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Ajita Atreya
University of Pennsylvania

Susana Ferreira

Erwann Michel-Kerjan
University of Pennsylvania

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Benefiting from access to detailed data on the federally run National Flood Insurance Program for the entire state of Georgia, USA, we analyze residential flood insurance purchasing behavior in that state over more than three decades (1978–2010). The demand for flood insurance on an extensive margin, based on take-up rates, is found to be relatively price inelastic. Aligned with the behavioral economics literature, recent flood events temporarily increase purchases, but this effect fades after 3 years. We also find that the proportion of developed area in floodplains has a significant positive impact on insurance take-up rates. Contrary to what is often assumed, we do not find evidence that insurance purchase and mitigation efforts are substitutes. Educated individuals, individuals over the age of 45, and African-Americans are, all else equal, more likely to purchase flood insurance.

Keywords
floods, disaster insurance, NFIP, race, georgia

Disciplines
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Ajita Atreya
Wharton Risk Center
University of Pennsylvania

Susana Ferreira
University of Georgia

Erwann Michel-Kerjan
Wharton Risk Center
University of Pennsylvania

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Risk Management and Decision Processes Center
The Wharton School, University of Pennsylvania
3730 Walnut Street, Jon Huntsman Hall, Suite 500
Philadelphia, PA, 19104
USA
Phone: 215-898-5688
Fax: 215-573-2130
http://opim.wharton.upenn.edu/risk/

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Evidence from Georgia

July 31, 2014

Abstract

Benefiting from access to detailed data on the federally run National Flood Insurance Program for the entire state of Georgia, USA, we analyze flood insurance purchasing behavior in the 153 counties in that state over more than three decades (1978-2010). Estimates from a fixed effects model show that the demand for flood insurance on an extensive margin, based on take-up rates, is relatively price inelastic. Aligned with the behavioral economics literature, recent flood events temporarily increase purchases, but this effect quickly fades. We also confirm that the proportion of a county in a floodplain has a significant positive impact on insurance demand. Contrary to what is often assumed, we do not find evidence that insurance purchase and mitigation efforts are substitutes. More educated individuals, older ones and African-Americans are, all else equal, more likely to purchase flood insurance.

Keywords: Floods, Disaster Insurance, NFIP, Racial Difference, Georgia

1. Introduction

Insurance is one of the widely recognized risk transfer tools for ex ante management of weather disasters such as floods. In the United States, after private insurers decided to leave the flood insurance market after the Great Mississippi Flood of 1927 and after several decades of reliance on government disaster relief, the federal government established the National Flood Insurance Program (NFIP) in1968 (Dacy and Kunreuther, 1969; Michel-Kerjan, 2010). This national program provides flood insurance coverage to residents of communities that adopt minimum floodplain management policies. The program is managed by the Federal Emergency Management Agency (FEMA) which maps flood risks and sets flood insurance premiums. As of April 2014, there were over 5.4 million flood insurance policies-in-force in the U.S. managed through this federal program.

While the program has been in operation for over forty-five years, academic research on its operation and the demand for flood insurance through the NFIP is fairly recent. Browne and Hoyt (2000) provide the first empirical analyses of homeowners' demand for flood insurance through a state-level analysis across the country. Their empirical analysis suggests that both price and income are influential factors in one’s decision to purchase flood insurance, and flood insurance purchases at the state level are found to be highly correlated with the losses in the state during the prior year. Kriesel and Landry (2004) use household-level data from coastal zones in the United States to examine participation in NFIP for nine southeastern counties. They find participation responsiveness to price to be inelastic. Expanding upon the analysis of Kriesel and Landry (2004), Landry and Jahan-Parvar (2011) find a price-inelastic demand for flood insurance and that higher income households are more likely to purchase flood insurance, a finding that suggests that flood insurance is viewed as a normal good. Three studies have looked at specific states or cities. Zahran et al. (2009) show that household flood insurance purchases in Florida correlate strongly with local government mitigation activities. Additionally, they also show that NFIP policy take-up correlates positively with prior flood experience, local hazard proximity conditions such as land area in floodplain, and the education attainment levels of individuals in a locality. Michel-Kerjan and Kousky (2010) find that the majority of policies in Florida are located within the FEMA-defined high risk floodplains. Kousky (2010) examines the demand for flood insurance in St. Louis, Missouri and finds the take-up rates to increase with more land in the high risk floodplains and the rates to decline with levee protection along major rivers.

Building upon these earlier studies, we examine the demand for flood insurance using county level flood insurance policies-in-force data in another coastal state, Georgia, which has nearly $24 billion flood insurance coverage in force as of 2014. We expand on previous analyses in a number of ways.

First, we explore a greater array of covariates in our analysis; in addition to controlling for economic variables (income, price) and risk related variables (recent floods, risk reduction efforts) as in earlier studies, we also control for demographic variables such as race, education and age. To the best of our knowledge, race has never been tested as an explanatory variable affecting flood insurance demand. This is surprising since it has been shown that minority groups often differ in terms of world view, socioeconomic status, family organization and structure, political efficacy and trust in social and political institutions compared to the majority group (see Perry and Mushkatel, 2008, for instance). We might thus expect to find variations between race representations in the decision to purchase flood insurance. If confirmed, this can have important implications on the way flood risk and flood insurance are communicated to these different groups. Georgia presents an excellent case to do so since the state has a fairly high percentage of minority compared to the national average (31% African-Americans versus 13% nationally). Georgia indeed ranks third in the U.S. by the proportion of the state population that is African American, after Mississippi (37%) and Louisiana (32%) (U.S. Census, 2010).

Earlier studies found that the adoption of disaster insurance increased with the level of education (Kunreuther et al., 1978; Baumann and Sims, 1978); we will test whether this has remained the case over time (since we analyze the period 1978-2010) and whether it applies specifically to flood insurance.

