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Riders on the Storm: Hurricane Risk and Coastal Insurance and Mitigation Decisions

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Riders on the Storm: Hurricane Risk and Coastal Insurance and Mitigation Decisions

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1. Introduction

Since the late 20th century, hurricanes and the resulting floods have been the costliest of all natural disasters in the United States both in terms of lives lost and property damaged. Especially deadly are floods caused by hurricane storm surge; it is estimated that nine of every ten deaths from hurricanes are caused by storm surge (Perry 2000; Meyer et al., 2012; King, 2012; Kousky, Michel-Kerjan, & Raschky, 2013; Michel-Kerjan and Kousky, 2015). The 2017 Atlantic Hurricane Season was both hyperactive and especially destructive; 2017 saw 17 named storms and is one of only five years on record which saw multiple Category 5 storms. (Dolce, 2017) Additionally, the 2017 season was the most costly on record due its three most powerful storms: Hurricanes Harvey, Irma, and Maria. Hurricane Harvey inflicted massive damage on this city of Houston, Texas and caused widespread flooding the likes of which had not been seen since Hurricane Katrina devastated New Orleans 12 years to the month in 2005. Just days after Harvey dissipated, Hurricane Irma attained Category 5 status East of the Lesser Antilles and tore through the Caribbean, eventually resulting in over 100 deaths and leveling 95% of all structures in the nation of Barbuda. Later on in September, Hurricane Maria hit the islands of Dominica and Puerto Rico causing widespread damage to critical infrastructure and hundreds of deaths. Preliminary estimates for the cost of the 2017 season generally center around the $200 billion dollar mark. (Drye, 2017; Sullivan 2017) Taking a longer perspective, the thirty most costly hurricanes making landfall in the United States from 1900-2010 inflicted close to $400 billion in damages (Blake, Landsea, & Gibney, 2011; Blake et al. 2013; Burris 2015).[1] Going forward, the effects of climate change are expected to increase both the frequency and severity of extreme weather events such as hurricanes (IPCC, 2007; Botzen, Aerts, van den Bergh 2009; Landry and Jahan-Parvar, 2011; Kousky, 2011; Michel-Kerjan, Lemoyne de Forges, & Kunreuther, 2012). Increased precipitation may result from a more erratic climate, and rising sea levels will bring storm surge further inland, increasing the probability and negative consequences of major flooding incidents in some coastal areas. Exacerbating this problem are significant increases in population and housing investment in coastal areas of the United States. During the period from 1960-2008, the population of coastal counties saw an 80% increase from 47 million people in 1960 to 87 million people in 2008. During the same period, the respective number of housing units in coastal areas more than doubled from 16.1 million to 36.3 million (Wilson and Fischetti, 2010).[2] An increasing number of structures coupled with more densely populated coastlines will result in both greater spatial correlation among damages

[1] Damage estimates adjusted for inflation using the United States Census Bureau Price Deflator for Construction

[2] Coastal counties are defined by NOAA as those with "at least 15% of the county's total land area located within the Nation's coastal watershed" or "a portion of the entire county accounts for at least 15% of a coastal cataloging unit." It is important to note that under this definition most coastal counties are not actually adjacent to the ocean.

and greater loss of life in the event of a catastrophic hurricane. Further, the escalating trend in population and capital investment in coastal areas calls into question the long term insurability of hurricane risk. Kousky (2011) specifically notes that the increased exposure to coastal wind peril has decreased the availability of reinsurance, putting greater strain on state-run wind insurance pools.

Hurricanes and the resulting floods have extraordinarily high socio-economic costs, and there is a clear need for protective and adaptive measures to deal with the risks they pose. Estimates for the total value of property in coastal areas of the United States vary. Kunreuther (1996) pegged the total insured value of coastal property at $4.26 trillion in 1993 (up from an estimated $2.51 trillion in 1988). Insurance firm AIR Worldwide estimated the total value of insured property in coastal states at $7.2 trillion in 2004 and updated their estimate to $10.6 trillion in 2012 (AIR Worldwide, 2005, 2013). Nordhaus (2006) estimates "the total value of capital in areas close to sea level" at a more conservative $1.46 trillion.[3] What is clear from these estimates is that the risk of hurricane damage in coastal areas and the level of people and capital investments exposed are increasing. Insurance is a natural tool for pooling and distributing risk, but it has been difficult to apply in the case of hurricanes and floods. In the past, private insurance markets were not willing to provide adequate levels of coverage for flood and wind peril, and thus governments stepped in to provide insurance coverage to those households at risk. Even with government intervention in the insurance markets, however, purchase rates for flood insurance remain low.

Building on recent research into household risk management decisions (Petrolia, Landry, and Coble 2013; Petrolia et al. 2015), this paper uses household-level, cross-sectional survey data combined with experimentally derived risk preference information to examine the decision to invest in flood and wind insurance contemporaneously with the decision to mitigate hurricane risk, focusing on households living in the Gulf Coast region of the United States. We probe the question of what factors hold significant influence over an individual's decisions to engage in these protective measures to safeguard property from hurricane risk and how the decisions are interrelated.

This paper contributes to the literature on decision-making under risk and uncertainty by examining integrated individual choices of insurance products and mitigation, examining the influence of observable factors on choice, and controlling for unobservable effects that can correlate across decisions. We specify a tractable modeling structure that permits correlated insurance and mitigation decisions, taking account of the nature of the available data.

[3] Kunreuther (1996) estimates converted to 2005 dollars, Nordhaus (2006) estimates in 2005 dollars

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2. Background

2.1. Flood Insurance in the United States

The private market for flood insurance in the US never fully developed. Major issues which have caused many private insurers to withdraw from the market include: certainty of loss in flood prone areas, adverse selection, moral hazard stemming from government disaster aid (known as the "charity hazard"), and high premiums resulting in low uptake rates (Anderson, 1974; Petrolia, Landry, & Coble, 2013). Additionally, the "catastrophic" nature of flood risk has always been a major stumbling block for the market. Kousky (2011) defines a catastrophic risk as having two main characteristics. First, the probability of occurrence declines slowly relative to the magnitude of the event, meaning that the strongest recorded magnitude event may be many times larger than the second strongest. Second, losses resulting from catastrophic risks are correlated in space. Spatial correlation of losses presents an especially difficult hurdle for private insurers because losses are not statistically independent. This leads to an intertemporal smoothing problem in which insurance companies incur massive losses some years and zero losses in others (Michel-Kerjan, 2010; Kousky 2011). Because of these factors, most private insurers had exited the flood insurance market by the 1950s. Following a series of large hurricanes ending in 1965 with Hurricane Betsy, Congress passed the National Flood Insurance Act in 1968, creating the National Flood Insurance Program (NFIP). The NFIP was designed to be a voluntary partnership between flood-prone communities, the federal government, and private insurance firms (Atreya, Ferriera, Michel-Kerjan, 2014). Though the program has been amended several times since the passage of the initial law, the overall structure and responsibilities of the respective stakeholders remains largely the same.

2.2. Wind Insurance in the United States

Traditionally, coverage for wind peril was available through homeowners insurance but individuals living in areas highly prone to hurricanes may find a limited number of insurers that offer such coverage. The lack of supply in the voluntary market for wind coverage has put pressure on the government to make coverage available in residiual markets for these high risk areas (Petrolia, Hwang, Landry, & Coble, 2015). Separate "wind-only" insurance in the United States can come in several forms: Fair Access to Insurance Requirements (FAIR) Plans[1], reinsurance funds, state wind

[1] Established under the Housing & Development Act of 1968, FAIR plans are designed to provide insurance in both rural and urban areas to individuals who cannot obtain coverage in the private market. Currently 32 states and Washington, D.C. have FAIR plans available (Hartwig & Wilkinson, 2014; Kousky, 2011).

pools, or hybrid programs that provide both homeowners' insurance and hazard-specific policies (Kousky, 2011). Currently, only Florida operates a state-run reinsurance program (the Florida Hurricane Catastrophe Fund), but state wind pools or hybrid programs exist in North and South Carolina, Georgia, Florida, Alabama, Mississippi, Louisiana, Texas, and Hawai'i. Similar to the National Flood Insurance Program, most state funded wind insurance programs were created in response to a single extreme weather event that forced private insurers to exit the market or raise premiums, which led to public outcry for a political response. Policymakers generally designed these programs to be lenders of last resort, but they have since evolved from this original role to become major property insurers in their respective states and sometimes the only option for high-risk properties. The structure and pricing strategy of wind insurance programs vary by state; for a detailed analysis of individual state programs see Kousky (2011).

