An Evaluation of the National Flood Insurance Program in Georgia

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Abstract

The NFIP has been a subject of tremendous interest since 2005 when it was flooded with claims from hurricanes Katrina and Rita, and was eventually drowned in debt. This paper focuses on the state of Georgia that has been neglected in terms of enforcing NFIP policies. We estimate a fixed effect model pooling the data from 1978-2010 across 153 counties in Georgia to determine the determinants that influence the decision to buy flood insurance. The empirical analysis supports the hypothesis that income and price significantly influences the decision to buy the flood insurance. Our empirical findings also suggest that recent flood event and the proportion of county in the floodplain has a significant positive impact on decision to buy flood insurance. Education level and age seemed to have a significant impact on one's decision to buy flood insurance; however, race didn't have a significant impact.

Keywords: NFIP, Flood Insurance, Fixed Effect Model

1. Introduction

The National Flood Insurance Program (NFIP), a FEMA managed program established by the National Flood Insurance Act of 1968, provides flood insurance coverage to communities that choose to adopt minimum floodplain management policies. Flood Insurance Rate Maps (FIRMs) produced by FEMA depict the flood elevation throughout the participating counties, to determine household's risk and associated premium. Due to low take-up rates, in 1973, Congress mandated flood insurance to properties in 100-year floodplains with a mortgage from a federally backed or regulated lender. The base flood, or 100-year flood, is the flood having 1% or greater annual chance of getting flooded. Homeowners can purchase up to $250,000 of building coverage and up to $100,000 of content coverage. However, as of June 2011, there were just over 5.5 million policies in force in the US, still indicating low take-up rates.

NFIP has been a subject of tremendous interest since 2005 when it was flooded with claims from hurricanes Katrina and Rita, and was eventually drowned in debt. The program was able to support itself through 2005, but after those hurricanes, NFIP had to borrow heavily from the treasury and its debt currently exceeds $19 billion. The NFIP doesn't bring in enough premiums to cover up all the incurred cost and therefore the program is currently the target of reform raising questions regarding the effectiveness and distributional implications of NFIP policies. A particular question regarding NFIP is whether the program reaches those most vulnerable to flood risk or whether it ends up subsidizing households in wealthier counties. This question has recently received great interest, and there are ongoing debates regarding who benefits and who bears the cost of this program (RFF, 2011).

The NFIP is highly concentrated geographically, with 40 percent of all policies in force nationwide located in Florida and close to 70 percent of all policies in force in just five states: Florida, Texas, Louisiana, California and New Jersey (Michel-Kerjan and Kousky, 2010). According to FEMA, for the state of Georgia, between 1978 and 2010 there were 97,723 policies in force, the total premium collected was almost 6.4 million dollars and the total coverage amount was more than 23 billion dollars. Probably because the NFIP policies in force were not as highly concentrated in Georgia as in Florida, between 1978 and 2007 there were three years where the payouts exceeded the premium collected (as opposed to none in Florida) suggesting that Georgia has been neglected in terms of enforcing NFIP policies.

A recent study by Bin, Bishop and Kousky (2011), determined how the NFIP's price and payouts correlate to per-capita county income. They found that the NFIP has spread costs and benefits fairly uniformly across county income levels. However, in Georgia, as of 2009, there were more than 91,000 NFIP policies in force and over a third of these belonged to homeowners living or working outside a high-risk floodplain where the purchase of flood insurance is not required. This scenario suggests that the NFIP in Georgia might be reaching out to certain income groups only, probably the wealthiest property owners.

There are three basic goals of NFIP: to better indemnify individuals for flood losses through insurance; to reduce flood damages through management and regulation; and to reduce federal expenditures for disaster assistance and flood control (FEMA, 2002). Effective loss prevention at individual, local, state and federal levels must begin well before a flood event. However, the performance of NFIP is, most of the time, evaluated only after significant losses, for example, after hurricanes Katrina and Rita. In order to avoid this for the state of Georgia, it is important to know whether the NFIP is reaching out to the area that are most vulnerable to flood risk.

