MANAGING NATURAL DISASTER RISK THROUGH INSURANCE

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MANAGING NATURAL DISASTER RISK THROUGH INSURANCE

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This dissertation consists of three articles. The first introduces a new modeling framework to help understand and manage primary insurers' roles in catastrophe risk management. The framework includes a new game theoretic optimization model of primary insurer decisions that interacts with a utility-based homeowner decision model, and is integrated with a regional catastrophe loss estimation model. Reinsurer and government roles are represented as bounds on the insurer-insured interactions. The modeling framework can be used to explore two primary questions. First, how should insurers, using a credible assessment of natural disaster risk, optimize their catastrophe risk insurance-policy design, portfolio, and risk-transfer decisions within a context defined by homeowners, reinsurers, and government agencies? Second, how do changes in the context affect insurers' ability to operate successfully? Specifically, it provides results that indicate, under equilibrium, the (1) primary insurers' optimal actions and outcomes, (2) homeowners' optimal actions and outcomes, (3) reinsurers' outcomes, and (4) loss distribution for each stakeholder.

The second article, using survey data, explores the roles of prior disaster experience and risk perception on flood insurance purchase decision-making. The survey was administered by a computer-assisted telephone interviewing system in the eastern half of North Carolina. A structural equation model was built to understand the direct and indirect effects of different variables on one another and on flood insurance purchase decision-making. The article provides

insight on the mediation effect of risk perception, by linking prior disaster experience to the undertaking of protective action. It also discusses the implications of this insight for designing effective risk communication tools, the timing of risk awareness campaigns, and the provision of affordable insurance policies.

The third article, using the same survey data from the eastern half of North Carolina, investigates the relationship between self-insurance and market insurance. An ordered logistic model was developed by using revealed preferences about structural retrofit measures and standard homeowners' insurance deductible choices. The article shows that self-insurance and market insurance are substitutes and discusses the implications of this finding in terms of setting appropriate standard homeowners' premium and deductible values.

BIOGRAPHICAL SKETCH

Yohannes Yemane Kesete earned a Ph.D. in Civil Infrastructure Systems from the School of Civil and Environmental Engineering at Cornell University. He holds M.Sc. and M.Eng. degrees in Civil Infrastructure Systems Engineering and Transportation Systems Engineering, respectively, from the same school; a M.Sc. in Transportation Engineering from Florida International University; and a B.Sc. in Civil Engineering from the University of Asmara. He has worked as a civil engineer with the Ministry of Public Works of Eritrea and as an engineer intern in the Research and Modeling Department of AIR-Worldwide, one of the leading catastrophe risk-modeling firms. He currently works as an extended-term consultant with the World Bank and has been involved in several projects in Sri Lanka, Bangladesh, Bhutan, and Bosnia and Herzegovina.

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CHAPTER 1

MODELING INSURER-HOMEOWNER INTERACTIONS IN MANAGING NATURAL DISASTER RISK

ABSTRACT

The current system for managing natural disaster risk in the United States is problematic for both homeowners and insurers. Homeowners are often uninsured or underinsured against natural disaster losses, and typically do not invest in retrofits that can reduce losses. Insurers often do not want to insure against these losses, which are some of their biggest exposures and can cause an undesirably high chance of insolvency. There is a need to design an improved system that acknowledges the different perspectives of the stakeholders. In this paper, we introduce a new modeling framework to help understand and manage the insurer's role in catastrophe risk management. The framework includes a new game theoretic optimization model of insurer decisions that interacts with a utility-based homeowner decision model, and is integrated with a regional catastrophe loss estimation model. Reinsurer and government roles are represented as bounds on the insurer-insured interactions. We demonstrate the model for a full-scale case study for hurricane risk to residential buildings in eastern North Carolina; present the results from the perspectives of all stakeholders—primary insurers, homeowners (insured and uninsured), and reinsurers; and examine the effect of key parameters on the results.

1.1. INTRODUCTION

Insurance plays a crucial role in managing regional catastrophe risk, both by spreading large losses associated with catastrophic events, and by providing incentives to encourage risk reduction efforts. Nevertheless, problems persist in catastrophe insurance markets. Property owners tend not to buy insurance; nor do they invest in pre-event mitigation activities that can reduce losses (Kreisel and Landry 2004, Dixon et al. 2006, Kunreuther 2006). As a result, they frequently do not have sufficient financial resources to recover and may require relief from the government (Kunreuther and Pauly 2004). Major disasters thus are followed by large, unplanned government expenditures that create major difficulties for local and state government budgets (Kunreuther and Pauly 2004). The current system is problematic for insurers as well, with natural disasters being some of their biggest exposures (U.S. GAO 2007). As a result, insurers have limited their policy-writing in at-risk regions (U.S. GAO 2007). In the worst case, disaster events can cause insolvency, as happened, for example, to eight small Florida insurance companies after Hurricane Andrew (Grier 1996).

In this paper, we introduce a new modeling framework to help better understand and manage the insurer's role in catastrophe risk management. The framework includes a new game theoretic optimization model of insurer decisions that interacts with a utility-based homeowner decision model, and is integrated with a regional catastrophe loss estimation model. Reinsurer and government roles are introduced as exogenous constraints on the insurer-insured interactions. We demonstrate application of the model to a full-scale case study for hurricane risk to residential buildings in eastern North Carolina, and examine the results from the perspectives of all stakeholders—primary insurer, reinsurer, and homeowners (insured and uninsured). The modeling framework can be used to examine two main questions:

- How should insurers optimize their catastrophe risk insurance policy design, portfolio, and risk transfer decisions within a realistic context defined by homeowners, reinsurers, and government agencies, using an assessment of actual natural disaster risk?

- How do changes in that context affect insurers' ability to operate successfully and sustainably?

The study is novel in integrating game theoretic optimization with a catastrophe loss model that provides a credible, disaggregated representation of the risk to be managed, including spatial correlation and variability among properties. Compared to previous work, including the loss model provides more accurate representation of the insured and uninsured loss distributions under different homeowner insurance purchasing decisions, allows the opportunity to design an insurance portfolio that combines an appropriate combination of properties, and enables future integration within the same framework of the possibility that homeowners could retrofit their buildings instead of or in addition to purchasing insurance. By allowing examination of the resulting distribution of losses from all perspectives, the framework can provide insights useful for public policy as well as the insurance industry.

Following a literature review in Section 1.2, the modeling framework is introduced in Section 1.3. The case study application is presented in Section 1.4, including base case results and sensitivity analyses.

1.2. BACKGROUND

Seminal work on the economic theory of insurance, including Borch (1962), Arrow (1963), and Mossin (1968), provides a theoretical foundation for the strategic behavior of insurers that has been further enriched by extensions (Miller 1972, Raviv 1979, Cummins and Mahul 2003, Gollier 2000, Louberge 2000). Kelly and Kleffner (2003) examine the interaction between the premiums an insurer sets and an individual's decisions to purchase market insurance and/or undertake mitigation. Kousky and Cook (2012) examine the premiums a solvency-constrained insurer would have to charge given a loss distribution with fat tails, microcorrelations, or tail dependence. They find that, faced with those premiums, it may be rational for a utility-maximizing homeowner not to purchase insurance.

The theoretical research is based on stylized models of catastrophe risk that assume a smooth aggregated total loss distribution or a distribution of a binary (loss/no loss) variable. While this is adequate for addressing many questions, an engineering model can provide a more accurate and detailed representation of the risk. Importantly, it can also capture the great variability among individual property loss distributions, which is necessary to optimize design of a portfolio of insured properties. Use of an explicit loss model also allows joint optimization of insurance purchasing and retrofit decisions since the effect of the latter on the distribution of insured loss can influence both optimal insurer and homeowner behavior. Despite these benefits, loss models have rarely been integrated into the economic catastrophe risk literature. Kleindorfer and Kunreuther (1999) and Kunreuther and Michel-Kerjan (2009) have used loss model results from engineering modeling firms to investigate the impact of mitigation on insurer losses and insolvency probabilities, and on how losses are distributed among stakeholders. In this paper, we integrate that type of loss model results with an insurer decision optimization model. Grossi and Kunreuther (2005) offer a useful summary of how catastrophe modeling can be integrated with insurance management. Hayek and Ghanem (2005) and Hayek (2005) create an insurance portfolio optimization model that takes input from a catastrophe model, including disaggregation of insured properties by location and building type. They focus on the role of the primary insurer and demonstrate the model for a relatively small example (6 locations, 10 structural types, and 34 earthquake scenarios).

Finally, researchers at the International Institute for Applied Systems Analysis (IIASA) have developed and applied a spatial-dynamic stochastic optimization model to generate insurance strategies (Amendola et al. 2013, Ermoliev et al. 2000, Amendola, Ermolieve, and Ermolieva 2000, Amendola et al. 2000, Ermolieva et al. 2003). Specifically, in Ermolieva and Ermoliev (2013), the geographic area is divided into cells with random catastrophic events simulated over time, and loss estimated for each cell and event. The stochastic optimization model solves for a set of decision variables, such as premium and coverage for each cell, and amount to transfer to reinsurers. It is solved using methods of adaptive Monte Carlo optimization. The IIASA models are similar to what we present, but the specifics differ. In particular, we represent the interaction between homeowners and insurers including rules as to what homeowners are willing to pay as well and what policies insurers are willing to offer, describe the hazard with a complete yet efficient set of thirty-year scenarios of hurricane occurrence; and use different solution methods.

1.3. MODELING FRAMEWORK

1.3.1. Scope and Main Assumption

Building inventory. The framework addresses single-family residential buildings only. The inventory of residential buildings is divided into groups, where each is defined by its geographic area unit or location i (e.g., census tract), building category m, resistance level c, and risk region v. Building categories m are defined based on architectural features and are assumed to perform similarly and have similar value (e.g., one-story home with a garage and hip roof). A building's resistance level c represents its vulnerability and is a function of structural details that define the probability of damage given wind speed and flood depth. Risk regions v are larger geographic areas comprised of many area units i. They are defined to allow insurer premiums and homeowner risk attitudes to vary geographically, but at greater aggregation than area units. The initial building inventory is defined using X_{imcv}, the number of buildings of type i, m, c, v.

We assume the building inventory is constant with time. Commercial or other buildings could be considered with some modifications.

Time. The durations of the time steps *t* vary (a few days to a few weeks). They are defined to be short enough so that we can reasonably assume no two hurricanes occur in the same time period, and so that the probability a hurricane occurs in one time period is equal across time periods. Since hurricane occurrence varies during the year, this means the time periods are shorter, for example, in September when hurricanes are more likely than in June when they are less likely. Since hurricanes are highly unlikely mid-December to mid-May, we omit those months from the year.