Since 1990, the residual market for wind insurance has experienced substantial growth both in terms of the number of policies in force and the total loss exposure. The number of policies in force in the residual market (including both FAIR and state wind pools/hybrids) saw a three fold increase during the period from 1990 to 2014 but has stayed fairly level since 2006. Total exposure of the residual market increased eleven fold over the same period but has declined by one-third since 2011.[2]

2.3. Moral Hazard, Catastrophe Insurance, and Mitigation

A key problem facing both the NFIP and state wind insurance programs is the potential for moral hazard. Moral hazards arise in insurance markets because of a fundamental conflict of incentives between the buyer and seller: as the quality and quantity of insurance against some loss increases, the buyer's incentives to avoid the hazard decreases (Stiglitz, 1983). This conflict of incentives results in the buyer of insurance not bearing the full cost of their actions and may result in increased risk-taking because the agent feels protected from the hazard. In the market for catastrophe insurance, moral hazard can influence location choice and may lower incentives for mitigation if insurance rates are not adjusted to reflect the true risk of the hazard faced. A particular variety of moral hazard that is relevant in the context of catastrophe insurance is "charity hazard" (Browne & Hoyt, 2000). The charity hazard hypothesis argues that if individuals believe the provision of government-funded disaster assistance is likely in the wake of a loss event, they will be less apt to engage in protective behavior such as insurance purchases or mitigation activities, and thus they shift the costs of their risky behavior onto the taxpayer.

[2]Policies in force increased from 0.931 million in 1990 to 3.215 million in 2013; Exposure to loss increased from \$54.7 billion in 1990 to a high of \$884.7 billion in 2011 and declined to \$639.4 billion in 2014 (Hartwig & Wilkinson, 2014).

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Policymakers have attempted to address moral hazard problems through legal mandate, incentives to mitigate, limits on coverage, and use of deductibles. Laws such as the Coastal Barrier Resources Act (Pub.L. 97-348) and the Stafford Disaster Relief Act (Pub.L. 100-707) explicitly prohibit certain post-disaster reconstruction and provision of federal disaster assistance/flood insurance in prescribed areas, while permitting the federal buyouts of high-risk properties that are damaged or destroyed (DHS, 2002; Kriesel & Landry, 2004; Pompe & Rinehart, 2008). Other forms of legal mandates include local building codes designed to improve the resiliency of newly built structures. Incentives to mitigate in the NFIP are primarily available at the community/municipality level through the Community Rating System (CRS), which rewards communities with reduced premiums for voluntary mitigation activities or efforts to increase participation in the program. State run wind insurance programs focus their mitigation incentives at the household level and vary by state. For example, mitigation credits for wind-hardened structures are available in North and South Carolina, Florida, Alabama, Louisiana, and Hawaii, while Georgia and Texas require homes to meet hurricane building codes as a prerequisite for coverage. Despite these efforts, many of these programs do not price their coverage to risk and significant moral hazard problems likely remain.

3. Data

The household data in our sample were collected in August and September of 2010 from an online survey administered by Knowledge Networks. The survey consisted of 41 questions designed to measure insurance and mitigation behavior, as well as elicit individual risk preferences and environmental risk perceptions; if took an average of twenty minutes to complete. Participants were paid $5 for completing the survey and were also eligible to earn an additional $10 (on average) by completing the Holt-Laury (2002) risk preferences exercise at the end of the survey. The target population for the survey was property owners in coastal counties along the US Gulf Coast including Alabama, Florida, Mississippi, Louisiana, and Texas, plus the Atlantic coast of Florida. In total 96 counties were sampled for our analysis. Knowledge Networks sampled a total of 1,536 individuals from their KnowledgePanel®, and of those sampled, 1,070 responded (69.6%) and 859 allowed access to their street address.[1] Of the 859 responses with street addresses, only 670 were usable after dropping observations with unreliable street addresses/flood zones or missing values for variables included in the model. A map of the sample respondents is given in Figure 1.[2] Since

[1]Street addresses were used to calculate geographic variables including distance to the nearest shoreline and flood zone through the use of GIS methods. This further allowed us to expand the data set to include the year in which the home was constructed and the CRS score for each respondent's community using county tax assessor data and the FEMA DFIRM database.

[2]*Source*: BLINDED FOR REVIEW

we have a random sample of households in coastal counties, we have greater information on more populated areas. Over half of our observations are from Florida (67.8%) and roughly a quarter are from Texas (24.8%). The remaining observations are divided between Louisiana (3.1%), Alabama (3.0%), and Mississippi (1.3%)

Figure 1: Map of Survey Respondents

The survey required residents to indicate whether they held flood and/or wind insurance policies as well as the number and type of mitigation measures installed on their home. Table I breaks down the flood policy responses by state and by location in the 100-year flood plain. Overall only 233 individuals (34.8%) in our sample holds a flood insurance policy and of those policyholders, 93 (13.9%) are inside a SFHA. Looking at the breakdown by state, Florida had the greatest number of policies overall (129, 19.3% of total policies) and also the greatest number of policies in SFHAs (66, 9.9% of total policies). Texas had the greatest number of policies in Non-SFHA areas (68, 10.1% of total policies) and also had the highest in-state uptake rates for SFHAs (85.0%) excluding Mississippi which had only two observations in a SFHA. Texas also had the highest in-state uptake rate in Non-SFHA areas (46.6%). Louisiana had the highest overall in-state uptake rate at 52.4% but had significantly fewer observations than Texas which had an overall uptake rate of 51.2%.

Table I: Flood Policies by State and SFHA Status

	SFHA			Non-SFHA			Total		
	# obs	# w/ Policy	row %	# obs	# w/ Policy	row %	# obs	# w/ Policy	row %
AL	0	0	0.0	20	4	20.0	20	4	20.0
FL	110	66	60.0	344	63	18.3	454	129	28.4
LA	12	8	66.7	9	3	33.3	21	11	52.4
MS	2	2	100.0	7	2	28.6	9	4	44.4
TX	20	17	85.0	146	68	46.6	166	85	51.2
Total	144	93	64.6	526	140	26.6	670	233	34.8

Figure 2 indicates the classifications used to determine the type of wind peril coverage a homeowner had and to measure the level of mitigation undertaken by the homeowner. Table II displays

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the results for wind insurance. Most homeowners in our sample had some form of wind coverage (602, 90.0%) either through their homeowners policy (470, 70.2%) or under a separate wind-only policy (132, 19.7%). Florida had far and away the greatest number of total wind polices (419, 62.5%) while Alabama and Louisiana had the highest rates of in-state uptake at 95%.

Wind Insurance Question

Is **wind** coverage included in your regular homeowner's policy, or do you have a *separate* **wind** policy?

- Wind is included in my regular homeowner's policy.
- I have a separate wind-only policy.
- Wind is NOT included in my regular homeowner's policy, and I do NOT have a separate wind-only policy.

Mitigation Question

Please indicate whether your home has any of the following storm-resistant features:

Storm shutters	☐ Yes	☐ No	☐ Don't know
Roof anchors	☐ Yes	☐ No	☐ Don't know
Reinforced doors	☐ Yes	☐ No	☐ Don't know
Wind-resistant glass	☐ Yes	☐ No	☐ Don't know
Wind-resistant shingles	☐ Yes	☐ No	☐ Don't know
Hurricane ties	☐ Yes	☐ No	☐ Don't know
Elevated on piles	☐ Yes	☐ No	☐ Don't know

Other storm-resistant features (please describe): ______________________

Figure 2: Survey Questions Used to Determine Wind Insurance Type and Mitigation Measures Undertaken

Table II: Wind Peril Coverage Type by State

	State (% in State, Column)					
	AL	FL	LA	MS	TX	Total
Wind Included in Homeowners	17 (85%)	327 (72.03%)	15 (71.43%)	6 (66.67%)	105 (63.25%)	470 (70.15%)
Wind Excluded from Homeowners	1 (5%)	35 (7.71%)	1 (4.76%)	3 (33.33%)	28 (16.87%)	68 (10.15%)
Separate Wind Policy	2 (10%)	92 (20.26%)	5 (23.81%)	0 (0%)	33 (19.88%)	132 (19.7%)
Total	20	454	21	9	166	670

Table III breaks down the mitigation count by state. All responses marked "don't know" were recorded as "no" responses. Write-in answers were added to mitigation counts were appropriate. Examples of acceptable write-in responses included metal roofs, hip roofs, polypropylene screening, reinforced garage doors, concrete blocks, and boarded windows.The mean number of mitigation measures for our entire sample was 1.8 while over one-third of respondents reported not engaging in any mitigation measures whatsoever (207, 30.9%). Florida had the greatest number of total mitigation measures (454) followed by Texas (166). The state with the highest percentage of observations engaging in *at least one* mitigation measure was Mississippi (77.8%) followed by

Florida (75.8%) while Texas had the lowest (49.4%). Overall, 69.1% of our sample engaged in at least one mitigation measure.

