Flood Insurance Market Penetration and Expectations of Disaster Assistance

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Abstract

Concern over resilience to natural disasters often focuses on moral hazard; expectations of disaster assistance may lead households in hazard-prone communities to forego insurance. This has been dubbed "charity hazard" in the literature on natural disasters. We examine flood insurance uptake using household level survey data and employ instrumental variables (related to local history of aid distribution and political economy) to address endogeneity of individual expectations of eligibility for disaster assistance. To avoid potential problems with reverse causation, we drop any households that could have received payments in the past (triggering mandatory flood insurance purchase). We find coastal households that exhibit positive expectations of disaster aid eligibility are 25 to 42 percent less likely to hold flood insurance. We estimate that charity hazard could be responsible for 817,000 uninsured homes in the United States corresponding to a loss of \$526 million in forgone annual revenue for the National Flood Insurance Program.

Key Words: charity hazard, flood insurance, natural hazards

JEL Classification: Q54, G22

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1 Introduction

Despite significant and diverse flood risks across the United States and high vulnerability of many major metropolitan areas (e.g. Miami, Charleston, and Norfolk on the East Coast; Houston and New Orleans on the Gulf Coast), it is generally recognized that the National Flood Insurance Program (NFIP) suffers from low levels of market penetration (Ahmadiani, Ferreira, and Landry 2019). Even in high-flood-risk zones, market penetration often fails to reach levels greater than 50 percent (Kousky 2010; Landry and Jahan-Parvar 2011; Kousky et al. 2018). Additionally, total NFIP policies-in-force remained stagnant for most of the mid 2000s with recent years being characterized by a decrease in total policies (Kousky et al. 2018). While the U.S. Congress and the Federal Emergency Management Agency (FEMA) have made efforts to encourage participation through targeted premium subsidies, mandatory purchase requirements, flood risk information campaigns, and community mitigation programs, low levels of market penetration remain a persistent problem. Consequently, when a major hurricane or flood event occurs, many homeowners sustain significant and costly uninsured damages.

For example, Hurricane Harvey inflicted an estimated $125 billion in damages on Houston and the surrounding area (Snyder 2018), but only $4.9 billion was paid out in flood insurance claims (as of late January 2018 (Texas Department of Insurance 2018)). In response to natural disasters, Congress and FEMA routinely provide post-disaster aid in the form of public assistance (to states and municipalities) and individual assistance (to households and businesses) grants. In the wake of Hurricane Harvey, FEMA provided $4.8 million to 177,000 households for rental assistance, home repairs, and other aid (Snyder 2018). Although well intentioned, the injection of aid into disaster-prone communities may be partially to blame for low NFIP market penetration. If individuals consider government post-disaster aid as an alternative to formal insurance products, then forgoing insurance may be a rational response to flood risk. This idea of government aid functioning as a substitute to insurance has come to be known as "charity hazard" (Browne and Hoyt 2000).

Theoretical justification for charity hazard is well established (Lewis and Nickerson 1989; Kaplow 1991; Arvan and Nickerson 2000; Kelly and Kleffner 2003; Arvan and Nickerson 2006; Rashchy and Weck-Hannemann 2007), but existing empirical studies report conflicting results (Browne and Hoyt 2000; Petrolia, Landry, and Coble 2013; Petrolia et al. 2015; Botzen and van den Bergh 2012a, b; Kousky, Michel-Kerjan, and Raschky 2018; Deslevsheridze and Miao 2019). This paper investigates the determinants of NFIP uptake and the degree to which charity hazard may be interfering with household maintenance of flood insurance coverage, focusing on underlying behavioral mechanisms related to individual expectations of eligibility for disaster assistance payments.

We contribute to the sparse but growing literature on the moral hazard effects of government disaster aid and resolve some of the contradictory findings concerning charity hazard. We utilize household survey data to identify and measure expectations of eligibility for government aid in the wake of disaster declaration as a direct pathway to forgoing or decreasing flood insurance coverage. The survey data permit controls for important individual level factors, such as risk perceptions, risk preferences, flood experience, and household income. As such, our paper is the first to estimate the severity of charity hazard at the household level while controlling for other important factors and accounting for endogeneity stemming from individual histories and political economy. Additionally, we are able to identify a charity hazard effect on the extensive margin[1], something that has been elusive in the U.S. due to

[1]In this setting, "extensive margin" refers to the binary decision to hold a flood insurance policy, where as the "intensive margin" references the choice concerning the level of coverage for an existing flood insurance policy.

complications arising from regulatory stipulations that accompany the receipt of disaster aid. Using the data of Petrolia et al. (2013), we show that after instrumenting for expectations of eligibility for government disaster aid there is a significant charity hazard effect. Based on a series of model specifications and robustness checks, we find that those who express optimistic expectations of eligibility for government aid payments that cover property damage due to flooding are between 25% and 42% less likely to hold a flood insurance policy.

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature on charity hazard. Section 3 describes our data and survey procedure. Section 4 presents our empirical methodology and estimation procedure. Section 5 discusses the results while section 6 comments on the findings and offers some policy recommendations. Section 7 concludes.

2 Literature

Ehrlich and Becker (1972) introduced household mitigation and protective behaviors within the context of expected utility maximization. They characterize actions that reduce loss probabilities (e.g., locating outside of a flood zone) as self-protection and actions that reduce the size of conditional loss (e.g., flood proofing the ground floor of a structure, installing hurricane ties on roof) as self-insurance. A number of papers have expanded this theory to consider property investments, private insurance, and disaster assistance (Lewis and Nickerson 1989; Kaplow 1991; Arvan and Nickerson 2006). Disaster assistance payments can be considered a source of informal insurance, which can encourage excessive risky land investments, discourage private mitigation measures, and act as a substitute for holding a formal insurance policy. To complicate matters, natural hazards are characterized by low probability and high consequence. This domain of risk appears to fall prey to many behavioral anomalies, such as optimism bias, status quo bias, and the availability heuristic (Kunreuther el al. 2001), for example, rendering analysis multi-dimensional and complex, fraught with endogeneity (Ahmadiani, Ferreira, and Landry 2019). Despite the strong theoretical basis for charity hazard, there is limited empirical evidence for evaluating its magnitude.

In an analysis of state-level flood insurance demand, Browne and Hoyt (2000) were the first to explore the possibility of charity hazard, but they dismissed the idea after finding a positive correlation between flood insurance demand and federal disaster aid. Similarly, Petrolia, Landry, and Coble (2013) find that expectations of government disaster assistance are positively correlated with flood insurance uptake, while Petrolia et al. (2015) find that expectations of disaster assistance have no bearing on the decision to purchase windstorm insurance. Other investigations have utilized survey data to explore charity hazard in mitigation (rather than insurance). Botzen et al. (2019) find that expectations of federal disaster assistance payments are negatively correlated with homeowners' decisions to elevate their home in flood prone areas of New York City. Osberghaus (2015) finds heterogeneous effects of expectations of government disaster relief among German households; tenants who are highly educated and risk averse tend to reduce flood mitigation efforts in response to an expectation of financial disaster relief. On the other hand, homeowners increase mitigation efforts with expectations of government assistance. Andor, Osberghaus, and Simora (2020) find that German households who indicated "trust" in public institutions and charity organizations as a source of financial aid were less likely to hold a flood insurance policy, but only for homeowners in flood prone areas. Additionally, they find positive correlation between non-financial mitigation measures and trust.

Researchers have also used stated preference methods to assess intentions to purchase flood insurance or mitigate property against flood risk. Focusing on the Netherlands, Botzen and van den Bergh (2012a, b) show that demand decreases based on the government's ability to compensate individuals for flood damage. Similarly, Botzen, Aerts, and van den Bergh (2009) show that willingness to mitigate flood damage through the purchase of sandbags decreases when the government is perceived to be responsible for mitigating flood risk. Raschky, et al. (2013) find that stated WTP for insurance is lower among Austrian and German homeowners when survey respondents considered flood relief a government responsibility.

Recent work has utilized county-level or policy-level data and instrumental variables to identify charity hazard effects in the U.S. Kousky, Michel-Kerjan, and Raschky (2018) utilize zip code level data and instrumental variables and find a 3% decrease in flood insurance coverage following a year in which a positive distribution of individual assistance payments for flood damage are made by FEMA. Notably they find no effect on policies in force after eliminating policies from their data set initiated by the stipulation that recipients of disaster aid insure for the following year. Similarly, Davlasheridze and Miao (2019) instrument for receipt of both public and individual assistance grants at the county level. The find small negative elasticities for flood insurance take-up rates (-0.15%) and coverage levels (-0.14%) in response to greater spending on FEMA's public assistance grant program in the prior year. With respect to individual assistance grants, they find that increased spending on individual assistance increases the number of policy holders in the following year (consistent with legal stipulations that those receiving IA grants must obtain flood insurance).