Hazard. The model considers hurricane-related claims only (although it could be extended to other hazards), and includes coverage for both hurricane-related wind and storm surge flooding. Note that while hurricane-related wind and flood damage are currently insured separately in the United States—wind usually (though not always) as part of regular homeowner's policies and flood through the National Flood Insurance Program, in this analysis we consider both to assess how they might be managed together, as proposed, for example in U.S. GAO (2008). The framework is flexible enough however, that one could run it with only wind or only flood coverage as well.

The hurricane hazard is represented by an efficient set of probabilistic hurricane scenarios $h \in (1, \dots, H)$, defined as tracks with along-track parameters that determine the intensity, including central pressure deficit and radius to maximum winds. Each hurricane scenario has an associated hazard-adjusted annual occurrence probability P^h such that when probabilistically combined, the set of hurricane scenarios represents the regional hazard (Apivatanagul et al. 2011). For each hurricane, wind speeds and surge depths are estimated throughout the study area;

in a sense, each hurricane scenario represents all hurricanes that would produce similar wind speeds and surge depths in the study area. An efficient set of hurricanes *h* like this can be developed using the optimization-based probabilistic scenario (OPS) method (Apivatanagul et al. 2011) or possibly the joint probability method-optimal sampling (JPS-OS) (Toro et al. 2010) or other methods (Han and Davidson 2012) aimed at efficient scenario-based representation of probabilistic hazard for regional analysis. The occurrence probability for period t is calculated from the annual occurrence probability using the historical relative frequency of events over the course of the hurricane season (Peng 2013).

A series of hurricanes in quick succession can create very different outcomes for an insurer than the same hurricanes evenly spread over time. We therefore define a long-term (say, thirty-year) timeline of hurricanes as a *scenario* $s \in (1, \ldots, S)$. (To avoid confusion, we refer to a single *hurricane scenario* as simply a *hurricane h*.) Each scenario *s* is a $1 \times T$ vector, where T is total number of time periods, and for each time period t, either one of the possible hurricanes h occurs, or no hurricane occurs. For ease of notation, we refer to the case of no hurricane as $h = H + 1$. Each scenario has an occurrence probability P^s, such that $\sum_s P^s = 1$. The complete set of scenarios (on the order of hundreds or a few thousand) is defined so that it has the same key characteristics as the full set of $(H + 1)^T$ scenarios that is theoretically possible. In particular, the following should be approximately true: relative frequency of hurricanes $h \in (1, \ldots, H)$ in S scenarios is the same as defined by the P^h; number of hurricanes per year is Poisson-distributed with the parameter determined from the historical record; interarrival times of the hurricanes are exponentially distributed with the same parameter determined from the historical record; and distribution of total loss from the set of S scenarios is approximately normally distributed with mean and standard deviation as determined analytically (Peng 2013).

Development of these long-term hazard scenarios s is critical to representing the probabilistic hazard fully so as to capture the uncertainty that defines the natural disaster risk challenge, yet efficiently so that it can be included in the larger framework. This hazard modeling method is an important strength of the analysis.

Stakeholders. The collection of homeowners in the study area are disaggregated based on their homes' location i, building category m, building resistance level c, and risk region v. Since homeowners differ based on their i, m, c, v type (and therefore risk), and their risk attitude, the model does not assume they will all make the same decisions but instead captures the heterogeneous behavior of homeowners. We assume one primary insurer and one layer of catastrophe risk excess of loss reinsurance. While catastrophe risk excess of loss reinsurance is often combined with per risk excess of loss or quota share, for residential properties at the industry level, catastrophe reinsurance is the primary mechanism for transferring risk. The government may set constraints on the insurer and/or homeowners. We do not consider the government as an insurer or reinsurer, although in real life it sometimes plays that role. Capital markets are not considered.

1.3.2. Overall Modeling Framework

The interacting models aim to optimize insurer pricing and risk transfer decisions subject to a realistic representation of risk and homeowner, reinsurer, government behaviors. The framework includes three models and represents four main players (Fig. 1-1). The loss model is a simulation that combines hazard, inventory, and damage modules to compute a probability distribution of losses for each group of buildings (defined by location i, building category m, resistance level c, and risk region v) and each possible hurricane h in the study area. It is similar to regional loss estimation models, such as, HAZUS-MH 2.1 (FEMA 2012) or the Florida Public

Hurricane Loss Model (FPHLM 2005). The primary insurer and homeowners play a Stackelberg leader-follower game (Von Stackelberg 1934) in which the insurer (leader) determines what premiums to charge for policies at a specified deductible, and what reinsurance to purchase, and each homeowner (follower, defined by i, m, c, v) responds by deciding whether or not to purchase insurance. Specifically, the primary insurer model is a two-stage stochastic optimization in which the objective is to maximize profit, avoid insolvency, maintain sufficient yearly profitability (to preserve a high stock value, financial rating, and consumer confidence), and maintain sufficient capacity. Each homeowner's decision-making is modeled as a utility maximization. The reinsurer offers reinsurance at a specified price, and the government may set constraints on the insurer and/or homeowners, such as, establishing a maximum allowable capacity ratio.

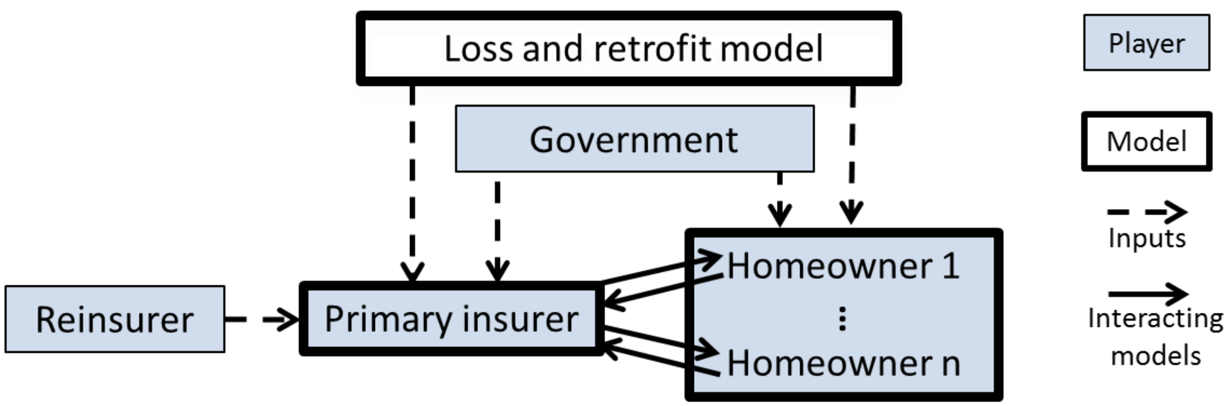

Figure 1-1. Structure of interacting models

In the event of a hurricane *h*, the loss to insured buildings is divided among the homeowners, primary insurer, and reinsurer as in Figure 1-2. The variables *A*, *M*, and β are the attachment point, maximum limit, and co-participation percentage of the reinsurance treaty, respectively. In the event of a hurricane *h*, the homeowners pay the first portion of the loss up to the deductible *D*; the reinsurer pays β% of any loss above the attachment point *A* and up to a maximum limit *β*% of (*M-A)*; and the primary insurer pays the remaining loss. The loss to uninsured buildings is paid by the owners of those houses, although the government has an interest in reducing the uninsured loss as well.

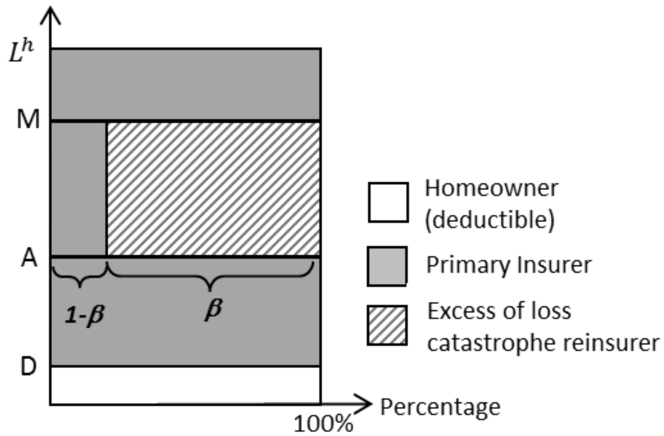

Figure 1-2. Loss structure showing how loss to insured buildings is divided among stakeholders

The models produce many outputs describing the recommended primary insurer and homeowner actions, and a probabilistic characterization of the resulting outcomes for the primary insurer, homeowners, and reinsurer, as well as how the total hurricane losses are divided among the players.

1.3.3. Primary Insurer Model Formulation

Loss definitions. The loss to a building in location i of category m and resistance level c in hurricane h is calculated as:

$$L_{imc}^{h} = \sum_{\delta} R_{mc}^{\delta} a_{imc}^{\delta h} \qquad \forall i, m, c, h \tag{1-1}$$

where $a_{imc}^{\delta h}$ is the probability a building of type i, m, c will experience damage state δ in hurricane h and R_{mc}^{δ} is the cost per building to reconstruct building of category m to its original building resistance c after it has been damaged to damage state δ. Note that combining wind speed and flood depth maps for each hurricane h with a damage model that computes damage as a function of wind speed and flood depth results in $a_{imc}^{\delta h}$, which is damage indexed by hurricane h and location i. Let X_{imcv} be the number of buildings of type i, m, c, v and w_{imcv} be binary decision variables output from the homeowner model (Section 1.3.4) that equal one if a homeowner of type i, m, c, v buy insurance and zero otherwise. Summing over all buildings, we get L^h, the total loss to insured buildings in hurricane h:

$$L^h = \sum_{imcv} L_{imc}^h X_{imcv} w_{imcv} \qquad \forall h \tag{1-2}$$

For simplicity, we assume damaged buildings are repaired to their pre-damage condition before another hurricane occurs, which implies that the model overestimates losses from hurricanes that affect the same properties during the same hurricane season. In practice, this error is likely to be modest because it is rare for multiple hurricanes to damage the same properties in the same season.

