How Income Inequality Influenced Personal Decisions on Disaster Preparedness: A Multilevel Analysis of Homeowners Insurance among Hurricane Maria Victims in Puerto Rico

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Abstract

Hurricane Maria ravaged Puerto Rico with massive winds and damaged more than 1/3 of its occupied homes. To achieve home recovery, Homeowners insurance (HI), provides an important financial resource for rebuilding and repairing. Yet, it is not known which factors determine the likelihood of homeowners adopting HI prior to such disasters. This study examines how individual income and community income inequality influenced personal decisions to adopt HI by homeowners suffering damage from Hurricane Maria. Using Individual Assistance Housing data collected by the Federal Emergency Management Agency (N=265,807), we employed four nested multi-level logistic regressions to estimate household probabilities of having HI. First, our simplest random-intercept model found significant variation in HI adoption probabilities across 881 census tracts. Second, when adding individual household and housing characteristics, households with higher incomes were significantly more likely to adopt HI. Third, the addition of income inequalities in terms of Gini quartile ranges showed that relative to the lowest range, households in the three higher-range census tracts were less likely to adopt HI. Finally, the addition of a possible interaction between income and income inequality showed that income inequality significantly influenced the relationship between income and HI adoption behavior. Specifically, income inequality played different roles for poor and rich: impeding HI adoption behavior for low-income households while facilitating such a behavior for high-income households. Policy formulation should consider public-private partnerships to address HI affordability for those low-income households most vulnerable to housing damage.

INTRODUCTION

In September 2017 Hurricane Maria ravaged Puerto Rico, with massive winds and flooding resulting in close to 3,000 fatalities (Amandolare, 2018). Nearly a third of occupied homes (300,000) were damaged, mostly by sustained wind forces of more than 160 mph (HUD 2018; Brown, 2018; NOAA, 2019). Even a year after the storm more than 60,000 homes remained roofless (Viglucci, 2018). As observed in other disasters, massive home displacement combined with a lack of speedy recovery can have devastating impacts on psychological and economic wellbeing, especially among low-income households (Fussell and Lowe, 2014; Hori and Schafer, 2010).

With respect to both the scope and speed of recovery for individual homeowners, the role of homeowners insurance (HI) can be critical (Scism and Friedman, 2017; Ma 2018). As noted by Scism and Friedman (2017), such insurance is the single "best source for most people after a disaster", especially "in terms of straight-up cash to pay for the work that has to be done". But among those homes damaged by Hurricane Maria, the extent of HI coverage has not yet been studied, either in relation to the characteristics of homeowners themselves or to the damage they suffered.

What then are the major factors influencing insurance coverage among disaster victims? Previous studies at the community level have found that low income status is the single major impediment to homeowner insurance coverage. For example, in analyzing aggregate data at the neighborhood level in New Orleans, Popkin, Turn and Burt (2006) found that on the eve of Hurricane Katrina "many low-income longtime homeowners opted out of costly homeowners insurance…". More generally, the affordability of insurance for mitigating real property loss in disasters is now a major research topic (Grace et al, 2004). However, the extent to which income influences individual owner's decisions about insurance coverage has not been fully explored.

Turning to other possible factors, it has been found in studies of public health [Kawachi and Kenndy (1999), Subramanian et al. (2003), Subramanian and Kawachi (2004); and Merlo et al, (2016)] that not only the incomes of individuals, but also the distribution of income within their communities determines their access to health care. This raises the question of whether income inequality might also influence access to homeowner insurance. For Puerto Rico in particular, income inequality has long been deeply rooted (Toro, 2008), and indeed their Gini-Index is among the highest in the world (Hernandez and Schmidt, 2018). But whether income inequalities at the local community level might play a role in individual access to homeowner insurance remains to be addressed.

Finally, one may ask whether such income inequalities have similar effects on both rich and poor individuals' decisions to purchase homeowners insurance. In this regard, social epidemiologists (Subramanian et al, 2003; Subramanian and Kawachi, 2004) proposed individual-community interaction hypotheses to test individual health and behavioral outcomes. In particular, Subramanian (et al., 2003) speculated that "there is a cross level interaction between community income inequality and household income, such that the most adverse effect of income inequality is on poor individuals, while income inequality may not have any impact on rich individuals (or may even be beneficial)" (p.847). We are thus interested in whether such an interaction hypothesis may be relevant for access to homeowner insurance as well.

In summary, the objective of this paper is to address the following questions about homeowners who suffered damage from Hurricane Maria in Puerto Rico:

1. To what extent were these homeowners covered by homeowners insurance prior to the disaster, especially in relation to their housing and damage characteristics?
2. To what extent were the incomes of these homeowners related to their decisions to take up homeowners insurance prior to the disaster?
3. To what extent was the community level of income inequality for these homeowners related to their decisions to take up homeowners insurance prior to the disaster?
4. To what extent did the community level of income inequality for homeowners influence the relationship between their incomes and decisions to take up homeowners insurance prior to the disaster?