The first empirical analysis that examined homeowner's demand for flood insurance is provided by Browne and Hoyt (2000). However, they aggregate the state level data failing to interpret the decision making results at an individual level. Also they do not account for any household characteristics in their model. As an initial effort to understand the characteristics of the counties that buy the flood insurance, we focus our analysis in Georgia. We focus our study on homeowner's response to flood risk in the form of purchase of flood insurance in Georgia. In particular, we try to answer i) What are the determinants (also in terms of county characteristics) of flood insurance purchasing decision? We find that income and price significantly influences the decision to buy the flood insurance. The estimated income elasticity is 0.48 price elasticity of demand for flood insurance to be -0.38. Consistent with this study we find price elasticity is -0.26. We also find that recent flood event has a significant positive impact on decision to buy flood insurance which is consistent with the Kunreuther's (1990) hypothesis that risk perception influence insurance purchasing behavior. However, we find that disaster relief effort crowd out the purchase of flood insurance consistent with the results of Brown and Hoyt (2000). Education level and age seemed to have a significant impact on one's decision to buy flood insurance; however, race didn't have any significant impact.

2. Literature review

2.1 NFIP Policy and Political History

In the United States, providing public relief for private disaster dates back to at least 1794, when Congress passed a Bill providing compensation to unidentified victims of disasters (Landis, 1998). Congress passed at least 128 specific legislative acts offering *ad hoc* relief from floods, fires and other disasters between 1803 and 1947 (Moss, 1999). A significant political problem with the NFIP lies in its implementation and depends a great deal on the ability and willingness of community planners and property owners to adapt to the program. In a survey conducted after a decade of the NFIP establishment 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 insurance mechanism to manage flood risk (Kunreuther et al, 1978).

In addition to problems with the implementation of the NFIP, hurricane Katrina in 2005 demonstrated that the federal flood insurance was insufficient to secure all policyholders and restore the damage. Limitations on federal claims and unwillingness of private insurers to pay for storm related damages left some policyholders unable to rebuild. Despite the limitations on federal flood insurance claims, hurricane Katrina Still led to almost $17 billion to NFIP policy holders (Cooper and Block, 2006). Various proposals regarding the reform of NFIP and or alternative have been suggested since Katrina brought NFIP to the front of policy agenda which include long-term contract instead of one year renewable policy (Kunreuther and Kerjan, 2010); using federal funds to compensate existing landowners and targeting properties deemed high-risk or environmentally sensitive for the program to purchase flood insurance (Barnhizer, 2003).

2.2 NFIP: Economic and Distributional Implications

Economically, the decision to purchase flood insurance can be based on a model of expected utility maximization. The expected utility model for an individual with a property valued at *W*; probability *p* that a flood will cause a capital loss of *L*; and insurance payment of πq where π is the actuarial estimate of the probability of a loss and *q* is the amount the insurance will pay if the loss happens is given by:

$$Max\{pU(W-L-\pi q+q)+(1-p)U(W-\pi q)\} \quad (1)$$

Maximized expected utility is found by differentiating this function with respect to the level of insurance coverage, q and setting the first order condition equal to zero which gives:

$$\frac{U'(W-L+q^*(1-\pi))}{U'(W-\pi q^*)}=\frac{1-p}{p}*\frac{\pi}{1-\pi} \quad (2)$$

where U' is the marginal utility and q^* is the optimum coverage. This condition states that the property owner will purchase insurance coverage up to the point where her marginal rate of substitution between consumption in the two outcomes is equal to the price ratio. Under risk aversion the expected utility function is concave i.e. $U''(W)<0$ and it follows that the total amount of wealth in each state must be equal given the marginal utility in each state are equal which leads to $L=q^*$. Therefore a risk averse individual will purchase an amount of insurance coverage that fully protects against the potential loss. However, NFIP does not ensure the full protection and the partial protection depends on the availability of maximum coverage rather than the degree of risk aversion.

Studies have shown that purchasing insurance can lead to moral hazard. Moral hazard implies a behavioral change by economic agents in response to a policy or program that makes them less careful about their actions than true losses would dictate, effectively changing the likelihood of incurring those losses (Zahran et.al. 2008). Boulware (2009) argues that the NFIP creates a moral hazard by encouraging development by under pricing insurance in developable areas with increased flood risk. Due to reduced cost of associated floodplain insurance homeowners are more willing to move into high flood risk areas increasing the overall social cost through the now-larger population residing in high-risk areas. Browne et. al. (2009) finds that NFIP participation increased both single family and multifamily development in Florida counties however; they find no evidence that induced development from the program is any more or less more severe in high flood risk areas.