Deductibles that homeowners pay. When a hurricane h occurs, the actual expenses B_{imc}^h that an insured homeowner of type i, m, c pays is the minimum between the loss he experiences and the specified per-building deductible d, defined in absolute dollars:

$$B_{imc}^h = \min\{L_{imc}^h,\ d\} \qquad \forall i, m, c, h \tag{1-3}$$

While we consider only one deductible, it is straightforward to extend this formulation to include multiple deductibles. Summing over all buildings, the total amount homeowners pay in deductibles in hurricane h is:

$$B^h = \sum_{imcv} B_{imc}^h X_{imcv} w_{imcv} \qquad \forall h \tag{1-4}$$

Premium collected from homeowners. We assume the homeowner premiums are risk-based, i.e., they vary by building type i, m, c, v. Specifically, the premium p_{imcv} collected for a building in location i, of category m, resistance level c, and risk region v is the expected value of the loss to an insured building of type i, m, c, v less the deductible, multiplied by one plus the loading factor τ, an assumed input constant, plus the loading factor λ_v, a decision variable (Eq. 1-5). The loading factors τ and λ_v represent the primary insurer's administrative cost and profit margin, respectively.

$$p_{imcv} = (1 + \tau + \lambda_v) \sum_h P^h \left(L^h_{imc} - B^h_{imc} \right) \quad \forall\, i, m, c, v \tag{1-5}$$

If the model recommends a premium so high that no homeowners will purchase insurance, that in effect, represents the insurer's decision not to offer insurance to buildings of that type. Summing over all buildings of type i, m, c, v, the total annual premium homeowners pay is:

$$p = \sum_{imcv} p_{imcv}\, X_{imcv} w_{imcv} \tag{1-6}$$

Loss that catastrophe reinsurer pays. The primary insurer must decide how much risk to transfer to the reinsurer, specifically, the attachment point *A* and maximum limit *M* it would like to set. We define q^h to be the loss above *A* and below *M* for hurricane h (Eq. 1-7). If the loss exceeds the attachment point *A*, then βq^h is recovered from the reinsurer and the primary insurer pays $(1 - \beta) q^h$, where β is a specified input constant.

$$q^h = \min\{\max\{L^h - A, 0\}, M - A\} \quad \forall h \tag{1-7}$$

For a given scenario *s* and time *t*, which hurricane *h* (or no hurricane) happens is known, so we can define e^{sy}, the loss between attachment *A* and limit *M* for scenario *s* and year *y* in Equation 1-8, where γ^{sth} is a binary indicator variable that is one if hurricane *h* happens in scenario *s* at time *t* and zero otherwise. Since at most one hurricane can happen in a time period *t*, $\sum_h \gamma^{sth} \leq 1 \quad \forall s, t$. The set $\omega(y)$ defines the set of time periods *t* in year *y*.

$$e^{sy} = \sum_{t \in \omega(y)} \sum_h \gamma^{sth} q^h \quad \forall s, y \tag{1-8}$$

Reinsurance premium. In each year *y*, the primary insurer pays the reinsurer a base premium *b*, and in the event of a hurricane *h*, it also pays a reinstatement premium to reinstate the limit *M*. The base premium is computed as the expected loss the reinsurer is responsible for multiplied by one plus a loading factor φ, plus the standard deviation σ of the net reinsurer loss multiplied by β and a user-specified constant g (Eq. 1-9) (Kunreuther and Michel-Kerjan 2009).

$$b = (1+\varphi)[\sum_h P^h \beta q^h] + g\beta\sigma \tag{1-9}$$

The loading factor φ represents the reinsurer's share of the loss adjustment expenses, its own expenses, and its profit, and g represents the reinsurer's risk aversion. The σ is the standard deviation over all scenarios *s* and years *y* of the reinsurer's loss, e^{sy}, less the reinstatement premium for scenario *s* and year *y*. The reinstatement premium is a pro rata amount of the expected reinsurer loss without adjusting for the length of the treaty's remaining term. That is, it equals the expected loss multiplied by the percentage of the original coverage that was used ($e^{sy}/(M-A)$). The total reinsurance premium for scenario s in year *y*, therefore, is the sum of the base reinsurance premium and the reinstatement payment:

$$r^{sy} = b + \left(\frac{e^{sy}}{M-A}\right)[\sum_h P^h \beta q^h] \quad \forall\, s, y \tag{1-10}$$

Primary insurer's profit and accumulated surplus. Equation 1-11 defines the insurer's net profit, F^{sy}, in scenario s and year *y*. The terms are, in turn, the total homeowner premiums collected, loss adjustment expenses portion of the premiums collected, total actual loss, actual deductibles recovered from the homeowners, actual loss recovered from the reinsurer, and reinsurance premium.

$$F^{sy} = p - \tau\left[\sum_h P^h \left(L^h - B^h\right)\right] - \sum_{t\in\omega(y),h} \gamma^{sth} L^h + \sum_{t\in\omega(y),h} \gamma^{sth} B^h + \beta e^{sy} - r^{sy} \quad \forall\, s, y \tag{1-11}$$

In reality, the funds available to the insurer at any time would be the policyholder surplus, which is defined as the insurer's admitted assets minus its liabilities, i.e., its net worth. In this model, we treat the profit accumulated in previous periods as the policyholder surplus, and thus we ignore the effect of investments and other lines of business. We assume the company starts its business at time $y = 0$ with a surplus equal to *k* times the annual premiums received, where *k* is a user-specified constant (Eq. 1-12). We further assume the primary insurer reallocates surplus greater than this amount in each year *y* by reinvesting in other lines of business or distributing it to investors as dividends. The surplus in scenario *s* and year *y* then is the minimum of the sum of the profit in *y* and the surplus in $y-1$, and the maximum allowable surplus kp (Eq. 1-13).

$$C^{s0} = kp, \quad \forall s \tag{1-12}$$

$$C^{sy} = min(C^{s,y-1} + F^{sy}, kp) \quad \forall s, y \tag{1-13}$$

If the accumulated surplus C^{sy} in year *y* equals zero or less, we assume that the insurer becomes insolvent, and the profit F^{sy} and surplus C^{sy} are set to zero for the remaining years $(y+1, \dots, Y)$ of the scenario *s*.

Insolvency. An important constraint on insurer decisions is that the probability of insolvency may not be larger than a user-specified constant α, where ϕ^s is a binary indicator variable that is one if the insurer becomes insolvent at any time in scenario *s* and zero otherwise.

$$\frac{1}{S}\sum_s \phi^s \leq \alpha \tag{1-14}$$

Capacity ratio. Another primary insurer objective is to maintain a sufficiently low capacity ratio. The capacity ratio (also known as leverage ratio) typically represents the insurer's capacity to write business and is defined as the net written premiums divided by the policyholder surplus (Eq. 1-15). State insurance regulators often require it to be less than three (Harrison 2004). We represent this objective as a constraint that the capacity ratio should not exceed a user-specified constant η for any scenario *s* and year *y*.

$$\frac{p-\tau[\sum_h P^h(L^h-B^h)]-r^{sy}}{C^{sy}} \leq \eta \quad \forall s, y \tag{1-15}$$

Return on equity. Investors seek a high and stable return on equity (ROE), a measure of how efficiently capital is used. We represent this idea as a constraint that the average annual ROE for the years *Z* that the insurer is solvent is at least a user-specified constant ζ, where annual ROE is defined as the profit divided by the average surplus over the last two years (Eq. 1-16).

$$\frac{1}{SZ}\sum_{s,y\in Z}\frac{F^{sy}}{0.5(C^{s,y-1}+C^{sy})} \geq \zeta \tag{1-16}$$

Objective function. The objective function is to maximize the total profit over the full time horizon, averaged over all scenarios S (Expression 1-17). The model thus chooses values of the decision variables λ_v, A and M defining the premium pricing and reinsurance purchase, subject to the constraints in Expressions (1-1) to (1-16). In this two-stage structure, λ_v, A and M are determined in the first stage, and then following the resolution of the uncertainty about which long-term scenario s occurs, the losses are computed in the second stage.

$$Max \quad \frac{1}{S}\sum_{sy} F^{sy} \tag{1-17}$$

1.3.4. Home Owner Model Formulation

Homeowners decide whether to buy the insurance offered by the insurer or not. The collection of homeowners in the study area is partitioned based on location i, building category m, building resistance level c, and risk region v. The model defined in Expressions (1-18) to (1-21) is run separately for each group of homeowners i, m, c, v, and since the models do not interact, the computation can be parallelized. Specifically, the model takes as input the premium and deductible payment from the insurer model (p_{imcv}, B^h_{imc}), and damage probabilities and reconstruction costs ($a^{\delta h}_{imc}, R^{\delta}_{mc}$) from the loss model, then provides as output w_{imcv}, binary decision variables that equal one if a homeowner of type i, m, c, v buys insurance and zero otherwise. The homeowner analysis is conducted on an individual building and annual basis.

We assume the decision is made by maximizing utility, represented by the function $U(x) = 1 - e^{-\theta_v x}$, where θ_v is the Arrow-Pratt coefficient of risk aversion for homeowners in risk region v and x is the total homeowner expenditures. The assumption that homeowners are risk averse, $\theta_v > 0$ supports the existence of a voluntary market for insurance given the loading factors on the premiums. The homeowner's objective function (Eq. 1-18) is to maximize the sum of the expected utilities over all possible hurricanes h if he buys insurance (first term) and if he does not (second term). In the first case, the homeowner pays the premium and loss up to the deductible. In the second case, the homeowner pays the loss due to building damage only. Note that when $h = H + 1$, no hurricane occurs, and the loss is zero.

$$Max \;\; w_{imcv} \left[\sum_h P^h \left(U\left(p_{imcv} + B^h_{imcv}\right)\right)\right] \; + (1 - w_{imcv}) \left[\sum_h P^h \left(U\left(\sum_\delta R^\delta_{mc} a^{\delta h}_{imc}\right)\right)\right] \quad (1\text{-}18)$$

We assume each homeowner has a maximum budget for homeowner insurance equal to a specified percentage κ_v of his home value V_m, assuming the percentage may vary by risk region v (Eq. 1-19). We also assume the insurer will only offer insurance if the premium is greater than some specified value ρ (Eq. 1-20). Finally, the w_{imcv} must be zero or one.

$$p_{imcv} \leq \kappa_v V_m \qquad \forall i, m, c, v \qquad (1\text{-}19)$$

$$p_{imcv} \geq \rho \qquad \forall i, m, c, v \qquad (1\text{-}20)$$

$$w_{imcv} = \{0,1\} \qquad \forall i, m, c, v \qquad (1\text{-}21)$$

1.3.5. Solution Procedure

In the case study, with two risk regions, $v \in [H, L]$ (Section 1.4.2), the insurer optimization requires solving for four continuous decision variables simultaneously (λ_H, λ_L, A, and M). We do so using simulated annealing (SA), an iterative, adaptive, and nondeterministic heuristic optimization algorithm that accepts better solutions at all times and worse solutions sometimes (Sait and Youssef 1999). The ability to go to a worse solution with a certain probability allows the algorithm to escape local maxima and minima. For ease of computation, the probability of insolvency, capacity ratio and return on equity constraints are incorporated into the objective function as penalties. The initial temperature and decrement factor parameters in the algorithm are determined based on 100 initial evaluations of average change in cost for an uphill move. Transitions are made randomly within neighborhoods of +/- 0.2 from the current loading factors, λ_L and λ_H and +/- 200 million from the current reinsurance terms, *A* and *M*. At each iteration, a random number from a uniform distribution is generated and the probability of going to a worse solution is computed. As iterations progress, the algorithm accepts worse solutions with a lower probability, and towards the end it resembles a greedy search. The optimization was implemented in MATLAB (R2011a) and a total of 40 trials of 1000 iterations each were executed in parallel on a Unix-based high performance computing cluster, with each trial requiring approximately 3.75 hours. The SA algorithm converges well with the last 100 iterations of each trial exhibiting only 0.01% improvement in the objective function.