Table III: Mitigation Count by State

	State (% in State, Column)					
	AL	FL	LA	MS	TX	Total
0	5 (25%)	110 (24.23%)	6 (28.57%)	2 (22.22%)	84 (50.6%)	207 (30.9%)
1	6 (30%)	83 (18.28%)	7 (33.33%)	3 (33.33%)	37 (22.29%)	136 (20.3%)
2	4 (20%)	89 (19.6%)	3 (14.29%)	1 (11.11%)	19 (11.45%)	116 (17.31%)
3	3 (15%)	68 (14.98%)	1 (4.76%)	1 (11.11%)	16 (9.64%)	89 (13.28%)
4	1 (5%)	59 (13%)	3 (14.29%)	1 (11.11%)	6 (3.61%)	70 (10.45%)
5	1 (5%)	33 (7.27%)	1 (4.76%)	1 (11.11%)	1 (0.6%)	37 (5.52%)
6	0 (0%)	9 (1.98%)	0 (0%)	0 (0%)	1 (0.6%)	10 (1.49%)
7	0 (0%)	3 (0.66%)	0 (0%)	0 (0%)	2 (1.2%)	5 (0.75%)
Total	20	454	21	9	166	670
Mean	1.6	2.1	1.6	1.9	1.0	1.8

Individuals carrying wind coverage included in their homeowner's policy or in a separate wind-only policy had higher mean levels of mitigation than those who carried no wind coverage. In contrast to the traditional economic theory of insurance, this could suggest that individuals in our sample do not view hazard mitigation as a substitute for insurance or that the pricing structure is sufficient to address moral hazard problems (Erlich & Becker, 1972; Mossin, 1968). It may also reflect a degree of salience of natural hazard risk that influences some individuals to purchase insurance, while also being aware of the level of mitigation present on their home. There could be errors in the mitigation count, which require attention in econometric modeling, in addition to correlations for unobserved factors across equations.

Finally, respondents were asked: "For storm resistant features that your home does not have, what is the main reason you have not installed them?" The two most common responses indicated 40% of individuals "do not think my home needs any additional storm resistant features" and 30% of individuals believe "the upfront installation costs are too high."

Figure 3 shows excerpts from the survey instrument used to measure individual risk preferences and risk perceptions. Measurement of risk preference was based on the experimental design of Holt and Laury (2002). Participants were presented with ten real-money gambles: five framed as a loss and five as a gain to test for asymmetry across the wealth domain consistent with Prospect Theory (Kahneman & Tversky, 1979). Payoff probabilities were set at (0.1/0.9), (0.3/0.7), (0.5/0.5), (0.7/0.3), and dollar amounts were fixed. Respondents were given \$10 prior to completing the exercise to prevent negative payoffs and were told one of their choices would be selected from each domain at random to determine their realized payoff. The total number of choices in which the participant selected low-variance risk over high-variance risk were tallied and used as our measure of risk aversion. The means over the gain and loss domains were 2.93 and 2.94, respectively, indicating our sample was slightly risk averse on average over both domains. This measure of risk-

Example of Experimental Question Used to Elicit Risk Preferences

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

Risk Perception Questions

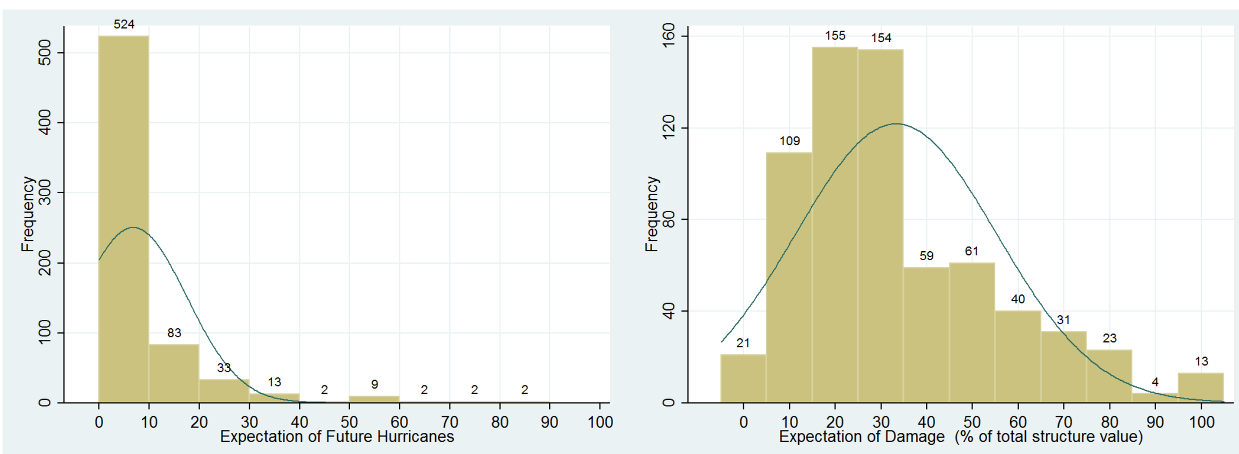
1. Suppose a Category 3 hurricane (wind speeds of 111–130 mph) did directly strike your community. How much damage (**expressed as a percentage of total structure value**) do you think your home would most likely suffer?

0%	20%	40%	50%	60%	80%	100%
(no damage)		(moderate damage)		(severe damage)		(total loss)

2. 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*?

_____ Major hurricanes (Category 3 or greater) over the next 50 years

Figure 3: Experimental Questions Used to Determine Risk Preferences, Survey Questions to Measure Risk Perceptions



(a) Expectation on the # of ≥Cat 3 Hurricanes over next 50 years

(b) Expectation of damage under ≥Cat 3 Hurricane

Figure 4: Risk Perceptions I

aversion is not without pitfalls, however. In the survey exercise we use low-stakes and relatively high probabilities to elicit risk preferences. This is potentially problematic because insurance decisions concerning catastrophic risks such as hurricanes deal with high-stakes and low-probability (Kachelmeier & Shehata, 1992; Petrolia, Hwang, Landry, & Coble, 2015).

In addition to risk preferences, the survey inquired about the respondent's perception of hurricane risk and recovery. We elicited the expected number of category 3 (or stronger) hurricanes that would pass within 75 miles of each respondent's community over the next 50 years, the expected level of damage that would be incurred in the event of a category 3 storm, the perceived likelihood that insurers would pay the full amount of a storm damage claim, and the perceived likelihood that the respondent's property would be eligible for government disaster assistance after a storm.[3] Histograms for the responses to these questions are detailed in Figures 4 and 5. For expected hurricanes, the majority of the respondents (524, 78%) indicated their expectation was from 0-10 Category 3 storms, implying a maximum of 0.2 storms per year. Yet, considerable proportions of respondents fall into the "11 - 20" and "21 - 30" response categories, 12% and 5% respectively. A very small number of respondents indicated expectations of more than 30 hurricanes of Category 3 or greater in the next 50 years; these subjects may have not understood the question, or they may harbor extremely pessimistic expectations of climate change. The mean of expected structural damage was around 33% of structure value, with the bulk of perceptions in the range of 10% to 50%. Perceptions of insurer credibility and the likelihood of disaster assistance were each centered around moderate response (category 3 on a 5-point Likert scale), with confidence in insurers payout skewed towards full confidence and likelihood of disaster assistance skewed towards very unlikely.

Ancillary data were collected on relevant variables such as aggregated county-level federal mitigation grants paid out through FEMA under the Flood Mitigation Assistance (FMA), Repetitive Flood Claims (RFC), and Severe Repetitive Loss (SRL) programs. Other pertinent variables include housing type, mortgage status, experience with past instances of wind/flood damage (to account for potential 'availability bias' consistent with the work of Tversky & Kahneman, 1973), and demographic variables such as income, race, gender, education, marital status, number of children, etc. Variable descriptions and summary statistics for all variables included in our model are given below in tables IV and V.

[3] Perceived likelihood of government assistance was used to test the charity hazard hypothesis (Brown & Hoyt, 2000; Petrolia, Hwang, Landry, & Coble, 2015)

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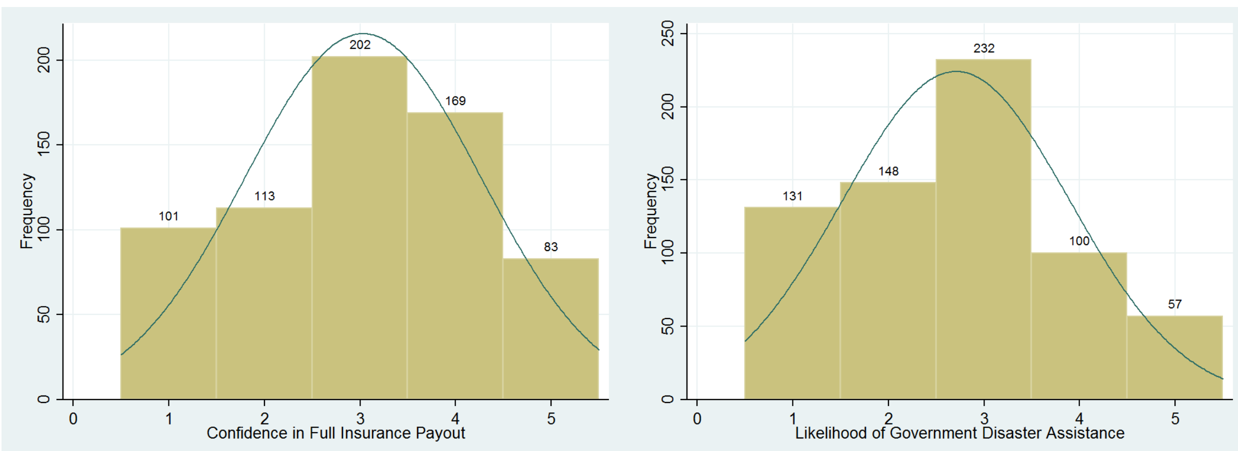
Table IV: Summary Statistics