At the start of 2010, there were 8.6 million people living within the 100-year Coastal Flood Hazard Area (CFHA), coastal areas with 100-year floods or larger every year (Crowell et. al, 2010). With the NFIP in place, there is a reduction in the cost to the government and insured individuals, Congress no longer needs to provide compensation to the affected individuals after a flood and there is no burden on the general federal budget because the fund from insurance comes from a dedicated source, the insurance premium. At individual level, there is a significant saving since individuals are unable to purchase insurance in private market and are not forced to self insure. This suggests that the NFIP is subsidizing homeowners in communities that choose to participate in the NFIP. Social inequality issues in how that benefit is distributed can be a subject of inquiry.

3. Model

We pooled data across 153 counties in Georgia for the period 1978-2010 and estimated the following equation as a fixed effect model.

$$\begin{aligned}\log(PIF/1000\,pop)_{it} = {} & \beta_0 + \beta_1 \log(Price_{it}) + \beta_2 \log(Income) \\ & + \beta_3 \log(Recent\_Flood_{it}) + \beta_4 \log(Relief\_Exp_{it}) \\ & + \beta_5 (Race)_{it} + \beta_6 (Education)_{it} + \beta_7 (Age)_{it} + \varepsilon_{it}\end{aligned}$$

The dependent variable is the number of flood insurance policies purchased per 1,000 population in a county during a year. We measured the cost per dollar of flood insurance coverage (*Price*) by dividing the dollar value of premium paid for flood insurance in the county during the year by the dollar value of insurance coverage (in thousands) in the state during the year. The Income (*Income*) variable is the per capita income in the county during the year. To control for the effect of a recent flood that may have on individual's 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. To measure the effect of disaster aid on the decision to buy flood insurance, we included per capita flood disaster relief expenditure (*Relief_Exp*) by FEMA. Our major objective is to determine the characteristics of the household in a county that buy the flood insurance. For that reason, we included in our model variables, *Race*, *Education*, *Marital Status* and *Age* of the owner occupied household.

We also wanted to determine whether the policies in force per thousand populations increased with the increase in the proportion of counties in the floodplain. Using zonal analysis in Arc GIS we determined the percentage of county in the floodplain and estimated a random effect model with an additional variable (*Percent FP*). A separate model was estimated since the fixed effect model would drop the variable "*Percent FP*" due to no variation over the years.[1]

4. Data

We collected our data from several sources. With more than 40 years of history behind NFIP, and results well documented, county level data on the NFIP policies in force (PIF) from 1978-2010 was provided to the author by FEMA. In addition, FEMA provided us the data on flood insurance premium dollars collected, flood insurance coverage, disaster relief expenditure by FEMA and, a GIS file of the floodplain map for all the counties in Georgia. Table 1 shows the summary statistics for total policies-in-force, total premium and total coverage for years 1978-2010 in Georgia. The number of NFIP policy holders has increased by almost 51 percent in the last 10 years and the premium intake has steadily increased over time, probably from more policies in force and rising prices. The Data on the total flood damage per capita was collected from SHELDUS, a county level hazard data derived from National Climatic data centre. All the other variables such as Income, Race, Education, Marital Status, and Age come from BEA and U.S. Census Bureau. Table 2 reports the summary statistics of the variables included in the model. The mean policies-in-force per thousand populations was 4.95. The cost per thousand dollar of flood insurance coverage was $4.46 in 2010 constant dollars. Per capita income was on an average almost $26,000. On an average 14.34 % of the county fall in the floodplain with minimum 2.03% and a maximum 72.24%. The mean flood damage per capita during the preceding year was $10.99, however, on an average only $0.004 per capita was spent on disaster relief by FEMA. Percent of whites per 1000 population was greater than the percent of black per thousand populations on an average county. On an average, there were more high school graduates than ninth graders or less.

[1] The Floodplain maps have not been updated in years. The map modernization program started in 2009 for Georgia.

5. Empirical Results

We report our empirical results in Table 3. The first column is the results from the fixed effect model. We compared these results with the random effect model in second column. Since, the proportion of floodplain in a county did not change across time we included the variable in column three (all else same) and estimated as a random effect model.[2]

Across all the specifications, the empirical analysis supports the hypothesis that income and price significantly influences the decision to buy the flood insurance. The estimated income elasticity is 0.38-0.55 which suggests that higher income individuals are more likely to purchase flood insurance. In all the models, we find the coefficient for the price which is the cost per thousand dollar of coverage is negative and significant. One of the studies by GAO (1983) estimated a price elasticity of demand for flood insurance to be -0.38. Somewhat consistent with this study we find a price elasticity of -0.26 to -0.27 suggesting that the amount of insurance policies in force in a county is sensitive to price changes.