1.4. CASE STUDY APPLICATION

1.4.1. Purpose and Scope

A case study was conducted in eastern North Carolina to demonstrate that the models can be applied in a full-scale analysis, and to show the type of results it provides and how they can be interpreted. The region includes 503 census tracts and covers the low-lying coastal part of the state with the most severe hurricane hazard, extending westward to include half of Raleigh, the state capital. A tropical storm or hurricane is expected to make landfall on the North Carolina coast on average every four years (SCONC 2010). The study focuses on single-family wood-frame homes, the wind and storm surge flooding hazards (not rainfall-induced flooding), and direct losses (structural, non-structural, interior, mechanical, electrical, and plumbing, but no contents or additional living expenses).

1.4.2. Inputs

The 2010 census tracts are the basic area unit of study, but each of the 143 census tracts that touch the coast was divided into three areas—a zone within one mile of the coastline, a zone one to two miles from the coastline, and the remainder of the census tract. The result is 732 locations *i*.

Eight building categories *m* were defined to represent all combinations of number of stories (one or two), garage (yes or no), and roof shape (hip or gable). Each building is defined as a collection of *components* represented in the damage and loss model (e.g., roof covering, openings). Each component in turn is made of many *component units* (e.g., a single window or section of roof covering). For each component a few possible physical *configurations* are defined, each with an associated mean *component resistance*. The *building resistance c* of each building is then defined by the vector of mean resistances of its components. The case study includes 192 building resistance levels (Peng 2013).

The component-based loss simulation model is a combination of a modified Florida Public Hurricane Loss Model for the wind- and debris-related damage (FPHLM 2005); and Taggart and van de Lindt (2009) and van de Lindt and Taggart (2009) for the flood-related damage. Described in detail in Peng et al. (2013) and Peng (2013) the loss model was used to compute the damage probabilities ($a_{imc}^{\delta h}$) and reconstruction costs (R_{mc}^{δ}). The building inventory data (X_{imcv}) was estimated using census data, with total building counts allocated among the building resistance levels *c* based on location (coastal or not) and year built relative to major building code and construction practice changes. Building values (V_m) were estimated using R.S. Means (2009).

We define two risk regions v—within two miles of the coast (high risk) or not (low risk), reflecting an assumption that homeowners who live in a particularly high risk areas may have a different risk attitude and may be charged a higher premium. The risk aversion parameter values θ_v used in the homeowner utility model were estimated using National Flood Insurance Program data (Gao 2014). Specifically, values of θ_v were chosen so that given our assumed utility model, they would result in the penetration rates reported in Dixon et al. (2006). The final base case parameter values are $\theta_H = 3.0(10^{-5})$ and $\theta_L = 1.7246(10^{-5})$ for high and low risk areas, respectively (and they are varied -100% to +100% in Section 1.4.4).

We used the set of $H = 97$ probabilistic hurricane scenarios developed in Apivatanagul et al. (2011) using the Optimization-based Probabilistic Scenario (OPS) method. The method involves first simulating tens of thousands of candidate hurricane scenarios with wind speeds and approximate surge depths. In this case, we used the empirical track method (ETM) to generate this candidate set of scenarios (Vickery et al. 2000). A mixed-integer linear optimization is then used to select a subset of scenarios and assign hazard-consistent annual occurrence probabilities to each so that the regional wind speed and coastline surge depth hazard curves estimated by the hurricanes in the reduced set match the "true" wind and coastline surge depth hazard curves based on the complete candidate set. Finally, a surge model is used to estimate accurate surge depths for the reduced set of events. For each scenario, open terrain 3-second peak gust wind speeds and surge depths were computed throughout the study region using the storm surge and tidal model ADCIRC (Westerink et al. 2008). This set of scenarios was shown to result in errors small enough to be inconsequential for regional loss estimation (Apivatanagul et al. 2011). We reevaluated the flood depths at more coastal locations than in Apivatanagul et al. (2011) to improve the geographic resolution. Using those hurricanes, we simulated a set of $S = 2000$

thirty-year scenarios that represent the full set of possible scenarios and confirmed that they have minimal error in the characteristics listed in Section 1.3.2 (see Peng 2013 for more detail). There are twenty time steps per year and $T = 600$ time steps per scenario s.

Other input parameter values include deductible $d = \$2500$, co-participation factor $\beta = 95\%$, primary insurer administrative loading factor $\tau = 0.35$ (personal communication, John Aquino, WillisRe), reinsurer loading factor $\varphi = 0.1$, reinsurer risk attitude $g = 0.1$ (varied from 0 to 0.3 in Section 1.4.4), factor defining allowed surplus $k = 3$ (varied from 0 to 3 with $g = 0.3$ in Section 1.4.4), maximum allowable thirty-year probability of insolvency $\alpha = 0.1$, maximum allowable capacity ratio $\eta = 3$, minimum allowable average annual return on equity ζ=0.05, minimum premium required $\rho = \$100$, and homeowner insurance budgets of $\kappa_H = 5\%$ and $\kappa_L = 2.5\%$ of building value for high and low risk homeowners, respectively.

1.4.3. Base Case Results

The modeling framework can be used to explore two primary questions. First, how should insurers optimize their catastrophe risk insurance policy design, portfolio, and risk transfer decisions within a context defined by homeowners, reinsurers, and government agencies using a credible assessment of natural disaster risk? Second, how do changes in the context affect insurers' ability to operate successfully? Specifically, it provides results that indicate under equilibrium the (1) primary insurer's optimal actions and outcomes, (2) homeowners' optimal actions and outcomes, (3) reinsurer's outcomes, and (4) loss distribution for each stakeholder. We discuss these results in Section 1.4.3, and then consider the effect of changes to the homeowners' risk attitudes, reinsurer risk attitude, and insurer surplus policy in Section 1.4.4. Note that it is important to look at the full set of results because they interact, and because while a solution may look appealing to one stakeholder, it may not to another. (Note also that these results differ from the current market because they reflect insurance for both wind- and flood-related hurricane hazards, and a different regulatory setting for the insurer and homeowners.)

1.4.3.1. Primary insurer's actions and resulting outcomes

For the base case, the results suggest the primary insurer should use profit loading factors of $\lambda_H = 1.48$ and $\lambda_L = 1.24$, respectively. This means they would make on average 148% and 124% profit per dollar insured in the high and low risk areas, respectively. These loading factors, together with the administrative loading factor τ and the expected loss result in average premiums of \$2574 and \$404, and penetration rates of 16% and 5% in the high and low risk areas, respectively.

The results also indicate that the insurer should buy reinsurance with an attachment point of $A = \$0.25$ billion and a maximum limit of $M = \$2.75$ billion. On Figure 1-3, which shows the probability density function (PDF) of annual loss to insured buildings, one can see that the recommended attachment point and maximum limit cover most but not all of the tail of that distribution. In fact, there is an 89% chance that the reinsurance will be activated at least once in a thirty-year scenario, and it may be activated as many as seven times or more with a probability of 1% (Fig. 1-4). Together these results highlight the important role reinsurance plays, especially in helping the insurer remain below its maximum allowable probability of insolvency. In Section 1.4.4, the influence of the reinsurer's risk attitude further emphasizes that point.

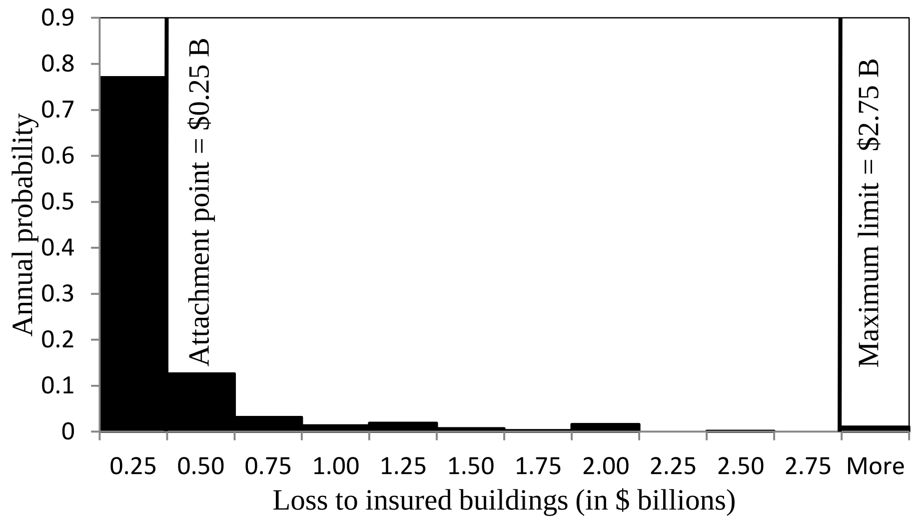

Figure 1-3. PDF of annual loss to insured buildings, with model-recommended attachment point and maximum limit

