RIDERS ON THE STORM:
HURRICANE RISK AND THE COASTAL INSURANCE DECISION

by

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(Under the Direction of Craig E. Landry)

Abstract

This paper utilizes cross-sectional, household-level, survey data combined with data on subjective risk perceptions and experimentally derived risk preferences to analyze the decision to insure against losses resulting from hurricanes. Our sample encompasses 670 individuals in five states of the United States Gulf Coast Region (Texas, Louisiana, Mississippi, Alabama, and Florida). This study represents one of the few papers to examine wind insurance empirically and the only study to examine flood insurance, wind insurance, and mitigation behavior simultaneously in the coastal context. Because these decisions are closely related, we employ a contemporaneous, mixed-process regression which allows for correlated error terms across a random-effects bivariate probit model (flood/wind insurance) and a Poisson Log-Normal count model (mitigation). Results indicate positive and statistically significant correlations between the errors of the insurance and mitigation models but no significant correlation between the disturbance terms of the two insurance models, conditioned on the covariates.

Index words: Hurricane, Flood, Insurance, National Flood Insurance Program, Wind Insurance Pools, Hazard Mitigation, Decision Under Risk, Mixed-Process Regression, Poisson Log-Normal

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Chapter 1

Introduction

Since the turn of the 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 tropical cyclones are caused by storm surge (Perry 2000; Meyer et al., 2012; King, 2012; Kousky, Michel-Kerjan, & Raschky, 2013; Michel-Kerjan and Kousky, 2015). Major flooding events due to tropical cyclones have occurred recently in the Northeastern and Southeastern United States. Hurricane Sandy decimated areas of New England in 2012 and a severe noreaster combined with Hurricane Joaquin to the south caused major flooding in North and South Carolina in 2015 (Santorelli 2015). Preliminary estimates of the damages caused by these two events alone exceed $60 billion. Further, the thirty most costly hurricanes making landfall in 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

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

Forges, & Kunreuther, 2012). Increased precipitation resulting from a more erratic climate and rising sea levels bringing storm surge further inland may increase the probability and magnitude of major flooding incidents in coastal areas. In 2015 and 2016, the United States experienced the strongest El Niño event of past 15 years that contributed to extreme droughts and wildfires on West Coast and heavy rains along the Eastern Seaboard. (National Weather Service Climate Prediction Center 2015). The 2015-2016 El Niño has also been a driving force behind increased CO_2 levels in the atmosphere (Betts et al., 2016). While positive correlation between El Niño events and CO_2 levels has been documented in the past, the 2015-2016 El Niño coincided with the first time mean CO_2 levels in the atmosphere were expected to rise above the symbolic threshold of 400 ppm for the remainder of the year (Betts et al., 2016; Kahn, 2016).[2] This threshold is symbolic because at no point in human history has CO_2 concentration in the atmosphere been this high. The NOAA researchers predict that while CO_2 measurements may fall back below the this threshold locally, the planet as a whole will remain above the 400 ppm threshold for the rest of our lifetimes (Betts et al., 2016).

Further exacerbating the problem is the general trend of population growth 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 number of housing units in coastal areas more than doubled from 16.1 million units in 1960 to 36.3 million in 2008 (Wilson and Fischetti, 2010).[3] An increasing number of structures coupled with more densely populated coastlines will cause greater correlation among losses if a disaster event occurs and calls in to question the insurability

[2]As measured at the NOAA Earth System Research Laboratory, Mauna Loa, and the NOAA South Pole Observatory

[3]Coastal counties are defined by NOAA if "at least 15% of the county's total land area is located within the Nation's coastal watershed" or "if 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.

of these risks if current trends continue. Kousky (2011) specifically notes that the increase in coastal population has resulted in increased exposure to wind peril from hurricanes and a corresponding decrease in 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 the need for protective and adaptive measures to deal with the risks they pose is clear. 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 $2.51 trillion in 1988). Insurance firm AIR Worldwide estimated the total value of insured property at $7.2 trillion in 2004 and updated their estimate to $10.6 trillion in 2012 (AIR Worldwide, 2005, 2012). Nordhaus (2006) estimates "the total value of capital in areas close to sea level at a more conservative $1.46 trillion.[4] What is clear from these estimates, the general trend towards coastal population growth, and the available literature on flood and wind insurance is that both the level of capital in coastal areas and the cost of hurricanes are increasing. Insurance is a natural tool for pooling and distributing risk but has been difficult to apply in the case of hurricanes and floods. In the past, the private insurance markets have failed to provide efficient levels of coverage for flood and wind peril and thus governments have stepped in to ensure households have access to coverage for these risks. Even after government intervention in the insurance markets, however, take up rates for flood insurance remain low.

Building on the work of Kriesel and Landry (2004), Petrolia, Landry, and Coble (2013), and Petrolia et al. (2015), this paper will use household-level, cross-sectional survey data combined with experimentally derived risk preference data to examine the decision to invest in flood and wind insurance contemporaneously with the decision to mitigate hurricane risk by individuals living in the Gulf Coast region of the United States. We will attempt to

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

address the question of what factors hold significant influence over an individual's decision to engage in these protective measures to safeguard property from hurricane risk and how the decisions are interrelated.

This paper will make two important contributions to the literature. First, this study represents the only analysis undertaken which addresses flood, wind, and mitigation decisions simultaneously in the coastal context using household-level data on both individual risk perceptions and risk preferences. Second, our analysis will extend and improve upon the work of Petrolia et al. (2015) through the use of an improved estimation procedure that fully takes into account the non-negative, integer valued count data on the number of mitigation measures taken by an individual.

Chapter 2

Background

2.1 Flood Risk and Flood Insurance in the United States

2.1.1 History of the National Flood Insurance Program

Since the first offering of coverage for flood peril, the private market for flood insurance has faced numerous problems and has generally failed to provide efficient levels of coverage. Major issues which 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 take-up 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 catastrophic risk as having two main facets. 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. That is to say, if a hurricane strikes a major population center on the Gulf Coast, many homes in the same area will all be damaged at once. Correlation of losses in space 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.

One of the first serious efforts to correct for failures in the private market for flood insurance was the Federal Flood Insurance Act of 1956 that was passed based on recommendations from a 1956 Senate Banking and Currency Committee report calling for the creation of a "flood insurance administrator" and for premium subsidies with the goal of "providing insurance protection at reasonable costs to achieve marketability." The 1956 program was experimental in nature and was designed to determine if it was possible for flood insurance to be provided by private insurers but was never implemented due to a lack of congressional appropriations and interest on the part of private insurers (Anderson, 1974; Michel-Kerjan, 2010). Following a series of large tropical cyclones ending in 1965 with Hurricane Betsy, Congress passed the Southeast Hurricane Disaster Relief act that in addition to proving federal disaster aid, required the Secretary of the Department of Housing and Urban Development to "undertake an immediate study of alternative programs which could be established to help provide financial assistance to those suffering property losses and other natural disasters, including alternative methods of federal disaster insurance" (DHS, 2002).

Drawing on the recommendations of the study undertaken by the Department of Housing, 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.

2.1.2 Structure of the NFIP

In order to become eligible for the NFIP, flood-prone communities are required to implement land-use measures such as building codes and restrictions on locations acceptable to development. These measures are designed to minimize overall flood risk and discourage over-development/poor use of flood prone areas known as "Special Flood Hazard Areas" (SFHAs).[1] The federal government, acting through the Federal Emergency Management Agency (FEMA), is responsible for creating flood risk maps and pricing the associated actuarial rates (compiled in Flood Insurance Rate Maps or FIRMs), setting deductible and coverage limits, managing the Community Rating System (rating system that incentivizes local communities to engage in mitigation activities in exchange for reduced premiums) and determining which properties are eligible for subsidized rates.[2] In addition to these responsibilities, the federal government serves as the sole underwriter for all policies written in the program and thus assumes all risk. Approximately 90 private insurance companies, initially through the National Flood Insurers Association and after 1983 through the "Write-Your-Own" (WYO) program, write and manage almost 95% of all policies and bear no risk (Anderson, 1974; Pompe & Rhinehart, 2008; Michel-Kerjan, 2010; Michel-Kerjan & Kousky, 2010; Petrolia, Landry, & Coble, 2013). In exchange for a commission which averages around 15% of paid premiums the NFIP policies are advertised and marketed by the private insurers. On top of commission, the WYO firms are paid a 15% "commission allowance," paid even if the insurance agent does not collect a commission. Additional payments to private firms are made in two cases: 2% on top of commission if the selling agent achieves 5% net growth in annual policies sold, and 3.3% on top of commission for claims adjustment expenses such as legal fees (Michel-Kerjan, 2010).

[1] SFHAs, or 100-year floodplains, are defined as areas in which there is a 1% chance of flood in any given year

[2] Properties eligible for subsidies include those which were built prior to the establishment of Flood Insurance Rate Maps for a given area and are referred to as "Pre-FIRM" properties.

The Write-Your-Own program is designed to be mutually beneficial to both the NFIP and the insurance intermediaries, but some have questioned whether this is actually the case. A 2009 report by the US GAO stated that "FEMA does not have the information it needs to determine whether its payments to Write-Your-Owns are reasonable" (GAO, 2009; Michel-Kerjan, 2010). While the program's intent was to harness both the government's ability to incentivize mitigation and control land use in concert with the marketing and information distribution capacity of private insurers, the NFIP has consistently faced problems which call into question both its effectiveness in this aim and financial sustainability.