In summary, the theoretical motivations for charity hazard are strong, but empirical evidence is mixed, possibly due to the complications that arise from regulatory provisions that vary by country. Studies based in the U.S. must contend with the mandate that recipients of federal disaster assistance are required to purchase flood insurance to remain eligible for future government aid. The most recent literature is consistent in the conclusion that charity hazard effects exists on the intensive margin, but recognizes the complications that arise with identification at the extensive margin (Kousky, Michel-Kerjan, and Raschky 2018; Davlasheridze and Miao 2019). Identifying whether there is a moral hazard effect from government disaster aid at the extensive margin is a relevant policy question that has not been sufficiently addressed in the empirical literature concerning U.S. flood insurance We address this issue and take advantage of cross-sectional survey data to explore potential causal mechanisms behind the charity hazard effect. By combining data on activations of FEMA's public and individual assistance programs personal damage histories, we are able to limit our sample to households that have not been subject to any regulatory conditions associated with receiving disaster aid. By using IA grant spending and aspects of political economy as instruments for expectations of eligibility for disaster aid, we show that a charity hazard effect exists on the extensive margin.

3 Data

Data for our analysis come from several sources. The individual survey data, which most notably contain individual insurance status and data on expectations of eligibility for government aid, come from a previously-collected data set used in Petrolia, Landry, and Coble (2013) and Petrolia et al. (2015). These data were collected under contract with GfK (previously known as Knowledge Networks) and utilized monetary incentives, garnering a response rate of 56%. The online survey targeted property owners near the Gulf Coast during September of 2010 with the focus being on attitudes, perceptions, and behavior in the context of natural disaster risk.[2]

[2]Citing a study by the Insurance Information Institute (2017) that reports 43% of US households erroneously perceive that flooding is covered by their homeowner's policy, an anonymous reviewer raises concern that our measure of flood insurance may be inaccurate. We note that our measure of flood insurance market

Household-level data believed to be particularly pertinent to the decision to purchase flood insurance were collected; this includes the expected number of future hurricanes to strike the household's community (specifically Category 3 or greater and occurring over the next 50 years), expected structural damage from such a hurricane, past experience with flood hazards, the perceived credibility of insurance payouts after a storm, and measures of risk preference over both gains and losses. Risk preference measures were obtained using a real money experiment via an instrument derived from Holt and Laury (2002).

To incentivize participation in the survey, respondent's were given \$5 for a completed survey, but there was potential for earning more during the risk preference elicitation portion of the survey. Respondents could expect to gain an additional \$5 on average by indicating their preferences over 5 paired lotteries in the gain domain. Additionally, risk preferences were elicited in the loss domain using the same methodology. Respondents indicated their preference for 5 paired lotteries in the loss domain and were told the loss would be subtracted from \$10, which insured that the net loss could not be less than zero. One lottery from each domain was chosen at random and played to determine the respondent's winnings. Overall, a respondent could expect \$15 in incentive payments on average for completing the survey and answering all of the risk preference questions Figure A1 provides the instructions respondents were given for the risk preference portion of the survey along with an example paired lottery. For a more complete description of our data and survey design see Petrolia Landry, and Coble (2013) and Petrolia et al. (2015).

penetration (35% overall; 65% in the SFHA) is consistent with previous studies of the South and Gulf coastal zone. Using NFIP policy data, Dixon, et al. (2006) report market penetration rates as high as 60% (80% in the SFHA) in the US south. Using survey data, Landry and Jahan-Parvar (2011) report market penetration in the coastal zone SFHA of 50%. Moreover, our survey instrument (Table A1) expressly measured whether the property was covered by a flood insurance policy [emphasis added] (not whether they were covered for flood damage more generally). Lastly, flood risk and the limits of coverage are likely to be more salient in the coastal zone, where standard homeowners policies often do not cover windstorm damage.

Data for instrumental variables come from two sources. Information on FEMA public assistance grants is directly from FEMA's website (FEMA 2017a, 2017b). Political representation data are obtained from *The Almanac of American Politics* (Barone and Ujifusa, 1990-2010). Table 1 lists definitions and descriptions of each variable used in our analysis.[3]

To eliminate any identification challenges associated with the conditional requirement of obtaining flood insurance when individual disaster assistance is received, we eliminate any observations for households that may have received disaster aid in the past. We drop observations where the respondent indicated their home had been damaged from flooding or wind in the same year individual disaster aid was distributed in their county of residence (FEMA 2019). Doing so left us with 548 household level observations (about 75% of our original sample), spanning 72 counties on the Gulf Coast, none of which have had their insurance purchasing decisions influenced by any of the regulatory policies associated with disaster assistance. Figure 1 depicts the counties represented in our data.

Systematically dropping observations from our full data set raises the concern that we over-emphasize (or under-emphasize) particular features of the data, thus making our sample unrepresentative of the population of interest. We investigate this issue by testing for differences in means between our sub-sampled data set and the full data set (reported in table 2). A two-proportions z-test is used to test equality of proportions for all binary variables and t-tests are used for the remaining variables.[4] Overall our data sub-sample is statistically indistinguishable from the full data set on most observable characteristics. The notable exceptions are past damages and the share of representatives residing in Alabama, Mississippi, and Louisiana. Our full sample contains 215 individuals (29.4 percent of the

[3]The full text for survey questions that are used to construct our key variables can be found in table A1.

[4]As an additional robustness check we run the non-parametric Mann–Whitney–Wilcoxon (MWW) test on all of our variables which is arguably more appropriate for ordinal data. All of the tests produce qualitatively equivalent results.

full sample) who had experienced personal property damage at least once due to flooding or wind. Our sub-sampled data set contains 33 individuals who had experienced damage (6 percent of the sub-sample), thus our analytical sample is somewhat under-representing individuals who have experienced previous damage, which we address in our discussion of results.

3.1 Summary Measures

Table 3 reports descriptive statistics for dependent, independent, and instrumental variables. Thirty-three % of our survey respondents had a flood insurance policy. The survey instrument inquires about expectations of eligibility for various types of assistance following a disaster declaration: humanitarian relief; public assistance with infrastructure repair and debris removal; low-interest loans for home repairs; and grants for home repairs. We focus on analysis on the most generous of these categories: eligibility for grants to cover home repairs. The mean response to eligibility for individual grants to cover home repair was 2.78 on a on a 5 point Likert scale (5 indicating the highest likelihood of eligibility). Sixty-two % responded with a 3 or greater, which we use to code a binary variable representing optimistic expectations of individual government aid. Twenty-one % of respondents lived in a special flood hazard area (SFHA - flood zone with an estimated one % chance of flooding per year). When asked about how likely it is that insurance companies will payout in the event of natural hazard damage, 68 % indicated a 3 or higher on a 5 point scale.

Sixty-five % had a mortgage, and approximately 13 % of respondents were residents in a SFHA and had a mortgage; a condition that triggers the mandatory purchase requirement for federal flood insurance. In practice, it has been shown that this rule is often circumvented (Kunreuther and Pauly 2006).

A majority of our sample comes from Florida (68 %), followed by Texas (22 %). Only 10 % of our sample is from Louisiana (43 observations), Alabama (11 observations), or Mississippi (1 observation). Accordingly, we combine Louisiana, Alabama, and Mississippi into one fixed effect.The average survey respondent had lived on or near the coast for 26.4 years, with a residence that was 15.38 kilometers from the shoreline. Only 6 % of our sample had experienced storm-related property damage, either from flooding or wind. On average, 6.9 category 3 hurricanes or greater were expected to to strike the respondent's coastal community over the next 50 years, with an expected average loss of 34 % of structure value.

Risk preferences over losses and gains had very similar descriptive statistics. In both domains, respondents chose the high variance choice approximately 3 times out of 5, on average. We create a simple index to measure individual's cognitive awareness of issues pertinent to insurance decisions. This includes a measure of whether the individual's stated SFHA status matched their actual SFHA status (according to the most current FEMA flood maps). The index is also based on an indicator of the respondents' understanding of the independence between the probability of a hurricane in two consecutive years. Interacting these two variables forms our simple index, indicating a respondent that knew their flood zone and claimed to understand independence in occurrence of random events. Overall, 28% of our sample qualified affirmative for both of these indicators. The mean response for household income was 12.07 corresponding to an income range of between $50,000 and $60,000. Fourty-four % of survey respondents were male, and 26 % had children in their household.