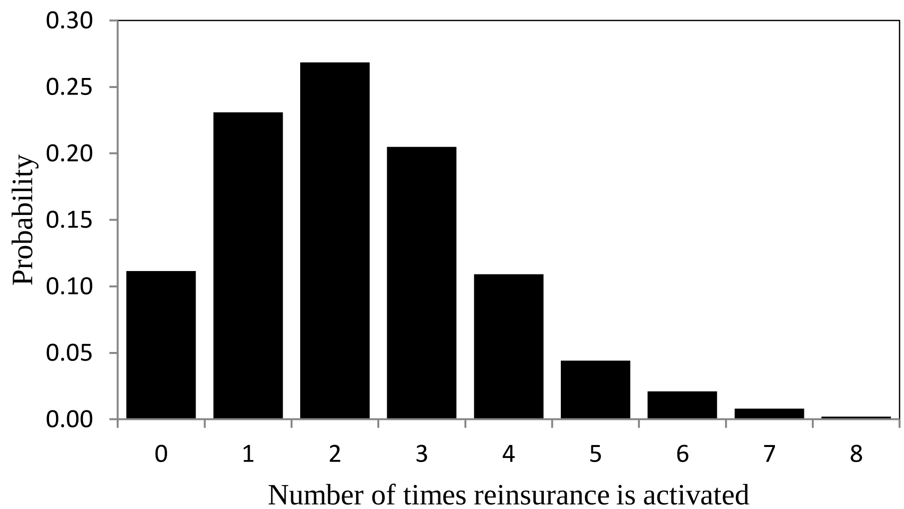

Figure 1-4. PDF of number of times reinsurance is activated over a period of thirty years

With those primary insurer actions (and the homeowners' responses), the model provides the resulting outcomes for the insurer. The insurer achieves an average annual profit of $56.9 million, and the scenario analysis allows us to see the variation surrounding the average results as well. The results show that in 72% of years (i.e., when there is no hurricane), the profit is $78 million, but there is a 9.4% chance that the annual profit will be negative (i.e., the insurer will lose money), in fact up to $6.5 billion if the most severe hurricane occurs. It is important to note that these profits are obtained while meeting the specified constraints on probability of insolvency, return on equity, and capacity ratio. In the base case, the probability of insolvency over thirty years is 0.033, equivalent to 0.001 per year and well below the assumed maximum allowable 0.1. Looking more closely at the 62 out of 2000 thirty-year scenarios in which the insurer goes insolvent shows that the primary predictor of insolvency is experiencing at least one hurricane that causes a very large loss (as opposed to many or closely-spaced events, for example). While the average number of hurricanes is actually larger among solvent scenarios than the insolvent scenarios (10 vs. 5), the maximum single-event losses are much larger for insolvent scenarios than solvent scenarios (Fig. 1-5). In fact, given a single-event total insured loss greater than $3 billion, there is a 95% chance of insurer insolvency. The average annual return on equity is 11%, above the desired minimum value of 5%. Finally, due to the assumed maximum allowable annual surplus, the average annual capacity ratio is 0.17, well below the maximum allowable of three.

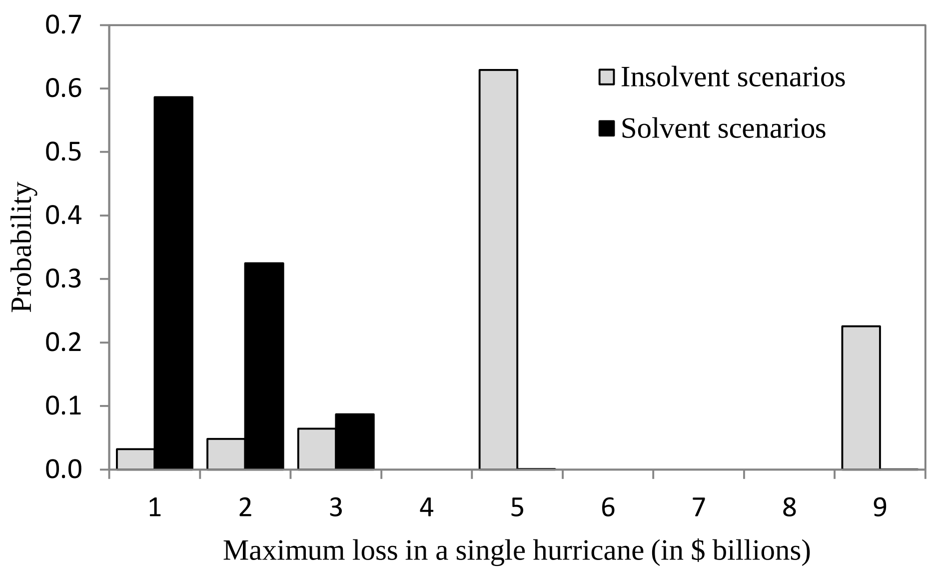

Figure 1-5. PDF of the maximum total insured loss in a single hurricane, for scenarios in which the insurer becomes insolvent and scenarios in which it remains solvent

1.4.3.2. Homeowners' actions and resulting outcomes

In the base case, 16% and 5% of homeowners in the high and low risk regions, respectively purchase insurance. More specifically, Figure 1-6 shows the geographic distribution of insurance penetration. Disaggregating by building category *m* also reveals that being two stories (vs. one), having a gable (vs. hip) roof, and not having a garage are all associated with increased likelihood of buying insurance (Fig. 1-7). The homeowner's decision to buy insurance depends on his initial loss distribution, risk attitude, and budget. It turns out that the pattern of insurance purchase in this case can largely be explained by the initial loss distributions, in particular the mean and coefficient of variation (COV) of loss. In Figure 1-8, each home making the corresponding decision—insure or do nothing—was plotted as a point on the associated graph based on the COV and mean of its loss distribution. For clarity, the scatterplots were then translated into the heat maps shown, in which a darker shade indicates a higher density of points. Homeowners with lower mean and coefficient of variation of loss tend to not buy insurance. The relatively high participation in the southwestern part of the study area, for example, is due to a relatively high COV of loss in that location. The pattern relates to the fact that insurance removes the tail of the loss distribution since it is certain that if a hurricane occurs the homeowner will not have to pay more than the deductible, so it is most useful when the variability in loss is highest.

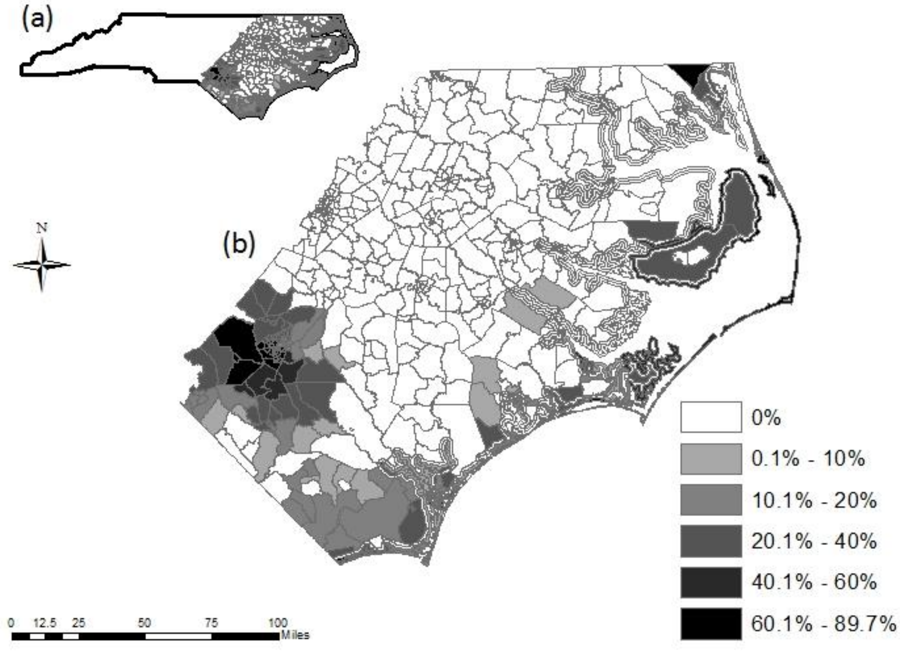

Figure 1-6. (a) North Carolina (b) percentage of homes in each area *i* that buy insurance in the base case.

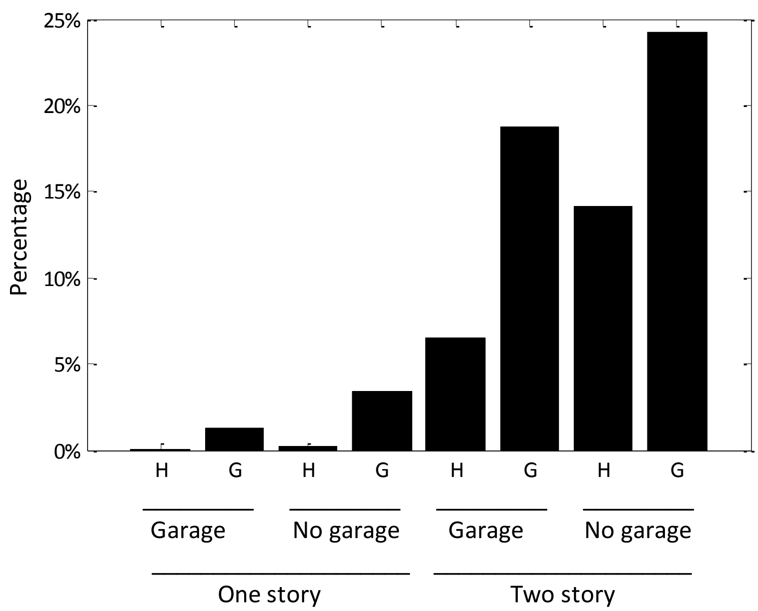

Figure 1-7. Percentage of homes of each building category *m* that buy insurance in the base case (*H* and *G* indicate hip and gable roof, respectively)

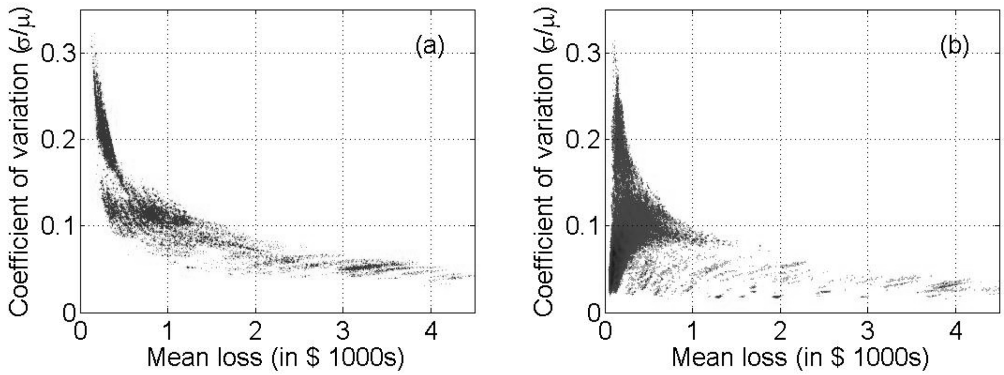

Figure 1-8. Coefficient of variation of loss vs. mean loss per home, for (a) insured and (b) uninsured homes.