Second, our empirical strategy controls for community participation in the NFIP, and also the proportion of owner-occupied homes in a county, which is new. It is imperative to control for the community participation in the NFIP as participation is mandatory to get the flood insurance and having fewer participating communities in a county drives down the insurance take up rates.

Third, our analysis benefits from a much longer period of data and a larger sample size compared to earlier studies which used only a few years of data and only a few counties to examine the demand for flood insurance (for example Kriesel and Landry (2004) and Landry and Jahn-Parvar (2011) used 1998-1999 survey data for nine coastal counties). Here we use extensive data from 153 counties in Georgia for a period of 32 years (1978-2010) to examine the demand for flood insurance.

We find evidence of price-inelastic demand for flood insurance and a positive income effect. We also find that recent flood damages have a positive impact on the adoption of flood insurance, consistent with Kunreuther's (1996) hypothesis that risk perception influences insurance purchasing decisions. Consistent with the availability heuristic (Tversky and Kahneman, 1973), wherein people use the ease with which examples of a hazard can be brought to mind as a cue for estimating the probability of a hazard, we find that this impact vanishes over time, though; the significance vanishes after 3 years. We find that publicly-funded mitigation efforts (dollars spent by the government on flood mitigation per capita) have a positive but insignificant effect on the decision to purchase flood insurance. This is contrary to insurance theory that assumes insurance and mitigation to be substitutes (e.g., Ehrlich and Becker, 1972; Mossin, 1968). Regarding the demographic variables, we find that the demand for flood insurance increases with an increase in the proportion of African-Americans in a county, higher education level and increasing age. The finding on race is important because this aspect has never been tested before. The proportion of floodplain in a county is found to be positively related to the number of policies purchased in a county whereas having fewer participating communities in a county is negatively related to the number of policies purchase.

The article is organized as follows. Section 2 introduces the operation of the National Flood Insurance Program. Section 3 discusses our hypotheses based on the literature and the data. Section 4 introduces our methodological approach. Section 5 discusses our results and Section 6 concludes.

2. The National Flood Insurance Program

The National Flood Insurance Act of 1968 created the NFIP as a voluntary partnership between the federal government, communities and private insurers. The NFIP develops flood maps, establishes the deductible/limit menu, and sets premiums, including subsidized premiums for certain existing properties (Michel-Kerjan, 2010). Over 90 private insurers collaborate with the program to sell flood insurance policies through their networks and provide claim adjustments. They receive an allowance for doing so on behalf of the federal government but do not bear any risk. While there is a small private market for flood insurance, it represents only 5 percent of what is sold through the NFIP (Dixon et al., 2006).

A significant problem with the NFIP lies in its implementation. Effective flood damage prevention depends a great deal on the ability and willingness of community planners and property owners to adapt to the program. In a survey conducted a decade after the NFIP was established, it was found that only 12 percent or fewer responding individuals of a community participating in the NFIP were aware of the building codes or land use regulations to mitigate flood damage; and only 1 percent were aware of the insurance mechanism to manage flood risk (Kunreuther et al, 1978). Using survey data, Chivers and Flores (2002) find evidence that the overwhelming majority of households living in flood zones of Colorado were unaware of the flood risk classification and flood insurance rates and requirements at the time they submitted their bid to purchase property. Similarly, a recent study by Bin and Landry (2013) indicates that homebuyers are unaware of flood risks and insurance requirements when bidding on properties

In addition to problems with the implementation of the NFIP, Hurricane Katrina in 2005 and Hurricane Sandy in 2012 demonstrated that federal flood insurance was insufficient to secure all policy holders and restore the damage. Limitations on federal flood insurance coverage[1] and the unwillingness of homeowners' insurance companies to pay for storm-related damages left some policyholders unable to rebuild. Despite the limitations on federal flood insurance coverage, Hurricane Katrina led to a debt of almost $18 billion to the U.S. Treasury. In order to pay claims from Hurricane Sandy in 2012, the NFIP was forced to borrow even more; as of July 2013 the NFIP's debt is approximately $24 billion in total. The NFIP's current debt and the current premium structure have raised concerns regarding its long term financial solvency.

[1] The NFIP's dwelling form offers coverage for: Building property, up to 250,000 and Content up to 100,000.

Some advocacy groups have argued that the program disproportionately benefits wealthy households with expensive waterfront properties, but with a few exceptions (e.g., Bin, Bishop and Kousky, 2011), there has not been much research to determine who benefits from and who bears the cost of the NFIP program.

In the years since Katrina, the NFIP has been at the forefront of the policy agenda. Various proposals for reforming the NFIP have been suggested, including long-term contracts tied to the property instead of one-year renewable policies tied to the individual homeowner (Kunreuther and Michel-Kerjan, 2010), and using federal funds to compensate existing landowners and targeting properties deemed high-risk or environmentally sensitive to purchase flood insurance (Barnhizer, 2003). In 2012, Congress passed the Biggert-Waters Flood Insurance Reform Act (BW-12) with key provision to increase the existing flood insurance premium to full-level risks. However, BW-12 was revised in March 2014 curbing the planned insurance rate increase. The program is up for renewal again in 2019 and could benefit from a more solid understanding of who is participating and thus will be affected by changes in the program.

3. Data and Hypotheses

3.1 Hypotheses

To establish the hypotheses of our empirical analysis we rely on findings from previous literature as well as theories underpinning the demand for insurance. Previous studies have noted that homeowners perceive the expenditure on insurance as a poor investment (Baumann and Sims, 1978; Johnson, 1978; Kunreuther et. al., 1978). Other research, both theoretical and empirical, suggests a positive relationship between income and insurance purchases, and a negative relationship between price and insurance purchases (Browne and Hoyt, 2000). We thus hypothesize that an increase in income will positively affect the decision to purchase flood insurance, while an increase in the price of the premium will affect it negatively.