METHODS

To address the research questions above, this study utilizes the Individual Assistance Housing Registrants (IAHR) file for major disasters published by the Federal Emergency Management Agency (FEMA) in 2018. More specifically, we use the registrant list from June 1, 2018, containing the 265,807 owner-occupied homes classified by FEMA as damaged by Hurricane Maria. FEMA also reported both the insurance status and incomes of homeowners, as well as the damage levels and other characteristics of their homes. In addition, we utilize US Census data (2013-2017 American Community Survey 5-year estimates) to obtain community data at the census-tract level (881 tracts) in Puerto Rico with respect to both income distributions and housing values.

Measurement and specifications

Our key outcome variable, *homeowners insurance* (HI), is a dichotomous variable with values "1 = yes" and "0 = no" in response to the FEMA question of whether or not the homeowner was covered by HI at the time of Hurricane Maria. Our key explanatory variable for individual homeowners is *income*, measured as a continuous variable denoting their reported annual income prior to the disaster. Given that this distribution of incomes is heavily right skewed, we use log values of income for purposes of logistic regression analyses [Table 1 and Table 2]. As noted above, our second key variable, namely community *income inequality*, is measured in terms of Gini coefficients at the census-tract level in Puerto Rico. In a manner similar to Subramanian et al. (2013), we employ four ordinal categories of Gini values to capture the community income inequality across 881 census tracts in Puerto Rico. As shown in Figure 1, we use the quartile points ($Q_k : k = 1, 2, 3$) of the Gini distribution to define each of these categories as follows: $G_1 = \{Gini \le Q_1\}$, $G_2 = \{Q_1 < Gini \le Q_2\}$, $G_3 = \{Q_2 < Gini \le Q_3\}$, $G_4 = \{Gini > Q_3\}$.

Finally, we include a number of relevant characteristics of individual damaged homes based on FEMA data. Most notable for our purposes is ordinal variable, *damage level*, with FEMA-defined values: "minor damage" (repair cost less than $17,000), "major damage" (repair cost at least $17,000), and "destroyed" (beyond repair) (FEMA 2017; HUD 2018). To reflect the prominence of wind damage from Maria, we also employ the dichotomous FEMA variable, *roof damage*, which is the most common form of wind damage (Scism and Friedman, 2017 Vulggici, 2019). Finally, to reflect possible differences in damage vulnerability among housing types, we employ the categorical variable, *housing type*, with FEMA-defined values: “Apartment”, “House/Duplex” “Townhouse”, “Condo”, “Mobile Home”, or “Other type”.

Statistical Analyses

To address research question 1, we use simple bivariate analyses to compare adopters and non-adopters of homeowners insurance (HI) with respect to each of our home characteristics, as shown in Table 1. This is accompanied by simple logistic regressions of taking up HI (also referred to as HI adoption) on each home characteristic in Table 1. To address research questions 2, 3, and 4, we employ a nested sequence of four multilevel logistic regressions designed to capture successively more complex relations between HI adoption behavior and the characteristics of both individual households and the communities in which they live. These models, designated as the (1) Null Model, (2) Household-Level Model, (3) Household-Community Model, and (4) Cross-Level Interaction Model, can be sketched as follows.

The *Null Model* is essentially a random intercept model without any predictor variables, which is designed to capture the variation of HI adoption behavior among households in different communities (census tracts). The *Household-Level Model* then incorporates all covariates at the individual household level (income, damage level, roof damage, and housing type). This not only allows us to estimate the effect of household income while controlling for other covariates, but also to compare community effects with those of the null model. The *Household-Community Model* focuses on the third research question by incorporating our Gini variable at the census-tract level to study the effect of community income inequality on HI adoption behavior while controlling for all individual covariates. Finally, to address our fourth research question, the *Cross-Level Interaction Model* allows for a possible interaction between income inequality at the community level and individual household income. (A more detailed mathematical formulation of these four models is provided in the Supplementary Material, Model Formulation.)

As mentioned above, the variance of the random intercept term in each model can be viewed as reflecting the influence of community differences on HI adoption other than those captured by the model covariates. However, we also employ the *median odds ratio* (MOR), which provides a more direct comparison with odds ratios for covariates (Larson and Merlo, 2005, Merlo et al., 2006). In our case, the odds ratio of each covariate measures the change in a household’s propensity to adopt HI resulting from a given change in that covariate, holding all other relevant covariates constant. Similarly, MOR measures the change in a household’s propensity to adopt HI resulting from a given change in communities, holding all covariates constant. Given the multitude of possible relocations among census tracts, MOR is calculated by first treating all relocation pairs as moves to the tracts with higher propensity (so that all odds ratios are at least one), and then choosing the median of these odds ratios.

Finally, with respect to statistical estimation of these models, all analyses were carried out using Stata 15MP software package. Here it must be emphasized that about 12% of our data exhibited missing values for the key *household income* variable (though missingness occurred in no other variables). We thus employed list-wise deletion in all logistic regression analyses, effectively reducing our samples size to 232,971 households (nested in 881 census tracts). For logistic regression in particular, it is well known that list-wise deletion is the single most robust procedure to violations of the missing-at-random assumption for missing data (Allison, 2001). However, as an additional check, we also employed multiple-imputations (M=10) to estimate each model, and obtained qualitatively similar results (Supplementary Table A).