We can now examine the resulting outcomes for the homeowners. Figure 1-9 shows the benefit of investment for the average uninsured and insured homeowners in terms of change in the inverse cumulative distribution function (CDF) of their annual expenditures, where expenditures include any premium, deductible, or loss due to damage. It shows that the initial expenditure distribution has a fatter tail for those who choose to insure, but after insurance, that tail is removed for the insured homeowners, so that their probability of spending more than $4,500 becomes zero (Fig. 1-9b). Peng (2013) examines homeowner insurance purchase decisions in more depth, including their interaction with retrofit decisions.

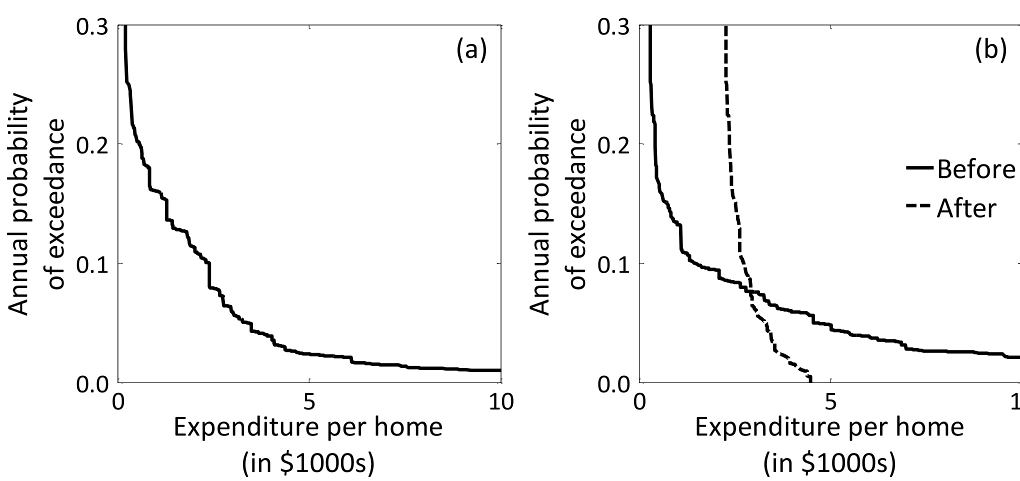

Figure 1-9. Inverse CDFs for per-home total expenditures for (a) uninsured and (b) insured homeowners.

1.4.3.3. Reinsurer's resulting position

While the modeling framework does not optimize the reinsurer's decisions, it does allow examination of how the recommended insurer and homeowner actions affect the reinsurer. Normalizing the initial balance to zero at $y = 0$, Figure 1-10 shows the reinsurer's accumulated profit over the thirty years (i.e., premiums received from the insurer minus loss paid) for the 2000 scenarios. Figure 1-10 suggests that on average the reinsurer will end up with \$1.2 billion profit after thirty years, but there is a 22% chance it would conclude the thirty years with a net loss. These results suggest that the arrangement described in the base case is reasonable from the reinsurer's perspective as well as the insurer's and homeowners'.

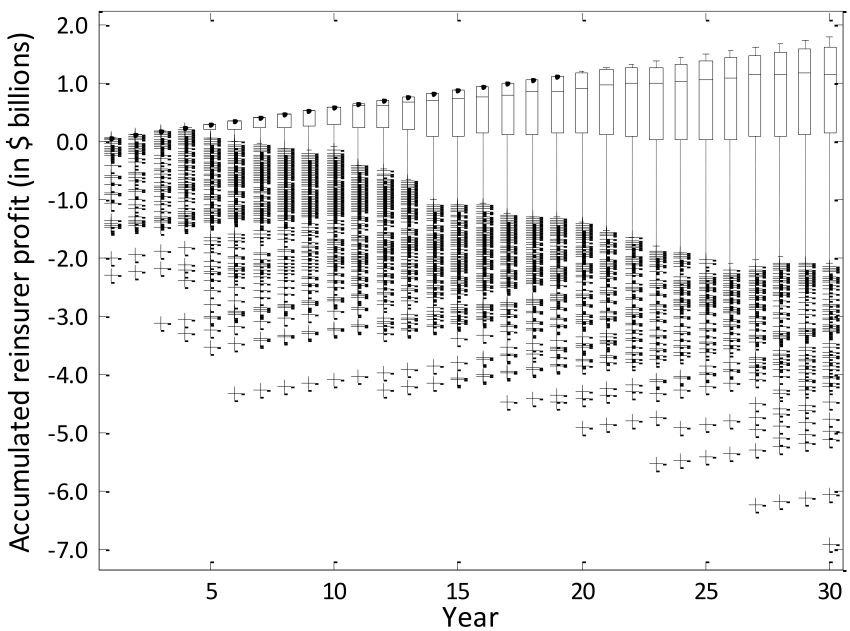

Figure 1-10. Accumulated reinsurer profit vs. time

1.4.3.4. Resulting loss profile

With each stakeholder taking the individually optimal actions, the model shows how the losses are distributed. The expected annual hurricane loss paid by each group of stakeholders—

primary insurer, reinsurer, insured homeowners, and uninsured homeowners, are \$21, \$36, \$18, and \$537 million dollars, respectively. Variability is important as well, and comparing the PDF of losses paid by each group (Fig. 1-11) shows that while the insurer and insured homeowners successfully shorten the tails of their loss distributions, the reinsurer and especially uninsured loss still have the potential to be very large. This analysis highlights the importance of considering the situation from all perspectives since a solution can look appealing for one stakeholder but not another.

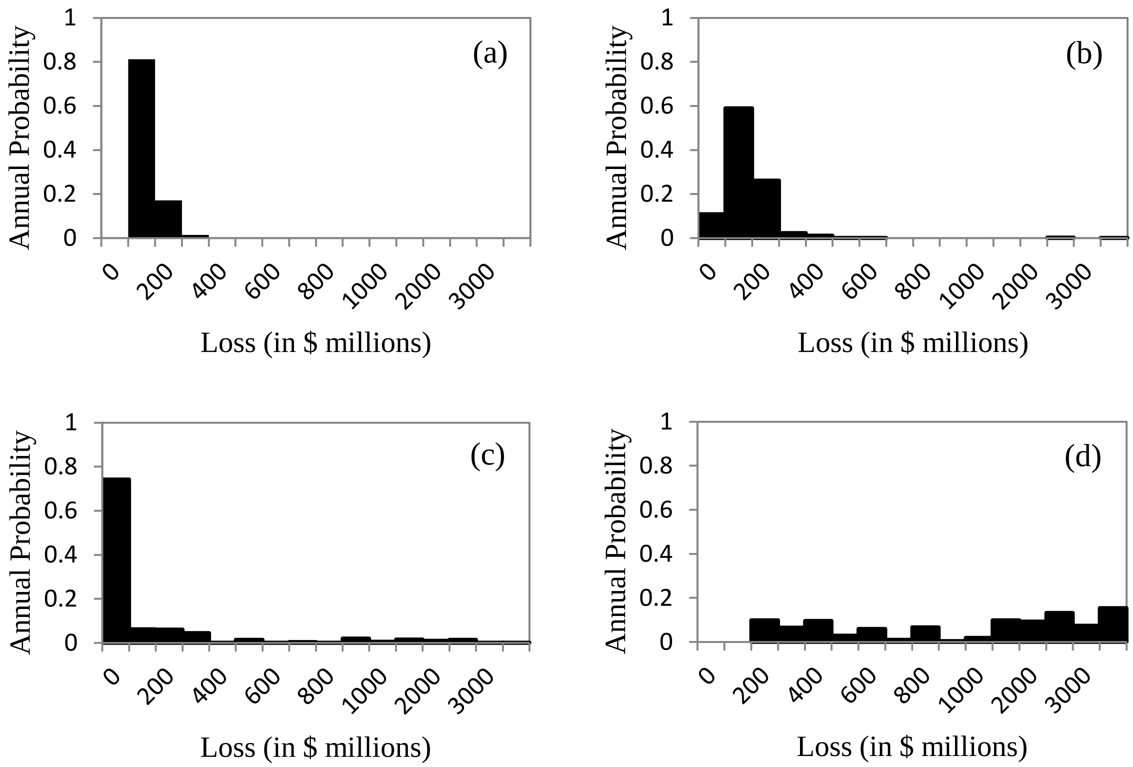

Figure 1-11. PDF of annual loss paid by (a) insured homeowners, (b) insurer, (c) reinsurer, and (d) uninsured homeowners

1.4.4. Effects of Key Parameters on Results

In addition to predicting optimal behavior for the insurer and homeowners, the modeling framework can help explain the influence of key parameters in determining the stakeholders' actions and resulting outcomes. Here we investigate the sensitivity of results to (1) homeowners' risk attitudes, θ_H and θ_L, (2) reinsurer's risk aversion g, and (3) amount of surplus profit the primary insurer can retain each year, k.

We first examine results when homeowner risk attitudes, θ_H and θ_L, are multiplied by a factor from zero to two. Figure 1-12 shows that the insurance penetration for high and low risk regions are both quite sensitive to homeowner risk attitudes. When the multiple equals one and θ_H and θ_L are at their base case values, the slopes of the curves are about 40% and 18%, respectively, so a -25% to +25% change in the risk attitude parameter can change the insurance penetration from 6 % to 26% for the high risk region and from 1% to 10% for the low risk region. As θ_H and θ_L increase and homeowners become more risk averse, the insurer is able to increase its profit loading factors λ_H and λ_L (up to 3.8 and 3.4, respectively, when the multiple is two), and the insurer profit and return on equity increase as well.

