover effects using counties adjacent to IA counties. These treatment counties may have been damaged by Irma but did not receive individual assistance from FEMA and therefore are not required to buy flood insurance. Our time variable Irma is negative but not statistically significant in columns 1-4. Our treatment variable is positive and significant at the 1% level across all columns. Irma did2 is negative and significant at the 10% level across all columns. We observe treated counties had a decrease in policies per capita and per household of 0.0002 and 0.0007 respectively. We also see a decrease in coverage per capita of $68.47 and per household of $165.78. Again, we see no significant effect from our control variables using this model.

Table 4 combines our IA counties and their adjacent counties for the treatment variable. Irma is negative and no significant across all columns while Irma ias (treatment) is positive and significant at the 1% level across all columns. Irma did3 is not significant for policies per capita or per household but does present an increase of 0.002 in columns 1 and 2. Irma did3 shows and increase of $212.28 for coverage per capita and an increase of $386.64 per household. These results are both significant at the 5% level in columns 3 and 4. Again, we do not have any significant results for our control variables.

In the appendix, we have included additional models to check for robustness of results. Tables 5-7 include additional control variables to our base models such as the natural log of persons per household, unemployment rate, population dummies, and a gender dummy. Our results are not significant at the 5% level in Table 5 (ia treatment) but they are consistent with our base model (Table 2). Irma did1 is significant at the 10% level and positive for coverage per capita and per household. Females have a positive effect on coverage per capita at the 5% significance level. In Table 6, our results are consistent with our base model (Table 3) and we see significance in Irma spill of 1% for coverage per capita and 5% for coverage per household. We also observe a significant negative effect with looking at Irma did2 across all columns at the

5% level consistent with our base model. Unemployment rate has significantly negative result on policies per capita and per household at the 5% level. Individuals between the ages of 20-39 have a negative significant result at the 5% level for coverage, those 40-59 have a positively significant result 5% coverage per capita and 10% coverage per household, and those 60+ also have a positive effect at the 5% level for coverage. In Table 7 the only significance we observe is with our Irma did3 variable. We see a positive effect on policies per capita at the 5% and on policies per household at the 10%. Coverage per capita and per household both have positive effects from did3 at the 1% level. There is also a negatively significant effect on policies per capita from the natural log of household income at the 5% significance level.

Another model we include uses regional dummies instead of county dummies for unobserved cross-sectional factors (Tables 8-10). We do not find any significant results for our time, treatment, or did variables in Tables 8 and 9. We do find negative significant effects in Table 10 for our time variable Irma. Policies per capita has negative significance at the 10% level, 5% for policies per household, 10% for coverage per capita, and 1% significance for coverage per household. Irma did has a positive significant effect on coverage per capita and per household at the 10% significance level.

Table 2

NFIP Policies and Coverage Levels (per capita and per-household): IA Base

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0003**	-0.0006	-40.5565	-84.6156
	(0.0000)	(0.0001)	(24.8624)	(34.4696)
irma_ia	-0.0015	-0.0044	-314.1709	-929.1992
	(0.0005)	(0.0018)	(282.8695)	(365.0292)
irma_did1	0.0011***	0.0018***	715.9567***	1385.8236***
	(0.0000)	(0.0000)	(1.0191)	(1.6863)
precipitat~h	-0.0000	-0.0000	0.2137	0.3535
	(0.0000)	(0.0000)	(0.6900)	(1.3005)
lag_precip	-0.0000*	-0.0000*	-0.4478	-1.1433
	(0.0000)	(0.0000)	(0.2489)	(0.4543)
linc	-0.0002	-0.0008	236.6508	386.3869
	(0.0005)	(0.0018)	(280.3096)	(358.0267)
County Dummies	YES	YES	YES	YES
_cons	0.0043	0.0157	-2265.3136	-3152.3817
	(0.0053)	(0.0209)	(3272.7117)	(4209.5865)
R-sq	0.999	0.999	0.999	0.999
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 3

NFIP Policies and Coverage Levels (per capita and per-household): Spill Base

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0002	-0.0004	14.4766	26.6793
	(0.0001)	(0.0002)	(19.9106)	(45.6308)
irma_spill	0.1566***	0.4056***	36128.1184***	93522.9032***
	(0.0003)	(0.0007)	(64.6300)	(146.9008)
irma_did2	-0.0002*	-0.0007*	-68.4704*	-165.7774*
	(0.0000)	(0.0001)	(6.4998)	(15.2957)
precipitat~h	-0.0000	-0.0000	0.1905	0.2984
	(0.0000)	(0.0000)	(0.1974)	(0.5018)
lag_precip	-0.0000	-0.0000	0.9683	1.7091
	(0.0000)	(0.0000)	(0.6425)	(1.5507)
linc	-0.0003	-0.0012	140.6478	190.0117
	(0.0010)	(0.0024)	(225.9212)	(515.7030)
County Dummies	YES	YES	YES	YES
_cons	0.0063	0.0199	-1256.5112	-1085.5269
	(0.0118)	(0.0272)	(2551.7641)	(5817.5337)
R-sq	0.999	0.999	0.999	0.999
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4

NFIP Policies and Coverage Levels (per capita and per-household): IA+Spill Base

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0002	-0.0005	-39.2214	-77.0180
	(0.0001)	(0.0001)	(46.8479)	(84.3572)
irma_ias	0.1564***	0.4053***	36021.3398***	93311.8569***
	(0.0002)	(0.0002)	(162.9205)	(281.4847)
irma_did3	0.0002	0.0002	212.2827**	386.6415**
	(0.0000)	(0.0001)	(8.6512)	(18.3167)
precipitat~h	-0.0000	-0.0000	0.2782	0.4707
	(0.0000)	(0.0000)	(0.6259)	(1.0626)
lag_precip	-0.0000	-0.0000	-0.3244	-0.7830
	(0.0000)	(0.0000)	(0.1976)	(0.7166)
linc	-0.0002	-0.0009	251.7621	405.4224
	(0.0006)	(0.0007)	(529.9131)	(922.5572)
County Dummies	YES	YES	YES	YES
_cons	0.0045	0.0169	-2450.2514	-3400.8151
	(0.0071)	(0.0076)	(6114.1953)	(10622.6034)

R-sq	0.999	0.999	0.999	0.999
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

CHAPTER 6

DISCUSSION

Referring back to Figures 1 and 2 for change in number of enforced policies, we see that Chatham County (region 12) had the largest decrease in number of policies from 6 months before Irma to 6 months after Irma. This initial qualitative analysis did not account for population, households, time treatment over multiple years, counties unaffected by Irma versus those affected, etc. Therefore, we needed the difference in difference regression to paint a more comprehensive picture of the effect Irma had on counties affected.