RESULTS

As shown in Table 1, about 20% of homeowners in our study group (N=265,807) had taken up Homeowners Insurance (HI) prior to the disaster. Moreover, less than 5% of the homes damaged at the major level were covered by HI, and only about 1% of destroyed homes were covered by HI. With respect to those households reporting income levels (N = 232,971) there was a large and significant disparity between the mean incomes of those with HI ($57,568) and not with HI ($24,980) [$p < 0.01$]. Significant disparities in HI coverage rates were also found among those households in census tracts with different levels of income inequality ($p < 0.01$), with the highest rate (23%) in G_1 (the lowest Gini quartile) and the lowest rate (18%) in G_4 (the highest quartile). Comparable results in terms of simple logistic regressions of HI coverage on these household characteristics are given in Table 1.

The results of our multilevel logistic regression models are given in Table 2. The Null Model, with its random intercept variance of 0.74 [95% Confidence Interval (CI) = 0.66, 0.82, $p < 0.01$] shows that there is significant variation in HI adoption rates between census tracts. The median odds ratio (MOR) of 2.28 (CI = 2.17, 2.38, $p < 0.01$) shows in particular that for typical pairs of tracts, the HI adoption odds in the higher propensity tract are more than twice those in the lower propensity tract. This finding underscores the relevance of our multilevel household-community approach. The Household-Level Model in Table 2 shows that when controlling for other relevant household and damage characteristics, income is a significant predictor of HI adoption (OR = 1.55, CI = 1.53, 1.57, $p < 0.01$). Moreover, compared to the Null Model, there is also a significant reduction in MOR from 2.28 to 1.86 (CI = 1.79, 1.92, $p < 0.01$), indicating that these household-level characteristics account for a substantial portion of the differences in HI adoption rates between communities. Similarly, the Household-Community Model shows that when adding our community-level Gini measure while controlling for all household-level characteristics (including income), there is a further impact of income inequality on HI adoption rates. In particular, such rates are found to be significantly lower in tracts with higher levels of income inequality, where for example the HI adoption odds in tracts with Gini coefficients in the highest quartile are only about 70% of those with Gini coefficients in the lowest quartile (OR = 0.73, CI = 0.64, 0.83, $p < 0.01$). Thus, the addition of Gini coefficients further reduces MOR to 1.83 (CI = 1.77, 1.90, $p < 0.01$), showing that community-level income inequalities indeed account for part of the difference in HI adoption rates among communities.

Finally, the Cross-Level Interaction Model shows that community-level income inequalities also have a contextual effect on HI adoption decisions by households at different levels of income. In comparison to census tracts with lowest levels of income inequality (G_1), HI adoption decisions by households are significantly more sensitive to income in tracts with higher income inequality (G_2, G_3, G_4). This is manifested by larger and positive beta coefficients of cross-level interaction effects for Census tracts with higher levels of income inequality (b = 0.04, 0.06, 0.11 for G_2, G_3 , G_4 , respectively, relative to G_1, with $p < 0.01$ in all cases). However, these contextual effects exhibit slight differences, as can be seen in Figure 2, where average marginal predictive probabilities of HI adoption are plotted against household incomes for G_1, G_2, G_3, and G_4. To better visualize the differences between these curves, we have plotted the contrasts in predictive probabilities (as shown in Figure 3), where again G_1 is the reference group. While the probability of taking up HI steadily increases with income in all cases (Figure 2), for households with lower income levels [up to $8000 (= 9 in log terms)] these increases are seen from Figure 3 to be much smaller in census tracts with higher income inequality. Thus, for these lower-income households (more than 30% of our sample), higher levels of income inequality tend to impede their likelihood of HI adoption. (We return to this issue the discussion below.) But for higher-income households the situation is actually reversed, where HI adoption is now more likely in tracts with higher levels of income (Figure 3). Finally, it should be noted that while MOR exhibits no noticeable change in the presence of this interaction effect, a likelihood ratio test suggests that this cross-level interaction model indeed provides a better fit to our data than the household/community model (chi2(3) = 53.40, $p < 0.01$).

DISCUSSION

Turning to the first of our four research questions, our findings show that the prevalence of homeowners insurance among owner-occupied homes damaged by Hurricane Maria was very low (about 20%). This figure is consistent with the survey among the adult population in Puerto Rico (N = 1500) done by the Kaiser Foundation (2017), in which only 22% of respondents were covered by either homeowners or renters insurance. We found that this lack of HI coverage was even more extreme (11%) for houses suffering roof damage (which is covered by HI), and was most extreme (1%) for those houses completely destroyed by Maria (Table 1). Finally, these damage characteristics were also found to be strongly associated with lower-income households (Supplementary Table B), which is also consistent with previous studies (Ma & Smith, 2019).