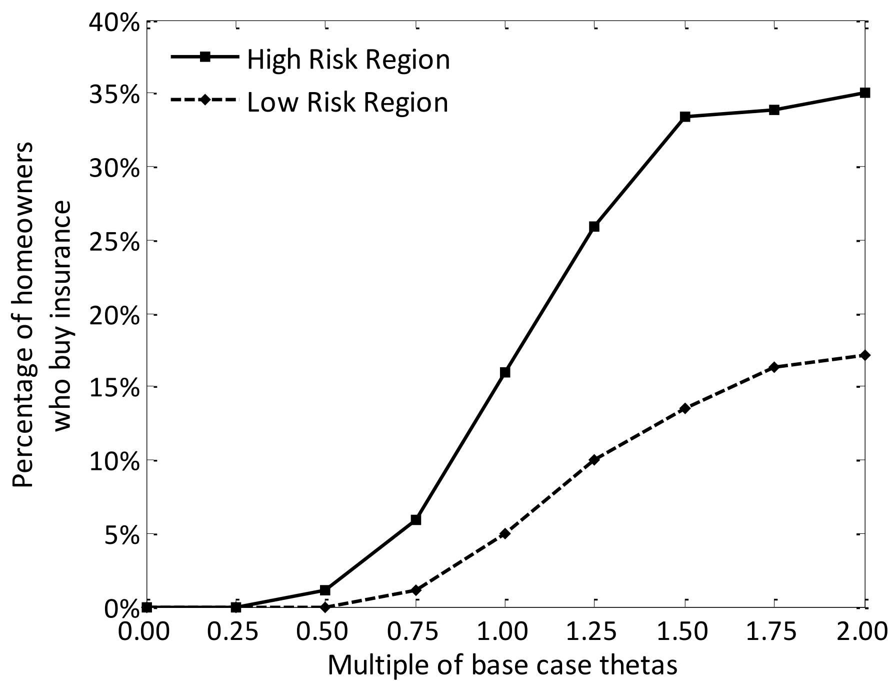

Figure 1-12. Insurance penetration rate for high and low risk regions vs. homeowner risk attitude, in terms of multiples of the base case values θ_H and θ_L

Since the insurer relies on reinsurance to maintain a sufficiently low probability of insolvency, the cost of reinsurance, which is largely driven by the reinsurer's risk aversion parameter g (Eq. 1-9), can be important as well. As g increases, the maximum limit of the reinsurance treaty *M* decreases, providing the insurer less protection from large losses (Fig. 1-13a). As a result, above $g = 0.15$, the thirty-year probability of insolvency increases dramatically, exceeding the allowable threshold of 0.1 when $g > 0.19$ (Fig. 1-13b). When the reinsurer becomes sufficiently risk averse, the insurer's derived demand for reinsurance cannot support the reinsurance premium therefore opting not to protect against insolvency. Figure 1-14 shows that as the reinsurer risk aversion increases, the penetration rate decreases and therefore, the insurer's average annual profit decreases as well.

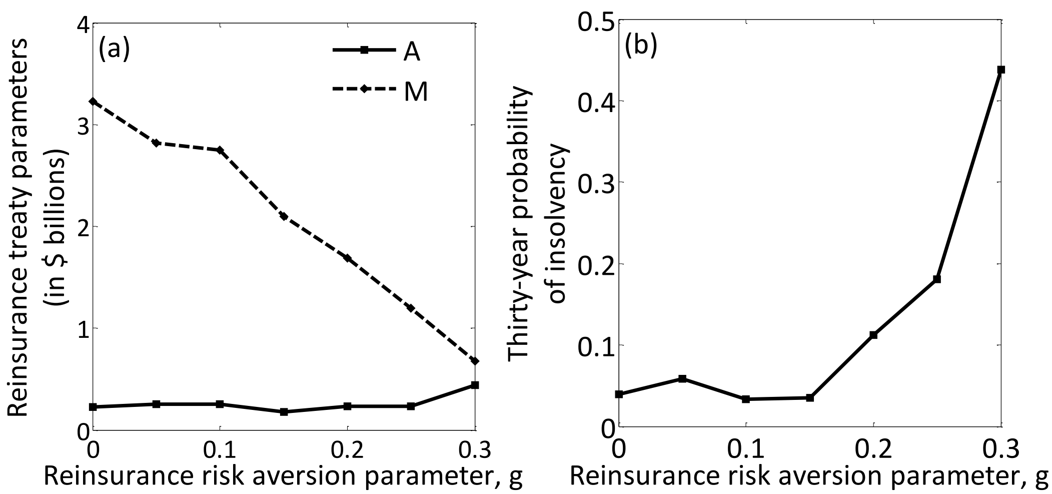

Figure 1-13. (a) Attachment point *A* and maximum limit *M* and (b) thirty-year probability of primary insurer insolvency vs. reinsurance risk aversion parameter g

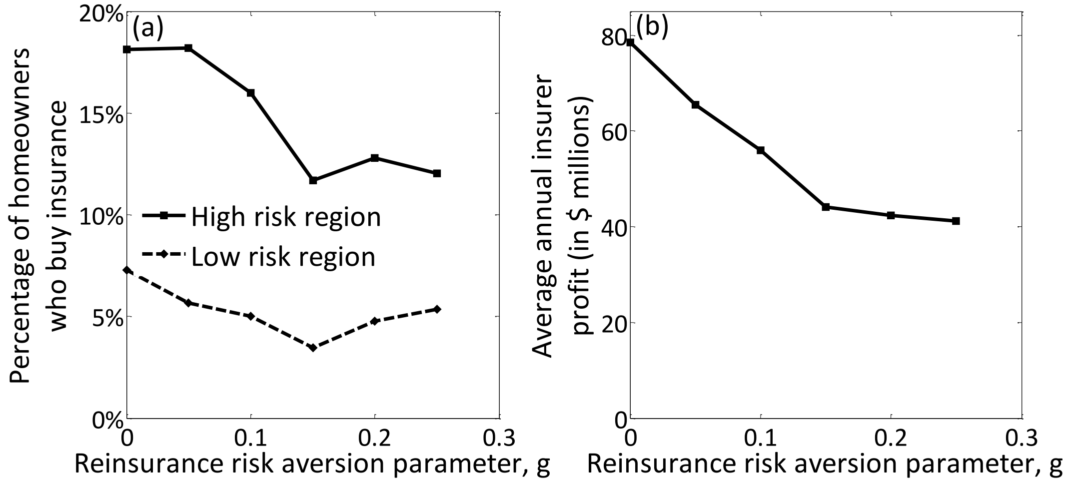

Figure 1-14. (a) Insurance penetration rates and (b) average annual primary insurer profit vs. reinsurance risk aversion parameter

The amount of surplus profit the primary insurer can retain each year, *k*, is another important model parameter. Insurers are reluctant to hold high cash reserve because of tax, accounting, and takeover risks (Jaffee and Russell 1997). They also pay dividends to their investors and use some of their profits to expand their business. We examine the effect of changing *k* using a value of reinsurer risk attitude $g = 0.3$ (rather than $g = 0.1$ as in the base case) because when the reinsurer is more risk averse (higher g), reinsurance becomes more scarce, and the effect of changing the allowable insurer surplus *k* becomes more important. Figure 1-15a shows that as the insurer surplus increases, the insurer relies more on its own reserve than on transferring the risk to the reinsurer. Figure 1-15b shows that market penetration rate increases with allowable insurer surplus because the insurer can optimally sell insurance at a lower profit margin since it does not pay as much for reinsurance.

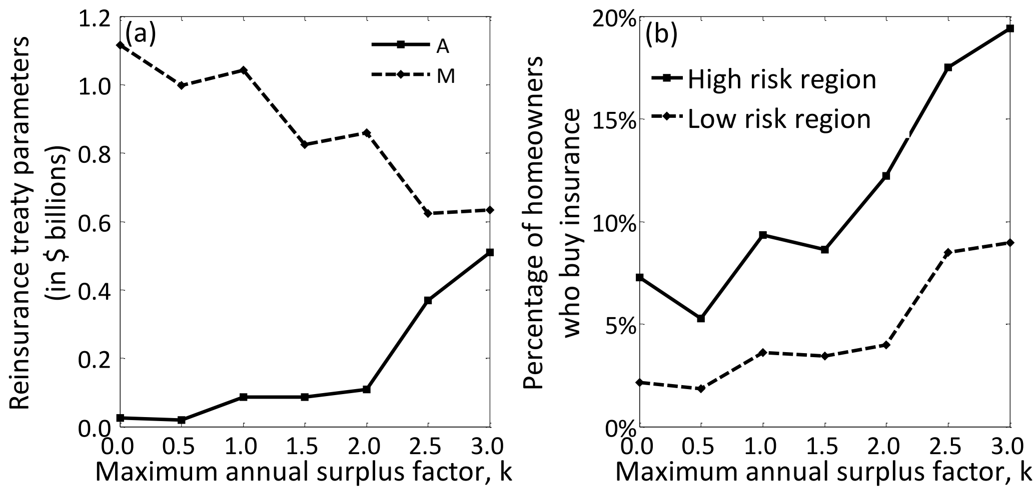

Figure 1-15. (a) Attachment point *A* and maximum limit *M* and (b) insurance penetration rate for high and low risk regions vs. maximum surplus

1.5. CONCLUSION

This paper introduces a new modeling framework to help better understand and manage the insurer's role in catastrophe risk management. The framework is novel in integrating the interactions between an insurer and a diverse population of homeowners, and linking those insurer and homeowner decision models to a catastrophe loss model that provides an accurate, disaggregated representation of the risk to be managed, including spatial correlation and variability among properties. The framework is also demonstrated for a large detailed regional case study.

This new modeling framework is intended to provide a structure with which to examine the complex natural disaster risk management system, and as such, it offers several opportunities for future extension and improvement. With adaptations to the framework, a different homeowner decision model, such as a discrete choice model based on prospect theory or empirical data, could replace the expected utility model. On-going and future work also includes the introduction of home retrofit options in addition to insurance to manage risk, imperfect and asymmetric information, competition among insurers, and regulator decision-making endogenous to the modeling.

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CHAPTER 2

THE ROLES OF PRIOR DISASTER EXPERIENCE AND RISK PERCEPTION ON FLOOD INSURANCE PURCHASE DECISION-MAKING

ABSTRACT

The low penetration rate of the flood insurance market in the United States has led to considerable attempts to understand the underlying factors that influence individuals to take *ex ante* protective actions. Better understanding of these factors has policy implications for both the structuring of the insurance market and for developing effective risk communication tools. This article explores the factors that influence flood insurance purchase decision-making. Specifically, the study tests the mediation effect of affect variables such as worry and fear between prior hurricane and hurricane-induced flood hazard experiences and flood insurance purchase decision-making. Using phone-survey data (n=318) from eastern North Carolina, we built a structural equation model to understand the direct and indirect effects of different variables on one another and on flood insurance purchase decision-making. The results of this analysis show that prior hazard experience and length of tenure positively influence flood insurance purchase decisions through the mediation effect of risk perceptions. The study also found that white males are less risk averse and that both income and proximity to hazard affect flood insurance purchase decision-making. The chi square p-value of the model is 0.72, which is significant. Finally, we discuss the policy implication of our findings.