2.1.3 Lack of Participation

A chronic problem with the NFIP observed to the present day is the low participation rate of residential homeowners (Landry & Jahan-Parvar, 2011). In the years following the 1968 law, purchase of flood insurance was not legally required of homeowners in flood prone areas and very few communities became eligible for insurance (Anderson, 1974). The landfall of Hurricane Agnes in 1972 laid bare this fact and was a major impetus for the passage of the Flood Disaster Protection Act of 1973. This act required all mortgages written by federally insured lenders for property purchased or constructed in SFHAs to carry a flood insurance policy and mandated participation in the NFIP as a prerequisite for certain classes of federal disaster aid (Kriesel & Landry, 2004; Michel-Kerjan, 2010; Landry & Jahan-Parvar, 2011).

While the 1973 law did lead to a jump in policies-in-force following their passage, it was widely recognized after large flooding events in Texas in 1989 and Hurricane Andrew in 1992 that insurance purchase requirements (as well as building codes for SFHAs) were not being rigorously enforced (Kunreuther, 1996; Michel-Kerjan, 2010). The lack of enforcement stemmed from an assumption on the part of lawmakers that lenders, acting in their own interest, would ensure policies were purchased when a mortgage was issued *and* were maintained across the life of mortgages. While homeowners in SFHAs were still required

to purchase flood insurance by law, lenders only made sure that homeowners had flood insurance at the outset when they purchased their home. Thus, many homeowners who did not experience losses or sold/transferred their mortgages let policies lapse.[3] In an effort to correct this, purchase requirements were strengthened again in 1994 with the passage of the National Flood Insurance Reform Act which instituted monetary penalties for lenders who did not comport with the legislation as well as incentives to communities for flood mitigation and management planning (Pompe & Rhinehart, 2008; Michel-Kerjan & Kousky, 2010).

2.1.4 Financial Status

Over the life of the program, the NFIP has accrued a considerable deficit, leading many to question the financial sustainability of the program. During the period from the program's inception in 1968 to year end 2004, the NFIP's cumulative deficit stood at $1.5 billion (Michel-Kerjan, 2010). In 2005, the landfall of Hurricane Katrina resulted in over $16 billion in flood insurance claims alone and subsequent claims stemming from Hurricane Ike and the Midwest Floods of 2008 of forced the program to borrow close to $20 billion from the US Treasury to cover losses from 2005 to 2011. Since 1969, the NFIP has borrowed over $23 billion and repaid only $6 billion, leaving it with a cumulative debt of $17.75 billion in 2011 (King, 2012). As Michel-Kerjan (2010) and King (2012) point out, congress did not endow the NFIP with initial reserves of capital and it thus operates outside the traditional definition of financial solvency for an insurer. Generally, commercial insurers are legally required to retain a capital surplus to allow them to sell policies. Practically, this means that NFIP was *not* set up to deal with exceptionally extreme events like Hurricane Katrina.

Though catastrophic losses and a lack of initial capital endowment account for some of NFIPs financial woes, actuarially unsound premiums, repetitive loss properties, and large

[3] A 1990 GAO report cited by Kunreuther, 1996 showed that of the households required to purchase flood insurance who experienced losses in the 1989 Texas floods, 79% did not have insurance

sums paid to private insurers through the Write-Your-Own play a large role as well. The NFIP faces two main issues when confronting the problem of less than actuarial rates: pre-FIRM properties built prior to January 1, 1974 pay actuarially favorable (subsidized) rates and outdated flood risk maps mean that "actuarial" rates likely do not reflect the true probability of flood risk in a given area. Additionally, Kousky and Michel-Kerjan (2010) find that both the absolute magnitude of claims and the ratio of claims as a percentage of total structure value are higher for Pre-FIRM properties across the board. Further compounding the high costs associated with pre-FIRM properties is the fact that approximately 90% of all Repetitive Loss Properties (RLPs) are pre-FIRM structures as well, meaning that the structures incurring the highest number losses are paying the lowest rates.[4] Though RLPs account for only 1% of total property insured by the NFIP, they are responsible for over a third of claims paid out (King, 2012). Finally, on top of all of these costs, are the payments made to the 90 private insurance firms participating in the Write-Your-Own program. These payments represent approximately one-third of all collected premiums and Michel-Kerjan (2010) estimates this as equivalent to a 50% loading cost for no added risk to the private insurer. For comparison, private firms participating in the Federal Crop Insurance Program are paid almost half this, taking only 24.5% of unsubsidized premiums (Skees, 2001). Recent reforms have taken aim at trying to improve the financial status of the program, but questions still remain about the long term sustainability of the program.[5] The fact is that the the NFIP's solvency will remain in question because it maintains no contingency financing to deal

[4]RLPs are defined by FEMA as those experiencing $\geq$ 2 losses in excess of \$1,000 in a 10-year span. Severe Repetitive Loss Properties are defined as those experiencing $\geq$ 4 losses of at least \$5000 or if the total amount of claims exceeds \$20,000, or $\geq$ 2 separate claims payments together exceed the total current value of the structure (FEMA, 2005, 2013).

[5]The Flood Insurance Reform Act of 2004 (introduced as the "Two Floods and You're Out of the Taxpayers' Pocket Act") was passed with the goal of reducing the impact of repetitive loss properties (Pub.L. 108264). The Biggert-Waters Flood Insurance Reform Act of 2012 was passed with the intention of making NFIP's rates actuarially sound through 25% increases every year for four years. Another recent law, The Homeowner Flood Insurance Affordability Act of 2013, was passed with the intention of delaying, and in some cases, undoing reforms passed in Bigger-Waters (Pub.L. 11389).

with catastrophic events and thus collected premiums will not cover claims and operating costs in the long term.

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 insurers do not 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 these high risk areas (Petrolia, Hwang, Landry, & Coble, 2015).[6] Separate "wind-only" insurance in the United States can come in several forms: Fair Access to Insurance Requirements (FAIR) Plans[7], reinsurance funds, state wind pools (commonly known as "beach plans"), 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, and Texas.

2.2.1 Structure of State Wind Insurance Programs

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 to unsustainable levels that in turn led to political uproar. 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 (Hartwig & Wilkinson, 2014). While the intention may have been to

[6]The market for policies written by state run programs is referred to as the "residual" market

[7]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).

create a lender of last resort, state run wind programs have effectively become the first and only choice for many high-risk properties.

The structure of wind insurance programs varies across states but some commonalities do exist. First, most if not all of these programs offer wind-only coverage in high-risk locales such as the coastal zone. Second, most programs require homeowners to meet eligibility criteria in an effort to ensure the state run program is an insurer of last resort. Third, all programs first pay claims out of their revenue from paid premiums and investments. In years with catastrophic losses, there is some variation in how programs cope, but generally bonds or reinsurance are the main remedies. In instances where the the premiums and investment cannot cover claims paid, the state is generally not responsible for losses the program incurs and insurance companies and their policyholders are levied to cover the difference (Kousky, 2011).

Pricing strategy also varies by state. Some states more rigidly adhere to the insurer of last resort approach and others offer policies that compete directly with the private market. For example, Louisiana's program is legally required to price their coverage above that of the private market so as to prevent competition entirely. Florida's program initially started with the same requirements as Louisiana, but the above-private pricing criteria was dropped and rates were then required to be "actuarially sound" and were further decreased and frozen until 2009 (GAO, 2007). Florida Citizens is now the largest property insurer in the state and competes directly with private insurers (Kousky, 2011).

2.2.2 Trends Toward Growth

Since 1990, the residual market 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 and the

total exposure of the residual market to loss increased eleven fold over the same period but has declined by one-third since 2011.[8]

2.2.3 Financial Status

Upward trends in growth mirror the National Flood Insurance Program and present similar challenges to the financial sustainability of the programs. It is crucial to note that all state run wind insurance programs face the same intertemporal smoothing problem as the NFIP and thus the programs are *not* immune to the fundamental challenges of dealing with catastrophic risk. That being said, because some of these programs do have sources of emergency funding that do not involve simply dipping into the taxpayer's wallet and many are not in as serious financial trouble as the NFIP. This is not to say that all are financially sound currently or sustainable in the long term. Generally speaking, it could be said that the closer a state run wind insurance program *actually* is to a lender of last resort, the better off it is financially. Those insurers who follow this maxim closely, price their policies to risk of the property, have higher premiums than those of the private market, offer higher deductibles with lower coverage limits, and retain a wide base of policyholders from which to obtain capital assessments. We provide two examples of programs in radically different states of financial strength to illustrate.

Florida Citizens is often cited as the least financially sound/sustainable wind insurance program in the nation. As stated in the previous section, Florida Citizens rates compete directly with those of the private market, and for this reason it has become the largest property insurer in the state. On top of its hefty market share in the state, Florida citizens rates have been legislatively set below that of the risk they face. Over half (56%) of its wind only policies in force are written for property in coastal counties near the southern tip

[8]Policies in force increased from .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).

of the state which face significant hurricane risk (Kousky, 2011). Further, Florida Citizens coverage limits for residential properties are tied with the Georgia Underwriters Association for highest coverage limits in the nation while offering as low as a 2% deductible. Even though the program is mandated by law to purchase sufficient reinsurance to protect against a 100-year storm event, a 2010 article in the Miami Herald by J. Frank entitled "Property insurance revamp could favor insurers, lawmaker say" cited lawmakers in the process of reforming the program who claimed that Florida Citizens was only able withstand a 25-year storm event and remain solvent (Kousky, 2011).