Subjective perception of risks – such as recent flooding – affects the decision to buy flood insurance. Baumann and Sims (1978) find evidence that past experience with disasters motivates insurance adoption. Similarly, Browne and Hoyt (2000); Dixon et al. (2006); and Lindell and Hwang (2008) all find that flood experience serves as an immediate reminder of exposure to flood risk, resulting in higher demand for flood insurance which is mostly attributed to the availability heuristic (Tversky and Kahneman, 1973). On the other hand, the "gambler's fallacy"[2] may lead some people to believe that the odds of another flood occurring in the area in subsequent years have declined. We hypothesize that a recent flood will have a positive impact on the decision to purchase flood insurance but based on the gambler's fallacy, the relationship is ambiguous.

Mitigation reduces the expected loss from flooding and, therefore, could reduce the perceived need for flood insurance. In the case of flood damage, Burby (2006) provides compelling evidence that actions taken by the federal government, such as building levees, make residents feel safe. In such a case we expect to find a negative relationship between mitigation assistance and the demand for flood insurance as found by Browne and Hoyt (2000). However, Zahran et al., (2009) have shown that local government mitigation activities translate to flood premium discounts leading to more people buying the flood insurance. There is also evidence that the same people who behave in a less risky manner are also more likely to purchase insurance (Finkelstein and McGarry, 2006).

[2] The "gambler's fallacy" is the belief that the probability of an event is lowered when that event has recently occurred.

No prior research tests for racial differences in the adoption of flood insurance. However, in regard to life insurance, Gutter and Hatcher (2008) found that there is little difference in life insurance ownership between black and white households, but that white households insure a larger proportion of their human capital than do black households. In regard to tolerance of risk, Sung and Hanna (1996) find that whites were more likely to be willing to take risk and that blacks tend to be less risk tolerant. Survey research by Palm (1998) suggests that non-white households exhibit a greater fear of disaster although it was unclear if that fear translates into the purchase of flood insurance or any other mitigation activities. Thus, the racial difference in the adoption of flood insurance is ambiguous and needs to be tested empirically.

As mentioned in the introduction section, the adoption of disaster insurance is found to be positively related to the level of education (Kunreuther et al, 1978; Baumann and Sims, 1978). Therefore, we hypothesize that a higher level of education will have a positive impact on the demand for flood insurance. The impact of age on the adoption of flood insurance is unclear. However, the findings of Riley and Chow (1992) that risk aversion rises at the age of 65 are consistent with the demand for flood insurance increasing with age.

We hypothesize that the owner-occupied home status will be positively correlated with the demand for flood insurance as for most homeowners, the house is a primary asset in their portfolio (Flavin and Yamashita, 2002) and one would want to protect it.

Objective exposure to risk such as the proportion of floodplain in a county may affect the decision to purchase flood insurance. We hypothesize that households in the floodplain demand more flood insurance due to perceived risk of flood and therefore, this variable should have a positive impact on the demand for flood insurance.

Botzen et al. (2009) finds that homeowners are willing to make investments in mitigation in exchange for premium discounts. In the US community participation in NFIP is required to get the flood insurance and thus to be eligible for the premium discounts if certain mitigation activities are undertaken. Therefore we hypothesize that the demand for flood insurance will be in reverse proportion to the number of communities within the county that do not participate in the NFIP.

Table 1 presents the variables that are expected to affect the flood insurance purchasing decision and their hypothesized signs.

Table 1: Hypotheses: Flood Insurance Purchasing Decision

Variables	Hypothesized Sign	Results
Income	+	+
Price	-	-
Recent Flood Event	+/-	+
Mitigation	+/-	+
Race	+/-	+ (for African-American) & - (for Whites)
Education	+	+
Age	+/-	+
Home Occupancy (Owner)	+	-
Percent of Floodplain in a County	+	+
NFIP Non-Participation	-	-

3.2. Data

We collected our data from several sources. County-level data on NFIP policies-in-force from 1978-2010 was provided by the Federal Emergency Management Agency which runs the

National Flood Insurance Program.[3] The dataset includes flood insurance premium collected, flood insurance coverage in force, flood mitigation assistance provided to residents in that county, all for a given year, and a GIS file with floodplain maps for all the counties in Georgia. Ideally, we would have performed the analysis using household-level data, but for privacy reasons, data at this level of disaggregation is not available from the federal government which runs the program. We use county-level data that provides more information than the state level data that previous studies have used. Table 2 shows the total policies-in-force, premium and coverage for years 1978-2010 in Georgia. Over this period, the number of NFIP flood insurance policies-in-force has increased almost 9-fold, from about 10,500 to over 91,000 (nearly nine times the population growth in the state over that period). As of 2010, the last year covered by the study, there was nearly $24 billion of flood insurance coverage in place through the NFIP in Georgia.

[3] The authors thank Susan Bernstein, Esq., I&PR Mitigation Directorate, NFIP, FEMA, DHS for providing the data.