In reviewing the literature, we recall perception of risk contributes significantly to the take-up rate of flood insurance according to Atreya, Ferreira et al. 2015. Since most of our treatment counties for Irma ia are along the coast of Georgia, one could make the assumption the individuals who live in these counties reasonably understand their level of risk. This could account for why they have the highest average policies and coverage per capita and per household. Our results show that these coastal counties (Irma ia) increased their policies and coverage per capita and per household after Irma. This could suggest that new information on climate risk may convince individuals to purchase or increase their coverage of flood insurance because they are more aware of their increasing risks. The Pentagon issued a report in 2015 identifying four areas of climate related security risks including: sea level rise, more frequent and severe extreme weather events, recurrent flooding and drought, and higher ambient temperatures (Ahmadiani, Ferreira et al. 2019). As people who are living in a perceived "safe haven" learn new information about a very rare event, their perceptions could change. Risk averse individuals would in theory purchase flood insurance if new information regarding their increased risk came to light. We see evidence of this in Finkelstein and McGarry (2006). Additionally, as people become more aware of their flood risk, they purchase flood insurance. We see evidence of this in the "Cover America" campaign of 1995. As people learned about their flood risk, we saw a significant increase in flood insurance market penetration (Michel-Kerjan 2010).

We also need to account for the mandatory purchase requirements after a county has received individual assistance from FEMA. We have attempted to do this by including adjacent counties to those receiving IA. We see an overall decrease in policies and coverage when analyzing just the spillover counties, but we see a positive effect in our interaction term when we combine IA and spillover counties. This suggests that perhaps we would see an increase in policies and coverage in counties severely affected by Hurricane Irma if the mandatory purchase requirement was not in place, but we cannot conclude this because our results are not significant. An avenue for future research would be to see if people change their coverage level of their mandatory insurance over time.

When we observe counties unaffected by Irma experience virtually no change in average number of policies in Figures 4, 5 ,6, and 7. This is consistent with the theory of probability neglect discussed in Kunreuther and Michel-Kerjan (2010), Sunstein (2002), and Zeckhauser and Sunstein (2010). Residents who might be at risk either underestimate their risk or disregard it, consistent with our results in counties unaffected by Irma. We see probability of neglect as a possible explanation when using counties adjacent to our IA counties as our treatment variable (Irma spill). We find significantly negative results for policies and coverage in our interaction variable leading us to believe those in spillover counties decreased their policies and coverage after Hurricane Irma. Another possible explanation could be the "Gambler's Fallacy" where residents think they will not see a major flooding event I the same area soon and do not see the need for flood insurance (Kunreuther and Michel-Kerjan 2010). This could be further exacerbated by the fact that individuals in these counties also did not receive individual assistance and do not have to purchase flood insurance.

Dividing policies and coverage by population and households per county ensures a consistent analysis across all counties. Controlling for average precipitation per year in each county also helps to accomplish this goal, although this control variable did not have a significant effect on our overall results. As discussed, when reviewing the literature, demographic factors such as income, education, age, race, etc. can explain take-up rates. Browne and Hoyt 2000 found that individuals with a higher income are more likely to purchase flood insurance. In our results, we find those over the age of 40 have a significant positive effect on coverage per capita and per household (Table 6). This is consistent with the findings of Atreya, Ferreira et al. (2015).

In our results, we are able to see Hurricane Irma had a significant positive effect on average policies and coverage per capita and per household in counties affected by the hurricane and had a negative effect on counties adjacent (Irma spill). In our review of literature, we discussed factors affecting take-up rates for food insurance in Georgia. We would expect higher take-up rates right after a hurricane consistent in our policies result and coverage results for Irma ia. Atreya, Ferreira et al. 2015 find that these initial effects wear off after about 3 years. Further research would need to be completed when FEMA's 2020 data is released to determine if the increase in policies and coverage is permanent.

CHAPTER 7

CONCLUSION

In our research, we find that Hurricane Irma significantly increased the take-up rate of flood insurance policies and coverage in areas severely affected by the hurricane that are considered “safe havens.” These results lead us to believe individuals in these areas realize climate change will yield more frequent and severe events. We also observe that individuals in spillover counties decrease their policies and coverage after the hurricane. We think this is because of “Gambler’s Fallacy” combined with the lack of mandatory flood insurance. Considering demographic data such as population per county and households per county allowed us to create balanced estimates across all counties. Accounting for average precipitation per year, household income, population data, and demographic variables in each county also allowed us to check the robustness of our results to further ensure the significance of our results. Future research includes gathering future data from FEMA’s policy data to evaluate Hurricane Michael (2018) in the same manner. This will help to determine what factors (i.e. demographics, flooding events, risk perception, etc.) contribute the most to changes in take-up rates. Larger implications for this study are determining how to target individuals for purchasing flood insurance based on the factors we find that contribute to up-take rates. Purchasing flood insurance helps to financially shield participants from the number one most costly natural disaster and therefore it is of the upmost importance to increase take-up rates before the next natural disaster.

REFERENCES

Ahmadiani, M., et al. (2019). "Flood Insurance and Risk Reduction: Market Penetration, Coverage, and Mitigation in Coastal North Carolina." Southern Economic Journal **85**(4): 1058-1082.

Anderson, D. R. (1974). "The national flood insurance program. Problems and potential." Journal of Risk and Insurance: 579-599.

Atreya, A., et al. (2015). "What drives households to buy flood insurance? New evidence from Georgia." Ecological Economics **117**: 153-161.

Baumann, D. D. and J. H. Sims (1978). "Flood insurance: Some determinants of adoption." Economic Geography **54**(3): 189-196.

Botzen, W. J., et al. (2009). "Willingness of homeowners to mitigate climate risk through insurance." Ecological Economics **68**(8-9): 2265-2277.

Bouwer, L. M. (2011). "Have disaster losses increased due to anthropogenic climate change?" Bulletin of the American Meteorological Society **92**(1): 39-46.

Browne, M. J. and R. E. Hoyt (2000). "The demand for flood insurance: empirical evidence." Journal of risk and uncertainty **20**(3): 291-306.

Cutler, D. M. and R. Zeckhauser (2004). "Extending the theory to meet the practice of insurance." Brookings-Wharton Papers on Financial Services **2004**(1): 1-53.

Dixon, T. H., et al. (2006). "Subsidence and flooding in New Orleans." Nature **441**(7093): 587-588.

Eldred, G. W. (1980). "How Wisely Do Consumers Select Their Property and Liability Insurance Coverages?" Journal of Consumer Affairs **14**(2): 288-306.