N = 670

	Mean	Std. Dev.	Min	Max	Sum	Exp. Sign
Flood Policy	0.348	0.477	0	1	233	
Wind policy	0.803	0.398	0	1	538	
Mitigation Count	1.784	1.694	0	7	1195	
Risk Aver., Gain	2.928	1.446	0	5	1962	+
Risk Aver., Loss	2.940	1.367	0	5	1970	+
Policy Reqd.	0.166	0.372	0	1	111	+
Past Damage	0.469	0.787	0	4	314	+
Eligibility	0.584	0.493	0	1	391	-
Credibility	0.681	0.467	0	1	456	+/+/-
Exp. Damage	3.327	2.195	0	10	2229	+/+/. . .
Exp. Hurr	6.791	10.655	0	90	4550	+
Dist. Shore	15.580	18.101	0	171.682	10438	-/-/-
CRS	6.951	1.472	5	10	4657	-
Florida x CRS	4.563	3.258	0	10	3057	+
Mortgage	0.672	0.470	0	1	450	+
SFHA	0.215	0.411	0	1	144	+
Mort x SFHA	0.146	0.354	0	1	98	+
X-Zone	0.601	0.490	0	1	403	-
Pre-FIRM	0.404	0.491	0	1	271	?
Property Age	28.760	20.910	1	210	19269	?
Mobile Home	0.0328	0.178	0	1	22	-/. . ./. . .
Condo	0.115	0.319	0	1	77	?
Gulf Years	27.263	18.010	0	93	18266	?
Oth. Property	0.060	0.237	0	1	40	?
Education	4.000	1.599	1	7	2680	+
White	0.816	0.387	0	1	547	?
Male	0.467	0.499	0	1	313	?
Income	12.299	3.895	1	19	8240	+
Employed	0.554	0.497	0	1	371	+
Kids	0.264	0.441	0	1	177	+
Flordia	0.678	0.468	0	1	454	-
Texas	0.248	0.432	0	1	166	?
AL or MS	0.0433	0.204	0	1	29	?
Louisiana	0.031	0.174	0	1	21	?
Wind Excluded	0.299	0.458	0	1	200	. . ./. . ./+
Internet Access	0.957	0.204	0	1	641	. . ./. . ./. . .

Where two or three signs given:
flood eq sign / wind eq sign / mitigation eq sign, ". . . " = not included



(a) Perceived likelihood of a full insurance payout covering all storm damages (1 = no confidence, 5 = full confidence)

(b) Perceived likelihood of state/federal post-disaster assistance (1 = very unlikely, 5 = very likely)

Figure 5: Risk Perceptions II

Table V: Variable Descriptions

Variable	Type	Description
Dependent Vars		
Flood Policy	Binary	Dependent Variable; =1 if purchased flood insurance policy, =0 otherwise
Wind Policy	Binary	Dependent Variable; =1 if purchased separate wind policy, =0 otherwise
Mitigation Count	Count	Dependent Variable; number of mitigation measures installed, range is from 0 - 7
Risk Preferences		
Risk Aversion (Gains)	Continuous	Number of instances where low-variance risk chosen over gain domain, ranges from 0 (risk loving) to 5 (risk averse)
Risk Aversion (Losses)	Continuous	Number of instances where low-variance risk chosen over loss domain, ranges from 0 (risk loving) to 5 (risk averse)
Risk Perceptions		
Flood Policy Required	Binary	=1 if told they were required to purchase flood insurance when getting mortgage, =0 otherwise
Wind Peril Excluded	Binary	=1 if wind coverage excluded from homeowner's policy, =0 otherwise
Past Damage Experience	Count	Number of instances of wind and flood damage experienced in the past
Disaster Assist. Eligibility	Binary	=1 if perceived likelihood of eligibility for postdisaster payments rated ≥3 on a scale from 1 (very unlikely) to 5 (very likely), =0 otherwise
Insurer Credibility	Binary	= 1 if perceived confidence that insurer will pay full amount of claims in event of major storm is ≥ 3 on scale from 1 (no conf.) to 5 (full conf.), = 0 otherwise
Expectation of Damage	Ordered Cat	Expected proportion of damage to home given Cat 3 storm, ranges from 0 (no damage) to 10 (total loss)
Expectation of Fut. Storms	Ordered Cat	Expected number of future Cat 3 or greater storms over next 50 years
Property Attributes		
Distance from Shoreline	Continuous	Distance in kilometers from nearest shoreline
Community Rating System	Ordered Cat	Community Rating System score; ranges from 1 (most mitigation) to 10 (no mitigation)
Florida X CRS	Ordered Cat	=CRS score if resident of Florida, =0 otherwise
Mortgage	Binary	=1 if home is mortgaged, =0 otherwise
Property Attributes Cont.		
SFHA	Binary	=1 if home is in A or V flood zone (100 yr floodplain), =0 otherwise
Mortgage X SHFA	Binary	=1 if home is mortgaged and in the A or V flood zone (100yr floodplain), =0 otherwise
X-Zone	Binary	=1 if home outside the 500-yr floodplain, =0 otherwise
Pre-FIRM Structure	Binary	=1 if home built prior to flood insurance rate maps, =0 otherwise
Property Age	Continuous	Age of property in years
Mobile Home	Binary	=1 if mobile home, =0 otherwise
Condo	Binary	=1 if housing type is condominium or apartment, =0 otherwise
Years Living on the Gulf	Continuous	Number of years living on the Gulf Coast
Owns Other Property	Binary	=1 if owns other non-coastal property worth ≥ $100k, =0 otherwise
Demographics		
Education	Ordered Cat	=1 if no HS degree, =2 if HS grad, =3 if some college no deg, =4 if associate deg, =5 if bachelors deg, =6 if masters deg, =7 if professional or doctoral deg
White	Binary	=1 if white, =0 otherwise
Male	Binary	=1 if male, =0 otherwise
Income	Ordered Cat	category ranges from "less than 5,000"*to*\175,000 or more"
Employment Status	Binary	=1 if employed, =0 otherwise
Kids	Binary	=1 if have children, =0 otherwise
State of Residence		
Florida Resident	Binary	=1 if florida resident, =0 otherwise
Texas Resident	Binary	=1 if Texas Resident, =0 otherwise
Ala. or Miss.Resident	Binary	=1 if Alabama OR Mississippi Resident, =0 otherwise
Louisiana Resident	Binary	=1 if Louisiana Resident, =0 otherwise

4. Conceptual Framework

To construct a joint model for insurance and mitigation decisions, we draw on previous literature on flood insurance demand, hazard mitigation under catastrophic risks, and the small number of studies addressing demand for wind insurance. Generalizing the models for flood insurance, wind insurance, and mitigation presented in Petrolia, Landry, and Coble (2013) and Petrolia et al. (2015) to fit our simultaneous approach, we assume individual agents maximize their subjective expectation of utility where the utility for individual i is

$$U_i = U(H_i, X_i, F_i, W_i, M_i) \tag{4.1}$$

where H_i is consumption of housing, X_i is consumption of a numeraire, F_i represents the decision to purchase ($F_i = 1/0$) flood insurance, W_i represents the decision to purchase ($W_i = 1/0$) wind insurance, and M_i represents the number of mitigation measures undertaken on structure i where M_i is an element of the set of all real, non-negative integers $(M_i \in \mathbb{Z}_+)$. We assume that households make insurance and mitigation choices that they perceive as optimal, resulting in Marshallian demand functions for insurance and mitigation. F_i, W_i, and M_i can further be decomposed as follows

$$\begin{aligned} F_i &= \{0,1\} = F\left[P_i, L_i(M_i), \omega_i, \gamma_i, \delta_i, \pi_f(r_i, M_i), \pi_m(r_i), y_i\right] \\ W_i &= \{0,1\} = W\left[P_i, L_i(M_i), \omega_i, \gamma_i, \delta_i, \pi_w(r_i, M_i), \pi_m(r_i), y_i\right] \\ M_i &= M\left[P_i, L_i(M_i), \omega_i, \gamma_i, \delta_i, \pi_m(r_i), y_i\right] \end{aligned} \tag{4.2}$$

where P_i is the perceived likelihood of a major storm event; $L_i(M_i)$ is the perceived conditional expected loss from wind/flood damage resulting from a storm, depending on the level of mitigation; ω_i is the perceived likelihood of an insurance payoff (insurer credibility); γ_i is the perceived likelihood of government disaster assistance; δ_i represents past experience with flood and wind damage; $\pi_f(r_i, M_i)$ and $\pi_w(r_i, M_i)$ are the prices of flood/wind insurance, depending on observable measures of risk (r_i) and the level of mitigation (M_i) for property i; $\pi_m(r_i)$ is the cost of mitigation measures; and y_i represents household wealth.

The decision to purchase insurance and the decision to mitigate risk are determined by many of the same observed and unobserved perceptual, risk, and economic factors and are jointly determined by the price of insurance and the cost of mitigation. Generally, the demand model for a market good should include the own price of the good as well as prices of substitutes. In our model, however, the prices of both insurance and mitigation are unobserved. In the NFIP, the price of flood insurance is set at the national level and is based on a defined set of objective measures for flood risk. Premiums vary by flood zone, size and type of structure, date of structure construction, distance above "base flood elevation,"[1], and community level mitigation measures. The price of wind insurance is determined by private actuaries (but regulated by the states) in the case of homeowners' insurance, or set at the state level in the case of wind pools, but in both cases will be based on a limited set of objective measures of risk and the level of mitigation undertaken by the property owner (Petrolia, Landry, and Coble, 2013; Petrolia et al., 2015). Because of this, our empirical model does not include proxy variables for the price of insurance or cost of mitigation; rather, we include the set of variables upon which the price of insurance is based. We interpret the estimated effects of these variables as the gross impact on both price and behavior.