Table 2: NFIP Policies-In-Force, Premium and Coverage in Georgia from 1978-2010

Year	Policies-In-Force (PIF)	Premium Collected (2010 $)	Coverage (2010 $ in thousands)
1978	10,502	861,713	343,034
1979	13,348	1,105,861	472,011
1980	14,570	1,250,727	578,935
1981	14,563	1,921,371	651,969
1982	15,036	2,771,714	711,642
1983	15,596	2,905,571	783,435
1984	16,774	3,391,955	938,647
1985	18,018	3,895,232	1,228,856
1986	19,706	4,651,514	1,498,005
1987	20,396	5,267,443	1,665,969
1988	21,271	5,595,801	1,839,428
1989	23,069	6,467,600	2,388,232
1990	32,741	9,128,278	3,170,013
1991	28,129	8,756,679	2,805,169
1992	29,383	9,744,305	2,963,670
1993	31,400	10,803,381	3,337,091
1994	39,337	13,974,896	4,205,946
1995	42,761	16,511,970	5,049,496
1996	46,445	19,206,888	5,938,711
1997	50,725	22,613,901	6,932,214
1998	54,655	25,853,306	7,813,618
1999	58,318	27,262,323	8,779,346
2000	61,600	28,446,564	9,768,575
2001	62,718	29,442,985	10,511,775
2002	63,730	30,852,160	11,221,265
2003	65,618	33,396,557	12,041,183
2004	68,106	35,963,182	13,520,381
2005	74,387	39,881,447	15,700,573
2006	81,607	45,786,366	18,320,810
2007	84,047	50,360,780	19,856,870
2008	85,632	54,860,728	20,894,858
2009	90,602	59,427,670	22,533,477
2010	91,131	63,256,224	23,047,444

Data on total flood damage per capita in previous years was collected from SHELDUS, a county-level hazard dataset derived from the National Climatic Data Centre.[4] The socio-demographic variables: *Income*, *Race*, *Education*, and *Age* come from the Bureau of Economic Analysis and the U.S. Census Bureau. The variable *Income* is available annually; for *Race, Education* and *Age* we interpolated decennial data from the U.S. Census Bureau on to get yearly estimates.[5]

Table 3 reports the summary statistics of the variables included in the model. The average number of policies-in-force per thousand population at the county level was 4.95.[6] The average per capita income over the period 1978-2010 was almost $26,000 (2010 prices). The average cost was $4.46 per $1,000 of flood insurance coverage (2010 prices) and it ranged widely across the state from less than a dollar to over $30. Browne and Hoyt (2000) in their state-level study found the average cost per thousand dollars of insurance to be $5.12. Similarly, Kriesel and Landry (2004) in their study of nine coastal counties find the cost to be $4.3. Michel-Kerjan (2010) shows that as of 2010, the average cost nationwide was $2.64 and was $2.05, $2.09, $3.00, $2.92, $3.70, $2.34 for the coastal states of Florida, Texas, Louisiana, California and New Jersey respectively.

The mean flood damage per capita during the preceding flooding event was $10.99; Brown and Hoyt (2000) found the mean flood damage per capita in the preceding year to be $9.825.

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[4] SHELDUS refers to Spatial Hazard Events and Losses Database for United States. Details on how the data is collected can be found at http://webra.cas.sc.edu/hvri/products/sheldusmetadata.aspx.

[5] We calibrated an exponential curve to the decennial data (1980, 1990, and 2000) for each county. Using a linear curve to estimate the data, however, did not change the results.

[6] There is a large difference in market penetration between coastal counties (21 policies-in-force per 1000 population) and inland counties (only 2 policies-in-force per 1000 population).

FEMA's Federal Insurance and Mitigation Administration (FIMA) implements a variety of programs authorized by Congress to reduce losses that may result from natural disasters. We find that on average only $0.004 per capita was spent on flood mitigation by FEMA.

On average 14.34% of the county areas are located in a floodplain with a minimum of 2.03% (Macon County) and a maximum of 72.24% (Glynn County).

Table 3: Variables and Descriptive Statistics for County-level Analysis (1978-2010)

Variable	Description	Mean	Std. Dev.	Min	Max
PIF/1000pop	Policies-in-force per 1000 population	4.95	19.25	0.01	240.28
Income	Per capita Income (in thousands, 2010 constant dollars)	25.5	6.13	12.22	65.91
Price	Cost per 1000 dollars of coverage (2010 price)	4.46	2.39	0.37	30.38
Recent_Flood	Flood damage per capita in prior year ($)	10.99	113.00	0	3986.23
Mitigation	Flood Mitigation Assistance per capita ($)	0.004	0.083	0	3.366
African-American %	Percent of African-Americans	25.60	17.17	0	82.99
White %	Percent of white	69.00	16.52	18.9	98.8
High school grads	Percent of high school graduates	32.81	5.36	16.5	54
College grads	Percent of college graduates	13.16	7.06	4.24	48.1
Occu_Owner %	Percent of Owner Occupied households	58.92	12.71	0	87.54
Occu_Renter %	Percent of Renter Occupied households	41.08	12.71	12.45	100
Age25to44	Percent of age group 25 to 44	32.20	6.39	16.9	66.96
Age45to64	Percent of age group 45 to 64	21.12	4.36	1.32	34.7
Age 65 & up	Percent of age group 65 & up	11.08	3.54	0.43	29.2
Floodplain %	Percent of the county in a floodplain	14.34	12.91	2.03	72.24
Bl_Ridge	1 if Blue Ridge Eco-region, Else 0	0.042	0.20	0	1
Ri_Valley	1 if Ridge and Valley Eco-region, Else 0	0.052	0.22	0	1
Piedmont	1 if Piedmont Eco-region, Else 0	0.425	0.49	0	1
SE_Plains	1 if South East Plains Eco-region, Else 0	0.374	0.48	0	1
Co_Plain	1 if Coastal Plain Eco-region, Else 0	0.104	0.30	0	1
No NFIP Participation	Number of communities in the county that do not participate in the NFIP	0.62	1.06	0	6

Table 4 reports the comparison of the summary statistics between the coastal and inland counties. We find much higher market penetration in coastal counties of the state. The cost per $1,000 of insurance coverage was not statistically different between inland and coastal counties, indicating that the level of risk is, according to the FEMA risk mapping, not that different on average (even though the risk perception might be). We found that the mean flood damage per capita was actually higher in inland counties ($11.86) compared to coastal counties ($6.63). It is worth mentioning that all the significant flood events during our period, such as Albany (1994 and 1998) and Atlanta (2009), occurred in inland counties.