Though not a wind insurance provider, California's Earthquake Authority which provides earthquake insurance to homeowners in the state is cited by Kousky as the most financially sustainable of any catastrophe insurance program in the United States. The differences are obvious when comparing the program to Florida Citizens: CEA's market share in state is minuscule in comparison to Florida Citizens, coverage limits are much lower ($100,000 residential maximum), minimum deductibles are much higher (10%), reinsurance purchases by CEA are higher, and commercial coverage is not offered (Kousky, 2011). Kousky cites G. Pomeroy's 2010 testimony before the House Committee on Financial Services in which he stated that CEA would incur claims that exceeded revenue once in 545 years.

2.3 Moral Hazard, Catastrophe Insurance, and Mitigation

Another 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 his/her actions and may result in an increased risk-taking because the agent feels protected from the hazard. The moral hazard problem essentially boils down to the simple fact that individuals are more willing to take risks if someone other than themselves bears all or some of the costs. A commonly cited example of this problem is the charity hazard hypothesis (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. While this may be one of the more studied forms of moral hazard relating to flood and wind insurance it is not the only way in which the problem manifests.

In the market for catastrophe insurance, moral hazard arises generally when coverage is not priced to reflect the true risk of the hazard faced, thus buyers do not bear the full cost of their decision to locate property in disaster prone areas. Pricing to risk involves not only the accurate calculation of loss probabilities based on objective measures of risk, but the implementation of effective financial incentives designed to motivate individuals to engage in risk mitigation. In any case where catastrophe insurance is available below the true actuarial rate, incentives are created for individuals to locate in disaster prone areas because they no longer have to pay the full cost of their risky behavior. For instance, in order to accurately reflect flood risk, FIRMs must be updated frequently to account for changes in erosion, development, environmental degradation, and climate patters. Evidence has shown that FIRMS are outdated and inaccurate (Michel-Kerjan, 2010). While FEMA is in the process of modernizing the maps, the current FIRM structure likely does not reflect the true risk (Michel-Kerjan, 2010; King 2010). Flood insurance is thus available to some high-risk property owners below the actuarial rate and to some low-risk property owners above the actuarial rate. This failure to price to risk will inevitably shift costs from high-risk homeowners onto the government.

Price subsidies also contribute to moral hazard in both the NFIP and state wind insurance programs. As stated previously, repetitive loss properties in the NFIP account for a small fraction of total insured property but a significant portion of claims paid out. Many of these properties pay subsidized rates, shifting the cost of their precarious location onto the taxpayer. Further, "cross-subsidies," in which low-risk property owners subsidize the cost insurance for high-risk property owners are implicit in the pricing strategy of many state wind insurance programs. Cross-subsidies may occur when programs implement geographically averaged rates using large unit areas such as "rating zones" (as implemented by the California Earthquake Authority) or counties/parishes (as implemented by Louisiana Citizens) (Kousky, 2011). In cases where the unit areas or rating zones are sufficiently large and a significant risk-differential exists across the geography of each zone, low-risk property owners will pay the zone-averaged rate which is priced above the actual risk they face while higher-risk property owners pay the same rate despite facing greater risk.

Policymakers have attempted to address moral hazard problems through legal mandate, incentives to mitigate, and limits on coverage/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 post-disaster reconstruction, the provision of federal disaster assistance/flood insurance in certain prescribed areas, and permits the federal government to buy homeowners out of destroyed high-risk properties (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 through the Community Rating System which rewards communities with reduced premiums for voluntary mitigation activities or efforts to increase participation in the program. Household level incentives to mitigate flood risk are primarily available through Flood Elevation Certificates but present significant upfront costs to the homeowner. A Flood Elevation Certificate documents a struc-

ture's elevation and is used to determine the price of insurance by comparing to Base Flood Elevation (BFE, 100 year flood plain). Generally, a homeowner will receive discounted rates the higher the structure's elevation above BFE. The process of raising an already existing home above BFE is high and requires a long-run calculation by the homeowner comparing the total cost of flood insurance at current elevation with the cost after elevating. Incentives to mitigate in state run wind insurance programs are primarily focused at the household level and vary by state. For example, mitigation credits for wind-hardened structures are available in North/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, however, the fact remains that many of these programs do not price their coverage to risk and significant moral hazard problems will persist until this problem is corrected. In the next section I will explore the explanatory factors included in our model in detail, providing justification for their inclusion based on previous results in the literature and describe our theoretical expectation for the relationships between these explanatory factors and the decision to purchase insurance or mitigate.

Chapter 3

Conceptual Framework

Generalizing the individual 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 agent maximizes their subjective expectation of utility where the utility for individual i is

$$U_i = U(H_i, X_i, F_i, W_i, M_i) \tag{3.1}$$

where H_i is consumption of housing, X_i is consumption of a numeraire good, F_i represents the decision to purchase ($F_i = 1$) or not purchase ($F_i = 0$) flood insurance, W_i represents the decision to purchase ($W_i = 1$) or not purchase ($W_i = 0$) wind insurance, and M_i represents the level of mitigation undertaken on structure i where $M_i \in \mathbb{Z}_+$. We assuming that utility maximizing agents make insurance and mitigation choices optimally resulting in Marshallian demand functions for insurance and mitigation. F_i, W_i, and M_i can further be decomposed

as follows

$$\begin{aligned} F_i = \{0,1\} &= F\big[P_i, L_i(M_i), \lambda_i, \gamma_i, \delta_i, \pi_f(r_i, M_i), \pi_m(r_i), \theta_i\big] \\ W_i = \{0,1\} &= W\big[P_i, L_i(M_i), \lambda_i, \gamma_i, \delta_i, \pi_w(r_i, M_i), \pi_m(r_i), \theta_i\big] \\ M_i &= M\big[P_i, L_i(M_i), \lambda_i, \gamma_i, \delta_i, \pi_m(r_i), \theta_i\big] \end{aligned} \tag{3.2}$$

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; λ_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 & wind damage; $\pi_f(r_i, M_i)$, $\pi_w(r_i, M_i)$ 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 price of mitigation, depending on observable measures of risk (r_i) for property i; and θ_i represents household wealth.

The decision to purchase insurance and the decision to mitigate are determined by many of the same observed and unobserved perceptual, risk, and economic factors and are both jointly determined by the price of insurance, the price of mitigation, and the level of mitigation undertaken. Generally, any model for a market good should include both the own price of the good as well as prices for substitute goods. However, in our model, both the price of 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 across flood zones, size and type of structure, date of structure construction, and distance above "base flood elevation."[1] Similarly, the price of wind insurance is set at the state level and is also 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 a proxy variable for the

[1]Estimated elevation of a 100-year flood as determined by FEMA on Flood Insurance Rate Maps

price of insurance or mitigation as an overarching measure of risk, rather, we include the set of variables upon which the price of insurance is based (r_i, distance to shoreline, CRS score, presence of an active mortgage contract, location inside the 100-year flood plain, etc.).

In our conceptual framework, 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 homeowners 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 his chances of incurring a large loss and thus his expectation of loss under a major storm event may fall. Additionally, homeowners are often rewarded by insurers 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). Thus it seems reasonable that $\partial \pi_f / \partial M_i \leq 0$, $\partial \pi_w / \partial M_i \leq 0$, and $\partial L_i(M_i) / \partial M_i \leq 0$.

While the decision by individuals at risk to purchase flood/wind coverage and to mitigate has the potential to be made simultaneously, there is also the possibility that these decisions are made sequentially or even independently of one another if households do not view them in the greater context of hurricane risk. Heterogeneity in the decision making process combined with spatial variation of the price of insurance and household level variation in the price of mitigation make econometric identification of these equations difficult. Further, traditional economic theory provides little in the way of direction concerning how to construct simultaneous models of insurance demand and mitigation. To construct a joint model for these three decisions we draw on the previous literature for flood insurance, hazard mitigation under several catastrophic risks, and the small number of studies addressing wind insurance specifically.

3.1 Risk Preferences

The traditional model for decision under risk in the expected utility formulation assumes that individuals harbor a certain level of risk aversion. A risk-averse agent is defined as having a utility function that increases at a decreasing rate with respect to wealth ($\partial^2 U_i/\partial\theta_i^2 < 0$). Intuitively this means that the utility derived from outcomes of a risky decision are valued differently by a person who has little wealth versus someone who is very rich. We would assume that individuals who are more risk averse will be more likely to insure or mitigate the risks facing them. Risk aversion has been theoretically shown to have a positive effect on risk-mitigation activities. Dionne and Eeckhoudt (1985) and Briys and Schlesinger (1990) show that for an expected utility maximizing agent, risk mitigation activity is increasing in the agent's level of risk aversion.

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 study of first-price auctions, Smith and Walker (1993) found that as the payoff conversion rate (the rate of realized payoff) increased, the vast majority of subjects bid in excess of the risk-neutral predictions, indicating increasing risk aversion as the real 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 as wind insurance deductibles increased, households were more likely to engage in mitigation but also found that as premiums increased total dollars spent on mitigation activities also increased.

We hypothesize that in our joint model of these insurance choices as an individual's level of risk aversion increases, the probability they will purchase insurance and the extent of mitigation will increase.