We hypothesize that the level of mitigation *indirectly* affects the decisions to purchase flood and/or wind insurance in two ways, first, by affecting the individual homeowner's expectation of a loss resulting from a major storm event, $L_i(M_i)$, and second, by affecting the prices of flood insurance, $\pi_f(r_i, M_i)$, and wind insurance, $\pi_w(r_i, M_i)$. Intuitively, it makes sense that a homeowner who mitigates the risk his/her property faces with respect to wind and flood peril will feel better about the chances of incurring a large loss and thus the expectation of loss from a major storm event may fall. Additionally, homeowners are often rewarded with premium discounts for engaging in risk-mitigation activities (Kousky, 2011). For example, the Florida Windstorm Underwriters Association (FWUA) began offering discounts in July of 2000 ranging from 3% to 18% for different mitigation activities (Simmons, Kruse, & Smith, 2002). It is reasonable to assume that $\partial\pi_f/\partial M_i \leq 0$, $\partial\pi_w/\partial M_i \leq 0$, and $\partial L_i(M_i)/\partial M_i \leq 0$.

The closely related nature of the insurance and mitigation decisions presents a risk of endogeneity problems in our joint analysis. To grapple with this, we employ the same strategy used by Petrolia, Landry, and Coble (2013). Decision variables for insurance and mitigation count are excluded from each other's equations and the decisions are treated as seemingly unrelated to one another. This framework does not assume the decision to purchase insurance or mitigate directly affects the other; rather, it assumes they are determined by the same set of observed and unobserved factors.

4.1. Risk Preferences

In the traditional expected utility formulation for decision making under risk, insurance demand is driven by risk aversion. A risk-averse expected utility maximizer is defined as having a utility function that increases at a decreasing rate with respect to wealth ($\partial^2 U_i/\partial y_i^2 < 0$). This implies that utility derived from risky outcomes are valued differently depending upon the level of wealth and assets exposed. Individuals that exhibit greater risk aversion have a larger risk premium and are more likely to insure or mitigate risks, all else equal (Smith, 1968; Mossin, 1968; Dionne and

[1]Estimated elevation of a 100-year flood as determined by FEMA on Flood Insurance Rate Maps. A detailed description of the different flood zones is available at www.FEMA.gov/flood-zones.

Eeckhoudt, 1985; Briys and Schlesinger, 1990).

Empirically, risk preferences have been shown to have significant explanatory power across a range of situations. Kachelmeier and Shehata (1992) found that as the real money payoffs for gambles were increased by a factor of 10, individuals exhibited increasing levels of risk aversion. In their experimental study of first-price auctions, Smith and Walker (1993) found that the vast majority of subjects bid in excess of the risk-neutral predictions, indicating increasing risk aversion as the payoffs increased. Similarly, Holt and Laury (2002) reported that as the real money payoffs increased by factors of 20, 50, and 90, risk aversion increased sharply. In the coastal insurance context, Petrolia, Landry, and Coble (2013) found that individuals with a higher degree of risk aversion, as measured by the method put forward in Holt and Laury (2002), were significantly more likely to hold a flood insurance policy. Using insurance deductibles as a proxy for risk aversion, Carson, McCollough, and Pooser (2013) found that risk aversion increased the likelihood of engaging in mitigation . We hypothesize that in our joint model, as an individual's level of risk aversion increases, the extent of mitigation and the probability of insurance purchases will increase (all else being equal).

4.2. Risk Perceptions

In addition to risk preferences, it is important to examine how individual perceptions of risk affect the decision to insure or mitigate. Expected utility theory predicts that the choice to insure is a function of both the perceived likelihood and magnitude of a loss (Rees and Wambach, 2008). The standard model for insurance choice presumes that perceived probabilities are based on objective, actuarial measures of risk (Smith, 1968; Mossin, 1968), though in practice this may not be the case. Kriesel and Landry (2004) use the mean return interval for hurricane landfall as a proxy for the expectation of hurricane risk. They find that the likelihood of holding a flood insurance policy is decreasing in the hurricane return interval (less likelihood of a hurricane). Empirical work in the coastal context by Petrolia, Landry, and Coble (2013) and Petrolia et al. (2015) found that the probability of holding a flood or wind insurance policy was increasing in the conditional expected loss resulting from a Category 3 storm event. Determining the effect of conditional expected loss on the number of mitigation measures is problematic because, as the number of mitigation measures installed increases, we would expect that the perceived magnitude of a loss would decrease. Without an appropriate instrument, Petrolia et al. (2015) were unable to identify this effect, and thus it was excluded from the mitigation equation. Additionally, Petrolia, Landry, and Coble (2013) and Petrolia et al. (2015) found no significant effect from the expected frequency of Category 3 storm events on the probability of holding a flood/wind insurance policy or the number mitigation measures installed. Nonetheless, we maintain the hypotheses that the probability of holding insurance will increase with perceived conditional expected loss and the expected frequency of hurricanes.

Past experience with storm events has also been shown to have a significant effect on the decision to insure. Baumann and Sims (1978) found that flood insurance uptake was significantly greater for those individuals who had some experience with past instances of flood events. Browne and Hoyt (2000) show a positive and significant relationship between the total amount of flood insurance damage claims paid in the previous year and demand for flood insurance. Petrolia, Landry, and Coble (2013) and Petrolia et al. (2015) used survey data which allowed them to obtain the number of flood and wind damage events experienced by an individual in the past. They found that the number of past flood events had a significant, positive effect on the probability of holding a flood insurance policy and the number of mitigation measures installed. The result for wind insurance was also positive but not statistically significant. Peacock (2003) utilized more general measures for hurricane experience and hurricane damage and found that, while past damage was insignificant, past experience had a positive and significant effect on the decision to mitigate. We employ an experience measure similar to Peacock (2003) and expect that, as the experience with past damage events increases, the probability of holding insurance and mitigating increases.

Past experience with storm events is closely related to two other important explanatory factors in our model: perceived insurer credibility and perceived eligibility for government disaster assistance. Dixon, MacDonald, and Zissimopoulos (2007) interviewed policyholders, insurers, and other stakeholders in the commercial wind insurance market and found that in the aftermath of Hurricane Katrina, highly publicized litigation and the resulting uncertainty over the language in insurance contracts likely had a significant effect on the commercial and residential wind insurance market. Petrolia, Landry, and Coble (2013) obtained results showing a positive and significant relationship between holding a flood policy and perceived insurer credibility. We hypothesize that increased confidence in insurers will have a positive effect on the probability of holding insurance, but could have a negative effect on mitigation if risk-reducing measures are not appropriately credited in insurance costs.

The charity hazard hypothesis posits that individuals who perceive a high probability of government funded disaster assistance in the wake of a storm are less likely to engage in protective measures (Browne & Hoyt, 2000). Thus, those individuals who believe they are likely to receive disaster assistance will be less likely to purchase flood/wind insurance or mitigate. While the charity hazard hypothesis makes intuitive sense, empirical findings on the subject have yielded mixed results. Botzen and van den Bergh (2012) find evidence in support of the charity hazard hypothesis while the findings of Browne and Hoyt (2000) and Petrolia, Landry, and Coble (2013) refute it. Thus we have no expectation for the sign of the relationship between perceived disaster assistance eligibility and insurance and mitigation.

5. Econometric Model

Petrolia, Landry, and Coble (2013) analyze the same survey data, but only focus on flood insurance. Petrolia et al. (2015) do as well, but they model the decision to purchase wind insurance coverage (over-and-above homeowners' insurance) simultaneously with the decision to mitigate wind risk in a seemingly unrelated regressions (SUR) framework. Petrolia et al. (2015) specify the decision to purchase wind coverage as a probit model and the number of mitigation measures undertaken as a Tobit model bounded between zero and maximum number of mitigation measures observed in the data set (seven). The SUR framework permits contemporaneous correlation of the error terms in each equation, allowing for common unobservable elements that affect each decision. Tobit regression can be used to model count data in situations where the counts are sufficiently high (Fair, 1978; Romer and Snyder, 1994; Campa, 1993), but this specification is less than optimal for discrete, non-negative integer data. Petrolia et al. (2015) elected for the Tobit model in order to simplify the correlation structure and estimation procedure. We implement a three-equation SUR specification, which models the decisions to purchase flood and wind insurance as a bivariate, random-effects probit model and the number of mitigation measures as a Poisson process with a log-normally distributed mean. This approach allows for contemporaneous correlation between the bivariate probit error terms and the log-normally distributed error of the Poisson mean, λ.