4 Empirical Methods

To assess the potential effect of expectations of eligibility for disaster assistance on household decisions to insure, we first specify a single equation probit model defined in equation (1). The dependent variable, F_i, is an indicator for household i holding a flood insurance policy. When the expression in brackets is true, the indicator function, I[.], takes on a value of one. Our key independent variable, G_i ,is a dummy indicating that respondent i exhibits confidence (3 or greater on our 5 point scale) in eligibility for the most generous form of government aid that we queried (grants for home repair) in the wake of a disaster declaration. The vector X contains variables that capture socioeconomic characteristics, individual expectations about future disasters and damages, and state-level spatial fixed effects; and ϵ_i indicates a Gaussian error term. Following the advice of Abadie et al. (2017), we cluster standard errors at the county level since there are counties in our population of interest that are not included in our sample.

The single equation model treats expectations of eligibility for government disaster aid as exogenous, which we consider unlikely given previous findings (Petrolia, Landry, and Coble 2013; Petrolia et al. 2015). Individual expectations of disaster assistance depend upon storm and flooding experience, as well as aspects of political economy. For example, past experiences with government assistance or observing others receiving government aid may influence individual perceptions of the likelihood of government assistance in the future. Previous researchers have found evidence of political motivation in aid distribution (Garrett and Sobel 2003). Provision of individual assistance (IA) grants, however, is (in principle) made only once per household and is predicated on a commitment that the receiver will hold flood insurance in the future. In an attempt to purge this endogeneity, we specify a two equation system that accounts for endogenous expectations of eligibility for government assistance. In addition to equation (1), we include equation (2) which specifies expectations of eligibility for government aid as a function of observables, $\mathbf{X}_i$, and a vector of instruments $\mathbf{Z}_i$. Together our system of equations comprises a bivariate probit model. Error terms are assumed bivariate normally distributed with zero mean and unit variance. Parameter ρ is the cross-equation correlation term for errors.

$$F_i = I[G_i + \mathbf{X}_i\beta_1 + \epsilon_i > 0] \tag{1}$$

$$G_i = I[\mathbf{Z}_i\delta + \mathbf{X}_i\beta_2 + \mu_i > 0] \tag{2}$$

$$(\epsilon, \mu|\mathbf{X}_i) \sim N(0, 0, 1, 1, \rho) \tag{3}$$

Following Greene (2012) our log likelihood function takes the following form:

$$lnL = \sum_{i=1}^{n} ln\Phi_2(q_{i1}\mathbf{X}_i\beta_1, q_{i2}(\mathbf{Z}_i\delta + \mathbf{X}_i\beta_2), q_{i1}q_{i2}\rho), \tag{4}$$

where Φ_2 is the bivariate normal CDF, $\rho = corr(\epsilon, \mu)$, and q_{i1} and q_{i2} take on the following values:

$$q_{i1} = \begin{cases} -1 & if\ F_i = 0 \\ 1 & if\ F_i = 1 \end{cases} \qquad q_{i2} = \begin{cases} -1 & if\ G_i = 0 \\ 1 & if\ G_i = 1 \end{cases}$$

When deriving the likelihood function, the joint density function is the same regardless of whether an endogenous regressor is present. The density of F_i is obtained by conditioning on G_i and the vector of covariates X_i. Deriving the likelihood function follows the same procedure whether in the presence or absence of endogeneity. Since G_i was already conditioned on, no further considerations are necessary even if G_i is contained in X_i (Wooldridge 2010). Consequently, obtaining coefficient estimates comes down to jointly maximizing equations (1) and (2) via Full Information Maximum Likelihood.

4.1 Identification Strategy

Our identification strategy relies on exogenous variation in expectations of eligibility for disaster assistance generated by several instrumental variables related to historical disaster aid distribution and political economy. FEMA provides post disaster aid to individuals primarily through its individual assistance (IA) grant program. By eliminating households from our sample that have personally experienced storm damage in the same year that individual assistance grants were awarded to their county, we eliminate the possibility of direct provision of aid causing future insurance purchase (as a condition for receipt of aid). Thus, we can use historical FEMA disaster assistance as an instrument for expectations of disaster aid. Our instruments based on disaster aid are defined as the amount of individual assistance dollars that were awarded to each household's county in a given year, normalized by county population. We construct and include this instrument for 2008, 2009 and 2010[5].

Our second set of instruments is influenced by the recent work of Kousky, Michel-Kerjan, and Raschky (2018) and Davlashveridze and Miao (2019). Both papers use US Congressional representation in Stafford subcommittees, which have direct oversight of FEMA spending, to instrument for county-level receipt of FEMA IA grants. Similarly, Davlasheridze, Fisher-Vanden, and Klaiber (2017) use a dummy variable for Stafford subcommittee representation to instrument for both ex-post and ex-ante FEMA grants. If a particular locale has more rep-

[5]For 2010, we only include IA grants that were awarded in response to events that occurred before our survey was distributed. The latest event to be included was Hurricane Alex which occurred in late June of 2010 which was approximately 2 months before our survey was distributed.

resentation on congressional subcommittees that have the power to allocate FEMA funds, then there is a higher likelihood that federal aid will be directed there in the event of a disaster and the aid may be more generous. A detailed discussion on how politics motivate government aid is beyond the scope of this paper. For a thorough discussion on the relationship between Stafford subcommittees and FEMA grant allocations, see Garret and Sobel (2003). We define two instruments based on congressional representation on Stafford subcommittees. The first is the cumulative number of US Senators that served on Stafford subcommittees from 1990 - 2010. Likewise, we define an equivalent instrument based on the number of Stafford subcommittee members in the US House of Representatives.

4.2 Validity of Instruments

To our knowledge, there are not well-defined diagnostics for assessing the validity of instrumental variables in non-linear models. We do, however, justify our use of instruments through what is available for linear models. Thus, we also estimate a two-stage least squares linear probability model and apply the standard instrumental variable diagnostics. If our instruments are valid, they should be relevant in explaining an individual's expectations of eligibility for disaster assistance (controlling for other covariates), and they should be redundant in the household's decision to purchase flood insurance. The first condition is easily verifiable through the estimation of equation (2) (see Table 4). The majority of our instrumental variables are statistically significant as determinants of expectations of eligibility for disaster assistance. The number of US Senators on Stafford subcommittees and FEMA individual assistance money dispersed in 2010 and 2008 are statistically significant, with expected signs, while representation in House subcommittees and individual aid dispersed in 2009 are not statistically significant.[6]

Given that our instruments are significant in explaining individual expectations of eligibility for government assistance, the validity of our instruments hinges on the second condition which, although not formally testable, is supported on conceptual grounds. Individual assistance grant spending is credibly excludable from equation (1), since our sample consists only of observations in which no direct causal pathway exists between dispersed aid and flood insurance decisions. Thus any influence of FEMA IA grants presumably acts through altering beliefs about the availability of disaster aid. Similarly, congressional representation on Stafford subcommittees presumably has no direct influence on individual flood insurance status, except through potentially altering expectations of eligibility for assistance.

To the extent of our knowledge, there are no formal tests for over-identifying restrictions or weak instruments for non-linear models. As a substitute, we continue to work with standard linear probability models using two-stage least squares, and we run the standard diagnostics for linear models. Applying a Sargan-Hansen test for over-identifying restrictions fails to reject the null that our instruments are valid. The first stage F-statistic from the linear model is 18.2, well above the Stock and Yogo (2005) threshold for the test for weak instruments. Lastly, to validate our concerns over endogeneity, we apply the test proposed by Knapp and Seaks (1998). Under the null hypothesis, the cross-equation correlation coefficient from the bivariate probit model, ρ, is zero and strict exogeneity holds. A Wald test rejects the null with a p-value of .072, providing support for the instrumental variables approach.

[6] 2009 was a very mild hurricane season (Berg and Avila 2011); thus, the insignificance of our aid instrument in 2009 is unsurprising.

5 Results

5.1 Extensive Margin

Table 4 reports results for two non-linear models of the decision to purchase flood insurance. The first column reports standard probit results that ignore potential endogeneity. The coefficient on expectations of eligibility for government aid is positive and significant with a coefficient of 0.28 and a marginal effect of 0.081 (note that marginal effects are not reported in table 4), indicating that someone who is optimistic about eligibility of receiving post disaster federal aid is 8.1 % more likely to hold a flood insurance policy.