3.2 Risk Perceptions

In addition to risk preferences, it is equally important to examine how an individual's perception of a risk affects the decision to insure or mitigate. In their 2008 article, Rees and Wambach show theoretically that the choice to insure is a function of both the perceived likelihood and magnitude of a loss. The standard model for insurance assumes that these perceived probabilities are based on objective, actuarial measures of risk (Smith, 1968; Mossin, 1968). There is a significant body of evidence which shows this not to be the case (Petrolia, Landry, & Coble, 2013). 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 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 the authors were unable to identify this effect and thus it was excluded from the mitigation equation. Additionally, These two papers 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. We hypothesize that the probability of holding insurance will increase with perceived conditional expected loss and that the expected frequency of hurricanes will not have a significant effect on either the insurance or mitigation decisions.

Past experience with storm events has also been shown to have a significant effect on

the decision to insure. In the first paper published on the subject, Baumann and Sims (1978) found that flood insurance uptake was significantly greater for those individuals in the sample who had some experience with past instances of flood events, but because their conclusions were formulated using only simple Chi-Square tests, the result may not hold when other covariates are accounted for. Browne and Hoyt (2000) show a positive and significant relationship between the total the amount of flood insurance damage claims paid in the previous year and demand for flood insurance. Kriesel and Landry (2004) use the mean return interval for hurricane landfall as a proxy for overall community experience with hurricane peril. They find that as the hurricane return interval decreases (recent community level experience increases), the probability of holding a flood insurance policy increases. 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 and individual in the past. They found that the number of past flood events had a positive and significant 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 a 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 insurer credibility. We hypothesize that increased confidence in insurers will have a positive effect on the probability of holding insurance but a negative effect on mitigation.

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.

3.3 Objective Risk Measures

Objective measures of risk, including property characteristics, play a key role in the decision to insure or mitigate. For insurers, objective risk measures represent the foundation of pricing schemes, and for homeowners, the geographic and structural characteristics of the property may influence their perceptions of hurricane risk. When modeling the choice to purchase any market good, the model should include both the own price of the good and the price of close substitutes; however, the price of insurance and mitigation is unobserved for those individuals who elected not to purchase them. In the NFIP, premiums are set at the federal level and vary based on observable risk measures such as location in the 100-yr flood plain (SFHA), elevation with respect base flood elevation, date of construction, and structure type. In state wind insurance programs, prices are set at the state level and generally vary

with the number of mitigation measures installed on the house. Mitigation costs will vary from household to household and will depend on the age and condition of the structure, choice of installation contractor or self-installation, and the type of mitigation measures installed. For these reasons, we do not include a proxy variables for the price of insurance or mitigation in the empirical model as an all-encompassing measure of exposure to hurricane risk, electing instead to include multiple measures of hurricane risk including state of residence, structure type (house, condo, mobile home), distance to the nearest shoreline, age of the structure, CRS score, location inside a SFHA, and the presence of an active mortgage contract on the property. We hypothesize generally that as exposure to hurricane risk increases, individuals will be more likely to purchase insurance or install mitigation measures.

3.4 Demographics

Though not part of the standard model for insurance demand, it is reasonable to assume that demand for insurance and mitigation will vary across demographic groups. Petrolia, Landry, and Coble (2013) found that those of Hispanic descent were significantly more likely to hold a flood insurance policy. In contrast, Petrolia et al. (2015) found race to have no significant effects on the probability of holding wind insurance but did find non-whites were significantly more likely to engage in mitigation. Peacock (2003), however, found black households were significantly less likely to engage in mitigation. Based on these conflicting results, we have no expectation for the sign of the relationship between race and insurance/mitigation purchases.

Income is included in the model as a proxy for wealth and has been shown to have a significant and positive effect on flood insurance purchases (Browne & Hoyt, 2000; Petrolia, Landry, & Coble, 2013), wind insurance purchases (Petrolia et al., 2015), and mitigation activities (Peacock, 2003; Pooser, 2013). Botzen, Aerts, and van den Bergh (2009), however,

find positive but insignificant income effects on the propensity to mitigate. We also include measures of education level, employment status, the presence of children in the household, and state of residence dummy variables.

Chapter 4

Data and Empirical Methods

4.1 Survey Instrument, 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 elicit individual risk preferences, environmental risk perceptions, and mitigation decisions and 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 risk preferences exercise at the end of the survey. The target population for the survey was all property owners between age 18 and 96 residing in coastal counties in states along the US Gulf Coast including Alabama, Florida, Mississippi, Louisiana, and Texas plus an additional set of inland counties with large amounts of their total land in flood zones. 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

[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.

responses with street addresses, only 670 were usable after dropping all 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 4.1.[2] 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 Alabama (3.0%), Mississippi (1.3%), and Louisiana (3.1%).

Figure 4.1: Map of Survey Respondents

Table 4.1: Flood Policies by State and SFHA

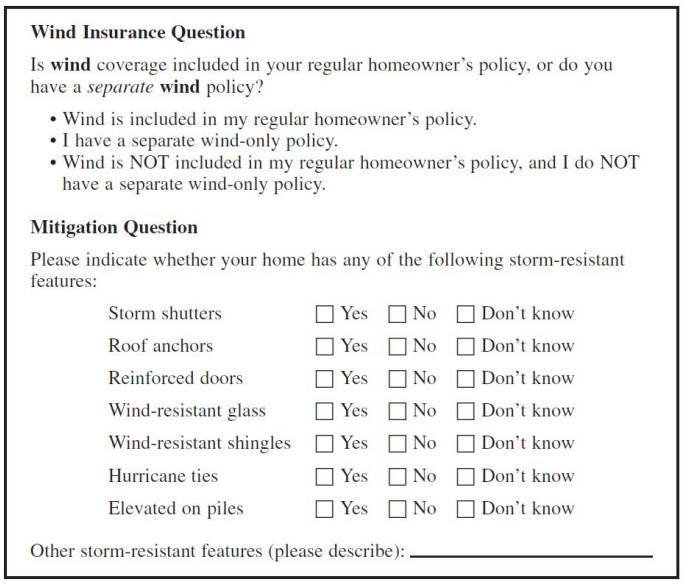
	SFHA			Non-SFHA			Total		
	# obs	# w/ Policy	row %	# obs	# w/ Policy	row %	# obs	# w/ Policy	row %
AL	0	0	0.0	20	4	20.0	20	4	20.0
FL	110	66	60.0	344	63	18.3	454	129	28.4
LA	12	8	66.7	9	3	33.3	21	11	52.4
MS	2	2	100.0	7	2	28.6	9	4	44.4
TX	20	17	85.0	146	68	46.6	166	85	51.2
Total	144	93	64.6	526	140	26.6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

The survey required residents to indicate whether they held flood or wind insurance policies as well as the number and type of mitigation measures they installed. Table 4.1 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

[2] *Source*: Dr. John Cartwright, Geosystems Research Institute, Mississippi State University

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 less observations than Texas which had an overall uptake rate of 51.2%.

Figure 4.2 shows the survey questions used determine the type of wind insurance a homeowner had and to measure the level of mitigation undertaken by the homeowner. All responses marked "don't know" were recorded as "no" responses and we also combed through the written-in responses for mitigation measures and included them in the total count when reasonable. Examples of this included metal roofs, hip roofs, polypropylene screening, reinforced garage doors, concrete blocks, and boarded windows.



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

Tables 4.2, 4.3, and 4.4 break down the responses to the wind insurance and mitigation question by state. Most homeowners in our sample (538, 80.1%) had some form of wind coverage either through their homeowners policy (470, 70.2%) or under a separate wind-only

policy (68, 10.1%). Florida had far and away the greatest number of total wind polices (327, 48.8%) while Alabama and Louisiana had the highest rates of in-state uptake at 95%. It is important to note, however, that there are only 41 total observations in Alabama and Louisiana so this estimate of in-state uptake rates is likely not accurate.

Table 4.2: Wind Policy 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

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 4.3: 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 homeowners 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 may 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).