5.1. The Poisson Log-Normal Distribution

The standard model for count data is the Poisson regression model, shown in equation 5.1, where the mean parameter of the Poisson distribution is given by $\lambda = \exp(x'\beta)$ to ensure that $\lambda > 0$ (Cameron & Trivedi, 2013). Estimation of Poisson regression assumes equi-dispersion, where the mean and variance of the distribution are equal ($\lambda = E[M] = Var[M]$) (Cameron & Trivedi, 2013).

$$Pr(M = m) = \frac{\lambda^m e^{-\lambda}}{m!} \quad \forall \quad m \in \mathbb{Z}_+ \ where\ \lambda = \exp(x'\beta) \tag{5.1}$$

In practice, the relationship between explanatory variables and the mean parameter is rarely parametrically exact and count data are often over-dispersed ($Var[M] > \lambda$). The most common way to test and account for the presence of over-dispersion is to model the conditional variance as a function of the mean (λ) and a scale parameter (α). This generalization of the Poisson model results in the Negative Binomial regression. [1] While the negative binomial model is the most com-

[1] We ran several Negative Binomial specifications, conducting likelihood ratio tests of the null hypothesis $H_0 : \alpha = 0, \lambda = E[M] = Var[M]$ against the alternative $H_1 : \alpha > 0, Var[M] > \lambda$. We rejected the null in all cases and conclude

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monly used method of dealing with over-dispersed counts, it is not the only approach. This class of models is generally referred to as "Poisson mixture models" and provides varied approaches for dealing with unobserved heterogeneity resulting in over-dispersion (Cameron & Trivedi, 2013).

A natural choice for our context is the Poisson Log-Normal mixture. As defined by Atichison and Ho (1989), the univariate Poisson Log-Normal probability mass function is derived from the Poisson probability mass function in which the mean parameter (λ) is assumed to be log-normally distributed.

$$Pr(M=m)=\int_{R_+}\frac{e^{-\lambda}\lambda^m}{\lambda m!}\frac{e^{-0.5(\log\lambda-\mu)^2}/\sigma^2}{\sigma\sqrt{2\pi}}d\lambda \quad \forall \quad m=0,1,2,\ldots \qquad where \quad \ln(\lambda)\sim N(\mu,\sigma^2) \tag{5.2}$$

Evaluating the integral in equation in 5.2 is difficult because of the restriction that $\lambda > 0$. To remedy this, we introduce the change of variable $\ln(\lambda)=\mu+\sigma\varepsilon$ where $\varepsilon\sim N(0,1)$, with the corresponding Jacobian of transformation, $\lambda\sigma$, resulting in the probability mass function shown in equation 5.3.

$$Pr(M=m)=\int_{-\infty}^{\infty}\frac{e^{-\lambda}\lambda^m}{m!}\frac{e^{-0.5\varepsilon^2}}{\sqrt{2\pi}}d\varepsilon \quad where \quad \lambda=\exp(\mu+\sigma\varepsilon) \tag{5.3}$$

5.2. The Joint Distribution of a Binary Response Variable and a Log-Normal Count Variable

We formulate insurance-purchase decisions on a latent variable specification:

$$f=\begin{cases}1 & \text{if } x_1\beta_1+v>0; \quad f^*>0\\ 0 & \text{if } x_1\beta_1+v\leq 0; \quad f^*\leq 0\end{cases} \tag{5.4}$$

when f is the likelihood of holding flood insurance, and x_1 is vector of characteristics believed to influence insurance choice (equations 4.2). Modeling equation (5.4) using the probit link function, the probability that $f=1$ conditional on some normally distributed random variable z is:

$$Pr(F=1|z)=\Phi\left[\frac{(x_1\beta_1+\rho(z-\mu_z))/\sigma_z}{\sqrt{1-\rho^2}}\right] \quad where \quad z\sim N(\mu_z,\sigma_z) \tag{5.5}$$

that our counts are indeed over-dispersed.

where $\Phi(.)$ represents the standard normal cumulative distribution function, and ρ is the correlation parameter.

Generally, the conditional probability in equation 5.5 cannot be used to represent count data because it is based on Gaussian distribution theory, but when count data are over-dispersed and can be reasonably represented by the Poisson Log-Normal distribution, the resulting conditional probability is:

$$Pr(F=1|\log\lambda) = \Phi\left[\frac{(x_1\beta_1+\rho(\ln(\lambda)-\mu))/\sigma}{\sqrt{1-\rho^2}}\right] \quad where \quad ln(\lambda) \sim N(\mu,\sigma^2) \tag{5.6}$$

To obtain the joint distribution of a binary response variable and a count variable we simply multiply the marginal and conditional distributions together and the resulting distribution takes the form:

$$\begin{aligned} Pr(F=1,M=m) = \int_{-\infty}^{\infty} \Phi\left[\frac{(x_1\beta_1+\rho\varepsilon)/\sigma}{\sqrt{1-\rho^2}}\right] \frac{e^{-\lambda}\lambda^m}{m!}\frac{e^{-0.5\varepsilon^2}}{\sqrt{2\pi}}\,d\varepsilon \\ where \quad \lambda = \exp(\mu+\sigma\varepsilon). \end{aligned} \tag{5.7}$$

5.3. The Bivariate Random-Effects Probit Model

We define a second binary response variable, w to construct the bivariate random-effects probit model for flood and wind insurance in equation 5.8.

$$\begin{aligned} Pr(F=1,W=1) = \int_{-\infty}^{\infty} \Phi(x_1\beta_1+\theta\eta)\Phi(x_2\beta_2+\theta\eta)\frac{e^{-0.5\eta^2}}{\sqrt{2\pi}}\,d\eta \\ where \quad \eta \sim N(0,1) \end{aligned} \tag{5.8}$$

The Gaussian error η is distributed standard normal, and θ permits correlation among flood and wind purchase decisions. For the case in which $\theta = 0$, the bivariate random-effects probit model maps directly to the ordinary bivariate probit model. When $\theta > 0$, equation (5.8) is equivalent to the bivariate random effects probit model, but computationally simpler to estimate, only requiring numerical integration across the domain of η. To obtain the population averaged parameter estimates (β_{Pop}) from the random-effects model we convert the individual estimates from the random effects model (β_{RE}) using the formula:

$$\beta_{Pop} = \frac{\beta_{RE}}{\sqrt{1+\theta^2}} \tag{5.9}$$

where the correlation between the two probit errors is given by

$$\rho_{f,w} = \frac{\theta^2}{1+\theta^2} \tag{5.10}$$

5.4. The Joint Distribution of Two Binary Response Variables and a Log-Normal Count Variable

We then combine the results obtained from the joint distribution of a binary response variable and a Poisson log-normal count variable with the bivariate random-effects probit model, resulting in the joint distribution in equation 5.11.

$$\iint_{-\infty}^{\infty} \Phi\left(\frac{x_1\beta_1+\theta\eta+\rho_1\varepsilon}{\sqrt{1-\rho_1^2}}\right)\Phi\left(\frac{x_2\beta_2+\theta\eta+\rho_2\varepsilon}{\sqrt{1-\rho_2^2}}\right)\frac{e^{-\lambda}\lambda^m}{m!}\frac{e^{-0.5(\eta^2+\varepsilon^2)}}{2\pi}\,d\eta\,d\varepsilon \tag{5.11}$$
$$where \quad \lambda = \exp(\mu+\sigma\varepsilon), \mu = x_3\beta_3,\ \eta \sim N(0,1)$$

In order to estimate the parameters of the joint model, we employ Gaussian integration based on Legendre polynomials using 32^2 abscissas (Abramowitz & Stegun, 1972, Table 25.4).

6. Results

Results from the joint model in equation 5.11 are given in table VI. Average marginal effects are given for each parameter in the column right of the parameter estimate. Consistent with the results of Petrolia et al. (2015), estimates for the joint correlation structure of the model support the hypothesis that the decisions to purchase flood or wind insurance and the decision to mitigate hurricane risk are interrelated. We find a significant, positive correlation between the error terms of the flood insurance and mitigation equations ($\rho_{f,m} = 0.2173$) as well as the wind insurance and mitigation equations ($\rho_{w,m} = 0.6556$). While these correlations confirm that a simultaneous, rather than independent, estimation framework is superior, the estimated population averaged correlation between the disturbance terms of the two insurance models was positive but insignificant ($\rho_{f,w} = 0.1327$). This indicates no gain in efficiency by allowing correlation between the flood policy and wind policy errors and that the model shown in equation 5.7 may yield more straightforward results when applied to the two bivariate responses individually. This result will be further addressed in the discussion and conclusion sections.