Federal Emergency Management Agency. 2017. Flood Insurance Requirments for Recipients of Federal Disaster Assistance, The National Flood Insurance Program

Federal Emergency Management Agency. 2018. The Watermark, Fiscal Year 2018, First Quarter, Volume 1, Federal Insurance and Mitigation Administration, The National Flood Insurance Program.

Federal Emergency Management Agency. 2019. About The Agency: History. Accessed January 10, 2020. Avaliable https://www.fema.gov/write-your-own-wyo-program

Federal Emergency Management Agency. 2019. FIMA NFIP Redacted Policies Dataset. Acessed January 10, 2020. Avaliable https://www.fema.gov/media-library/assets/documents/180376

Federal Emergency Management Agency. 2019. Flood Insurance Rate Map (FIRM). Accessed April 21, 2020. Avaliable https://www.fema.gov/flood-insurance-rate-map-firm

Federal Emergency Management Agency. 2019. Special Flood Hazard Area. Accessed April 21, 2020. Avliable https://www.fema.gov/special-flood-hazard-area

Federal Emergency Management Agency. 2019. The Write Your Own (WYO) Program. Accessed Febuary 1, 2020. Avaliable https://www.fema.gov/about-agency

Federal Emergency Management Agency. 2020. Data Visualization: Disaster Declarations for States and Counties. Accessed April 30, 2020. Available https://www.fema.gov/data-visualization-disaster-declarations-states-and-counties

Federal Emergency Management Agency. 2020. Data Visualization: Historical Flood Risk and Costs. Accessed March 30, 2020. Available https://www.fema.gov/data-visualization-floods-data-visualization

Finkelstein, A. and K. McGarry (2006). "Multiple dimensions of private information: evidence from the long-term care insurance market." American Economic Review **96**(4): 938-958.

Georgia Department of Economic Development. 2020. Regional Fact Sheets. Accessed March 30, 2020. Available https://www.georgia.org/business-resources/georgia-centers-of-innovation/center-innovation-logistics/resources/region-spotlights

Grossman, D. A. (1958). "Flood insurance: can a feasible program be created?" Land Economics **34**(4): 352-357.

Hallegatte, S., et al. (2013). "Future flood losses in major coastal cities." Nature climate change **3**(9): 802-806.

Ingraham, C. (2015). Earthquakes, floods and volcanoes: The most disaster-prone places in America *The Washington Post* Retrieved from https://www.washingtonpost.com/news/wonk/wp/2015/01/21/earthquakes-floods-and-volcanoes-the-most-disaster-prone-places-in-america/?arc404=true

Jaffee, D. M. and T. Russell (1997). "Catastrophe insurance, capital markets, and uninsurable risks." Journal of Risk and Insurance: 205-230.

Kaplow, L. (1991). "Incentives and government relief for risk." Journal of risk and uncertainty **4**(2): 167-175.

Kriesel, W. and C. Landry (2004). "Participation in the National Flood Insurance Program: An empirical analysis for coastal properties." Journal of Risk and Insurance **71**(3): 405-420.

Kousky, C. and H. Kunreuther (2010). "Improving flood insurance and flood-risk management: insights from St. Louis, Missouri." Natural Hazards Review **11**(4): 162-172.

Kunreuther, H. C. and E. Michel-Kerjan (2010). "Market and government failure in insuring and mitigating natural catastrophes: How long-term contracts can help." The economics of natural and unnatural disasters: 9-38.

Landes, D. S., et al. (2012). The invention of enterprise: Entrepreneurship from ancient Mesopotamia to modern times, Princeton University Press.

Landry, C. E. and M. R. Jahan-Parvar (2011). "Flood insurance coverage in the coastal zone." Journal of Risk and Insurance **78**(2): 361-388.

Lewis, T. and D. Nickerson (1989). "Self-insurance against natural disasters." Journal of Environmental Economics and Management **16**(3): 209-223.

Merriam-Webster. 2020. Loss Ratio. Accessed April 30, 202. Avaliable https://www.merriam-webster.com/dictionary/loss%20ratio

Michel-Kerjan, E. O. (2010). "Catastrophe economics: the national flood insurance program." Journal of economic perspectives **24**(4): 165-186.

Michel-Kerjan, E. O. and C. Kousky (2010). "Come rain or shine: Evidence on flood insurance purchases in Florida." Journal of Risk and Insurance **77**(2): 369-397.

National Oceanic and Atmospheric Administration. 2019. Frequentyly Ask Questions: About Hurricanes . Accessed March 18, 2020. Avaliable https://www.aoml.noaa.gov/hrd-faq/#landfalling-hurricanes

Perry, C. A. (2000). Significant Floods in the United States during the 20th Century: USGS Measures a Century of Floods, US Department of the Interior, US Geological Survey.

Petrolia, D. R., et al. (2013). "Risk preferences, risk perceptions, and flood insurance." Land Economics **89**(2): 227-245.

Pielke Jr, R. A. and M. W. Downton (2000). "Precipitation and damaging floods: Trends in the United States, 1932–97." Journal of climate **13**(20): 3625-3637.

Pielke Jr, R. A., et al. (2008). "Normalized hurricane damage in the United States: 1900–2005." Natural Hazards Review **9**(1): 29-42.

PRISM Climate Group. 2020. Recent Years (Jan 1981-Sept 2019). Accessed February 10, 2020. Avaliable http://www.prism.oregonstate.edu/recent/

Raschky, P. A., et al. (2013). "Uncertainty of governmental relief and the crowding out of flood insurance." Environmental and Resource Economics **54**(2): 179-200.

Raschky, P. A. and H. Weck-Hannemann (2007). "Charity hazard—A real hazard to natural disaster insurance?" Environmental Hazards **7**(4): 321-329.

Rejda, G. E. (1998). Principles of risk management and insurance, Pearson Education India.

Roth Sr, R. J. and H. Kunreuther (1998). Paying the price: The status and role of insurance against natural disasters in the United States, Joseph Henry Press.

Sunstein, C. R. (2002). "Probability neglect: Emotions, worst cases, and law." The Yale Law Journal **112**(1): 61-107.

Sydnor, J. (2006). Abundant Aversion to Moderate Risk: Evidence from Homeowners Insurance, Mimeo (Berkeley, CA: University of California).

U.S. Census Bureau. 2020. Explore Census Data. Accesed March 3, 2020. Avaliable https://data.census.gov/cedsci/

Walls, M., et al. (2018). "Modeling coastal land and housing markets: Understanding the competing influences of amenities and storm risks." Ocean & Coastal Management **157**: 95-110.