This preliminary result also may signal a positive correlation between higher levels of mitigation and holding an insurance policy. Respondents were asked to further elaborate on their mitigation decisions to shed light on the choice *not* to mitigate. Table 4.5 presents the results to the survey question which 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 their home needs any additional storm resistant features" and 30% of individuals believe "the upfront installation costs are too high." Figure 4.3 breaks down mitigation count by property age. It stands to reason that newer homes are built to meet more rigorous building codes and could thus require fewer mitigation measures. We ran a simple negative binomial regression of the mitigation counts on property age and obtained a statistically significant estimated coefficient of $-.0073$ indicating that as property age increases fewer mitigation measures are installed.[3]

Table 4.4: Mitigation Count by Wind Policy Type

Mit Count	Wind Included in Homeowners Policy	Separate Wind Policy	Wind Excluded from Homeowners Policy (No Wind Coverage)
0	133 (28.3%)	19 (27.94%)	55 (41.67%)
1	91 (19.36%)	7 (10.29%)	38 (28.79%)
2	86 (18.3%)	9 (13.24%)	21 (15.91%)
3	68 (14.47%)	15 (22.06%)	6 (4.55%)
4	54 (11.49%)	8 (11.76%)	8 (6.06%)
5	27 (5.74%)	8 (11.76%)	2 (1.52%)
6	7 (1.49%)	1 (1.47%)	2 (1.52%)
7	4 (0.85%)	1 (1.47%)	0 (0%)
Total	470	68	132
Mean	1.9	2.3	1.1

Table 4.6 breaks down mitigation count by flood policy status. It is important to note here that the only measure included in mitigation count for flood mitigation was the elevation of a home on piles; all other mitigation activities are related to wind mitigation. Even though we include only this one measure of flood mitigation, it seems reasonable to assume those individuals deciding to fortify their property against wind would also be considering possible damage to their home as a result of floods in the larger context of hurricane risk

[3]Two observations where the age of the property was 210 years were omitted to make for a graph that was easier to read, but were included in the simple negative binomial

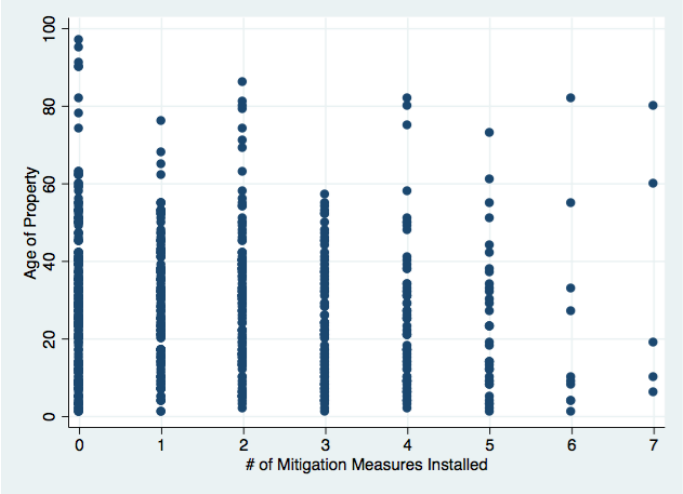


Figure 4.3: Mitigation Count by Property Age

mitigation and thus these two decisions would be correlated. Table 4.6 indicates that both flood policyholders and those without a flood policy have similar mean levels of mitigation. Both groups have comparable proportions of individuals engaging both in at least one mitigation measure (68.4% and 70.4%, respectively) and also are commensurate in the number of individuals undertaking at most two mitigation activities (53.55% and 46.78%, respectively.)

Figure 4.4 shows an example of the type of question used to measure an individual's risk preferences based on the instrument designed by 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 their choices over the loss domain from affecting their payment for taking the survey 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

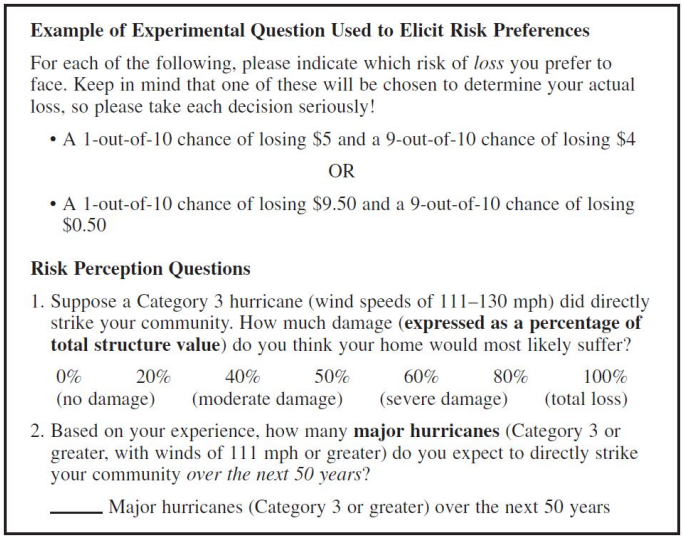
Table 4.5: Survey Question: For Storm Resistant Features That Your Home Does NOT Have, What Is the Main Reason You Have Not Installed Them

	Freq.	%
I am unsure of the level of protection they would provide	58	8.72
The insurance benefits (discounts) don't outweigh the installation costs	49	7.37
The up-front installation costs are too high	206	30.98
I do not think that my home needs any additional storm-resistant features	284	42.71
Other	65	9.77
Refused	3	0.45
Total	665	

Table 4.6: Mitigation Count by Flood Policy Status

Mit Count	Holds Flood Policy	No Flood Policy
0	138 (31.58%)	69 (29.61%)
1	96 (21.97%)	40 (17.17%)
2	76 (17.39%)	40 (17.17%)
3	54 (12.36%)	35 (15.02%)
4	44 (10.07%)	26 (11.16%)
5	24 (5.49%)	13 (5.58%)
6	3 (0.69%)	7 (3%)
7	2 (0.46%)	3 (1.29%)
Total	437	233
Mean	1.7	2.0

risk aversion. The mean of our risk aversion measures over the gain and loss domains were 2.93 and 2.94, respectively, indicating our sample was slightly risk averse on average. This measure of risk-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).



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 4.4: Example of Experimental Questions Used to Determine Risk Preferences, Survey Questions to Measure Risk Perceptions

In addition to risk preferences, the survey asked questions designed to measure the respondent's perception of hurricane risk. We collected data on 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.[4] The responses to these questions are de-

[4]Perceived likelihood of gov't assistance was used to test the charity hazard hypothesis (Brown & Hoyt, 2000; Petrolia, Hwang, Landry, & Coble, 2015)

tailed in Figures 4.5-4.8. Examining the results shown in Figure 4.5, it seems quite possible that some respondents to the survey question "How many major hurricanes (Category 3 or greater, with winds of 111 mph or greater) do you expect to pass within 75 miles of the city you live in over the next 50 years" may not have fully understood the question and thus entered inflated values for their expectations. The majority of the respondents (607, 90%) indicated their expectation was from 0-20 Category 3 storms, equating to a average rate as high as 0.4 storms per year. Of the remaining respondents, 15 indicated their expected average rate as high as 1.8 Category 3 storms per year. While approaches exist for dealing with inflated or nonsensical survey responses, these approaches all involve arbitrarily truncating the sample above or below a certain point which has the potential to cause more problems than it solves. It is for this reason we chose to leave the sample intact at 670 observations.

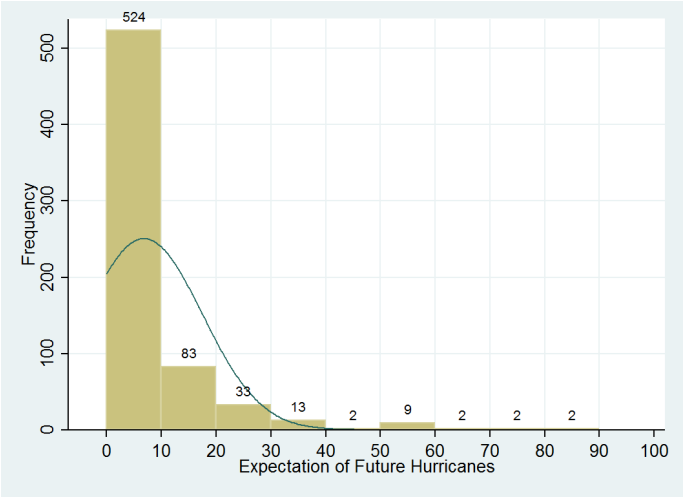


Figure 4.5: Expectation of the number of category 3 or stronger hurricanes passing within 75 miles of respondent's home city over the next 50 years

Additional 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

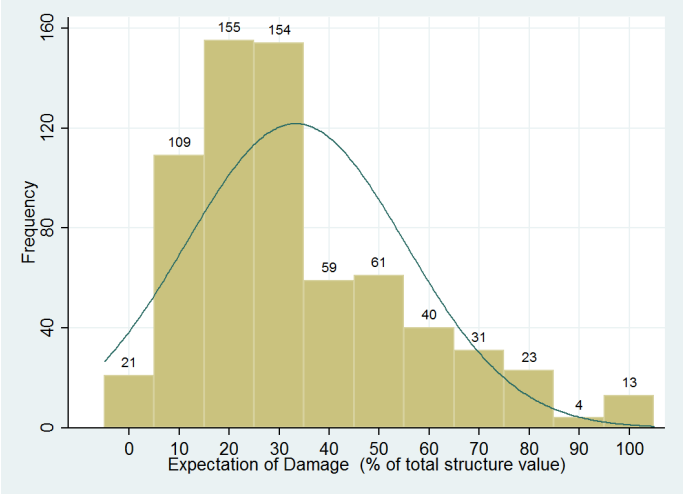


Figure 4.6: Expectation of damage to property under category 3 hurricane (wind speed 111-130 mph)

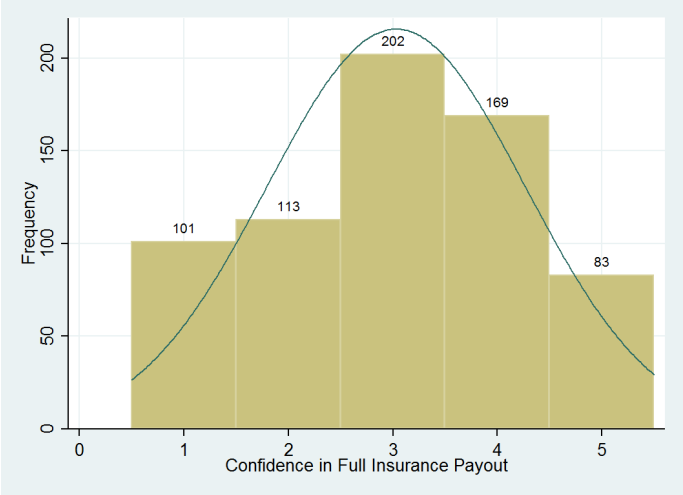


Figure 4.7: Perceived likelihood of a full insurance payout covering all storm damages (1 = no confidence, 5 = full confidence)

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 4.7 and 4.8.