Turning to our second research question, our study found strong evidence that individual households with lower income levels were less likely to be covered by homeowners insurance. This is consistent with many previous findings at the community level, such as the study of the Lower Ninth Ward in New Orleans by Popkin et al. (2006), mentioned in the Introduction. But what is more telling for the case of Puerto Rico is that even within this high-poverty area of New Orleans, at least 52% of all homeowners had homeowners insurance prior to Hurricane Katrina (Popkin, 2006). This stands in stark contrast to the 20% figures for Puerto Rico above. One additional piece of information here relates to the mortgage market in Puerto Rico. As in the continental US, banks in Puerto Rico 'require people with mortgages to take out homeowners policies to protect the bank's financial interest.' (Scism and Friedman, WSJ, 2017). So one may infer that no more than 20% of damaged homes in Puerto Rico have active mortgages. Moreover, as mentioned in our data-limitations discussion below, those homeowners without mortgages are primarily in the informal housing market of Puerto Rico, which is predominantly low-income housing (Suarez, 2019).

Our third research question is answered affirmatively by the findings of the Community-Household Model. Even after accounting for individual income effects, the likelihood of taking up homeowners insurance prior to Hurricane Maria was significantly less for households in census tracts with higher levels of income inequality. But the full effects of such inequalities are seen most clearly in terms of our findings for the final research question, which focuses on possible interactions between individual incomes and community-level income inequalities. Here we found that the relation between household incomes and the likelihood of HI adoption is actually quite different depending on community levels of income inequality. For low-income households, this likelihood is significantly reduced in communities with higher income inequality. However, the situation is reversed for high-income households where the likelihood of HI adoption is greater in communities with higher income inequality. Here, one may recall from the Introduction that this relationship exactly parallels the individual-community interaction hypothesis posed by Subramanian et al. (2003) in the context individual health outcomes.

With respect to low-income households in particular, this naturally raises the question of *why* higher community income inequalities should reduce the likelihood of HI adoption. It appears that this effect may be partially explained by the relation between income inequality and housing prices at the community level, once income levels are controlled for. In particular, a multiple regression of median housing prices on median incomes and Gini coefficients at the census-tract level in Puerto Rico shows that after controlling for income effects, higher income inequalities are a significant predictor of higher housing prices (Supplementary Table C). This suggests a possible economic pathway from higher income inequalities to a reduced likelihood of HI adoption for low-income households. In particular, the presence of higher income households in those communities with higher income inequalities effectively drives up local housing prices, making both housing and homeowner insurance less affordable for low-income households. This is further supported by evidence from the insurance literature (Grace et al, 2004) that such "catastrophe" insurance is substantially more price sensitive than other types of insurance.

It should also be noted that our present study is not without limitations. The most important issues for our present purposes relate to missing data. First, as already discussed, approximately 12% of households did not report their incomes. While the agreement of both our listwise deletion and multiple-imputation results do suggest some degree of robustness in these results, there is still a possibility for bias. In this regard, Table 1 provides one additional piece of evidence, namely that the HI adoption rate among missing-income households was substantially larger than for the sample population as a whole (28.04% versus 19.87%). This, together with the generally observed positive relation between income and insurance coverage in existing literature (e.g., Showers and Shotick 1994), suggests that these households should tend to have higher incomes – which is in fact consistent with all of our findings. We should also note that in addition to income, we lack data on other sociodemographic groups who may be more risk averse (such as those with higher education), and are thus more likely to adopt HI.

A more general missing-data problem stems from the massive informal housing market in Puerto Rico, which is predominantly low-income housing (Suarez, 2019), and is estimated to include more than half of the entire housing stock (HUD, 2017; Viglucci, 2018). Households in this informal sector almost never have legal proof of ownership (Benach et al, 2019), and are thereby unable to qualify for homeowners insurance (Viglucci, 2018). Moreover, because proof of ownership is a FEMA requirement for housing assistance, (Acevedo and Pacheco, 2018, Viglucci, 2018) it is reasonable to speculate that a substantial portion of informal-sector households suffering damage never even applied to FEMA, and are necessarily missing from our data. These observations suggest that our present results may seriously underestimate the true lack of homeowners insurance coverage among Puerto Rico's low-income households.[1]

However, we believe this is the first paper to link both income and income inequality to individual disaster preparedness decisions in terms of homeowners insurance. In particular, we find new relevance for the individual-community interaction hypothesis first postulated in the context of public health. More specifically, our study provides evidence that poor households living in communities with high income inequalities tend to have less access to affordable homeowners insurance. Nonetheless, as noted by Grace et al. (2004), homeowners "tend to buy

[1] It should also be noted that we have no data on those individuals who own their homes outright, and are thus not required to have HI. But while this missing data is another possible source of underestimation, it seems reasonable to speculate that such homeowners are less likely to be in the low-income group.

more insurance when it is subsidized through regulatory price constraints”. To the extent that this lack of access is generated by price effects arising from income inequalities, our study thus suggests the need for a public-private partnership (Kunreuther, 2015) in developing disaster-mitigation insurance programs that are more accessible to all.

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Figure 1. The Distribution of Gini Index across Census Tracts.