Upon instrumenting for expectations of eligibility for government assistance, our results shift dramatically. Column 2 reports results from equation (1) and column 3 reports estimation of equation (2). Estimates from the bivariate probit model indicate that expectations of eligibility for disaster assistance have the opposite sign from the standard probit model (which ignores endogeneity), with a larger effect (in absolute value) and a greater level of statistical significance. The coefficient on expectations of eligibility for disaster assistance in the bivariate probit estimation is -1.09 with a marginal effect of -.329 (95% confidence interval of -.086 to -.568). This indicates that individuals who express optimistic expectations of eligibility for disaster relief payments for home repair are 32.9 % less likely to hold a flood insurance policy, controlling for other important factors (such as being located in a special flood hazard area). The rest of our covariates have intuitive and expected effects on the decision to insure.

Having a mortgage and being located in a SFHA zone have significant and positive marginal effects of 8.4 % and 19.7 %, respectively. As expected, having confidence in receiving an insurance settlement in the event of flood damage increases the likelihood of holding insurance with a marginal effect of 15.6 %. Individuals that perceive greater damage in the event of hurricane are also more likely to hold flood insurance, though the marginal effect is small at 1.7 %. The ceofficients on state fixed effects (not presented in Table 4) suggest that coastal residents of Texas are more likely to hold a flood insurance policy relative to all other states in our sample (marginal effect of 1.5 %).

Two-stage least squares estimates, reported in table 5, tell the same story as the bivariate probit, with a positive and significant estimate on expectations of eligibility for disaster aid that switches sign and increases in magnitude upon employing instrumental variables. Coefficients for the remaining covariates are similar in sign, magnitude, and level of statistical significance to those in the non-linear models.

5.2 Robustness Checks

As a robustness check, we estimate linear models treating expectations of eligibility government aid as an ordinal variable. In these specifications, expectations of eligibility for government aid takes on the full range of values (1-5) that were elicited in the survey. Table 6 reports OLS and 2SLS estimates using the alternative expectations of eligibility for aid variable. Overall, results are robust to how the expectations of eligibility for aid variable is constructed. The OLS model still reports a positive and statistically significant relationship between expectations of eligibility for aid and likelihood of holding a flood insurance policy. Upon instrumenting, we find that optimistic expectations of eligibility for government aid are associated with a lower likelihood of holding a flood insurance policy; the marginal effect is -22%. Validity tests of our instruments are slightly less favorable under this specification. Neither of our instruments constructed from political economy data are significant in the first stage regression, but all instruments based on historical IA spending are positive and statistically significant. The first stage F-statistic is 11.9 which is lower than the F-statistic of 18.1 reported in the previous 2SLS estimates. The Sargan over-identification test still fails to reject the null of being over-identified, but the Wu-Hausman test has a p-value of .105 indicating that endogeneity is not as obvious a concern in this specification.[7]

Dropping a portion of our data allows for cleaner identification of the charity hazard effect, but removing observations in a systematic way is less than ideal if we seek inferences about the population. Our final robustness check involves estimation of a bivariate probit model on our full sample without instrumental variables. There is an extensive literature on the necessity of exclusion restrictions in bivariate probit models with binary endogenous regressors. Some authors suggest identification can be achieved through functional form (Heckman 1978; Wilde 2000; Freedman and Sekhon 2010; Wooldridge 2010 ; Greene 2012). Dissenting opinions, however, also exist (Maddala 1983; Mourifie and Meango 2014), in addition to recent work which suggests identification through functional form is possible, but results may be sensitive to small changes in the model and results are suspect if the underlying model assumptions aren't satisfied (Li, Poskitt, and Zhao 2019). Thus, we don't believe results identified through functional form are robust enough to stand alone, but instead offer them as complementary evidence to our main results.

Table 7, column 1 reports probit estimates of the decision to insure, and columns 2-3 report estimates from the bivariate probit model (without instruments). Results are qualitatively equivalent to our main specification, under the naive probit; probability of insuring is increasing in expectations of eligibility for aid, while a significant charity hazard effect ma-

[7] To address the possibility that the political variables (and consequently the IA payments) might be correlated with other, unobservable county-level characteristics, an additional robustness check involves adding county-level covariates that measure education, race, and age, in addition to a dummy variable indicating majority vote for Republican presidential candidate in the 2008 election. None of these covariates were statistically significant, and primary results remain unchanged.

terializes once expectations of eligibility are treated as endogenous. Under this formulation, individuals with optimistic expectations of eligibility for disaster aid are 25% less likely to hold a flood insurance policy (95% confidence interavl of -0.05 to -0.52). This is a slightly lower marginal effect that in our main specification (marginal effect of 33%), possibly a result of the full sample containing individuals that may be mandated to insure following receipt of individual aid.

5.3 Intensive Margin

To complete our analysis, we also include an investigation at the intensive margin of flood insurance demand. As part of our survey, respondents with flood insurance were also asked about levels of coverage for structure and contents. Table 8 presents both OLS and 2SLS results using flood insurance coverage levels as the dependent variable. Overall, these results are supportive of the charity hazard narrative. Both OLS and 2SLS results indicate that individuals with optimistic expectations of eligibility for government aid that covers home repairs tend to have lower levels of insurance coverage. We hesitate to offer an unconditional endorsement of these results, however, primarily due to the small sample size. Of the 548 observations that make up our primary sub-sample, only 136 respondents had coverage and elected to indicate how much coverage they had. Also, the first stage F-stat from the 2SLS estimates is 6.9 leaving doubt as to whether endogeneity has been sufficiently addressed in these models.

6 Discussion

Although previous studies have found mixed evidence of charity hazard, most empirical approaches were not trained on identification. Recent papers that employ instrumental variables (Kousky, Michel-Kerjan, and Raschky 2018; Davlasheridze and Miao 2019) have been helpful in formulating identification strategies to assess charity hazard in disaster insurance demand. Still, precise details on how charity hazard manifests has not been fully explored, primarily due to limitations in using aggregate level data. To our knowledge, the results presented here are the first to attempt to measure and identify a plausible causal mechanism linking disaster assistance to individual insurance decisions and are the first to provide compelling evidence of a charity hazard effect at the extensive margin. By directly assessing individual expectations of eligibility for government disaster aid and controlling for variation with local history of disaster aid provision and political economy, we are able to exploit exogenous variation in factors that appear to engender charity hazard at the household level.

Table 9 summarizes the marginal effects for our ”optimistic expectations of eligiblity for government disaster aid” variable across all specifications of the extensive margin of flood insurance purchase. Overall, point estimates based on a binary measure of expectations of aid suggest that charity hazard reduces flood insurance market penetration by somewhere between 25% and 42%, with 95% confidence intervals suggesting a range from 5% to 56%. Our preferred estimate is 32.6% (95% confidence interval 8.6% to 56.8%). Regarding the intensive margin, two-stage least squares estimates suggest individuals who harbor optimistic expectations of eligibility for government grants to pay for property damage hold $72,000 less in flood insurance coverage than those who are less optimistic about disaster aid. This is a rather large effect compared to the mean coverage level of approximately $163,000.

Our results complement previous findings that identify charity hazard effects at the intensive margin. Kousky, Michel-Kerjan, and Raschky (2018) find a 3% decrease in mean flood insurance coverage (intensive margin) following receipt of individual government assistance payments at the zip-code level, but find no effect on number of policies (extrnsive margin) after removing policies initiated through mandates. Davlasheridze and Miao (2019) examine the flood insurance effects of individual and public assistance in the wake of disaster. They find evidence of charity hazard at the extensive and intensive margin for public assistance grants, but no evidence of charity hazard with respect to individual assistance. Their results indicate that a 10% increase in PA spending at the county level corresponds to a decrease of 1.4% in insurance coverage and a 1.5% increase in policies in force.

Davlasheridze and Miao (2019) find no charity hazard effect at the extensive margin with respect to individual assistance, but as noted by the authors, this is likely an artifact of some households in their dataset being mandated to purchase flood insurance after aid is dispersed. On the other hand, Kousky, Michel-Kerjan, and Raschky (2018) find no effect at the extensive margin after removing mandated policies. We address the potential problem of policy mandates associated with disaster relief by removing observations in which households sustained damage in a year in which disaster aid was dispersed in their county.