Our empirical findings also suggest that recent flood event has a significant positive impact on decision to buy flood insurance which is consistent with the Kunreuther's (1990) hypothesis that risk perception influence insurance purchasing behavior. In a recent study by Atreya et. al (2013), the authors found that in Dougherty county, Georgia, the number of policies in force increased dramatically immediately after the "1994 flood of the century" suggesting that recent flood experience in a county leads to more individuals buying the flood insurance.

[2] The Hausman test rejected the null of fixed effect model against the random effect model (p-value=0.5).

However, we find that disaster relief effort crowd out the purchase of flood insurance consistent with the results of Brown and Hoyt (2000).

Regarding the characteristics of household purchasing the flood insurance, we find that education has a significant impact. Across all the specifications, we find that high school graduates were more likely to buy flood insurance compared to those who have ninth grade or less education. We find that increase in white population in a county would degrease the policies in force indicating that these populations are less likely to buy the flood insurance. We divided the age group of owner occupied household in four different ranges. Age group 25 to 44 did not have any significant impact on decision to buy flood insurance. We find that the age group 45 to 64 was more likely to buy the flood insurance. However, age group 65-84 was more unlikely to buy the flood insurance. Interestingly, the age group 84 and above were more likely to buy flood insurance across all the three models.

In column 3 of Table 3, we estimated a random effect model to be able to determine the impact of the proportion of floodplain in a county on the number of flood insurance policies in force. As expected, we find a positive relationship between the proportion of floodplain in a county and the policies in force in a county implying that the vulnerable counties in fact are more likely to buy flood insurance.

6. Conclusions

In United States a significant portion of the flood losses that occur each year remains uninsured (Brown and Hoyt, 2000). It is important to determine who are buying the flood insurance and who are not to determine the individuals to be focused on to enforcing the NFIP policies towards building a resilient community. Our analysis of the determinants that influence the purchasing decision of the flood insurance is an effort to identifying the vulnerable groups to be focused on.

Our county level analysis between the year 1978-2010 and 153 counties in Georgia suggest that higher income groups are more likely to buy flood insurance. We find that higher the price of the flood insurance per 1000 dollars of coverage lower will be the policies in force. This suggests that lower income groups are more vulnerable to not having covered with the flood insurance if a flood occurs. We also find that the recent flood event will have a positive significant effect on the number of policies in force purchased. However, this is an example of learning a hard way and supports the hypothesis of “availability bias”.

We find that race do not have significant effect on the decision to buy flood insurance. However, education level does. Thus, educating more and more people can be the first step towards building a flood resilient community. We find that the age groups 45-64 are more risk averse than the age group 65-84.

Analysis at the household level data would have been more accurate, however, given that the household level data are not available, county level data provides more information than the state level data that the previous researches have used.

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Table 1: NFIP Policies-In-Force, Premium and Coverage in Georgia from 1978-2010.

Year	Policies-In-Force (PIF)	Premium Collected ($)	Coverage ($ thousands)	Average Premium ($)	Average Coverage ($)
1978	10,502	861,713	343,034	32,664	82
1979	13,348	1,105,861	472,011	35,362	82
1980	14,570	1,250,727	578,935	39,735	85
1981	14,563	1,921,371	651,969	44,769	131
1982	15,036	2,771,714	711,642	47,329	184
1983	15,596	2,905,571	783,435	50,233	186
1984	16,774	3,391,955	938,647	55,958	202
1985	18,018	3,895,232	1,228,856	68,202	216
1986	19,706	4,651,514	1,498,005	76,018	236
1987	20,396	5,267,443	1,665,969	81,681	258
1988	21,271	5,595,801	1,839,428	86,476	263
1989	23,167	6,467,600	2,388,232	103,088	279
1990	32,844	9,128,278	3,170,013	96,517	277
1991	28,238	8,756,679	2,805,169	99,340	310
1992	29,511	9,744,305	2,963,670	100,426	330
1993	31,816	10,803,381	3,337,091	104,887	339
1994	40,234	13,974,896	4,205,946	104,537	347
1995	45,271	16,511,970	5,049,496	111,539	364
1996	49,049	19,206,888	5,938,711	121,077	391
1997	53,431	22,613,901	6,932,214	129,741	423
1998	57,335	25,853,306	7,813,618	136,280	450
1999	61,480	27,262,323	8,779,346	142,800	443
2000	64,933	28,446,564	9,768,575	150,441	438
2001	66,539	29,442,985	10,511,775	157,979	442
2002	67,840	30,852,160	11,221,265	165,408	454
2003	70,080	33,396,557	12,041,183	171,821	476
2004	72,699	35,963,182	13,520,381	185,978	494
2005	79,317	39,881,447	15,700,573	197,947	502
2006	87,478	45,786,366	18,320,810	209,433	523
2007	90,206	50,360,780	19,856,870	220,128	558
2008	92,182	54,860,728	20,894,858	226,670	595
2009	97,396	59,427,670	22,533,477	231,359	610
2010	97,723	63,256,224	23,047,444	235,845	647