We find that the amount per capita spent on mitigation was much higher for the coastal counties; a 5-to-1 ratio compared to spending in inland counties.

Interestingly, we find no significant differences among the socio-economic variables between coastal and inland counties.

Table 4: Variables and Descriptive Statistics: Coastal Counties Vs. Inland Counties

Variables	Coastal Counties		Inland Counties	
	Mean	Std. Dev.	Mean	Std. Dev.
PIF/1000pop	20.53	43.43	1.83	3.05
Income ($ thousands)	23.32	5.94	26.40	6.66
Price	4.16	2.14	4.52	2.43
Recent_Flood	6.63	57.56	11.86	121.07
Mitigation	0.01	0.14	0.002	0.07
African-American%	26.59	11.10	25.40	18.14
White %	69.62	11.91	68.87	17.29
High school grads	34.88	5.56	32.39	5.22
College grads	11.45	5.32	13.51	7.32
Occu_Owner %	60.31	12.64	58.63	12.71
Occu_Renter %	39.68	12.64	41.36	12.71
Age 25 to 44	32.08	5.40	32.23	6.58
Age 45 to 64	19.71	4.75	17.03	3.64
Age 65 & up	10.03	3.50	12.94	1.84
Floodplain %	31.37	21.21	10.93	6.37
No NFIP Participation	0.49	0.87	0.64	1.09

4. Methods

4.1 Econometric Model

Based on the data described above we analyze the demand for flood insurance across 153 counties[7] in Georgia for the period 1978-2010. We estimate the following demand equation:

$$\begin{aligned}
&\log(PIF/1000pop)_{it} = \beta_0 + \alpha_i + \beta_1 \log(Income)_{it} + \beta_2 \log(price)_{it} \\
&+ \beta_3 \mathrm{Re}cent_flood_{it} + \beta_4 \log(Mitigation) + \beta_5 PercentFP_i \qquad (1) \\
&+ \sum \gamma Ecoregions_i + \beta_6 Race_{it} + \beta_7 Education_{it} + \beta_8 Age_{it} + \varepsilon_{it}
\end{aligned}$$

The dependent variable is the logarithm of the number of flood insurance policies-in-force (*PIF*) purchased per 1,000 population in a county-year.[8] The income variable (log (*Income*)) is the log of per capita income in the county during the year. We measured the cost per $1,000 of flood insurance coverage (*Price*) by dividing the dollar value of the premium paid for flood insurance in the county during the year by the dollar value of insurance coverage (in thousands) in the county during the year.

According to the availability heuristic, recent large flood events could heighten risk perceptions and this could influence the decision to purchase flood insurance. To control for the effect of recent flooding on individuals' demand for flood insurance we use the variable *Recent_Flood* that measures the dollar value of total flood damage per capita in the county during the preceding year. Atreya et al. (2013) and Bin and Landry (2013) find that large flood events result in a flood-risk discount for properties in floodplains but that this effect vanishes over time, as early as four years after the flood (Atreya et al. 2013). To capture this decay, we included up to six-year lags for the *Recent_Flood* variable. The Flood Mitigation Assistance

[7] Out of 159 counties in Georgia 153 counties were included in the analysis since the data were missing for 6 counties: Clay, Lincoln, Marion, Schley, Treutlen and Webster.

[8] Following Zahran et al. (2009), we replaced the dependent variable with the number of policies-in-force per 100 households in a county as a robustness test to our results.

(FMA) program of FEMA provides funds to assist states and communities implement measures that reduce or eliminate the long term risk of flood damage to buildings, manufactured homes, and other structures insured under NFIP. To measure the effect of such assistance on the decision to purchase flood insurance, we included per capita flood mitigation assistance by FEMA per county-year (*Mitigation*)

Using zonal analysis in Arc GIS we determined the percentage of county land within the 100-year floodplain (*Percent FP*).[9] More than one-third of the policies in Georgia are purchased by residents outside of a high-risk 100-year flood zone. The decision to buy flood insurance could also depend on whether the county is coastal or is located inland. Dixon et al, 2006, found a significant regional variation and higher market penetration in coastal counties. We control for regional variation in Georgia by including dummies for the five eco-regions in Georgia: Blue Ridge, Ridge and Valley, Piedmont, Southeast Plains; the control group being the southern coastal plains. This distinction separates the higher elevation Blue Ridge, Ridge and Valley, and Piedmont from the low-lying southeast plains and southern coastal plains.

All the regressions include the socio-demographic characteristics of the households at the county level. *Race* is measured with two variables, one for the percent of the population who is African-American and one for the percent of white population in a county. The *Education* variable measures the percent of high school graduates and the percent of college graduates in a county. Three different *Age* categories are included in the model: age groups 25 to 44, 45 to 64, and 65 & up. All these variables are entered as the percentage of total population in a county. We also include the percentage of houses in the county that are rented and the percentage of houses that are owner-occupied. The distinction between the owner-occupied and non-owner

[9] 100-year floodplain was used since flood insurance is mandatory for the 100 year floodplain properties only.

occupied properties is important since a substantial portion of the non-owner occupied properties are located in flood zones.

Lastly, to control for the fact that community participation is required for homeowners to be able to buy the flood insurance, we included a variable *NoNFIP* in our model which is the number of communities in a county that do not participate in the NFIP.