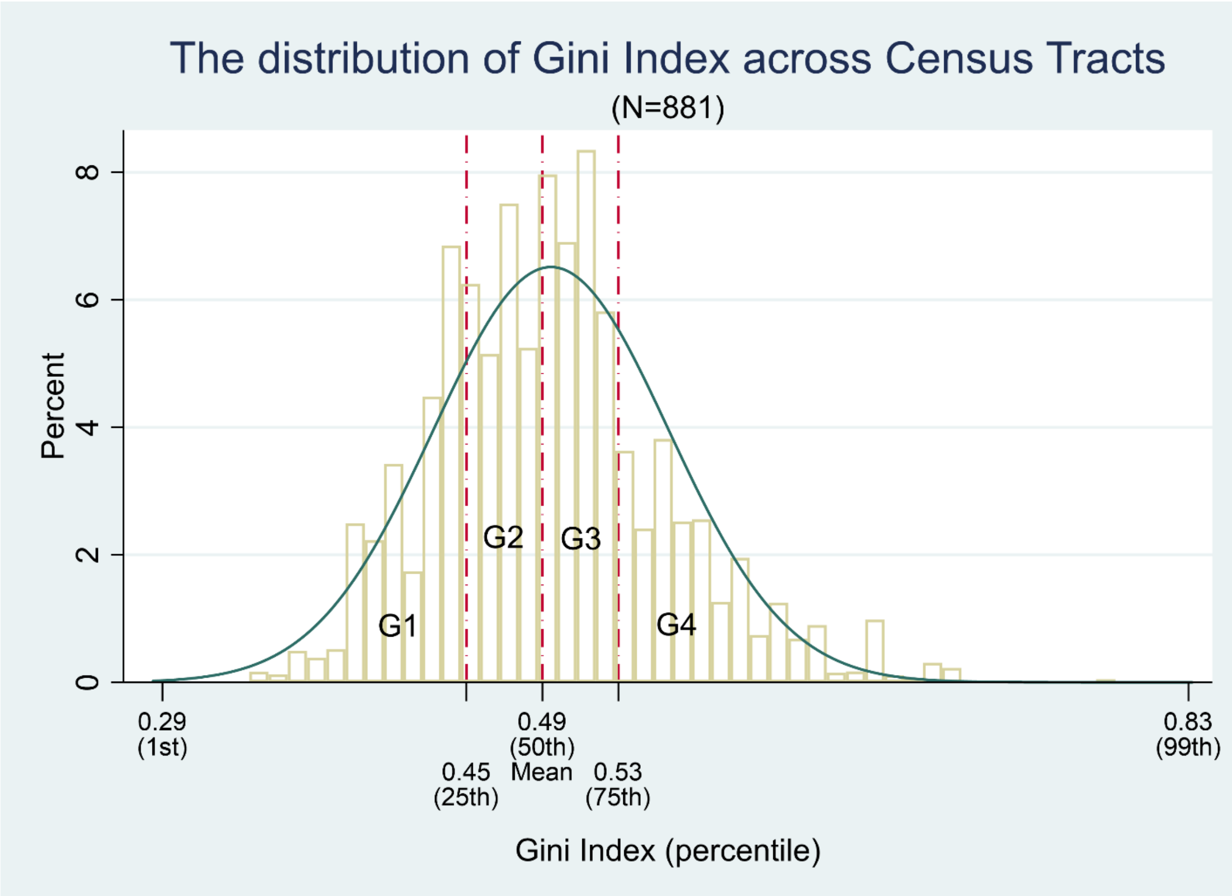

Figure 2. Predictive Margins of Gini-index quartiles with 95% Confidence Interval (CI).