Kousky, Michel-Kerjan, and Raschky (2018) and Davlasheridze and Miao (2019) each explore charity hazard by analyzing a one-period lag for the effect of aid dispersal on flood insurance uptake. Our approach is more general, as we account for aid dispersal and political economy in multiple years prior to our measure of expectations of eligibility for disaster assistance. Our results differ from previous findings in that our indicator variable is a psychometric measure for individual expectations, whereas previous papers have used lagged aid payments. In this light, we interpret our results as suggesting that perceptions of eligibility for disaster assistance are formed over time as households experience or witness flooding disasters, observe patterns of public and individual assistance, and learn about the potential influence that members of Congress can have on aid provision.

Overall, our results suggest charity hazard may have sizable impacts on NFIP revenues and important implications for insuraing against flood hazard. While our data are focused on coastal households, we make some projections about the potential magnitude of charity hazard for the NFIP, more broadly. As of 2018, the NFIP had approximately 5.2 million policies in force generating $3.3 billion in earned premiums, meaning the average premium was approximately $642 (FEMA 2018a, b). Based on our full Gulf Coast sample (table 2, Full Sample), 59 % of coastal residents express optimism in eligibility for government disaster aid for property damage; if those optimistic about aid are 33 % less likely to hold an insurance policy, then approximately 19 % of residents living near the coast are not purchasing insurance who otherwise would, absent a charity hazard effect. This, however, does not account for effects of insurance mandate that comes with receipt of federal disaster aid. Within our full sample, approximately 30% of respondents indicated they had incurred either wind or flood damage at some time in the past. Assuming that all households that incur damage receive some type of federal disaster assistance and comply with accompanying insurance mandate allows us to generate a lower bound on lost revenues due to charity hazard. Thus, of the 19 % of residents who prefer to be uninsured due to charity hazard, we assume 30% hold insurance as required.[8] This leaves us with roughly 13% of residents who are not insuring due to charity hazard. Consequently, if our Gulf Coast results are applicable more generally, the NFIP could be losing out on approximately $525 million in revenue due to charity hazard every year. Similarly, assuming no insurance mandate allows us to generate

[8]The 30% metric is unrealistically high for several reasons and is a defensible assumption to generate a lower bound on lost revenue. For one, most households that incur damage will not receive any form of federal disaster aid. Secondly, 30% of households in our full sample sustained damage in the past, but this is likely to be significantly lower for households that are not located near the Gulf Coast.

an upper bound which is calculated to be roughly $804 millions per year.

Our results also highlight the importance of using econometric techniques that control for endogeneity when conducting analyses related to charity hazard. Our naive probit model exhibits bias suggesting that confidence in government disaster aid results in a higher probability of holding insurance, whereas the bivariate probit produces plausible results of charity hazard, with supporting validity tests associated with conventional linear modeling approaches. Combined with recent empirical analyses of Kousky, Michel-Kerjan, and Raschky (2018) and Davlasheridze and Miao (2019), this suggests that instrumental variables and control function approaches can be extremely useful in assessing charity hazard in empirical analysis of disaster insurance. Our results are relevant for future public policy discussions surrounding FEMA and the NFIP. The policy maker's dilemma when it comes to dealing with charity hazard is to incentivize homeowners to optimally insure against flood risk, but not cut off aid for those that have insufficient information on flood risk or lack the financial means to fully insure. For the remainder of the discussion, we focus on policy suggestions under the premise that significant charity hazard effects are likely to transpire in response to government disaster assistance.

6.1 Policy Implications

The charity hazard effect is predicated on confidence in eligibility for government aid that compensates for some level of property damage. In reality, however, individual assistance (when granted) is often targeted towards living expenses and rarely is dispersed in magnitudes that might cover property damage (if allowed). Thus, managing expectations of government aid could be helpful in reducing the charity hazard effect. The actual magnitude of individual aid is capped at $34,000 (42 USC §5174), but the average payment is approximately \$5,000 per household (FEMA 2019). Given this, targeted information campaigns may be sufficient to dissuade intentional dependence on government aid. This is a preferable policy tool, since it does not require a major restructuring of how government aid is administered, but more substantial policy options may be required to address the effect of charity hazard.

The lack of a strict eligibility criterion for FEMA individual disaster aid has created the canonical situation that Kydland and Prescott (1977) describe in their Nobel prize winning paper. In essence, their premise is built on the idea that attempts to optimize a dynamic system in which rational economic agents are forward looking and can anticipate, and thus potentially influence, future policy decisions, can lead to inefficient and perverse outcomes. In the case of government assistance, the implication is that governments will always be forced into succumbing to the will of the people if there is any flexibility in aid eligibility since politicians will seek to please constituents even if the outcome is inefficient in the long term. As such, limiting federal disaster aid could reduce the charity hazard effect, but only in the case of a credible threat. A rigid policy that forbids discretion and is exceptionally difficult to alter, something akin to a constitutional amendment (Coglianese 2018), could be considered as a means to remove the inefficiencies associated with discretionary relief policy.

If the government has superior information on the likelihood and consequence of flood disasters, mandatory flood insurance can be an efficient policy approach (Lewis and Nickerson 1989; Kaplow 1991; Kunreuther and Pauly 2006; Raschky and Weck-Hannemann 2007). In the US, mandatory purchase requirements (MPR) were put in place in 1973 for properties with a federally-backed mortgage within the SFHA. Nonetheless, estimates of market penetration in high-risk zones range from 16-90 percent of single-family residences, with significant regional variation (American Institutes for Research 2005; Tobin and Calfee 2005;

Dixon et al. 2006; Kousky 2010; Landry and Jahan-Parvar 2011). Better enforcement of MPR, coupled with escrowing provisions for flood insurance payments (as is typically done with homeowners and primary mortgage insurance) could be helpful in improving market penetration.

Additionally, combining risk-based premiums with compulsory flood insurance for all that choose to live in flood prone areas could provide a more efficient approach to managing flood plane development (Kunreuther and Pauly 2006). When premiums are reflective of risk, compulsory insurance can serve as a guide in development decisions, discouraging settlement in risky areas (Krutilla 1966). Building on this idea, Kunreuther (2019) has suggested providing means-based vouchers to address the affordability concerns resulting from premiums that are reflective of actual risk. This policy may address many of the issues concerning charity hazard. Homeowners would no longer be relying on disaster aid that may or may not materialize. The application of vouchers could help to address the issue of affordability, while still keeping premiums that are informative of the risk levels. Phasing out vouchers at some planned rate or retiring vouchers when properties change hands can help to address efficiency and move land-use towards more suitable utilization of flood plains.

Finally, continued promotion of individual and community hazard mitigation, via the Community Ratings System, Hazard Mitigation Grants, and other mechanisms has been shown to be an effective way to increase insurance uptake (Frimpong et al. 2019). Combining hazard mitigation with flood insurance premium adjustments to address moral hazard problems, may enhance resilient investment in flood prone communities and further improve market penetration (Sadiq and Noonan 2015; Li and Landry 2018).

7 Conclusions

Employing a dataset for which previous analysis found evidence contrary to the charity hazard hypothesis, we revisit the question of flood insurance market penetration at the household level, this time addressing endogeneity of survey responses regarding the likelihood of government aid in the wake of a disaster. We instrument for confidence in post-disaster aid to compensate for property damage using data on congressional subcommittee membership and payment histories of the Federal Emergency Management Agency Individual Assistance (IA) grant program. After controlling for endogeneity, we find that the sign on our variable controlling for expectations of eligibility for post-disaster aid switches signs, and is now consistent with charity hazard; that is, we find that households that exhibit optimism in eligibility for post-disaster aissistance that covers property damages are significantly less likely to purchase a flood insurance policy.

Although Browne and Hoyt (2000) dismissed a charity hazard effect for the NFIP after investigating the issue using aggregated (state-level) data and finding the opposite effect, more recent work by Davlasheridze and Miao (2019), who used county-level data, and Kousky et al. (2018), who used policy-level data, did find evidence of charity hazard for the NFIP. The only work to our knowledge investigating the issue using household-level revealed preference survey data and homeowner's own subjective perceptions of post-disaster aid was Petrolia et al. (2013) who, like Browne and Hoyt, found the opposite effect. Our results reverse their findings (though charity hazard was not their primary focus).

Our finding is consistent with, but subtly different from the stated preference findings of Botzen, Aerts, and van den Bergh (2009) and Raschky et al. (2013), who find lower flood mitigation activity and lower WTP for flood insurance when the government is perceived as being responsible for mitigating flood risk or providing flood relief. In our case, it is not necessarily true that respondents perceive that the government is ultimately responsible, but rather that they merely express optimism in eligibility for government provision of household-level financial support for disaster damage to property. Previous findings were also specific to The Netherlands (Botzen, Aerts, and van den Bergh 2009), Austria, and Germany (Raschky et al. 2013), where perceptions and expectations of government aid and flood insurance programs may differ from that of the U.S.