Table VI: Mixed-Process Regression Results

Parameter	FloodPolicy	AME	WindPolicy	AME	Migitation	AME	Mitigation Elasticitiy
Risk Aver., Gain	0.0139	0.0032	-0.043	0.0022	-0.0005	-0.0009	-0.0014
	(0.0445)		(0.0430)		(0.0242)		
Risk Aver., Loss	0.0803	0.0185	-0.0441	0.0011	-0.0277	-0.0502	-0.0814
	(0.0496)		(0.0441)		(0.0248)		
Policy Reqd.	1.8579***	0.4289					
	(0.2398)						
Past Damage	0.1441*	0.0333	-0.0928**	0.0412	0.1366***	0.2479	0.0640
	(0.0858)		(0.0928)		(0.0491)		
Eligibility	0.2795**	0.0645	-0.1418	-0.0144	0.032	0.0580	0.0187
	(0.1375)		(0.1418)		(0.0761)		
Credibility	0.1666	0.0385	-0.1477***	0.1074	0.1628**	0.2955	0.1108
	(0.1409)		(0.1477)		(0.0829)		
Exp. Damage	0.0613*	0.0141	-0.0287	-0.0048			
	(0.0318)		(0.0287)				
Sqrt(Exp. Hurr)	0.0996**	0.0230	-0.045	-0.0059	0.0337	0.0611	0.0730
	(0.0486)		(0.0450)		(0.0246)		
Km	-0.0083**	-0.0019	-0.0033	-0.0009	-0.0053**	-0.0097	-0.0830
	(0.0038)		(0.0033)		(0.0023)		
CRS	-0.1005*	-0.0232					
	(0.0569)						
Florida x CRS	0.1327	0.0306					
	(0.0962)						
Mortgage			-0.1463***	0.0946			
			(0.1463)				
SFHA	-0.3808	-0.0879					
	(0.2954)						
Mort x SFHA	0.9108***	0.2102					
	(0.3063)						
X-Zone	-0.3871**	-0.0894					
	(0.1767)						
Mobile Home	-1.2367**	-0.2855					
	(0.5936)						
Property Age			-0.0033	-0.0012	-0.0083***	-0.0151	-0.2390
			(0.0033)		(0.0026)		
Condo			-0.1959***	-0.1145	-0.4566***	-0.8286	-0.0525
			(0.1959)		(0.1314)		
Gulf Years	-0.0049	-0.0011					
	(0.0037)						
Education	0.0938**	0.0217					
	(0.0427)						
White			-0.1604**	0.0885			
			(0.1604)				
Income	0.0601***	0.0139	-0.0186***	0.0151	0.0147	0.0267	0.1810
	(0.0196)		(0.0186)		(0.0101)		
Employed			-0.136	-0.0395			
			(0.1360)				
Kids	-0.249*	-0.0575	-0.1526***	-0.1202	-0.2591***	-0.4702	-0.0685
	(0.1452)		(0.1526)		(0.0884)		
Florida	-1.5437*	-0.3563	-0.4259	-0.1480	0.3004*	0.5452	0.2036
	(0.7997)		(0.4259)		(0.1683)		
Texas	0.3682	0.0850	-0.4412	-0.1159	-0.399**	-0.7241	-0.0989
	(0.3406)		(0.4412)		(0.1945)		
Louisiana	-0.5701	-0.1316	-0.5196*	-0.2244	-0.165	-0.2994	-0.0052
	(0.5246)		(0.5196)		(0.2750)		
Wind Excluded					0.2262**	0.4104	0.0675
					(0.1007)		
Intercept	-1.3345*		-0.5999		0.3021		
	(0.7554)		(0.5999)		(0.2858)		

Variance, Correlation Structure

σ^2	0.245***	$\rho_{f,w}$	0.1327
	(0.0494)		(0.1074)
θ	0.3911**	$\rho_{f,m}$	0.2173*
	(0.1825)		(0.1153)
		$\rho_{w,m}$	0.6556***
Log-Likelihood	-1720.6		(0.1169)

*Robust standard errors in parenthesis * $p < .10$, ** $p < .05$, *** $p < .01$*

First we address the results from our measures of risk aversion, risk perception, and household wealth which are included in all three equations. In contrast with previous findings (Kachelmeier & Shehata, 1992; Holt & Laury, 2002; Petrolia, Landry & Coble, 2013; Petrolia et al., 2015) risk aversion over the loss domain was found to have no significant effect on the decision to purchase insurance or install risk mitigation measures. The estimated coefficients for risk aversion over both gains and losses were positive with respect to flood and wind insurance, negative with respect to mitigation, and similar in magnitude to those estimated previously by Petrolia, Landry, & Coble (2013) and Petrolia et al. (2015). Turning to risk perceptions, we find that respondents harboring a higher expectation of damage in the event of a Category 3 storm were significantly more likely to hold a flood insurance policy. A one unit increase in expectation of damage increases the probability of holding flood insurance by only 1.4%. This result did not hold for wind insurance.[1] The expected frequency of future storms was found to have a significant effect on the probability of holding flood insurance, but not wind insurance or mitigation. A one-unit increase in the number of expected storms over the next 50-years increases the likelihood of holding flood insurance by 2.3%. We find that the number of experiences with past wind/flood damage events has a significant, positive effect on the probability of holding flood or wind insurance as well as the number of mitigation measures installed, a result echoing those found by Botzen, Aerts, and van den Bergh (2009), Petrolia, Landry, and Coble (2013), and Petrolia et al. (2015). Each additional damage event increases the probability of holding flood and wind insurance by 3% and 25% respectively, and results in an additional 0.04 mitigation measures installed.

Insurer credibility was found to have a significant and positive effect on the probability of holding a wind insurance policy and the number of mitigation measures installed, but had no significant effect on holding a flood insurance policy. A one unit increase in credibility increased the probability of holding wind insurance by 10.7% and results in an additional 0.3 mitigation measures installed. We find no evidence in support of the charity hazard hypothesis in our data. While perceived eligibility for government disaster assistance was not statistically significant in the wind and mitigation equations, those who perceived a high likelihood of disaster assistance were significantly more likely to hold a flood insurance policy. A one unit increase in perceived eligibility increased the probability of holding a flood policy by 6.5% on average. Consistent with the previously published findings (Baumann & Sims, 1978; Browne & Hoyt, 2000; Kunreuther, 2006; Landry & Jahan-Parvar, 2011) we find positive income effects across all three equations, with marginal effects of 1.4% for flood insurance, 1.5% for wind insurance, and 2.7% for mitigation. The following sections address the remaining covariates equation-by-equation.

6.1. Flood Insurance Model

Results from the flood model show that individuals who were required to hold flood insurance (presumably those individuals with federally insured mortgages inside SFHAs) were significantly

[1] Expectation of damage was excluded from the mitigation equation to avoid potential endogeneity problems: an individual who mitigates may have a lessened expectation of damage or vice versa

more likely to actually hold flood insurance, increasing the probability of an insurance purchase by almost 43%. Further, the interaction term for those households with active mortgages inside of SFHAs was statistically significant and positive. Those individuals with active mortgages in a SFHA were 21% more likely to purchase insurance. These effects, also found by Petrolia, Landry, and Coble (2013) and Petrolia et al. (2015), were robust at the 1% level of statistical significance and had exhibited some of the strongest effects on the probability of holding flood insurance. These results provide evidence in support of the effectiveness of mandatory purchase requirements for the 100-year flood plain. SFHA status alone, however, did not significantly affect the probability of holding flood insurance.

As expected, households farther away from the nearest shoreline were found to be less likely to hold flood insurance, consistent with Kriesel and Landry (2004), Landry and Jahan-Parvar (2011), and Petrolia, Landry, and Coble (2013). In line with this result, households located in areas outside the 500-year flood plain (estimated probability of flood annually $< .02\%$) were significantly less likely to purchase flood insurance. Florida residency significantly reduced the probability of holding flood insurance by a significant margin of almost 36%. This surprising result, given that Florida has the highest number of total flood policies, may be partially explained by flood mitigation efforts at the municipal and state levels as measured by the CRS. The CRS coefficient was negative and statistically significant as expected, indicating that uptake of flood insurance is greater in NFIP communities that are engaged in mitigation efforts. However, when CRS is interacted with the Florida residence dummy, the result becomes insignificant and the sign is reversed. This result, also obtained by Petrolia, Landry, and Coble (2013), may indicate that homeowners in Florida view community level mitigation projects as a substitute for traditional flood insurance.

Structure type also appears to play a significant role in the decision to insure against flooding. Those individuals who resided in mobile homes were significantly less likely to hold flood insurance than those in houses or condominiums. Demographic variables for education level and the presence of children in the home were also found to have significant effects, each positive. The number of years a respondent had lived on the Gulf Coast had no significant effect.

6.2. Wind Insurance Model

Here we evaluate the results from the parameters unique to the wind insurance equation. The presence of a mortgage contract was found to increase the probability of holding wind coverage despite the fact that no mandatory purchase requirements exist for wind peril (Petrolia et al. 2015). An active mortgage contract increased the probability of holding wind insurance by almost 10%. Those respondents living in condominiums were less likely to hold wind insurance policies than those in houses or mobile homes. Regarding demographics, white households were significantly more likely to hold a wind policy than non-whites (by 9%), and those households with children in the home were significantly less likely to have wind insurance (by 12%). Wind insurance uptake in Louisiana was found to be significantly less than other states in our data. On average, Louisiana residency decreased the probability of purchase by 22%. The distance to the nearest shoreline, age of the property, and employment status all had insignificant effects.

6.3. Mitigation Model

Finally, we look to the results from the mitigation model. Distance to the nearest shoreline was found to have a negative and significant effect on the number of mitigation measures installed. This effect is, however, extremely small, with an average marginal effect is only -0.01 mitigation measures for each additional kilometer from shore. Structural characteristics play a role in the mitigation decision. We find that households in condominiums and those living in older structures install significantly fewer mitigation measures. Additionally, we find that residents of Florida install significantly more mitigation measures, while residents of Texas install significantly fewer. Contrary to the findings of Carson, McCullogh, and Pooser (2013), we find a significant and negative effect of the presence of children in the home.