4.2 Estimation Methods

We estimate equation (1) using a linear regression model that included county fixed effects (FE). That is, in equation (1) α_i denotes a county-specific intercept that controls for unobserved characteristics at the county level that are constant over time. We note, however, that the location in the floodplain variable ("*Percent FP*"), the *Eco-region* dummies and the *NoNFIP* variable do not vary over time and drop from the FE model. Thus, we estimated equation (1) using random-effects (RE) when the model included these time-invariant variables.[10] A Hausman test failed to reject the null that the coefficient estimated by the efficient RE estimator are the same as the ones estimated by the consistent FE estimator (χ^2=19.25, p-value=0.99), and thus it was safe to use the RE model over the FE model. With over 30 years of data, serial autocorrelation is a concern in our model. We performed a Wooldridge test (Wooldridge, 2002; Drukker, 2003) and found evidence of serial autocorrelation (F=130.40, p-value<0.001). The RE panel regression is inappropriate given the presence of serial autocorrelation. Thus, following Zahran et al. 2009, we estimated a Prais-Winsten Regression with Correlated Standard Errors (PCSE) model which is preferred over pooled OLS if serial autocorrelation is present.

[10] The floodplain maps in Georgia have not been updated in years. Georgia started a map modernization program in partnership with FEMA in 2009 to develop and update flood hazard maps for all its counties.

5. Results

5.1 Market Penetration

We first estimate county-level market penetration rates, that is, the proportion of households in a county that have purchased flood insurance. As expected, flood insurance market penetration rates are highest in coastal counties where the proportion of land in the floodplain is higher. This result supports the finding by Dixon et al. (2006) that the probability of purchasing insurance is substantially higher in communities subject to coastal flooding than in communities that are not. Kousky (2010) also finds a higher market penetration in census tracts with more land in the 100-year and 500-year floodplains in St. Louis County, Missouri.

Figure 1 shows market penetration rates by county for 2010. We divided the total number of residential policies-in-force by the total number of household with data from the 2010 U.S. Census. The top five counties with the highest percentage of market penetration in 2010 were Glynn (44.86%), Bryan (40.28%), Chatham (27.42%), Camden (19.22%), and McIntosh (10.50%).