Table 2: Variables and Descriptive Statistics

Variables	Description	Mean	Std. Dev.	Min	Max
PIF_Pop	Policy in Force per 1000 population	4.95	19.25	0.01	240.28
Price	Cost per 1000 dollar of coverage	$4.46	$2.39	$0.37	$30.38
Income	Per Capita Income (In thousands)	$25.76	$6.13	$12.22	$65.91
Percent FP	Percent of Floodplain in a county	14.34	12.91	2.03	72.24
Recent_Flood	Flood Damage per capita during prior year	$10.99	$113.00	$0.00	$3986.23
Relief_exp	Disaster Assistance per capita	$0.004	$0.08	0.00	$3.37
Blkpct	Percent of Black per 1000 population	1.49	2.24	0.00	35.49
whitepct	Percent of White/ 1000 population	3.54	3.08	0.05	38.65
High_schl	Percent of high school grads/1000 population	1.88	1.85	0.02	19.19
Lessthan_9^{th}	Percent of Nine graders or Less/1000 population	0.61	0.75	0.01	12.6
Age_25to44	Age group 25-44/1000 population	20.74	14.95	0	93.27
Age_45to64	Age group 45-64/1000 population	20.88	14.57	0	77.10
Age_65to84	Age group 65-84/1000 population	9.95	7.80	0	47.68
Age_85&up	Age group 85&up/1000 population	1.26	1.16	0	10.59

Table 3: Empirical Results (Dependent Variable: Policies in force/1000 population)

Variables	Fixed Effect	Random Effect[3]	Random Effect[4]
Log(Income)	0.384**	0.495***	0.553***
	(0.171)	(0.161)	(0.159)
Log(Price)	-0.271***	-0.269***	-0.261***
	(0.0321)	(0.0320)	(0.0319)
Log(Recent_Flood)	0.0205**	0.0206**	0.0204**
	(0.00819)	(0.00831)	(0.00833)
Fld_event	0.112*	0.115*	0.117**
	(0.0580)	(0.0588)	(0.0589)
Log(Relief_exp)	0.140*	0.136*	0.137*
	(0.0807)	(0.0818)	(0.0820)
Blkpct	-0.0896	-0.0900	-0.0719
	(0.148)	(0.0901)	(0.0812)
Whitepct	-0.255***	-0.165**	-0.124**
	(0.0782)	(0.0662)	(0.0631)
High_schl	0.988***	0.587***	0.457***
	(0.215)	(0.158)	(0.149)
Lessthan_9th	-1.107***	-0.583***	-0.488**
	(0.399)	(0.222)	(0.199)
Age25to44	0.00396	0.00948	0.00844
	(0.00662)	(0.00625)	(0.00609)
Age45to64	0.0622***	0.0367***	0.0370***
	(0.0141)	(0.0129)	(0.0125)
Age65to84	-0.308***	-0.208***	-0.207***
	(0.0439)	(0.0312)	(0.0285)
age85andup	0.913***	0.701***	0.746***
	(0.263)	(0.173)	(0.154)
Percent FP			**0.0694*** **
			(0.00687)
Constant	-4.391***	-6.015***	-7.547***
	(1.656)	(1.583)	(1.562)
Observations	3,795	3,795	3,795
R-squared	0.646		
Number of id	153	153	153

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

[3] We do not include the proportion of FP in a county (**Percent FP**) in this model to compare the results of Fixed effect model with that of Random effect model
[4] We include the proportion of FP in a county in this random effect model