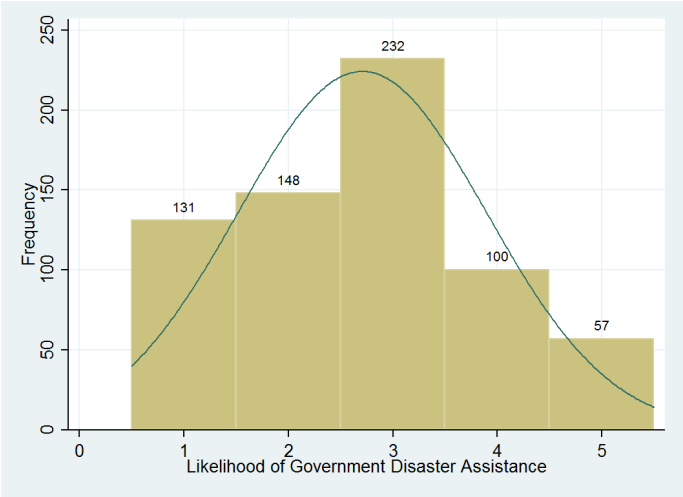


Figure 4.8: Perceived likelihood of state/federal post-disaster assistance (1 = very unlikely, 5 = very likely)

Perceived Insurer Credibility Question

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).

Perceived Eligibility for Governmental Postdisaster Assistance

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 his? (Indicate how likely, with 1 being very unlikely and 5 being very likely.)

Figure 4.9: Survey Questions Used to Measure Perceived Insurer Credibility & Perceived Eligibility for Government Disaster Assistance

Table 4.7: Variable Descriptions

Variable	Type	Description	Variable	Type	Description
Dependent Vars			*Property Attributes*		
Flood Policy	Binary	Dependent Variable; =1 if purchased flood insurance policy, =0 otherwise	SFHA	Binary	=1 if home is in A or V flood zone (100 yr floodplain), =0 otherwise
Wind Policy	Binary	Dependent Variable; =1 if purchased separate wind policy, =0 otherwise	Mortgage X SHFA	Binary	=1 if home is mortgaged and in the A or V flood zone (100yr floodplain), =0 otherwise
Mitigation Count	Count	Dependent Variable; number of mitigation measures installed, range is from 0 - 7	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
Risk Preferences			Property Age	Continuous	Age of property in years
			Mobile Home	Binary	=1 if mobile home, =0 otherwise
Risk Aversion (Gains)	Continuous	Number of instances where low-variance risk chosen over gain domain, ranges from 0 (risk loving) to 5 (risk averse)	Condo	Binary	=1 if housing type is condominium or apartment, =0 otherwise
Risk Aversion (Losses)	Continuous	Number of instances where low-variance risk chosen over loss domain, ranges from 0 (risk loving) to 5 (risk averse)	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 $\geq$ \$100k, =0 otherwise
Risk Perceptions			*Demographics*		
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	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
Past Damage Experience	Count	Number of instances of wind and flood damage experienced in the past	White	Binary	=1 if white, =0 otherwise
Disaster Assist. Eligibility	Binary	=1 if perceived likelihood of eligibility for postdisaster payments rated $\geq$3 on a scale from 1 (very unlikely) to 5 (very likely), =0 otherwise	Male	Binary	=1 if male, =0 otherwise
Insurer Credibility	Binary	= 1 if perceived confidence that insurer will pay full amount of claims in event of major storm is $\geq$ 3 on scale from 1 (no conf.) to 5 (full conf.), = 0 otherwise	Income	Ordered Cat	category ranges from less than $5,000 to 175,000 or more
Expectation of Damage	Ordered Cat	Expected proportion of damage to home given Cat 3 storm, ranges from 0 (no damage) to 10 (total loss)	Employment Status	Binary	=1 if employed, =0 otherwise
Expectation of Fut. Storms	Ordered Cat	Expected number of future Cat 3 or greater storms over next 50 years	Kids	Binary	=1 if have children, =0 otherwise
Property Attributes			*State of Residence*		
Distance from Shoreline	Continuous	Distance in kilometers from nearest shoreline	Florida Resident	Binary	=1 if florida resident, =0 otherwise
Community Rating System	Ordered Cat	Community Rating System score; ranges from 1 (most mitigation) to 10 (no mitigation)	Texas Resident	Binary	=1 if Texas Resident, =0 otherwise
Florida X CRS	Ordered Cat	=CRS score if resident of Florida, =0 otherwise	Ala. or Miss.Resident	Binary	=1 if Alabama OR Mississippi Resident, =0 otherwise
Mortgage	Binary	=1 if home is mortgaged, =0 otherwise	Louisiana Resident	Binary	=1 if Louisiana Resident, =0 otherwise

Table 4.8: Summary Statistics

N = 670						
	Mean	Std. Dev.	Min	Max	Sum	Exp. Sign
Flood Policy	0.347761	0.4766156	0	1	233	
Wind policy	0.802985	0.3980408	0	1	538	
Mitigation Ct.	1.783582	1.693926	0	7	1195	
Risk Aver., Gain	2.928358	1.445865	0	5	1962	+
Risk Aver., Loss	2.940299	1.366704	0	5	1970	+
Policy Reqd.	0.165672	0.3720634	0	1	111	+
Past Damage	0.468657	0.7874594	0	4	314	+
Eligibility	0.583582	0.4933328	0	1	391	-
Credibility	0.680597	0.4665937	0	1	456	+/+/-
Exp. Damage	3.326866	2.195054	0	10	2229	+/+/...
Exp. Hurr	6.791045	10.65485	0	90	4550	+
Dist. Shore	15.58042	18.10068	0	171.682	10438	-/-/-
CRS	6.950746	1.471896	5	10	4657	-
Florida x CRS	4.562687	3.258395	0	10	3057	+
Mortgage	0.671642	0.4699668	0	1	450	+
SFHA	0.214925	0.4110775	0	1	144	+
Mort x SFHA	0.146269	0.3536394	0	1	98	+
X-Zone	0.601493	0.4899567	0	1	403	-
Pre-FIRM	0.404478	0.4911573	0	1	271	?
Property Age	28.7597	20.9096	1	210	19269	?
Mobile Home	0.032836	0.1783398	0	1	22	-/.../...
Condo	0.114925	0.3191701	0	1	77	?
Gulf Years	27.26269	18.00954	0	93	18266	?
Oth. Property	0.059702	0.23711	0	1	40	?
Education	4	1.598766	1	7	2680	+
White	0.816418	0.3874322	0	1	547	?
Male	0.467164	0.4992934	0	1	313	?
Income	12.29851	3.895169	1	19	8240	+
Employed	0.553731	0.4974759	0	1	371	+
Kids	0.264179	0.4412245	0	1	177	+
Flordia	0.677612	0.4677398	0	1	454	-
Texas	0.247761	0.4320349	0	1	166	?
AL or MS	0.043284	0.2036468	0	1	29	?
Louisiana	0.031343	0.1743739	0	1	21	?
Wind Excluded	*0.298508*	*0.4579452*	*0*	*1*	*200*	.../.../+
Internet Access	0.956716	0.2036468	0	1	641	.../.../...

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

4.2 Econometric Model

In their 2015 paper using the same survey data (but utilizing a different subset of observations), Petrolia et al. modeled the decision to purchase wind-only insurance coverage simultaneously with the decision to mitigate in a seemingly unrelated regressions (SUR) framework. This SUR system of two equations specified 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, allowing for contemporaneous correlation of the error terms of each model to account for unobservable effects between each equation. The authors compared the pre-

liminary results from the independent Tobit regression of mitigation count to the results obtained from count models utilizing the same explanatory factors and found only slight differences in marginal effects and no reversals of sign.

The use of a Tobit regression to model count data is not entirely unheard of, or incorrect in a situation where the counts are sufficiently high (Campa, 1993; Fair, 1978; Romer and Snyder, 1994). However, this specification generalizes fundamentally discrete, non-negative integer data to a continuous distribution and therefore is less optimal than equivalent models designed to deal with counts. Due to the constraints of the computational methods used to actually estimate the model and the necessity to model the decisions simultaneously, the authors determined this to be an acceptable generalization. This paper implements an improved SUR specification which models the decisions to purchase flood and wind insurance as a bivariate, random-effects probit model and mitigation count as a Poisson process with a log-normally distributed mean (rate parameter), allowing for contemporaneous correlation between the bivariate probit error terms and the log-normally distributed error of the Poisson mean, λ.