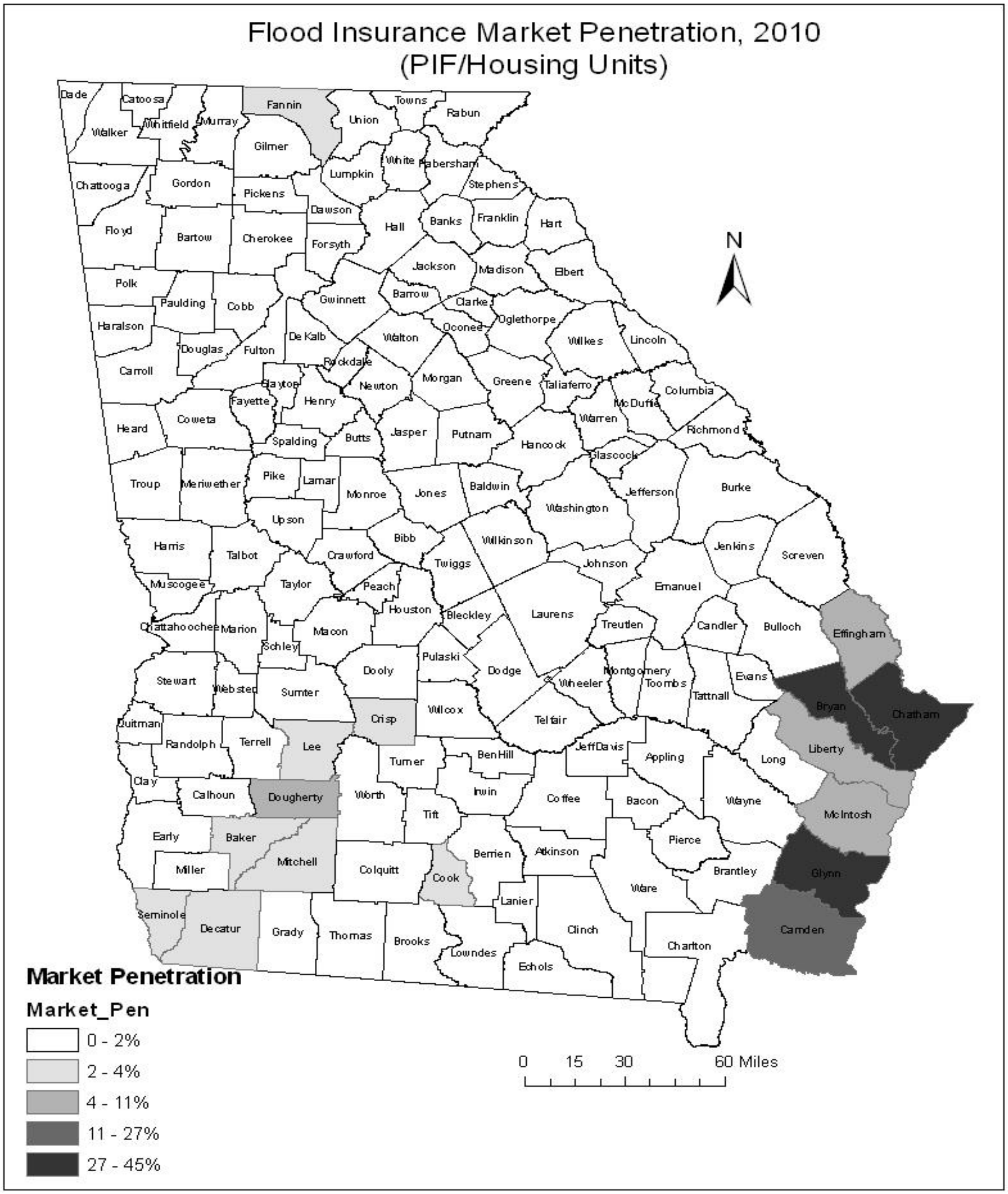

FIGURE 1: FLOOD INSURANCE MARKET PENETRATION IN GEORGIA, 2010

Source: Author prepared map based on data provided by FEMA

Not surprisingly, there is a strong correspondence between the market penetration and the proportion of floodplain area within a county.[11] The coastal counties where the percentage of floodplain is larger tend to have the highest penetration rates (Figure 1 and Table 5), most likely because the purchase of flood insurance is mandatory for properties in 100-year floodplains with a mortgage from a federally backed or regulated lender and because residents may be more aware of the risk they face. Our measure of market penetration, however, refers to the total number of properties in a county, and not specifically to those in the floodplain. Another factor that could potentially explain the market penetration rate is a recent flooding event in a county. Previous studies (Kriesel and Landry, 2004; Carbone, Hallstrom, and Smith, 2006; Petrolia, Landry, and Coble, 2013) suggest that the sensitivity to flood risk is heightened by experience with hazard events. Atreya et al (2013) find that after a significant flood event ("the flood of the century") in 1994 in Dougherty County, GA, the take up rates increased dramatically. Dougherty is precisely the county with the largest market penetration among inland counties in Georgia (Figure 1).

Table 5: Percent of Floodplain Area and Market Penetration Rate (Top 5) in Georgia (2010)

County	Floodplain (%)	County	Market Penetration (%)
Glynn	72.24	Glynn	44.86
Chatham	72.22	Bryan	40.28
Camden	54.68	Chatham	27.42
Bryan	54.14	Camden	19.22
Ware	52.43	McIntosh	10.50

[11] The correlation coefficient between the two is 0.70.

5.2 Regression Results

We report the results of the estimation of equation (1) in Table 6. The first column shows the estimates from the FE model. We compare these results with those from a RE model in the second column. In the third column we estimate a RE model that includes important time-invariant variables that drop from the FE model: *Percent FP*, the *Eco-region dummies* and *No NFIP* participation. In column four, we present the results of a Prais-Winsten Regression with Correlated Standard Errors (PCSE).In column five, we present the results of a Prais-Winsten Regression with the alternative dependent variable (PIF/100 households).

Table 6: Regression Results (Dependent Variable: Policies-in-force/1000 population)

VARIABLES	FE	RE	RE + time invariant controls	Prais-Winsten	Prais_Winsten (dependent:PIF/ 100 housholds)
	(1)	(2)	(3)	(4)	(5)
Ln (Income)	0.258	0.330*	0.418**	0.274	0.0479
	(0.200)	(0.197)	(0.196)	(0.230)	(0.230)
Ln (Price)	-0.306***	-0.301***	-0.293***	-0.136***	-0.141***
	(0.0397)	(0.0398)	(0.0396)	(0.0295)	(0.0295)
Ln (Recent_Flood)	0.0160**	0.0167**	0.0167**	0.0268***	0.0266***
	(0.00793)	(0.00803)	(0.00802)	(0.00443)	(0.00444)
L. Ln (Recent_Flood)	0.0174**	0.0179**	0.0180**	0.0247***	0.0247***
	(0.00772)	(0.00782)	(0.00781)	(0.00564)	(0.00565)
L2. Ln (Recent_Flood)	0.0153*	0.0160**	0.0163**	0.0230***	0.0227***
	(0.00793)	(0.00803)	(0.00802)	(0.00617)	(0.00618)
L3. Ln (Recent_Flood)	0.00301	0.00363	0.00358	0.00719	0.00692
	(0.00797)	(0.00807)	(0.00806)	(0.00610)	(0.00611)
L4. Ln (Recent_Flood)	0.00743	0.00774	0.00751	0.00886	0.00853
	(0.00767)	(0.00776)	(0.00775)	(0.00558)	(0.00560)
L5. Ln (Recent_Flood)	0.000839	0.00128	0.00106	0.00496	0.00490
	(0.00783)	(0.00793)	(0.00792)	(0.00446)	(0.00447)
Mitigation	0.0730	0.0772	0.0834	0.0148	0.0154
	(0.0700)	(0.0709)	(0.0709)	(0.0339)	(0.0339)
High school grad %	0.0504***	0.0501***	0.0511***	0.0189	0.0122
	(0.00584)	(0.00581)	(0.00577)	(0.0147)	(0.0147)
College grad %	0.0303***	0.0363***	0.0406***	0.0584***	0.0655***
	(0.00812)	(0.00770)	(0.00755)	(0.0144)	(0.0142)
Black %	0.0175***	0.0137***	0.0143***	0.00879*	0.0121**
	(0.00342)	(0.00323)	(0.00318)	(0.00476)	(0.00473)
White %	-0.00918**	-0.00392	-0.00505	-9.55e-05	-0.000146
	(0.00426)	(0.00381)	(0.00376)	(0.00277)	(0.00277)
Occu_Owner %			-0.0115*	-0.00203	-0.000965
			(0.00683)	(0.00687)	(0.00678)
Age25_44	0.0216**	0.0178*	0.0208**	0.0225	-0.00285
	(0.00999)	(0.00969)	(0.00957)	(0.0230)	(0.0229)
Age45_64	0.0653***	0.0563***	0.0642***	0.0394	0.0175
	(0.0145)	(0.0139)	(0.0137)	(0.0308)	(0.0306)
Age65_up	0.102***	0.0759***	0.0670***	0.0456	0.0560*
	(0.0179)	(0.0164)	(0.0157)	(0.0324)	(0.0321)
Bl_Ridge dummy			0.115	-0.178	-0.265
			(0.607)	(0.585)	(0.577)
Ri_Valley			0.516	0.0415	0.144
			(0.576)	(0.537)	(0.529)
Piedmont dummy			-1.285***	-1.537***	-1.581***
			(0.442)	(0.419)	(0.414)
SE_Plains dummy			-0.913**	-0.963**	-0.958**
			(0.416)	(0.387)	(0.382)
Floodplain %			0.0400***	0.0345***	0.0341***
			(0.0102)	(0.00944)	(0.00931)
No NFIP Participation			-0.321***	-0.267***	-0.254***
			(0.0782)	(0.0741)	(0.0731)
Constant	-7.448***	-8.324***	-8.143***	-6.025**	-4.293*
	(2.079)	(1.984)	(2.035)	(2.489)	(2.470)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Rho				0.95	0.95
Observations	2,887	2,887	2,887	2,887	2,887
R-squared	0.668	0.66	0.66	0.181	0.317
Number of id	138	138	138		