The coefficient on our indicator for location inside an area where wind peril is specifically excluded from homeowners policies is also statistically significant and positive, meaning that after controlling for other relevant explanatory factors, those individuals who have no wind coverage in their homeowners policy install more mitigation measures than those who are covered. This finding runs counter to Petrolia et al. (2015) but is in line with the findings of Carson, McCullogh, and Pooser (2013) who found that individuals located in the "Wind Borne Debris Region (WBDR)"[2] where wind coverage was unavailable, were generally more likely to engage in mitigation and spent more money on mitigation activities.

7. Discussion

Modeling household choice in a contemporaneous regressions framework, we find statistical evidence of correlated errors among hazard insurance and mitigation decisions. To model simultaneous insurance and mitigation decisions jointly, we introduce a random effect in a bivariate probit model and allow for this effect to be correlated with a log-normally distributed error term from a hazard mitigation count data model. We find the decisions to purchase flood insurance and wind insurance are each positively correlated with the extent of hazard mitigation, while the correla-

[2] FEMA defines the WBDR as Portions of hurricane-prone regions that are within 1 mile of the coastal mean high-water line where the basic wind speed is 110 mph (49 m/s) or greater; or portions of the hurricane-prone region where the basic wind speed is equal to or greater than 120 mph (54 m/s); or Hawaii." (FEMA, 2009)

tion among flood and wind insurance holdings is not statistically significant. Our econometric approach is a parsimonious and tractable way to permit correlation among insurance and mitigation decisions. Marginal effects are relatively simple functions of the estimated model and their standard errors are calculated by the delta method. Our approach has general applicability to any analysis that wishes to link binary choice models to one or more count data models?as long as the counts are over-dispersed (which is a fairly common feature of count data).

Our expectations were that this framework would create efficiency gains that would provide substantial insight into factors that influence hazard insurance and mitigation decisions. While we do find evidence of reasonably good fit (in terms of likelihood ratio tests and information criteria), support for the effects of structural parameters, like risk preferences and risk perceptions, is mixed. In a break from previous results, we found no significant relationship between an individual's experimentally-derived risk preference measures and their decision to insure or mitigate. Since our model could be viewed as a more complete and flexible formulation of insurance and mitigation decisions (compared to previous work with the same dataset–Petrolia, Landry, and Coble (2013) and Petrolia, et al. (2015)), this result calls into question the external validity of experimentally-derived risk preference measures in application to actual insurance and mitigation decisions. Our findings, however, could be related to the magnitude of stakes, the context of the experiment, subject confusion regarding the experiment instructions, or some other artifact of the survey instrument and experiment.

We do find evidence that individual perceptions of risk have an influence on insurance decisions, but only for flood insurance. The magnitude of the effects seem reasonable; a one unit increase in the expected number of large coastal storms (Cat 3 or greater) in the next 50 years increases the likelihood of holding flood insurance by 2.3%, and a one percent increase in expected structural damage increases flood insurance likelihood by 1.4%. Risk perception measures, however, have no detectible effect on wind insurance holdings or hazard mitigation. Our survey instrument measures offer an intuitive way to approximate risk perceptions, but there is a clear need for additional research on potential instruments and internal and external validity. A more simplistic measure of risk perception based on experience (the number of past occurrences associated with disaster damage) had a much more robust influence on insurance and mitigation choices (increasing the probabilities of flood and wind insurance by 3.3% and 4.1%, respectively, and mitigation count by 0.6 measures).

Also relevant to the discussion of risk perceptions are beliefs about the credibility of insurance providers in honoring valid damage claims and the likelihood of disaster assistance. Each of these aspects were measured using a Likert-scale, but converted to a binary indicator for purposes of regression analysis. The credibility of insurance providers has no influence on flood insurance holdings (perhaps due to the backing of the Federal government), but has positive effects on wind insurance (increasing likelihood by 10%) and hazard mitigation (an additional 0.11 measures).

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While the positive effect on wind insurance is expected, the effect on mitigation is less intuitive. This result, too, could be related to overall salience of risk, suggesting that general measures of hazard awareness (vis-a-vis other day-to-day concerns) may be useful frames to qualify more detailed measures of risk perception and beliefs about the aftermath of large-scale disasters.

Consistent with previous analyses of these data, we find an unexpected positive relationship between beliefs about the likelihood of being eligible for disaster assistance and flood insurance holdings (with no effect on wind insurance or mitigation measures). This result may reflect salience of flood risk and awareness of disaster assistance programs, rather than expectations of receiving assistance. Additional research into the charity hazard hypothesis, especially as related to hurricane risk, is warranted. Qualitative analysis of individual experiences, attitudes, perceptions, and beliefs about government disaster assistance could provide useful insight into the potential for charity hazard and would likely aid in designing reliable quantitative measures of expectations of assistance.

The effect of a mortgage contract had consistently large effects on insurance holdings. Those located in a SFHA with a mortgage contract were 21% more likely to have flood insurance (the largest marginal effect of all covariates), and the likelihood of having wind insurance coverage was 9.5% greater for those with a mortgage (the second largest effect in the wind equation). These results suggest that legal requirements and the leverage of lending institutions could be some of the most important determinants of insurance coverage. Consistent with previous literature, household income had a positive effect in the insurance equations (Baumann and Sims, 1978; Browne & Hoyt, 2000; Kunreuther, 2006; Landry & Jahan-Parvar, 2011; Petrolia, Landry, and Coble, 2013; Petrolia et al., 2015), but no effect on mitigation, whereas those living in a mobile home were less likely to have flood insurance, and those living in a condo were less likely to have wind coverage.

Those households for which wind insurance is excluded on their homeowners' policy undertook about 0.4 more mitigation measures, on average. This effect is among the largest determinants of the extent of mitigation (along with residence in a condominium and presence of kids in the household, each of which was negative). Analysis of mitigation, however, could be improved upon. In our survey, respondents were asked only to indicate if the mitigation measures were installed on their home and were not asked if they themselves elected to install the measures. Thus, it is entirely possible that some mitigation measures were already installed on the home when the survey respondent purchased it or the respondent included both pre-existing and onwer-installed mitigation measures. While we model this choice as a decision by the homeowner, a conservative interpretation of the results seems prudent. Also important to note is the lack of alternative forms of flood mitigation in the survey. While elevation of the home is the most effective method of mitigation, other mitigation activities such as dry flood-proofing (sealing structures, waterproof membranes), wet flood-proofing (elevation of key household appliances electrical panels, water heaters, HVAC, washers/dryers, etc.), and levees/floodwalls were not included in the mitigation count (Eckroth, 1999). Future research should explore other ways to measure and model disaster mitigation, perhaps using indexes.

8. Conclusions

This paper presents results from a household-level analysis of decisions to insure against or mitigate hurricane risk along the United States Gulf Coast and Florida Atlantic Coast. Our analysis represents the only study to consider wind insurance, flood insurance, and mitigation activities contemporaneously, while including information on risk preferences, risk perceptions, objective measures of hurricane risk, and demographics. We find evidence that risk perceptions and other household factors have some influence on storm risk management, but the strongest effects tend to be related to mandatory insurance requirements associated with location in high-hazard areas. This suggests that behavioral factors, such as optimism bias, ambiguity, or under-weighting of low probability events may be at play. Experience with storm-related damages has a consistent positive effect on all forms of risk management we analyze, but previous research has shown that the role of experience in risk assessment can decay over time (e.g. via the availability heuristic (Bin and Landry 2013; Atreya, Ferreria, and Kriesel 2013)). Experimentally-derived measures of risk preference over both the loss and gain domains were not statistically significant explanatory factors in our analysis, and expectations of eligibility for disaster assistance had an unexpected positive sign on risk management decisions (indicating no support for the charity hazard hypothesis).

Future research should seek to build upon these findings by exploring other ways to measure risk preferences (perhaps using larger stakes, introducing additional real-world context, or amending elicitation instruments to improve individual understanding). Our measures of risk perception include expected storm frequency and proportion of home damage due to a storm. While intuitive, future research could seek to formulate and test different measures. Similarly, expectations of disaster assistance and the possibility of charity hazard deserves more exploration. Innovative survey designs based on insights derived from qualitative research with coastal households should provide a solid foundation for future research.

In addition, future research should seek to explicitly incorporate insurance prices, subsidy levels, and other incentives for hazard mitigation that may exist at the state or local level. Flood insurance rates are based on flood zone, housing structure attributes, and community factors (e.g. CRS scores); detailed data are required to estimate flood insurance rates, and since rates are based on risk factors and set at the federal level, econometric identification of price effects can be challenging (though time-series data with differences in rates may be helpful). Wind insurance rates vary by state, but are based on diverse calculations that many insurance providers consider proprietary. Survey-based methods can potentially be used to measure wind insurance costs, with

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imputation and bootstrapping employed to estimate the likely price of those that do not hold wind insurance and regression standard errors, respectively. The costs of mitigation vary greatly, but prices of some measures may be approximated, though this would necessitate a more disaggregated approach.

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