Wetmore, F., et al. (2006). "An evaluation of the National Flood Insurance Program: final report." American Institutes for Research, Washington DC.

Zahran, S., et al. (2009). "Modeling national flood insurance policy holding at the county scale in Florida, 1999–2005." Ecological Economics **68**(10): 2627-2636.

Zeckhauser, R. and C. R. Sunstein (2010). "Dreadful possibilities, neglected probabilities." The irrational economist: making decisions in a dangerous world: 116-124.

APPENDIX

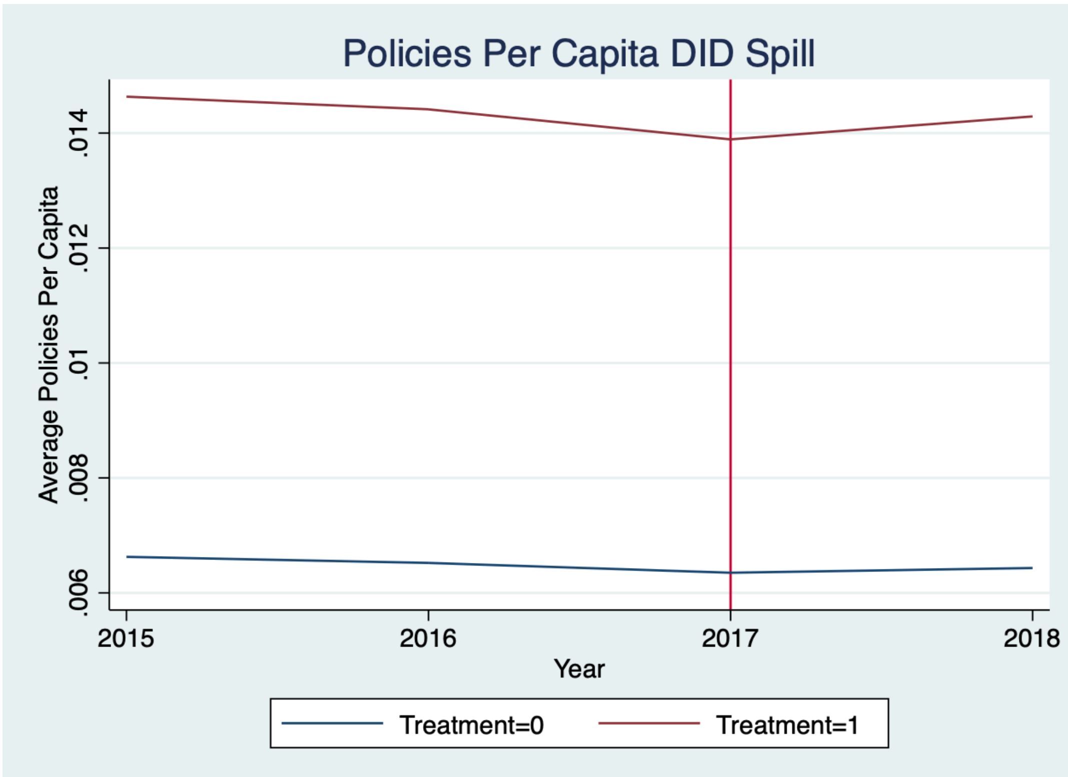

Figure 8

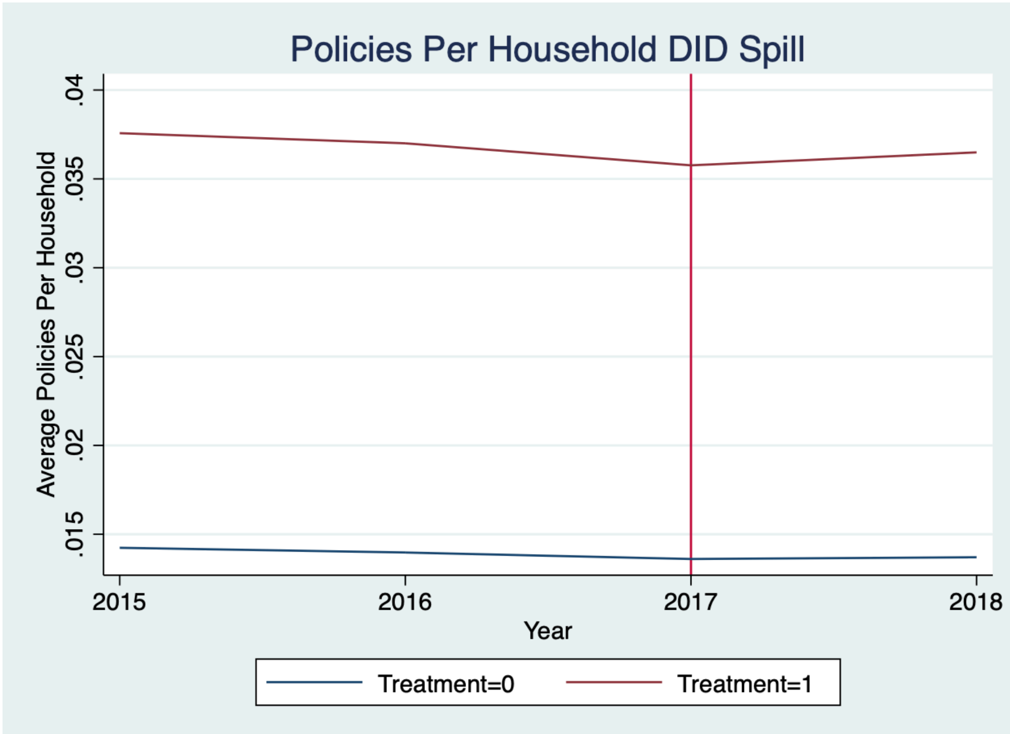

Figure 9

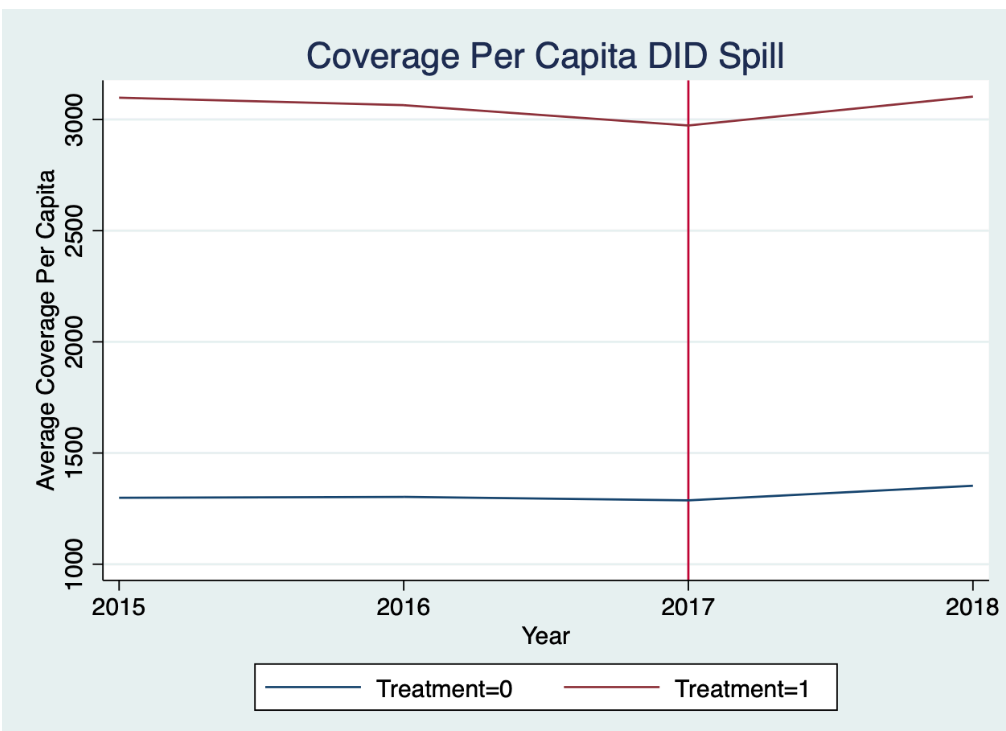

Figure 10

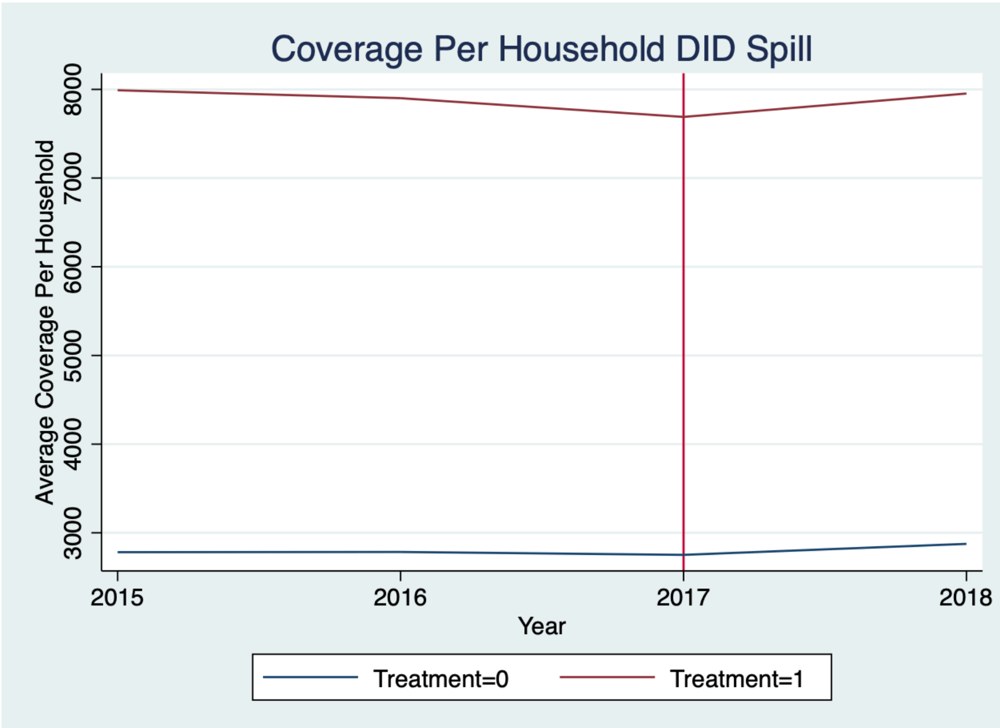

Figure 11

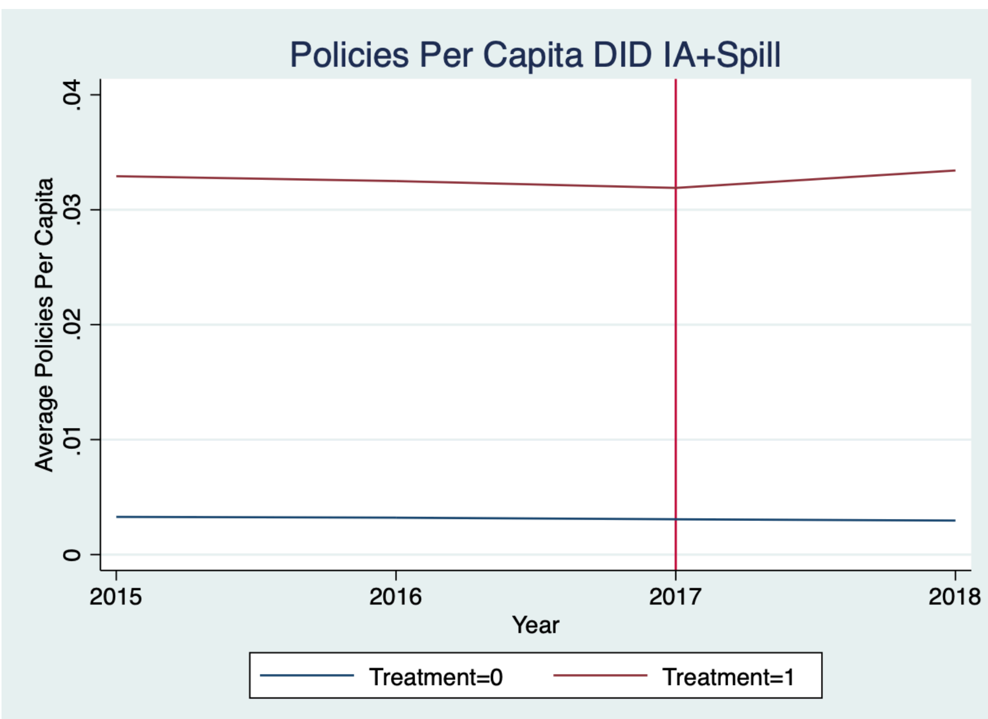

Figure 12

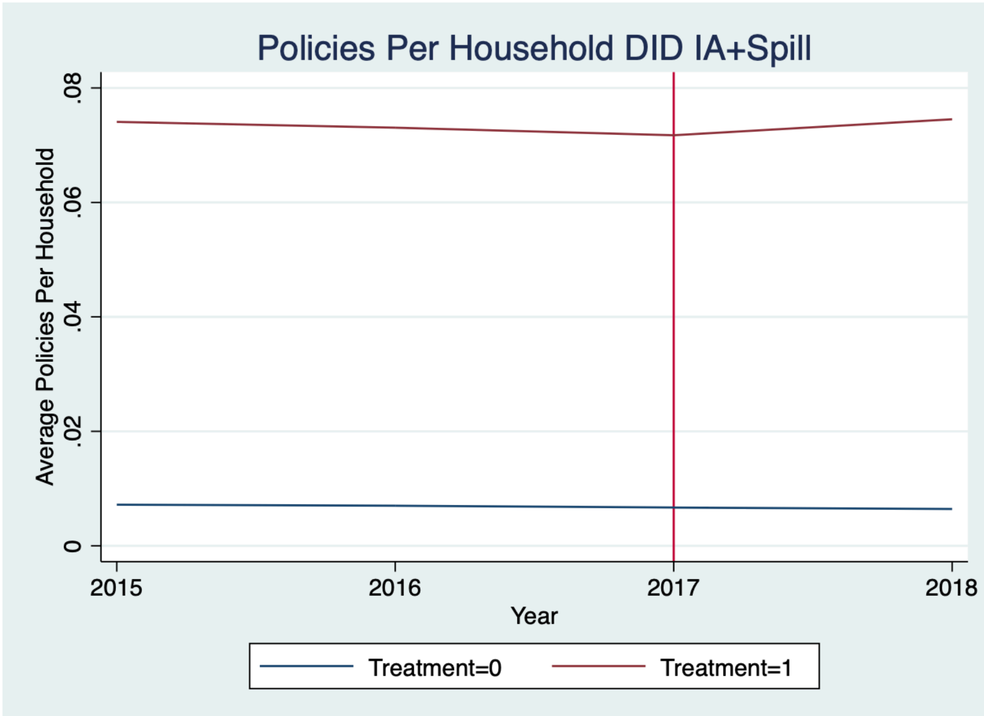

Figure 13

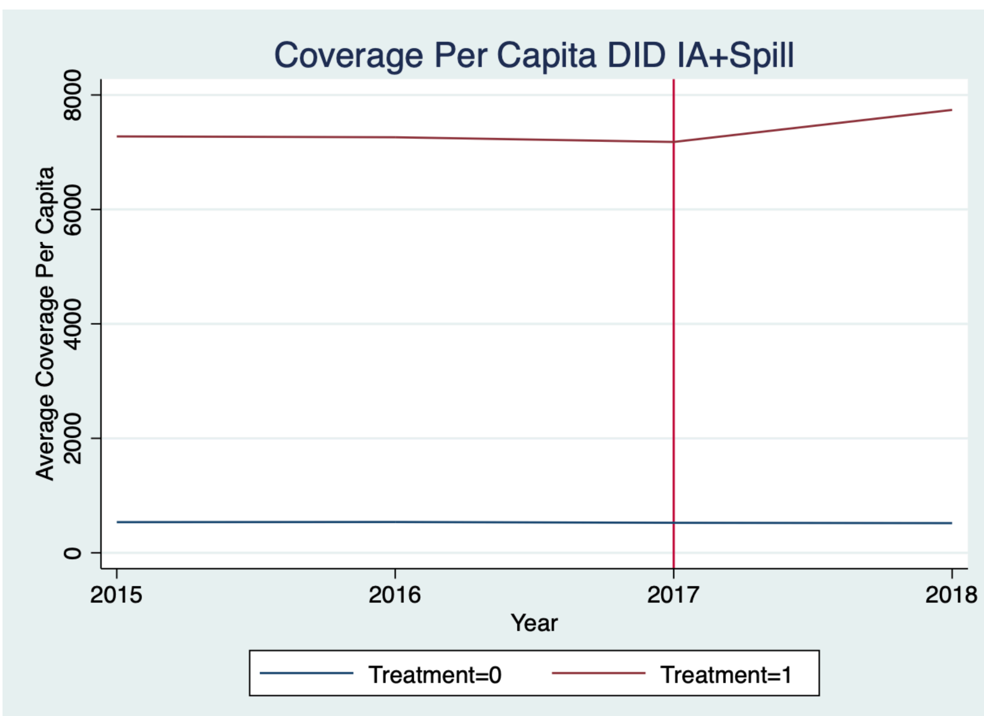