Our paper explores some policy implications of these results, including possible policy interventions. Our results indicate that homeowners with optimistic expectations of eligibility for post-disaster aid are 33 percent less likely to purchase a flood policy, and 62 percent of our sample indicated that they held such expectations, implying that charity hazard is a real problem facing the NFIP, potentially costing the program hundreds of millions of dollars in foregone revenue from premiums and leaving hundreds of thousands of homes uninsured, which only serves to undermine efforts to increase flood resilience and exacerbates reliance on post-disaster aid. We recommend that the NFIP consider ways to change expectations of post-disaster aid by making homeowners more aware of the limitations of post-disaster assistance to cover home damage expenses (the NFIP does this on one website, but the extent of the effectiveness of this and other efforts remains to be seen) and/or adding means-testing provisions to disaster aid programs.

Although enforcement of mandatory purchase requirements (MPR) have improved in recent years, flood insurance uptake remains low; the NFIP could consider adding escrow and default re-enrollment provisions for flood insurance on MPR properties and making escrow and re-enrollment the default option for other households. The Community Rating System could play a major role in disseminating new information on flood risk provisions, especially given that it carries with it an explicit incentive (premium discounts) for communities and individual homeowners to comply. Recent work has shown that communities participating in the CRS had significantly higher insurance uptake (Zahran et al. 2009; Petrolia et al. 2013; Frimpong et al. 2019), and that communities heavily invested in the CRS realize reductions in flood claims (Brody et al. 2007a, 2007b; Michel-Kerjan and Kousky 2010; Highfield and Brody 2013; Frimpong et al. 2019).

Addressing the issue of affordability remains important for the NFIP. Making vouchers for flood insurance available in tandem with adding means-testing provisions for aid could increase market penetration for NFIP and decrease overconfidence in disaster assistance. This approach could encourage homeowners with higher incomes to not rely on aid, potentially increasing the likelihood that they purchase disaster insurance. This would also provide the means of obtaining insurance for those with low incomes, thus reducing further the burden of post-disaster aid programs.

Future work should further investigate homeowner expectations of post-disaster aid by better understanding the mechanisms by which they form these expectations, and to understand the potential changes in such expectations when confronted by some or all of the policy interventions discussed here. Much additional work is needed to understand homeowner preferences for flood insurance more generally when presented with scenarios involving these policy recommendations. Finally, the specters of climate change, increasing intensity of coastal storms, and sea-level rise provide both important context, but also motivation for future research.

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8 Tables

Table 1: Variable Descriptions

Variable	Type	Description
Panel A: Dependent Variable		
Policy	Binary	= 1 if has flood insurance
Panel B: Endogenous Variables		
Exp. of Aid (Binary)	Binary	= 1 if answered 3 or above on 1 - 5 scale on expectations of federal disaster aid
Exp. of Aid (1-5)	Discrete	1- 5 response on expectations of federal disaster aid
Panel C: Instrumental Variables		
Senate Stafford Count	Count	Sum of senators on Stafford subcommittees from 1990 - 2010.
House Reps. Count	Count	Sum of house reps. on Stafford subcommittees from 1990 - 2010.
IA "Year"	Continuous	The total amount of individual assistance aid the respondent's county received in "year" divided by the county's 2010 population
Panel D: Covariates		
Past Damage	Binary	= 1 if respondent has experienced flood damage to home in the past
Knew Zone	Binary	= 1 if respondent accurately reported their SFHA status
Independence	Binary	= 1 if respondent understood that the probability of two separate floods is independent
SFHA	Binary	= 1 if home is in SFHA
Mortgage	Binary	= 1 if home is mortgaged
Required	Binary	= 1 if home is in SFHA and mortgaged
Exp. of Fut. Hurr.	Continuous	Expected number of future hurricanes (Category 3 or greater) over next 50 years
Exp. Hurr. Damage	Continuous	Expected damage from a cat. 3 hurricane, ranges from 0 (no damage) to 1 (complete destruction)
Risk Averse (gain)	Continuous	Number of times low-variance risk was chosen over gain domain
Risk Averse (loss)	Continuous	Number of times low-variance risk was chosen over loss domain
Insurer Confidence	Binary	= 1 if answered 3 or above on 1-5 scale on expectation of insurance payout in event of flood
Coastal Tenure	Continuous	Number of years lived on or near the coast.
Distance from Coast (km)	Continuous	Distance from the coast in km.
Income	Ordered Categorical	= 1 if "less than $5000" up to = 19 if "more than $175,000"
Male	Binary	= 1 if male
Kids	Binary	=1 if have kids
TX	Binary	= 1 if home is in Texas
FL	Binary	= 1 if home is in Florida
Al-Ms-La	Binary	= 1 if home is in Alabama, Mississippi, or Louisiana

Table 2: Difference in Means: Sub-Sampled vs Full Data Set

	Sub-sample			Full Sample			
	n	mean	sd	n	mean	sd	Difference
Policy	548	0.33	0.47	730	0.35	0.48	0.02
Exp. of Aid (Binary)	548	0.62	0.49	730	0.59	0.49	-0.03
Exp. of Aid (1-5)	548	2.78	1.16	730	2.72	1.19	-0.06
Past Damage	548	0.06	0.26	730	0.38	0.67	0.32***
Knew Zone x Independence	548	0.28	0.45	730	0.27	0.44	-0.01
Required	548	0.13	0.34	730	0.14	0.34	0.00
Exp. of Fut. Hurr.	548	6.81	10.88	730	6.81	10.45	0.00
Exp. Hurr. Damage	548	3.40	2.28	730	3.33	2.24	-0.07
SFHA	548	0.21	0.41	730	0.22	0.41	0.00
Mortgage	548	0.64	0.48	730	0.65	0.48	0.01
Risk Averse (gain)	548	2.96	1.45	730	2.93	1.44	-0.03
Risk Averse (loss)	548	2.90	1.37	730	2.93	1.36	0.03
Insurer Confidence	548	0.68	0.47	730	0.67	0.47	-0.01
Coastal Tenure	548	26.40	18.06	730	27.60	18.33	1.20
Distance from Coast (km)	548	15.38	16.98	730	16.59	18.50	1.21
Income	548	12.07	3.97	730	12.26	3.94	0.19
Male	548	0.44	0.50	730	0.44	0.50	0.00
Kids	548	0.26	0.44	730	0.27	0.44	0.01
Texas	548	0.22	0.41	730	0.22	0.42	0.00
AlMsLa	548	0.10	0.30	730	0.15	0.36	0.05***

Table 3: Descriptive Statistics

	mean	sd	min	max
Policy	0.33	0.47	0	1
Exp. of Aid (Binary)	0.62	0.49	0	1
Exp. of Aid (1-5)	2.78	1.16	1	5
Senate Count	1.63	2.61	0	8
House Reps. Count	1.16	1.41	0	5
IA 2010	0.03	0.24	0	2
IA 2009	0.28	1.59	0	10
IA 2008	59.32	313.86	0	5844
Past Damage	0.06	0.26	0	2
Knew Zone x Independence	0.28	0.45	0	1
Required	0.13	0.34	0	1
Exp. of Fut. Hurr.	6.81	10.88	0	90
Exp. Hurr. Damage	.34	2.28	0	1
SFHA	0.21	0.41	0	1
Mortgage	0.64	0.48	0	1
Risk Averse (gain)	2.96	1.45	0	5
Risk Averse (loss)	2.90	1.37	0	5
Insurer Confidence	0.68	0.47	0	1
Coastal Tenure	26.40	18.06	0	80
Distance from Coast (km)	15.38	16.98	0	78
Income	12.07	3.97	1	19
Male	0.44	0.50	0	1
Kids	0.26	0.44	0	1
Texas	0.22	0.41	0	1
AlMsLa	0.10	0.30	0	1
Observations	548			