4.2.1 The Poisson Log-Normal Distribution

The standard model for count data is the semi-log Poisson regression model, shown in equation 4.1, where the mean, or "rate" parameter of the Poisson distribution is given by $\lambda = \exp(x'\beta)$ to ensure that $\lambda > 0$ (Cameron & Trivedi, 2013). The standard Poisson regression is derived from the Poisson distribution and makes a key assumption. The relationship between the relationship between the rate parameter and the exogenous covariates is assumed to be parametrically exact, that is, it contains no stochastic error term. This implies that the standard model also assumes equidespersion: the mean and variance of the distribution are

assumed to be equal ($\lambda = \sigma^2$) (Cameron & Trivedi, 2013).

$$Pr(Y = y) = \frac{\lambda^y e^{-\lambda}}{y!} \quad \forall \quad y \in \mathbb{Z}_+ \; where \; \lambda = \exp(x'\beta) \tag{4.1}$$

In practice, the relationship between explanatory variables and the rate parameter is rarely parametrically exact, violating this assumption. Additionally, count data are often overdispersed, meaning the variance of the counts is greater than the mean ($\sigma^2 > \lambda$). The most common way to test and account for the presence of overdispersion is to model the conditional variance as a function of the mean (λ) and a scale/dispersion parameter (α). This generalization of the Poisson model results in the Negative Binomial regression model. We ran several Negative Binomial specifications using the command *nbreg* in Stata which automatically runs a likelihood ratio test of the null hypothesis $H_0 : \alpha = 0, \lambda = \sigma^2$ against the alternative $H_1 : \alpha > 0, \sigma^2 > \lambda$. We rejected the null in all cases and conclude that our counts are indeed overdispersed.

While the negative binomial model is the most commonly used method of dealing with overdispersed counts, it is not the only approach. Generally, this class of models is referred to as "Poisson mixture models" in the literature, and provide varied approaches for dealing with unobserved heterogeneity resulting in overdispersion. These mixture models entail defining a probability distribution for the unobserved heterogeneity believed to be driving the overdispersion; in the case of the negative binomial, the unobserved component of the model is assumed to be distributed Gamma. This particular specification has a critical limitation in our simultaneous framework for insurance and mitigation. As stated previously, we model the decisions to purchase flood/wind insurance as a bivariate random-effects probit which assumes the unobserved heterogeneity between equations is distributed normally. Because no meaningful correlation between the Gamma and Normal distributions exists, specifying the counts using a negative binomial model precludes us from including a third equation in

our model and forces us to consider alternative specifications.

A natural choice for our simultaneous 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 rate parameter (λ) is assumed to be log-normally distributed.

$$Pr(Y = y) = \int_{R_+} \frac{e^{-\lambda}\lambda^y}{\lambda y!} \frac{e^{-0.5(\log\lambda - \mu)^2}/\sigma^2}{\sigma\sqrt{2\pi}}\, d\lambda \quad \forall \quad y = 0, 1, 2, ... \\ where \quad \ln(\lambda) \sim N(\mu, \sigma^2) \tag{4.2}$$

Evaluating the integral in equation in 4.2 is difficult because of the restriction that $\lambda > 0$. To remedy this, we introduce the change of variable $\ln(\lambda) = \mu + \sigma\epsilon$ where $\epsilon \sim N(\mu, \sigma^2)$, with the corresponding Jacobian of transformation, $\lambda\sigma$, resulting in the probability mass function shown in equation 4.3.

$$Pr(Y = y) = \int_{-\infty}^{\infty} \frac{e^{-\lambda}\lambda^y}{y!} \frac{e^{-0.5\epsilon^2}}{\sqrt{2\pi}}\, d\epsilon \quad where \quad \lambda = \exp(\mu + \sigma\epsilon) \tag{4.3}$$

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

Consider the latent variable model shown in equation 4.4

$$y_1 = \begin{cases} 1 & \text{if } x_1\beta_1 + v > 0; \quad y_1^* > 0 \\ 0 & \text{if } x_1\beta_1 + v \leq 0; \quad y_1^* \leq 0 \end{cases} \tag{4.4}$$

When y_1 is modeled using the probit link function, the probability that $y_1 = 1$ conditional on the normally distributed random variable z is:

$$Pr(Y_1 = 1|z) = \Phi\left[\frac{(x_1\beta_1 + \rho(z-\mu))/\sigma}{\sqrt{1-\rho^2}}\right] \quad where \quad z \sim N(\mu, \sigma^2) \tag{4.5}$$

where $\Phi(.)$ represents the standard normal cumulative distribution function. Generally, the conditional probability in equation 4.5 cannot be used to represent count data because it is based on normal distribution theory, but when count data are overdispersed and can be reasonably represented by the Poisson Log-Normal distribution, the resulting conditional probability is:

$$Pr(Y_1 = 1|\log\lambda) = \Phi\left[\frac{(x_1\beta_1 + \rho(\ln(\lambda) - \mu))/\sigma}{\sqrt{1-\rho^2}}\right] \quad where \quad ln(\lambda) \sim N(\mu, \sigma^2) \tag{4.6}$$

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:

$$Pr(Y_1 = 1, Y = y) = \int_{-\infty}^{\infty} \Phi\left[\frac{(x_1\beta_1 + \rho\epsilon)/\sigma}{\sqrt{1-\rho^2}}\right] \frac{e^{-\lambda}\lambda^y}{y!} \frac{e^{-0.5\epsilon^2}}{\sqrt{2\pi}}\, d\epsilon \tag{4.7}$$
$$where \quad \lambda = \exp(\mu + \sigma\epsilon)$$

4.2.3 The Bivariate Random-Effects Probit Model

We define a second binary response variable, y_2, analogously to y_1 to construct the bivariate random-effects probit model.

$$Pr(Y_1 = 1, Y_2 = 1) = \int_{-\infty}^{\infty} \Phi(x_1\beta_1 + \theta\eta)\Phi(x_2\beta_2 + \theta\eta)\frac{e^{-0.5\eta^2}}{\sqrt{2\pi}}\, d\eta \tag{4.8}$$
$$where \quad \eta \sim N(0, 1)$$

For the case in which $\theta > 0$ the bivariate random-effects probit model maps directly to the ordinary bivariate probit model. When $\theta > 0$ the two models are equivalent but the random-effects models is computationally simpler to estimate, only requiring us to numerically integrate across the domain of η. To obtain the population averaged parameter estimates (β_{Pop}) from the random-effects model we simply convert the individual estimates from the random effects model (β_{RE}) using the formula

$$\beta_{Pop} = \frac{\beta_{RE}}{\sqrt{1+\theta^2}} \tag{4.9}$$

where the correlation between the two probit errors is given by

$$\rho_{f,w} = \frac{\theta^2}{1+\theta^2} \tag{4.10}$$

4.2.4 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 4.11.

$$\begin{gathered}\int\int_{-\infty}^{\infty} \Phi\left(\frac{x_1\beta_1 + \theta\eta + \rho_1\epsilon}{\sqrt{1-\rho_1^2}}\right) \Phi\left(\frac{x_2\beta_2 + \theta\eta + \rho_2\epsilon}{\sqrt{1-\rho_2^2}}\right) \frac{e^{-\lambda}\lambda^y}{y!} \frac{e^{-0.5(\eta^2+\epsilon^2)}}{2\pi}\, d\eta\, d\epsilon \\ where \quad \lambda = \exp(\mu + \sigma\epsilon),\ \ln(\lambda) \sim N(\mu, \sigma^2),\ \eta \sim N(0,1)\end{gathered} \tag{4.11}$$

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).

Chapter 5

Results

Results from the joint model in equation 4.11 are given in table 5.1. 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 and mitigation equations ($\rho_{f,m} = 0.2416$) as well as the wind and mitigation equations ($\rho_{w,m} = 0.6525$). While these statistically robust correlations confirm 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 ($\rho_{f,w} = 0.1213$). This indicates no gain in efficiency by allowing correlation between these two errors and that the model shown in equation 4.7 may yield more straightforward results when applied to the two bivariate responses individually. This result will be further addressed in the discussion and conclusions section.

Table 5.1: Mixed-Process Regression Results

Parameter	**FloodPolicy (1)**	**WindPolicy (2)**	**Migitation (3)**
Risk Aver. (Gain)	0.0086	0.0097	-0.0007
	(0.044)	(0.043)	(0.024)
Risk Aver. (Loss)	0.0802	0.0041	-0.0263
	(0.049)	(0.044)	(0.025)
Past Damage	0.1417*	0.1815**	0.1399***
	(0.085)	(0.092)	(0.049)
Eligibility	0.2748**	-0.0668	0.0334
	(0.136)	(0.140)	(0.076)
Credibility	0.1319	0.4745***	0.1599*
	(0.139)	(0.147)	(0.083)
Exp. Damage	0.0627**	-0.0224	
	(0.031)	(0.029)	
Exp. Future Hur.	0.0074	-0.0086	0.0019
	(0.007)	(0.006)	(0.004)
Income	0.058***	0.0649***	0.0145
	(0.020)	(0.018)	(0.010)
Dist. To Shore (km)	-0.0072*	-0.0034	-0.0051**
	(0.004)	(0.003)	(0.002)
SFHA	-0.3814		
	(0.288)		
Mortgage		0.4045***	
		(0.145)	
Mortgage x SFHA	0.8004***		
	(0.298)		
Mobile Home	-1.3125**		
	(0.620)		
Condo		-0.5026***	-0.452***
		(0.195)	(0.131)
Property Age		-0.0039	-0.0081***
		(0.003)	(0.003)
Wind Excluded			0.2285**
			(0.101)
CRS	-0.1389***		
	(0.051)		
Florida x CRS	0.1845**		
	(0.090)		
X-Zone	-0.4316***		
	(0.165)		