Figure 14

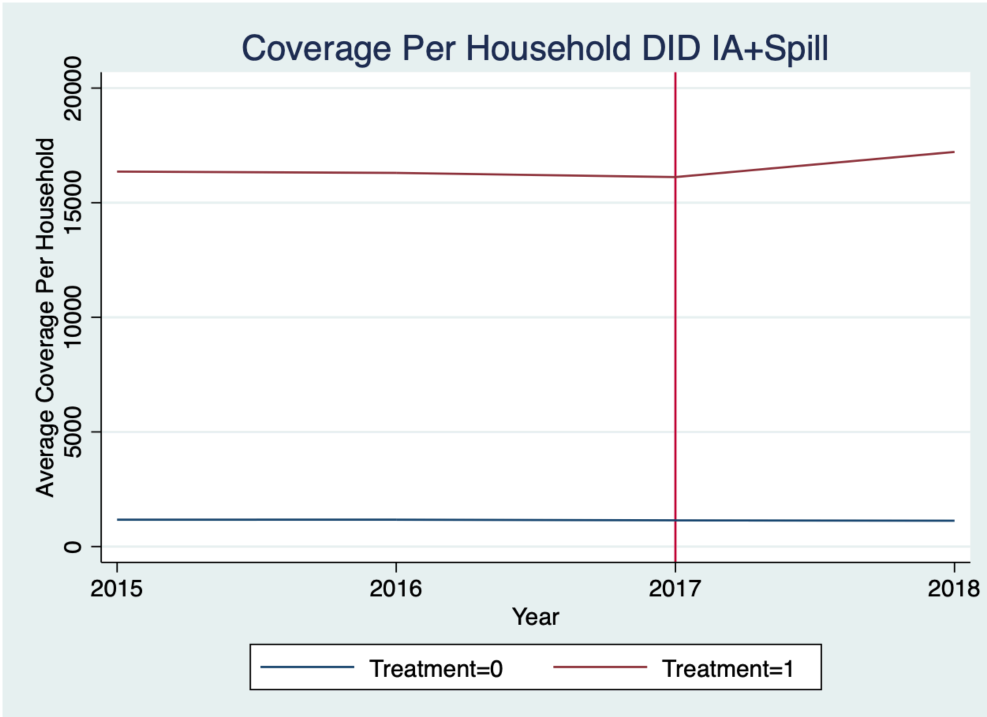

Figure 15

Table 5

NFIP Policies and Coverage Levels (per capita and per-household): IA

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0004	-0.0009	-114.2183	-228.2858
	(0.0003)	(0.0005)	(149.1699)	(276.0497)
irma_ia	0.0901	0.2117*	17316.8152	42120.3243
	(0.0180)	(0.0334)	(10589.0407)	(20916.7828)
irma_did1	0.0009	0.0014	677.7568*	1303.4000*