Table 4: Estimates from Non-linear Models

	Probit	Bivariate Probit		Reduced Form Probit
	Policy	Policy	Exp. of Aid (Binary)	Policy
Exp. of Aid (Binary)	0.28**	-1.09***		
	(0.14)	(0.42)		
Past Damage	0.13	0.09	-0.04	0.13
	(0.21)	(0.18)	(0.23)	(0.21)
Knew Zone x Independence	0.03	0.09	0.22	0.04
	(0.15)	(0.12)	(0.15)	(0.15)
Required	0.65**	0.70***	0.44*	0.66**
	(0.28)	(0.26)	(0.25)	(0.28)
Exp. of Fut. Hurr.	0.01	0.01	0.00	0.01
	(0.01)	(0.00)	(0.01)	(0.01)
Exp. Hurr. Damage	0.04*	0.05**	0.03	0.05*
	(0.02)	(0.02)	(0.03)	(0.02)
SFHA	0.75***	0.60**	0.07	0.68***
	(0.25)	(0.24)	(0.22)	(0.25)
Mortgage	0.21*	0.24**	0.16	0.24*
	(0.12)	(0.11)	(0.11)	(0.12)
Risk Averse (gain)	0.02	0.00	-0.01	0.02
	(0.04)	(0.04)	(0.03)	(0.04)
Risk Averse (loss)	0.07	0.06	0.01	0.07
	(0.04)	(0.04)	(0.04)	(0.04)
Insurer Confidence	0.10	0.41***	0.66***	0.18
	(0.13)	(0.16)	(0.10)	(0.12)
Coastal Tenure	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.01)
Distance from Coast (km)	-0.01**	-0.01*	-0.00	-0.01**
	(0.00)	(0.00)	(0.00)	(0.00)
Senate Count			0.14***	-0.11
			(0.04)	(0.12)
House Reps. Count			0.01	0.05
			(0.04)	(0.04)
IA 2010			2.84***	-0.12*
			(0.12)	(0.07)
IA 2009			-0.00	-0.03
			(0.02)	(0.02)
IA 2008			0.00*	-0.00***
			(0.00)	(0.00)
Constant	-2.46***	-1.10	0.33	-2.25***
	(0.33)	(0.70)	(0.33)	(0.37)
Observations	548	548		548
ρ		0.811		
State FE	Yes	Yes	Yes	Yes
Demographics (Male, Kids, Income)	Yes	Yes	Yes	Yes

Notes: Cluster-corrected standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Estimates from Linear Models using Binary measure of Exp. of Aid

	OLS	2SLS		
		Second Stage	First Stage	Reduced Form
Exp. of Aid (Binary)	0.08**	-0.42***		
	(0.04)	(0.08)		
Past Damage	0.04	0.03	-0.01	0.04
	(0.07)	(0.07)	(0.08)	(0.07)
Knew Zone x Independence	0.01	0.05	0.06	0.01
	(0.04)	(0.04)	(0.05)	(0.04)
Required	0.24**	0.31***	0.12	0.24**
	(0.09)	(0.10)	(0.08)	(0.10)
Exp. of Fut. Hurr.	0.00	0.00*	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Exp. Hurr. Damage	0.01*	0.02**	0.01	0.01**
	(0.01)	(0.01)	(0.01)	(0.01)
SFHA	0.24***	0.23**	0.03	0.22**
	(0.09)	(0.09)	(0.08)	(0.09)
Mortgage	0.06*	0.09**	0.05	0.07**
	(0.03)	(0.04)	(0.04)	(0.03)
Risk Averse (gain)	0.00	-0.01	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Risk Averse (loss)	0.02	0.03**	0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Insurer Confidence	0.03	0.14***	0.24***	0.05
	(0.04)	(0.04)	(0.04)	(0.04)
Coastal Tenure	0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Distance from Coast (km)	-0.00*	-0.00***	-0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Senate Count			0.05**	-0.03
			(0.02)	(0.03)
House Reps. Count			0.00	0.02
			(0.02)	(0.01)
IA 2010			0.17***	-0.04*
			(0.03)	(0.02)
IA 2009			-0.00	-0.01
			(0.00)	(0.00)
IA 2008			0.00**	-0.00***
			(0.00)	(0.00)
Constant	-0.25***	0.09	0.64***	-0.20*
	(0.09)	(0.12)	(0.11)	(0.10)
Observations	548	548	548	548
First Stage F-Stat		18.280		
Sargan Over ID Test		0.643		
Wu-Hausman Test		0.112		
State FE	Yes	Yes	Yes	Yes
Demographics (Male, Kids, Income)	Yes	Yes	Yes	Yes

Notes: Cluster-corrected standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimates from Linear Models using Discrete measure of Exp. of Aid

	OLS	2SLS		
		Second Stage	First Stage	Reduced Form
Exp. of Aid (1-5)	0.04**	-0.22***		
	(0.02)	(0.05)		
Past Damage	0.03	0.06	0.12	0.04
	(0.07)	(0.07)	(0.20)	(0.07)
Knew Zone x Independence	0.01	0.02	0.08	0.01
	(0.04)	(0.05)	(0.11)	(0.04)
Required	0.24**	0.29***	0.21	0.24**
	(0.09)	(0.10)	(0.18)	(0.10)
Exp. of Fut. Hurr.	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Exp. Hurr. Damage	0.01*	0.02*	0.03	0.01**
	(0.01)	(0.01)	(0.03)	(0.01)
SFHA	0.24**	0.26***	0.07	0.22**
	(0.09)	(0.10)	(0.19)	(0.09)
Mortgage	0.06*	0.07**	0.05	0.07**
	(0.03)	(0.03)	(0.09)	(0.03)
Risk Averse (gain)	0.00	-0.01	-0.01	0.00
	(0.01)	(0.01)	(0.03)	(0.01)
Risk Averse (loss)	0.02	0.04***	0.01	0.02
	(0.01)	(0.01)	(0.03)	(0.01)
Insurer Confidence	0.03	0.13***	0.34***	0.05
	(0.04)	(0.05)	(0.10)	(0.04)
Coastal Tenure	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Distance from Coast (km)	-0.00**	-0.00***	-0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Senate Count			0.05	-0.03
			(0.04)	(0.03)
House Reps. Count			0.01	0.02
			(0.04)	(0.01)
IA 2010			0.26***	-0.04*
			(0.07)	(0.02)
IA 2009			0.05***	-0.01
			(0.01)	(0.00)
IA 2008			0.00*	-0.00***
			(0.00)	(0.00)
Constant	-0.32***	0.51**	2.96***	-0.20*
	(0.08)	(0.22)	(0.33)	(0.10)
Observations	548	548	548	548
First Stage F-Stat		11.908		
Sargan Over ID Test		0.391		
Wu-Hausman Test		0.105		
State FE	Yes	Yes	Yes	Yes
Demographics (Male, Kids, Income)	Yes	Yes	Yes	Yes

Notes: Cluster-corrected standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Bivariate Probit Without Instruments

	Probit	Bivariate Probit	
	Policy	Policy	Exp. of Aid (Binary)
Exp. of Aid (Binary)	0.25**	-0.95**	
	(0.13)	(0.39)	
Past Damage	0.12*	0.05	-0.11
	(0.07)	(0.08)	(0.08)
Knew Zone x Independence	0.06	0.12	0.23**
	(0.13)	(0.12)	(0.11)
Required	0.63***	0.61***	0.23
	(0.20)	(0.19)	(0.24)
Exp. of Fut. Hurr.	0.01	0.01*	0.01
	(0.01)	(0.01)	(0.01)
Exp. Hurr. Damage	0.04**	0.05**	0.02
	(0.02)	(0.02)	(0.02)
SFHA	0.76***	0.70***	0.13
	(0.20)	(0.20)	(0.19)
Mortgage	0.20**	0.21**	0.11
	(0.10)	(0.09)	(0.12)
Risk Averse (gain)	0.02	0.01	-0.00
	(0.04)	(0.03)	(0.03)
Risk Averse (loss)	0.08*	0.06	0.00
	(0.04)	(0.04)	(0.03)
Insurer Confidence	0.25**	0.47***	0.61***
	(0.12)	(0.13)	(0.07)
Coastal Tenure	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Distance from Coast (km)	-0.01***	-0.01**	-0.00
	(0.00)	(0.00)	(0.00)
Constant	-2.53***	-1.32*	0.57**
	(0.27)	(0.73)	(0.24)
Observations	730	730	730
ρ		.711	
State FE	Yes	Yes	Yes
Demographics (Male, Kids, Income)	Yes	Yes	Yes

Notes: Cluster-corrected standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: 2SLS Estimates on Coverage using binary measure of Exp. of Aid