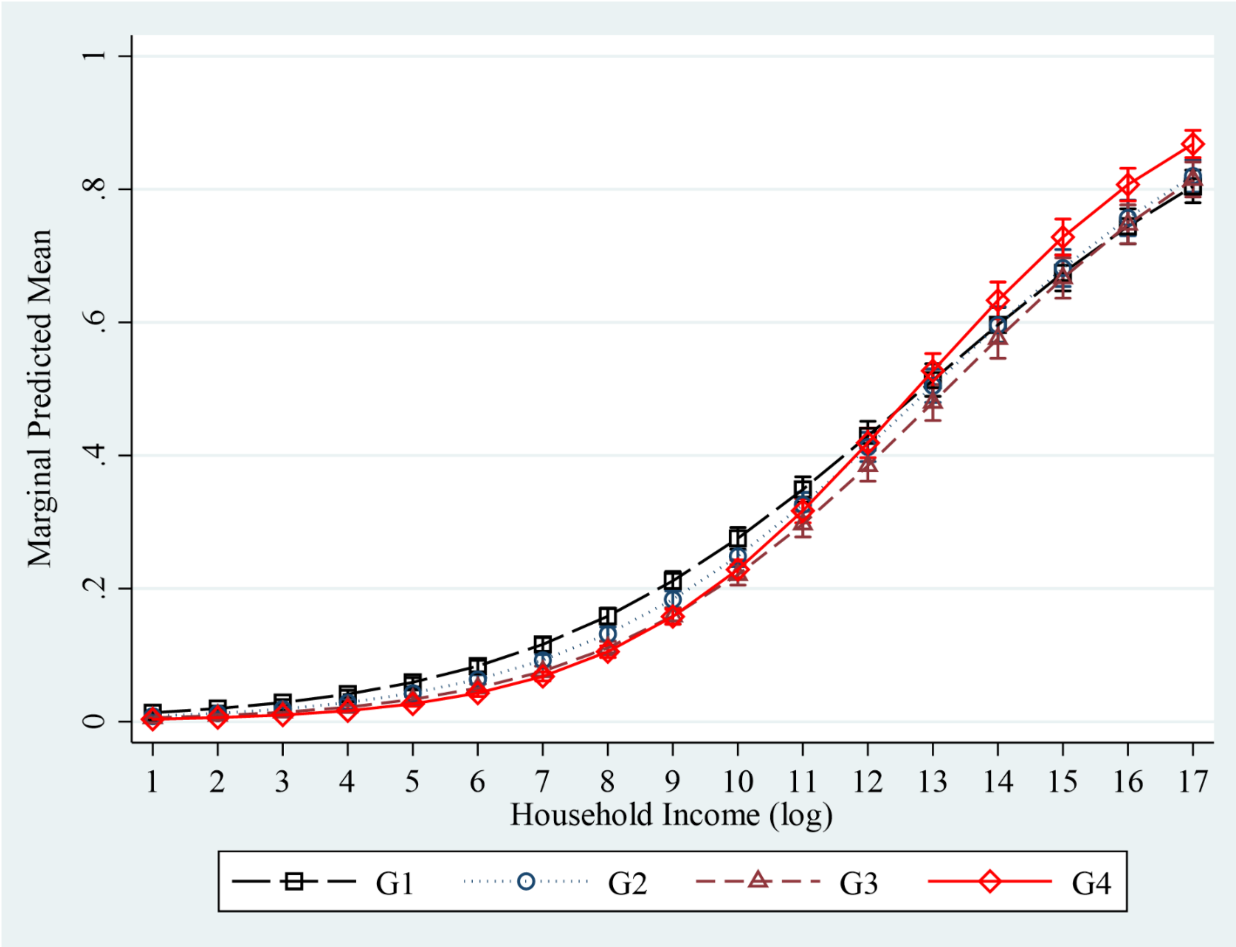

Figure 3. Contrasts of Predictive Margins for Gini-index Quartiles with 95% Confidence Intervals (CI).