	(0.0002)	(0.0005)	(67.1973)	(157.5115)
precipitat~h	-0.0000	-0.0000	-0.1938	-0.4475
	(0.0000)	(0.0000)	(0.0696)	(0.0825)
lag_precip	-0.0000	-0.0000	-1.6799	-3.5458
	(0.0000)	(0.0000)	(1.7433)	(3.4018)
linc	-0.0004	-0.0012	85.1901*	93.2416
	(0.0012)	(0.0031)	(11.8136)	(201.1790)
lphh	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
unemployme~e	-0.0001	-0.0002	-45.7415	-88.1630
	(0.0002)	(0.0004)	(76.3165)	(146.2925)
tot_popag~19	-0.0000	-0.0000	-0.0417	-0.0831
	(0.0000)	(0.0000)	(0.0681)	(0.1396)
tot_popag~39	-0.0000	-0.0000	-0.0863	-0.1863
	(0.0000)	(0.0000)	(0.1594)	(0.3485)
tot_popag~59	0.0000	0.0000	0.0692	0.1504
	(0.0000)	(0.0000)	(0.1068)	(0.2370)
tot_popag~60	0.0000	0.0000	0.0522	0.1117
	(0.0000)	(0.0000)	(0.1001)	(0.2158)
percent_fe~e	0.0209	0.0384	1449.6785**	2785.1165
	(0.0086)	(0.0216)	(36.9518)	(1821.6115)
County Dummies	YES	YES	YES	YES
_cons	0.0127	0.0316	6755.0348	13981.1285
	(0.0432)	(0.0906)	(17375.7857)	(35915.0262)
R-sq	0.999	0.999	0.999	0.999

N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 6

NFIP Policies and Coverage Levels (per capita and per-household): Spill

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0003	-0.0006	-41.4371	-81.9207
	(0.0001)	(0.0002)	(19.6939)	(48.5100)
irma_spill	0.1343	0.3668	22201.9967***	67104.3467**
	(0.0272)	(0.0874)	(306.1152)	(4891.9816)
irma_did2	-0.0002**	-0.0005**	-37.2481**	-103.7954**
	(0.0000)	(0.0000)	(2.3948)	(7.3492)
precipitat~h	-0.0000	-0.0000	-0.1655	-0.3959
	(0.0000)	(0.0000)	(0.3250)	(0.8113)
lag_precip	-0.0000	-0.0000	-0.0354	-0.2436
	(0.0000)	(0.0000)	(0.5429)	(1.4285)
linc	-0.0004	-0.0013	104.8834	125.4126
	(0.0010)	(0.0025)	(169.9536)	(411.3062)
lphh	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
unemployme~e	-0.0001**	-0.0001**	-24.5342	-46.4750

	(0.0000)	(0.0000)	(4.2926)	(10.9208)
tot_popag~19	-0.0000	-0.0000	-0.0571*	-0.1123
	(0.0000)	(0.0000)	(0.0049)	(0.0334)
tot_popag~39	-0.0000*	-0.0000	-0.1126**	-0.2369**
	(0.0000)	(0.0000)	(0.0025)	(0.0114)
tot_popag~59	0.0000	0.0000	0.0757**	0.1633*
	(0.0000)	(0.0000)	(0.0056)	(0.0225)
tot_popag~60	0.0000	0.0000	0.0677**	0.1408**
	(0.0000)	(0.0000)	(0.0015)	(0.0073)
percent_fe~e	0.0275	0.0477	7009.9869	13319.7455
	(0.0128)	(0.0320)	(2377.9138)	(5936.6447)
County Dummies	YES	YES	YES	YES
_cons	0.0175	0.0395	10427.6999**	21062.0433
	(0.0238)	(0.0808)	(308.5947)	(3703.0021)
R-sq	0.999	0.999	0.999	0.999
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 7

NFIP Policies and Coverage Levels (per capita and per-household): IA+Spill

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh

irma	-0.0004	-0.0008	-110.8740	-214.8854
	(0.0003)	(0.0006)	(150.9439)	(291.6373)
irma_ias	0.0849	0.2025	13487.3112	34664.9422
	(0.0485)	(0.1173)	(18673.6247)	(39842.1413)
irma_did3	0.0002**	0.0001*	209.9693***	380.2023***
	(0.0000)	(0.0000)	(1.0675)	(5.6037)
precipitat~h	-0.0000	-0.0000	-0.1538	-0.3715
	(0.0000)	(0.0000)	(0.1682)	(0.5592)
lag_precip	-0.0000	-0.0000	-1.5679	-3.1765
	(0.0000)	(0.0000)	(1.7882)	(3.9048)
linc	-0.0004**	-0.0011	140.5592	196.4558
	(0.0000)	(0.0004)	(257.7824)	(405.1275)
lphh	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
unemployme~e	-0.0001	-0.0002	-37.7292	-71.3896
	(0.0002)	(0.0003)	(56.7126)	(111.4023)
tot_popag~19	-0.0000	-0.0000	-0.0541	-0.1072
	(0.0000)	(0.0000)	(0.0953)	(0.2163)
tot_popag~39	-0.0000	-0.0000	-0.1051	-0.2234
	(0.0000)	(0.0000)	(0.1932)	(0.4208)
tot_popag~59	0.0000	0.0000	0.0705	0.1535
	(0.0000)	(0.0000)	(0.1096)	(0.2541)
tot_popag~60	0.0000	0.0000	0.0677	0.1416
	(0.0000)	(0.0000)	(0.1294)	(0.2772)
percent_fe~e	0.0276	0.0500	6448.4390	12481.9872

	(0.0079)	(0.0114)	(6878.9106)	(13778.6263)
County Dummies	YES	YES	YES	YES
_cons	0.0163	0.0386	9158.1531	18742.8886
	(0.0734)	(0.1830)	(21950.4385)	(49100.1352)
R-sq	0.999	0.999	0.999	0.999
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 8