	OLS	2SLS		
		Second Stage	First Stage	Reduced Form
Exp. of Aid (Binary)	-34064.06***	-72687.55**		
	(10450.51)	(32963.74)		
Past Damage	-8137.40	-16313.35	-0.24*	-0.24*
	(20138.23)	(23867.15)	(0.13)	(0.13)
Knew Zone x Independence	-13701.60	-18779.02	0.19*	0.19*
	(18629.92)	(20546.20)	(0.11)	(0.11)
Required	-18586.63	1323.18	-0.01	-0.01
	(27272.07)	(21722.16)	(0.17)	(0.17)
Exp. of Fut. Hurr.	1073.34**	1565.40***	0.01**	0.01**
	(418.47)	(433.78)	(0.00)	(0.00)
Exp. Hurr. Damage	-2834.85	-3049.99	0.01	0.01
	(2904.41)	(2363.89)	(0.02)	(0.02)
SFHA	29498.52	19912.47	0.08	0.08
	(23936.42)	(20121.33)	(0.13)	(0.13)
Mortgage	4014.97	-2153.18	-0.05	-0.05
	(17788.34)	(14555.91)	(0.10)	(0.10)
Risk Averse (gain)	5819.74	4239.69	-0.02	-0.02
	(6085.78)	(5565.01)	(0.03)	(0.03)
Risk Averse (loss)	8278.47	2674.52	-0.01	-0.01
	(6167.20)	(5669.56)	(0.03)	(0.03)
Insurer Confidence	17615.29	23547.59*	0.13	0.13
	(11480.08)	(12944.64)	(0.08)	(0.08)
Coastal Tenure	-539.37	-331.35	-0.00	-0.00
	(365.89)	(291.85)	(0.00)	(0.00)
Distance from Coast (km)	-102.17	-327.29	-0.00	-0.00
	(449.18)	(427.04)	(0.00)	(0.00)
Senate Count			0.10***	0.10***
			(0.03)	(0.03)
House Reps. Count			-0.00	-0.00
			(0.03)	(0.03)
IA 2010			0.20***	0.20***
			(0.07)	(0.07)
IA 2009			-0.28***	-0.28***
			(0.10)	(0.10)
IA 2008			0.00**	0.00**
			(0.00)	(0.00)
Constant	61497.19	128325.80*	0.88***	0.88***
	(66953.17)	(67337.32)	(0.29)	(0.29)
Observations	136	136	136	136
First Stage F-Stat		6.934		
Sargan Over ID Test		0.208		
Wu-Hausman Test		0.860		
State FE	Yes	Yes	Yes	Yes
Demographics (Male, Kids, Income)	Yes	Yes	Yes	Yes

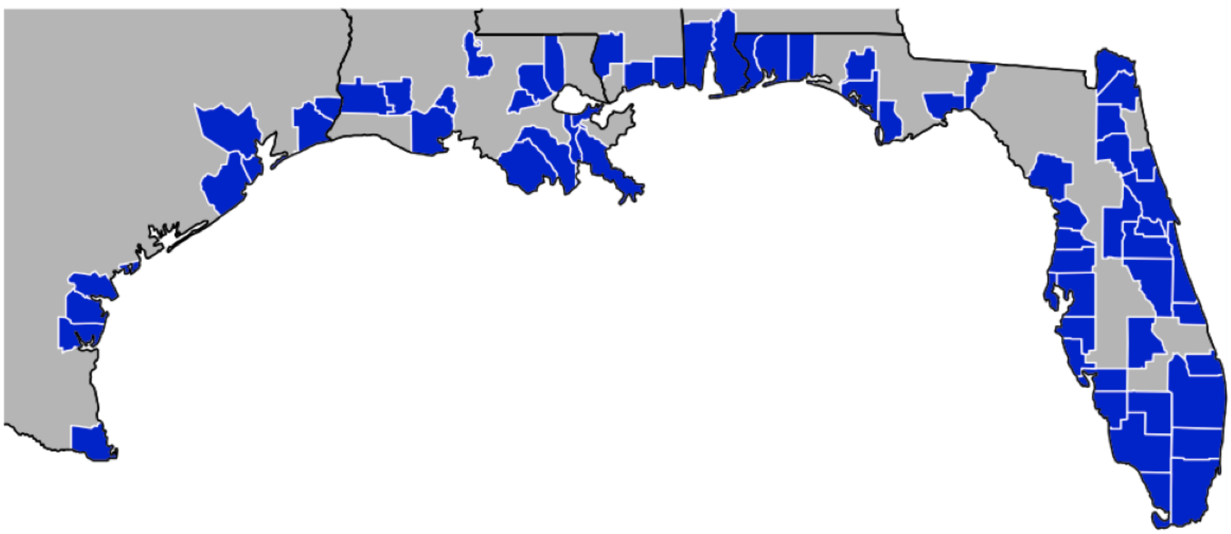
Notes: Cluster-corrected standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Charity Hazard Marginal Effects

Model Specification	Point Estimate	95% Confidence Interval
Panel A: Non-Linear Models		
Bi-variate Probit (with instruments)	-0.326	[-0.568 , -0.086]
Bi-variate Probit (no instruments)	-0.251	[-0.518 , -0.050]
Panel B: Linear Models		
2SLS (Binary Expectations of Aid)	-0.416	[-0.567 , -0.266]
2SLS (Likert Expectations of Aid)	-0.219	[-0.318 , -0.118]

Figure 1: Sampled Counties



9 Appendix

Table A1: Key Variables and Corresponding Survey Question Text

Variable	Survey Question Text
Policy	"Is your home currently covered by a flood insurance policy?" Possible Responses: (1: Yes; 2: No)
Exp. of Aid	"If a major hurricane hit your community and the federal government set up a program to provide disaster payments for home damage, how likely do you think that you would be eligible for a program like this? (Indicate how likely, with 1 being very unlikely and 5 being very likely.)"
Past Damage	"Please tell us about any previous storm and/or wind damage that has occurred to your current home since you have lived there." Possible Responses: (1: My home has not experienced any flood or wind damages ; 2: My home has experienced flood and/or wind damages)
Knew Zone	Self reported SFHA status was elicited with the following text which was then compared to actual SFHA status†: "Do you know if your home is in a flood zone? If so, which?" Possible Responses: (1: V-zone (highest risk, with storm surge); 2: A-zone (high risk); 3: B-zone / X-zone (shaded) (moderate risk); 4: C-zone / X-zone (unshaded) (low risk); 5: I am in a flood zone, but I don't know exactly which; 6: My home is not located in a flood zone; 7: I don't know if my home is in a flood zone or not.
Independence	"In the following questions, please indicate whether you agree or disagree with each statement. 'If I live in a location with a 1 in 50 chance of flooding, and it floods this year, then the chances of flooding again next year will be reduced.'" Possible Responses: (1: Agree; 2: Disagree)
Exp. of Fut. Hurr.	"Based on your experience, how many major hurricanes (Category 3 or greater, with winds of 111 mph or greater) do you expect to directly strike your community over the next 50 years?"
Exp. Hurr. Damage	"Suppose a Category 3 hurricane (wind speeds of 111-130 mph) did directly strike your community. How much damage (expressed as a percentage of total structure value) do you think your home would most likely suffer?"
Insurer Confidence	"If a major hurricane hit your community, how much confidence do you have that insurance companies will pay the full amount on storm damage claims? Please rate on a scale of 1 to 5 (with 1 having no confidence and 5 having full confidence)".
Coastal Tenure	"How many years have you spent living within 100 miles of the Gulf or Florida's Atlantic Coast?"

†Answers 5 and 7 resulted in the "Knew Zone" variable being automatically coded as 0 and answer 6 was interpreted as non-SFHA

Figure A1: Question Used to Elicit Risk Preferences With Example Choice

In the following section, we are interested in how you make decisions about possible *losses*. You will be asked to choose between two different possibilities of *losing* money.

So that you don't lose any of your previously earned money, Knowledge Networks is providing you with $10 in order to participate in the exercise. The average loss is about $5, so you can expect (on average) to walk away with $5. However, there *is some chance* that you will lose all of the $10 you're given to participate, *but you WILL NOT lose any more than $10.*

Therefore you cannot lose any more than what is given to you and you may actually get to keep some of it.

This exercise WILL NOT affect any previous earnings or any incentive you've been given for participating in this survey.

For each of the following, please indicate which risk of *loss* you prefer to face. Keep in mind that one of these will be chosen to determine your actual loss, so please take each decision seriously!

- A 1-out-of-10 chance of losing $5 and a 9-out-of-10 chance of losing $4

OR

- A 1-out-of-10 chance of losing $9.50 and a 9-out-of-10 chance of losing $0.50