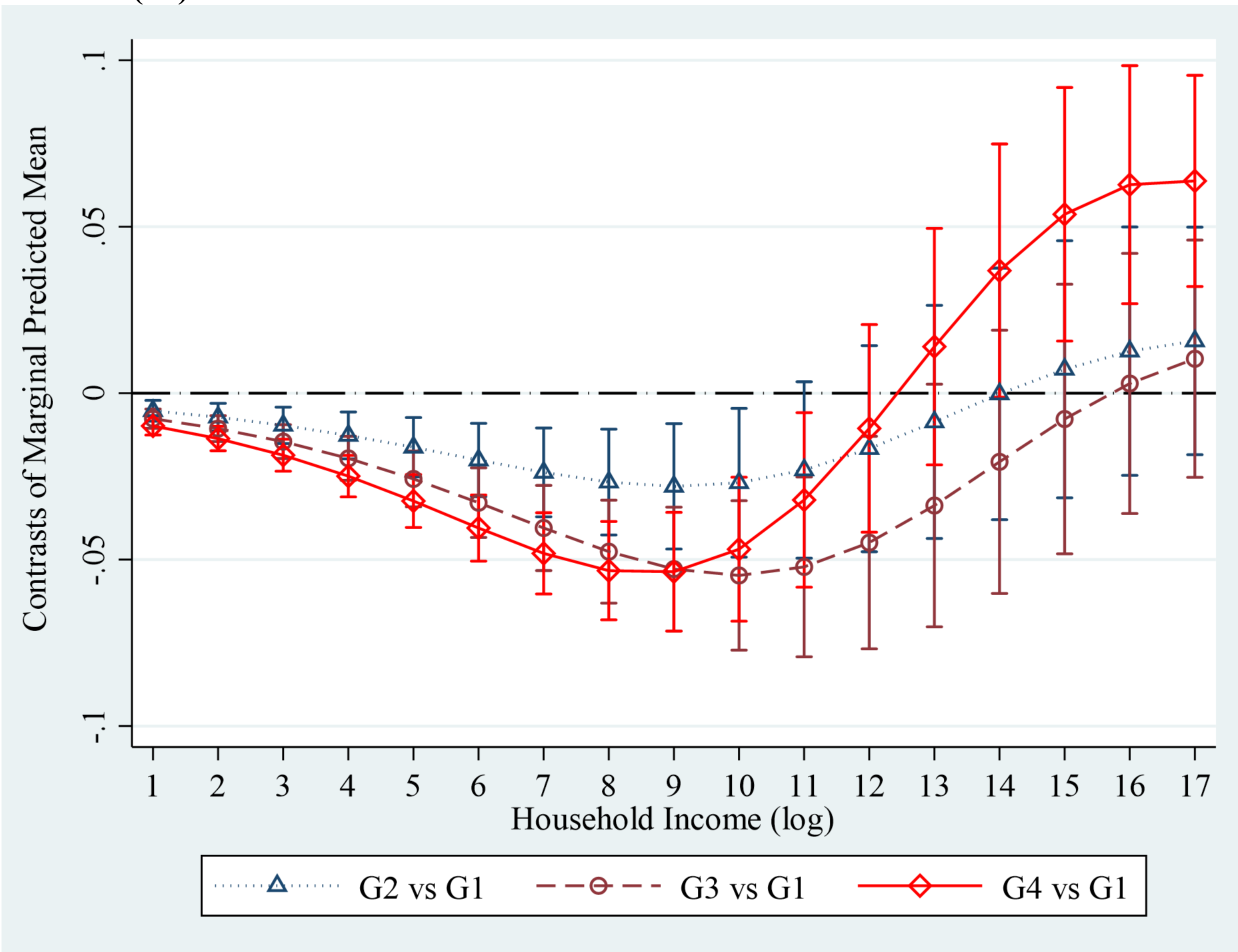

Table 1. Bivariate analyses of Homeowners Insurance and home characteristics.

VARIABLES		Homeowners Insurance No	Homeowners Insurance Yes	Homeowners Insurance Total	Statistical Tests
	Total	52,821	212,986	265,807	
		80.13 %	19.87%	100%	
Damage Level	Minor Damage	207,164	52,642	259,806	
		79.74%	20.26%	100%	
	Major Damage	2,643	138	2,781	*Chi2(2)*
		95.04%	4.96%	100%	1.1e+03***
	Destroyed	3,179	41	3,220	
		98.73%	1.27%	100%	
Roof Damage	No	106,786	40,171	146,957	
		72.66%	27.34%	100%	*Chi2(1)*
	Yes	106,200	12,650	118,850	9.5e+03***
		89.36%	10.64%	100%	
Housing Types	House/Duplex	204,530	47,689	252,219	
		81.09%	18.91%	100%	
	Condo/Apartment	3,359	3,221	6,580	
		51.05%	48.95%	100%	
	Townhouse	4,264	1,860	6,124	*Chi2(4)*
		69.63%	30.37%	100%	4.2e+03***
	Mobile Homes	551	30	581	
		94.84%	5.16%	100%	
	Others	282	21	303	
		93.07%	6.93%	100%	
Household Income (in dollars)	Count	189,357	43,614	232,971	*t*(54089.5)
		81.28%	18.72%	100%	-17.78***
	Mean	24,980	57,568	31,080	
	Missing	23,629	9,207	32,836	
		71.96%	28.04%	100%	
Gini-index (G)	G_1 (Gini <= 25^{th} percentile)	53,668	15,615	69,283	
		77.46%	22.54%	100%	
	G_2 (Gini > 25^{th} & <= 50^{th} percentile)	51,728	13,405	65,133	
		79.42%	20.58%	100%	*Chi2(3)*
	G_3 (Gini > 50^{th} & <= 75^{th} percentile)	54,631	12,366	66,997	594.75***
		81.54%	18.46%	100%	
	G_4 (Gini > 75^{th} percentile)	52,959	11,435	64,394	
		82.24%	17.76%	100%	

*** p<0.01, ** p<0.05, * p<0.1.
Chi2(k) = Chi-square with k degrees of freedom.
t(k) = t score with Welch's degrees of freedom.
First row has *frequencies*; second row has *row percentages*

Table 2. Simple logistic regression estimates of taking up Homeowners Insurance by home characteristics (N=232,971).

	Estimates		Constant	
VARIABLES	*b*	OR	*b*	OR
Damage level				
Minor Damage^				
Major Damage	-1.63*** (-1.82, -1.43)	0.19*** (0.65, 0.23)	-1.44*** (-1.35, -1.43)	0.24*** (0.23, 0.24)
Destroyed	-2.81*** (-3.12, -2.50)	0.06*** (0.05, 0.08)		
Roof Damage				
No^	-1.14***	0.32***	-1.04***	0.35***
Yes	(-1.17, -1.12)	(0.37, 0.39)	(-1.05, -1.03)	(0.31, 0.32)
Housing Type				
Mobile Homes^				
House/Duplex	1.47*** (1.06, 1.90)	4.38*** (2.88, 6.66)	-3.00 (-3.42, -2.58)	0.050 (0.03, 0.08)
Condo/Apartment	2.87*** (2.45, 3.30)	17.74*** (11.63, 27.06)		
Townhouse	2.11*** (1.69, 2.54)	8.27*** (5.42, 12.63)		
Others	0.06 (-.64, 0.76)	1.06 (0.53, 2.13)		
Income (log)	0.58*** (0.57, 0.59)	1.79*** (1.77, 1.80)	-6.99*** (-7.10, -6.88)	0.00*** (0.00, 0.00)
Gini-index (Gini)				
G_1(Gini <= 25^{th} percentile)^				
G_2 (Gini> 25th & <= 50th percentile)	-0.12*** (-0.15, -0.09)	0.88*** (0.86, 0.91)	-1.30*** (-1.31, -1.28)	0.27*** (0.27, 0.28)
G_3 (Gini > 50th & <= 75th percentile)	-0.26*** (-0.30, -0.23)	0.76*** (0.74, 0.79)		
G_4 (Gini > 75th percentile)	-0.31*** (-0.34, -0.28)	0.73*** (0.71, 0.75)		

Abbreviations: *b*= beta coefficient; OR= odds ratio.
95% Confidence Interval in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3. Multilevel logistic regression estimates of taking up Homeowners Insurance (N=232,971).