NFIP Policies and Coverage Levels (per capita and per-household): Regions IA

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0013	-0.0034	-292.1781	-739.7029
	(0.0006)	(0.0010)	(141.2767)	(250.4337)
irma_ia	0.0340	0.0604	7849.2269	14113.3112
	(0.0115)	(0.0216)	(2702.8879)	(5120.9610)
irma_did1	0.0003	0.0007	551.2862	1130.1994
	(0.0010)	(0.0020)	(252.9636)	(517.9883)
precipitat~h	0.0000	0.0001	10.4422	15.6290
	(0.0001)	(0.0001)	(14.0256)	(28.9377)

lag_precip	0.0000	0.0000	6.9630	6.2533
	(0.0000)	(0.0001)	(12.6995)	(28.5538)
linc	0.0197**	0.0574	4496.9822**	13096.9215*
	(0.0004)	(0.0091)	(114.4690)	(2043.5920)
lphh	-0.0399	-0.0819	-9134.0902	-19079.5862
	(0.0282)	(0.0595)	(6877.0507)	(14429.0922)
unemployme~e	0.0007	0.0019	147.2274	398.6324
	(0.0002)	(0.0010)	(42.6876)	(221.2290)
tot_popag~19	0.0000	0.0000*	0.0548	0.1844**
	(0.0000)	(0.0000)	(0.0399)	(0.0038)
tot_popag~39	-0.0000	-0.0000	-0.0860	-0.1121
	(0.0000)	(0.0000)	(0.2004)	(0.3467)
tot_popag~59	-0.0000	-0.0000**	-0.0722	-0.2670*
	(0.0000)	(0.0000)	(0.0817)	(0.0269)
tot_popag~60	0.0000	0.0000	0.1935	0.3550
	(0.0000)	(0.0000)	(0.3126)	(0.6318)
percent_fe~e	0.0239	0.0282	5053.0361	6008.0241
	(0.0179)	(0.0085)	(4421.6584)	(2682.8267)
Regional Dummies	YES	YES	YES	YES
_cons	-0.1977**	-0.5748*	-44944.8243**	-130962.4188*
	(0.0071)	(0.0811)	(1719.5151)	(18443.4229)
R-sq	0.619	0.583	0.606	0.571
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 9

NFIP Policies and Coverage Levels (per capita and per-household): Regions Spill

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0016	-0.0041	-351.2911	-845.8369
	(0.0003)	(0.0008)	(97.5774)	(228.9900)
irma_spill	-0.0019	0.0020	-459.4183	378.6970
	(0.0003)	(0.0010)	(81.4499)	(234.9521)
irma_did2	0.0005	0.0011	112.2290	251.6501
	(0.0002)	(0.0003)	(40.4578)	(71.7986)
precipitat~h	0.0001	0.0001	13.2094	20.3986
	(0.0000)	(0.0001)	(7.2526)	(18.3150)
lag_precip	0.0000	0.0000	9.5264	10.5326
	(0.0000)	(0.0001)	(8.9632)	(22.0002)
linc	0.0171	0.0522	3875.6455	11863.4380
	(0.0216)	(0.0589)	(4952.9898)	(13533.9287)
lphh	-0.0358	-0.0753	-8146.5596	-17463.8805
	(0.0316)	(0.0726)	(7350.1940)	(16961.3652)
unemployme~e	0.0006	0.0017	122.3922	354.3106
	(0.0012)	(0.0030)	(281.8265)	(714.5339)
tot_popag~19	0.0000	0.0000	0.0715	0.2242
	(0.0000)	(0.0000)	(0.0961)	(0.2190)

tot_popag~39	-0.0000	-0.0000	-0.1112	-0.1592
	(0.0000)	(0.0000)	(0.0474)	(0.1440)
tot_popag~59	-0.0000	-0.0000	-0.1147	-0.3575
	(0.0000)	(0.0000)	(0.1212)	(0.2752)
tot_popag~60	0.0000	0.0000	0.2911	0.5421
	(0.0000)	(0.0000)	(0.0547)	(0.2010)
percent_fe~e	-0.0041*	-0.0225	-1600.7826**	-6166.3502
	(0.0004)	(0.0042)	(50.9369)	(1053.9872)
Regional Dummies	YES	YES	YES	YES
_cons	-0.0885	-0.3451	-19633.9981	-77591.7813
	(0.2058)	(0.5670)	(47405.9648)	(130530.7217)
R-sq	0.563	0.548	0.547	0.533
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 10

NFIP Policies and Coverage Levels (per capita and per-household): Regions IA+Spill

	(1)	(2)	(3)	(4)
	policy_cap~a	policy_hh	cov_capita	cov_hh
irma	-0.0016*	-0.0039**	-364.9381*	-867.2188***
	(0.0002)	(0.0001)	(36.4201)	(4.0597)

irma_ias	0.0126	0.0281	2912.3151	6488.9527
	(0.0091)	(0.0200)	(2110.2602)	(4645.4777)
irma_did3	0.0005	0.0010	278.4952*	583.1048*
	(0.0002)	(0.0004)	(38.6419)	(76.0355)
precipitat~h	0.0000	0.0001	11.6585	17.1974
	(0.0000)	(0.0001)	(9.8273)	(16.4045)
lag_precip	0.0000	0.0000	6.7544	5.0027
	(0.0000)	(0.0000)	(7.0643)	(12.9450)
linc	0.0168	0.0522	3809.3472	11842.9702
	(0.0187)	(0.0644)	(4247.9547)	(14685.5297)
lphh	-0.0393	-0.0822	-8976.7765	-19114.6249
	(0.0470)	(0.1078)	(11181.3247)	(25544.0720)
unemployme~e	0.0007	0.0018	130.2257	372.0426
	(0.0014)	(0.0040)	(336.0620)	(961.9817)
tot_popag~19	0.0000	0.0000	0.0912	0.2570
	(0.0000)	(0.0000)	(0.0519)	(0.1953)
tot_popag~39	-0.0000	-0.0000	-0.1056	-0.1451
	(0.0000)	(0.0000)	(0.1615)	(0.2154)
tot_popag~59	-0.0000	-0.0000	-0.1358	-0.3888
	(0.0000)	(0.0000)	(0.0538)	(0.2572)
tot_popag~60	0.0000	0.0000	0.2832	0.5125
	(0.0000)	(0.0000)	(0.3085)	(0.5075)
percent_fe~e	0.0047	-0.0022	467.8729	-1387.5234
	(0.0116)	(0.0369)	(2547.6533)	(8233.7999)
Regional Dummies	YES	YES	YES	YES
_cons	-0.0970	-0.3692	-21548.5265	-83056.6531

	(0.1350)	(0.5419)	(30524.1558)	(123230.4972)
R-sq	0.581	0.566	0.566	0.552
N	636	636	636	636

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01