Table 5.1: Mixed-Process Regression Results

Parameter	**FloodPolicy (1)**	**WindPolicy (2)**	**Migitation (3)**
Coastal Tenure	-0.0045		
	(0.004)		
Texas			-0.716***
			(0.108)
AL or MS		0.6428	-0.289*
		(0.418)	(0.170)
Louisiana			-0.3989*
			(0.209)
Florida	-2.1364***		
	(0.638)		
Fl Policy Reqd.	1.7654***		
	(0.244)		
Kids	-0.2383*	-0.5171***	-0.257***
	(0.143)	(0.151)	(0.088)
White		0.3698**	
		(0.157)	
Employed		-0.1717	
		(0.135)	
Education	0.0902**		
	(0.042)		
Intercept	-0.5482	-0.194	0.6525***
	(0.561)	(0.410)	(0.225)
Variance, Correlation Structure			
σ^2	0.2474***	$\rho_{f,w}$	0.1213
	(0.049)		(0.108)
θ	0.3716**	$\rho_{f,m}$	0.2416**
	(0.188)		(0.113)
Log-Likelihood	-1725.5108	$\rho_{w,m}$	0.6525***
			(0.116)

*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 coefficient for risk aversion over both gains and losses was positive with respect to flood and wind insurance, negative with respect to mitigation, and similar in magnitude to those found by Petrolia, Landry, & Coble (2013) and Petrolia et al. (2015). Examining the results from our measures of risk perception, we find that the number of experiences with past wind/flood damage events has a significant, positive effect on the probability of holding a 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). We find no evidence in support of the charity hazard in our data and while perceived eligibility was statistically insignificant 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. 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. While 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 this result does not hold for wind insurance.[1] Expectations for the frequency of future storms was found to have no significant effect on insurance or mitigation. 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

[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

and robust income effects in the two insurance models. The following sections will address the remaining covariates, some of which are only included in one or two of the models, equation-by-equation.

5.1 Flood Insurance Model

Results from the flood model show that those individuals who had an active mortgage contract on their property and located inside a SFHA were significantly more likely to purchase flood insurance and households located in the X-Zone (areas outside the 500-year flood plain, probability of flood annually $< .02\%$) were significantly less likely to purchase flood insurance. Location inside of a SFHA alone did not have a significant effect on the probability of an insurance purchase. Further, individuals who were told that flood insurance was mandatory for their property (in theory, those individuals with federally insured mortgages inside SFHAs) were significantly more likely to actually hold flood 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 the second strongest effect on the probability of holding flood insurance behind the Florida residence dummy, providing evidence that the mandatory purchase requirements for the 100-year flood plain are being enforced. As expected, households further 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), Petrolia, Landry, and Coble (2013), and Petrolia et al. (2015).

Florida residents were significantly less likely to hold flood insurance than residents of our other sample states. This is a surprising result, given that Florida has the highest number of total flood policies and may be partially explained by flood mitigation efforts at the community and city level 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 is still robust but 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. Those individuals who resided in mobile homes were significantly less likely to hold flood insurance than those in houses or condominiums. This effect is the third strongest of all our covariates behind Florida residency and the interaction of mortgage and SFHA. Demographic variables for education level and the presence of children in the home were also found to have significant effects. The number of years living on the coast had no significant effect.

5.2 Wind Insurance Model

Looking next to the wind model, 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). 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 and those households with children in the home were significantly less likely to have wind insurance. The distance to the nearest shoreline, age of the property, state of residence, and employment status all had insignificant effects.

5.3 Mitigation Model

Finally, we look to the results from the mitigation model. Distance to the nearest shoreline was again found to have a negative and significant effect on the number of mitigation measures installed. Structural characteristics again play a key role in the mitigation decision. We find that households with condominiums and older structures install significantly less mitigation measures. Additionally, we find that residents of Alabama, Mississippi, Louisiana, and Texas installed significantly less mitigation measures than those of Florida. 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," where wind coverage was unavailable, were generally more likely to engage in mitigation and spent more money on mitigation activities.

Chapter 6

Discussion and Conclusions

This paper has presented results from our household-level analysis to insure 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 in the coastal context using data on risk preferences, risk perceptions, objective measures of hurricane risk, and demographics. The findings of this study support the idea that the decision to insure and the decision to mitigate are closely related. We conclude that there is a positive correlation between holding a flood or wind insurance policy and the number of mitigation measures installed on a home. However, our findings do not support the notion that there is a significant relationship between the decision to insure against flood risk and the decision to insure against wind risk. The lack of a significant correlation between the two insurance decisions may have occurred for a variety of reasons. One potential explanation could be the relatively few observations from states such as Alabama and Mississippi that require flood insurance as a pre-requisite for wind coverage if the structure is located in a SFHA. Though we model the wind insurance equation as an explicit decision, our dependent variable includes both households who have purchased wind-only policies *and* households who have coverage as part of their homeowners policy. It is possible

that individuals who are covered through their homeowners policy had the opportunity to forgo this coverage, but it is also possible that they may not have explicitly chosen the policy because it included wind coverage. The dependent variable in our model differs from the one used by Petrolia et al. (2015), which utilized the subset of the sample for which wind peril was excluded from the homeowners policy and thus the decision to purchase was explicit. Crucially, Petrolia et al. were able to take advantage of a pre-programmed estimation routine which allowed each equation to vary by observation. While this is possible with our approach, the programming is sufficiently involved to warrant significant time outlay and thus we elected to create an even *(n x k)* matrix for our simultaneous system. In future specifications we may be able to re-define our dependent variable and re-examine this link.

In a break from the previous findings in the literature, we found no significant relationship between an individual's risk preferences and their decision to insure or mitigate. This finding may be related to the way in which the dependent variable was defined or the insignificant correlation between flood and wind insurance. Overall, we find that as an individual's perception of risk increases, the more likely they are to insure or install mitigation measures. The probability of holding insurance was increasing in past experience with flood or wind damage, insurer credibility, conditional expectations for damage, and eligibility for government disaster assistance, in contravention to the charity hazard hypothesis. The positive and significant relationship between strong perceptions of eligibility for government disaster aid and the probability of holding insurance could reflect the general sense that because an individual lives in a high risk region, like the Gulf Coast, that such an area would be a logical recipient of disaster aid. As evidenced by the overly high responses from Figure 4.5, we believe the insignificance of the expectations for future storm events may reflect the difficulty individuals have with interpreting and fully understanding low-probability catastrophic risks which has been documented previously in the literature (Anderson, 1974; Kunreuther, 1979; McClelland, Schulze, & Coursey, 1993; Botzen, Aerts, van den Bergh 2009).

Generally, our results suggest that objective measures of risk do have pronounced effects on the decision to insure or mitigate. The effect of structure type is particularly strong as those individuals living in mobile homes were much less likely to purchase flood insurance than those living in houses or condominiums. In contrast to the findings of Petrolia, Landry, and Coble (2013), location in a SFHA alone did not have a significant effect but when taken in context with the significant results on the SFHA and mortgage interaction and the indicator for being informed flood insurance is mandatory it seems that the legal mandate appears to be the driving force for purchase. Older homes and those properties at larger distances from the shoreline were less likely to insure and installed fewer mitigation measures, though the effects of property age on wind insurance was insignificant. The effects of property age on flood insurance purchases manifests primarily through the Pre/Post-FIRM designation. After testing for restrictions on the model it was later dropped because it was insignificant and allowed for the use of additional observations for which FIRM status was unavailable. The findings also suggest that community mitigation efforts are a significant factor in the decision to insure. As the level of community mitigation increases, insurance uptake increases as well. However, we find that the opposite is true in Florida, suggesting community mitigation efforts provide a substitute for flood insurance in that state.

Demographic variables also appear to influence the purchase of insurance and the extent of mitigation efforts. The presence of children was again found to have a robust, negative effect on the decisions to insure and mitigate, consistent with Petrolia et al. (2015) and in contrast to the results of Petrolia, Landry, and Coble (2013) and Carson, McCullogh, and Pooser (2013). We add further evidence to the literature supporting a positive income effect on the decision to purchase insurance that has been arrived at repeatedly in the past (Baumann and Sims, 1978; Browne & Hoyt, 2000; Kunreuther, 2006; Landry & Jahan-Parvar, 2011; Petrolia, Landry, and Coble, 2013; Petrolia et al., 2015) It also appears that education level has some effect on the decision to insure and may be related to an individual's

ability to more accurately interpret the frequency of low-probability events. It does appear that expectations for future category 3 storms are decreasing in education level in our sample.

Here we also wish to address a key caveat concerning our model for the mitigation decision. 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. While we model this choice as a decision by the homeowner, a conservative interpretation of the results seems prudent.

6.1 Direction for Future Research

The market for catastrophe insurance is complex and consumers must navigate a virtual maze of deductibles, limits, mitigation discounts, and legal mandates which vary widely across the country. Future research should focus on examining potential alternatives to the current framework designed to simplify the process for consumers and increase participation. Examples of this include the bundling of wind and flood coverage into multi-peril policies, multi-year flood insurance contracts, and tying catastrophe insurance contracts to multi-year mitigation loans (Pompe & Rhinehart, 2008; Michel-Kerjan, 2010; Michel-Kerjan, Lemoyne de Forges, & Kunreuther, 2012). Future research should also focus on how consumers obtain and integrate the information currently available to them in the decision process. Other opportunities also exist to test the robustness of structural frameworks for decision under risk such as expected utility, prospect theory, or regret aversion.

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