VARIABLES	Null Model *b*	 OR	Household Model *b*	 OR	Household-Community Model *b*	 OR	Cross Level Interaction Model *b*	 OR/ROR
Damage level Minor Damage^								
Major			-1.09*** (-1.29, -0.89)	0.34*** (0.28, 0.41)	-1.09*** (-1.29, -0.89)	0.34*** (0.28, 0.41)	-1.09*** (-1.29, -0.89)	0.34*** (0.28, 0.41)
Destroyed			-2.80*** (-3.11, -2.49)	0.06*** (0.04, 0.08)	-2.80*** (-3.12, -2.49)	0.06*** (0.04, 0.08)	-2.80*** (-3.11, -2.49)	0.06*** (0.04, 0.08)
Roof Damage No^ Yes			-0.91*** (-0.93, -0.88)	0.40*** (0.39, 0.41)	-0.91*** (-0.93, -0.88)	0.40*** (0.39, 0.41)	-0.91*** (-0.93, -0.88)	0.40*** (0.39, 0.41)
Housing Type Mobile Homes^								
House/Duplex			1.21*** (0.78, 1.64)	3.35*** (2.18, 5.17)	1.21*** (0.78, 1.64)	3.35*** (2.18, 5.16)	1.21*** (0.78, 1.64)	3.36*** (2.18, 5.18)
Condo/Apartment			2.00*** (1.56, 2.43)	7.36*** (4.75, 11.38)	2.00*** (1.56, 2.44)	7.39*** (4.77, 11.43)	2.00*** (1.57, 2.44)	7.41*** (4.79, 11.47)
Townhouse			1.55*** (1.12, 1.99)	4.73*** (3.06, 7.32)	1.55*** (1.12, 1.99)	4.73*** (3.05, 7.31)	1.56*** (1.12, 1.99)	4.74*** (3.06, 7.34)
Others			0.25 (-0.47, 0.97)	1.29 (0.63, 2.64)	0.25 (-0.47, 0.97)	1.28 (0.62, 2.63)	0.25 (-0.47, 0.97)	1.29 (0.63, 2.65)
Income (log)			0.44*** (0.43, 0.45)	1.55*** (1.53, 1.57)	0.44*** (0.43, 0.45)	1.55*** (1.53, 1.57)	0.39*** (0.37, 0.41)	1.48*** (1.45, 1.51)
Gini-index (Gini) G_1 (Gini <= 25th percentile)^								
G_2 (Gini > 25th & <= 50th percentile)					-0.17** (-0.30, -0.04)	0.85** (0.74, 0.96)	-0.54*** (-0.86, -0.23)	0.58*** (0.42, 0.79)
G_3 (Gini > 50th & <= 75th percentile)					-0.35*** (-0.48, -0.21)	0.71*** (0.62, 0.81)	-0.91*** (-1.23, -0.59)	0.40*** (0.29, 0.56)
G_4 (Gini > 75th percentile)					-0.31*** (-0.44, -0.19)	0.73*** (0.64, 0.83)	-1.43*** (-1.75, -1.10)	0.24*** (0.17, 0.33)
Interaction of Gini-index and Income G_1* Income (log)^								
G_2* Income (log)							0.04*** (0.01, 0.07)	1.04*** (1.01, 1.07)
G_3 * Income (log)							0.06*** (0.03, 0.09)	1.06*** (1.03, 1.09)
G_4 * Income (log)							0.11*** (0.08, 0.15)	1.12*** (1.09, 1.16)
Constant (Fixed portion)	-1.40*** (-1.46, -1.34)	0.25*** (0.23, 0.26)	-6.46*** (-6.91, -6.01)	0.002*** (0.001, 0.003)	-6.25*** (-6.71, -5.80)	0.002*** (0.001, 0.003)	-5.78*** (-6.26, -5.30)	0.003*** (0.002, 0.005)
Random effect parameters (VAR)	0.74*** (0.66, 0.82)		0.42*** (0.37, 0.47)		0.40*** (0.36, 0.45)		0.40*** (0.35, 0.45)	
MOR	2.28*** (2.17, 2.38)		1.86*** (1.79, 1.92)		1.83*** (1.77, 1.90)		1.83*** (1.77, 1.90)	

Abbreviations: *b*= beta coefficient; OR = odds ratio; ROR = ratio of odds ratios for the interaction term; VAR= variance; chi2: chi-square; MOR= median odds ratio.
95% Confidence Interval in parentheses
*** p<0.01, ** p<0.05, * p<0.1
^denotes the reference category