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The empirical analysis supports the hypothesis that income and price significantly influence the decision to buy flood insurance. The estimated income elasticity in the RE models ranges between 0.33 and 0.42. The estimated coefficient for the price elasticity of insurance (where price is measured by the cost per $1,000 dollars of coverage) is negative and statistically significant at a 1% level across all models, with point estimates ranging between -0.14 (column 4) and -0.31 (column 1). This is broadly consistent with previous studies at the state level (Browne and Hoyt, 2000) and individual level (Kriesel and Landry, 2004).

Our empirical findings also suggest that, as expected, flood damage in previous years has a significant positive impact on the decision to buy flood insurance. This effect is significant for damages up to three years back. (Replacing per capita damage in previous years by the number of flood events in the county did not change the results). This result is consistent with Zahran et al. 2009, who find a positive impact of previous flood damage on the decision to buy flood insurance.

We find a positive but insignificant relationship between flood mitigation assistance and flood insurance purchases at the county level which is in contrary to a general assumption that the mitigation and insurance are substitutes.

Regarding the characteristics of the households, education has a significant impact on flood insurance purchases. The results suggest that for the average county, a unit change in the percent of college graduates is associated with over a 3% (6.5 % in column 5) increase in NFIP policies per 1000 population. We find that an increase in the proportion of African-American population in a county is also associated with an increased demand for flood insurance. To put this in perspective, a 1 percentage point increase in the African-American population in a county is associated with a 1% increase in flood insurance policies. The variable age also a statistically significant effect in the RE regression. For example, in column 3, a one percentage point increase in the age group 25 to 44 in the average county is associated with an approximately 2% increase in the policies-in-force per 1000-population. This increase is 6.4% for the age group 45-64 and 6.7% for the age group 65 and above. However, these results are not robust to controlling for serial autocorrelation in column 4 and 5 except for percentage of black population and age group 65 and up. Contrary to our hypothesis, we find that an increase in owner-occupied homes in a county is associated with decreased flood insurance policies-in-force (significant at 10% level in the RE regression). This result may be attributable to tax benefits of owning rental properties, that is, landlords get to deduct insurance from income, which homeowners do not. Also, according to the Congressional Budget Office (CBO) (2007), roughly one-quarter of the coastal properties with subsidized flood insurance are not primary residences and 20% of the NFIP flood insurance contracts were for non-principal residences which could also be driving our results.

A result that is robust across models is the positive relationship between the proportion of floodplain and the policies-in-force in a county, implying that people in vulnerable counties , are in fact more likely to buy flood insurance. According to our results, a unit increase in the percent of floodplain area in a county increases the NFIP policy purchases per 1000 population by approximately 3.5%. In addition, we controlled for different eco-regions and also controlled for the number of communities in a county that do not participate in the NFIP. We find that compared to coastal plains in Georgia, other eco-regions buy fewer flood insurance policies. The results were robust to including a dummy for coastal counties.[12] As expected, an increase in the

[12] Results available upon request.

number of communities that do not participate in the NFIP is associated with a drop in the number of policies-in-force per county.

6. Conclusions

U.S. Congress created the NFIP to mitigate flood losses through community-enforced building and zoning ordinances and to provide access to affordable, federally backed flood insurance protection to homeowners. The program is not structured to build a capital surplus nor is it able to purchase reinsurance to cover catastrophic losses. Intended to be funded with premiums collected from policyholders, the NFIP remained solvent until 2005 when Hurricane Katrina struck and led to billions in debt.

Our analysis of the factors that influence Georgia homeowners' decisions to purchase flood insurance should contribute to the emerging research literature aiming to better understand the drivers of flood insurance purchases in the United States and abroad. We were also able to depict market penetration in the state of Georgia.

Unsurprisingly, the flood insurance market penetration rate is higher in coastal counties than inland. More generally, our analysis at the county level for the period 1978-2010 suggests that, as we would expect, the counties with higher proportion of land within floodplains purchase more flood insurance policies. We also find the price elasticity of flood insurance to be fairly low (at -0.31, -0.14) suggesting that those exposed the most want that coverage. At a time when issues of affordability are at the forefront of the NFIP's reform debate, the result that an increase in the price of premium do not highly impact the take-up of flood insurance can help policymakers make informed policy decisions.

Our findings suggest that other determinants of risk perception, such as having experienced recent flood events, have a positive significant effect on the number of policies-in-force purchased, supporting the hypothesis of the availability heuristic. A recent flood event can be easily brought to mind and therefore heightens the perceived probability of a future flood which eventually leads to purchasing flood insurance. We also tested the impact of race and found that areas with higher concentration of African-Americans had, all things being equal, a higher demand for flood insurance. It would be interesting to perform a similar analysis at the level of the entire United States and in other countries. Indeed, FEMA flood risk awareness campaigns have never segmented target audience by race. Our analysis suggest that it might be important to do so.

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