2.1. INTRODUCTION

In spite of attempts to increase the adoption of household flood insurance, the penetration rate (proportion of people who have insurance) remains low (Dixon et al. 2006). This reality has resulted in frequent and large uninsured losses. These losses have led to considerable attempts to understand the underlying factors that influence individuals to take *ex ante* protective actions. Better understanding has policy implications for both the structuring of the insurance market and for developing effective risk communication tools. This paper contributes to the literature attempting to understand the factors and constraints that impact the decision process around flood insurance.

More than 39% of the US population lives in coastal counties, and approximately 3% are exposed to at least a 1% annual probability of coastal flood hazard (Crowell et al. 2010, NOAA 2013). If we apply these rates to current population estimates, this means that almost 9.5 million people have a one in 100 chance of flooding each year. In spite of the availability of flood insurance through the National Flood Insurance Program (NFIP), only approximately 60% of people who live in a Special Flood Hazard Zone (SFHA) with risks of coastal flooding carry insurance (Dixon et al. 2006), meaning that almost 3.8 million people are uninsured. Since the inception of the NFIP in 1968, subscription has been a major problem. One reason for the 1994 reform act was to increase market penetration by requiring mortgage lenders to include flood insurance as part of loan qualifications (Blanchard-Boehm et al. 2001). Nonetheless, even the mortgage requirement has not improved the flood insurance penetration rate. A recent study on the effects of Hurricane Sandy in New York City and New Jersey revealed that 80% of households and 95% of small businesses were uninsured, although many are eligible to receive subsidized rates (Aerts et al. 2014).

Some researchers have used survey data to attempt to understand the factors that influence flood hazard adjustment decisions–both insurance purchase and mitigation (e.g., Blanchard-Boehm et al. 2001, Brilly and Polic 2005, Peacock 2003, Peacock et al. 2005, Lindell and Hwang 2008, Botzen et al. 2009, Botzen and Van den Bergh 2012). Others have developed theoretical frameworks such as the Protective Action Decision Model (PADM), the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Person Relative to Event Theory (PrE), and the Protective Motivation Theory (PMT), to understand the variables that form risk perceptions and lead to protective actions (Lindell and Hwang 2008).

Previous studies have found recurring factors, such as risk perception and proximity to hazard, to have significant effects on protective action (e.g., Brilly and Polic 2005, Landry and Jahan-Parvar 2011). Research results on the effects of other variables, such as age, income, and other socio-demographics, have been mixed. For example, whereas Dohmen et al. (2011) found age to be a significant factor, Botzen and Van den Bergh (2012) did not.

Using survey data, this study focuses on the role of six factors in influencing flood insurance adoption rates in the eastern part of North Carolina. The factors considered are (i) prior hazard experience, (ii) risk perception, (iii) socio-demographic characteristics, (iv) proximity to hazard, (v) the role of government aid, and (vi) tenure.

Most studies have used single-equation models to analyze data (e.g., Peacock 2003, Peacock et al. 2005), and a few have employed multiple-equation models and structural equation models (e.g., Lindell and Hwang 2008, Zaalberg et al. 2009) to better understand the causal relationship between the different factors. In this study, we build a structural equation model using stated flood insurance purchase data to better understand the causal relationship between different factors and their combined effect on flood insurance purchase decisions. Structural equation models have numerous advantages compared to single-equation models. First, they allow latent constructs to represent feelings that are hard to measure with single variables. Second, they allow the inclusion of mediation effects. For example, prior hazard experience might not directly lead to protective action, but it can lead to a high degree of hazard risk perception, which in turn might lead to taking protective action. Structural equation models can easily incorporate these types of indirect or mediated effects. Third, in structural equation models, path diagrams make it convenient to easily illustrate relationships and causal effects.

After the theoretical and empirical studies that serve as a basis for our hypotheses are introduced in Section 2.2, the hypotheses are given in Section 2.3. The survey instrument, the variables, and the analytical approach are detailed in Section 2.4. Results are given in Section 2.5, followed by discussion and conclusions in Sections 2.6 and 2.7, respectively.

2.2. THEORETICAL AND EMPIRICAL STUDIES

Currently, there is no consensus regarding how households process risk and take protective action. In the broadest sense, the factors that influence protective decision-making can be grouped into "situational" and "cognitive" categories (Tobin 1997). Situational factors include physical conditions, such as proximity to the hazard, and socio-demographic features, such as age, income, and so forth. Cognitive factors include personality characteristics and risk attitudes. Tobin (1997) argues that these factors can influence responses individually, in combination, or in sequence and that their interactions can persist or change over time.

Broad theoretical frameworks, although important for understanding the fundamental relationship between different factors, are difficult to use in empirical analysis. For example, because of their breadth, TRA, TPB, and the expectancy theory have limited ability to identify measurable variables that positively correlate with protective measures (Lindell and Hwang 2008). Lindell and Hwang (2008) also discuss the merits of more focused theoretical models, such as PMT and PrE, which account for self-efficacy.

Several empirical studies are based on theoretical frameworks (e.g., Lindell and Hwang 2008, Bubeck et al. 2012). For example, Lindell and Hwang (2008) extend the PADM proposed by Lindell and Perry (Lindell and Perry 1992, Lindell and Perry 2003) in a multistage, multi-equation analysis that proposes a causal chain of the many factors that lead to a household protective-action decision.

Several hazard-adjustment empirical studies have also been conducted (e.g., Blanchard-Boehm et al. 2001, Brilly and Polic 2005, Peacock 2003, Peacock et al. 2005, Lindell and Hwang 2008, Botzen et al. 2009, Botzen and Van den Bergh 2012, Browne and Hoyt 2000). Although no single framework or empirical study explains every complex process in protective decision-making, recurring themes in the empirical findings have helped researchers and policy makers to understand why some people choose not to buy insurance. Some of these findings include the following: people ignore risk below a certain threshold (Weinstein 1984, Kunreuther 1996); government aid lowers people's incentives to purchase flood insurance (Browne and Hoyt 2000); risk perceptions are associated with protective actions (Ge et al. 2011); prior hazard experiences are predominantly responsible for risk perception (Hertwig et al. 2004, Siegrist and Gutscher 2008, Holmes et al. 2013); and people think that insurance is a bad investment unless they reap its benefits through a payout (Michel-Kerjan and Kunreuther 2011).

2.3. HYPOTHESES

The following sections discuss the proposed hypotheses regarding the effects of six factors on homeowner flood insurance purchase decisions: (i) prior hazard experience, (ii) risk perception, (iii) socio-demographic characteristics, (iv) proximity to hazard, (v) the role of government aid, and (vi) tenure. These hypotheses are based on previous theoretical and empirical studies.

2.3.1. Prior Hazard Experience

Tversky and Kahneman (1974) show that there is a heuristic effect to decision-making and that our past experience significantly shapes our current risk perceptions. Insurance uptake increases immediately after a natural disaster. For example, Browne and Hoyt (2000) found that recent flood experience is significantly associated with flood insurance purchases.

Krantz and Kunreuther (2007) found that prior hazard experience affects risk perception, even though it affects neither the cost of insurance nor the probability of an adverse effect. Similarly, Brilly and Polic (2005) found that experience with a flood influences risk perception. Hertwig et al. (2004) argue that this phenomenon is due to variation of probability weighing and found that people who have experienced flooding over-weigh the probability of occurrence, whereas those who have not experienced flooding under-weigh the likelihood. This result shows the profound effect that prior experience could have in shaping risk perception and initiating protective action. The effects of personal experience on responses to other types of natural disasters, such as wild fires, are similar. For example, Holmes et al. (2013) found that only respondents with prior experience were willing to pay more for protection. According to Siegrist and Gutscher (2008), the high risk perception of people who have experienced a flood hazard is due to the negative affect that the experience creates. In this study, we hypothesize as follows:

H1. Prior hurricane experience is measured by number of hurricanes and level of prior hurricane damage experienced.

H2. Higher hurricane experience is positively associated with higher hurricane risk perception.

2.3.2. Risk Perception

Fear and affect have been found to significantly influence perceived risk (Slovic et al. 2004). Findings from experimental studies such as the work of Keller et al. (2006) have also corroborated these relationships. Past experience appears to have a strong influence on negative affect, which leads to a perception that the risk is more severe (Siegrist and Gutscher 2008). Based on these studies, we state the following three hypotheses:

H3. Hurricane risk perception is manifested by individuals' level of worry and emotion.

H4. Higher hurricane risk perception is positively associated with higher storm related flooding risk perception.

H5. Higher flood risk perception is positively associated with flood insurance purchase decision-making.

2.3.3. Socio-demographic Characteristics

Conducting a comprehensive literature review of gender-difference experiments, Croson and Gneezy (2009) found significant differences between males and females, with females being more risk averse. Several other studies have also found that women are generally more risk averse (Flynn et al. 1994, Lindell and Hwang 2008, Botzen et al. 2009, Ge et al. 2011). Using 1500 individual surveys on environmental health risks, Flynn et al. (1994) found that white males are less risk averse than white females, but no significant difference was found between non-white male and female respondents. Moreover, the study found no significant difference between white females and all non-whites. The authors suggest that the underlying cause of the significant difference in the white males' attitude could be due to sociopolitical factors.

Race has been found to influence risk perception and protective actions. The predominant finding is that minorities are more risk averse but are less likely to take protective actions

(Fothergill et al. 1999, Peacock 2003, Lindell and Hwang 2008, Ge et al. 2011). There are numerous suggested reasons for this, including lower access to scarce resources such as loans (Flynn et al. 1994, Peacock 2003).

Age also seems to affect both risk perception and protective action, but research results are not always consistent. For example, Dohmen et al. (2011) found that risk aversion increases with age, whereas Botzen and Van den Bergh (2012) found no statistical significance. Ge et al. (2011) found that age was not significant in the whole range, but when they used a dichotomous variable with 65-years-of-age as a cutoff, they found a significant difference in both risk perception and the taking of protective measures. Those above 65-years-of-age had high risk perception but took less protective measures, especially if high costs were involved (Peacock 2003, Ge et al. 2011). Reliance on fixed incomes by those over 65 has been offered as an explanation of this result.

Most studies have found that more education is directly related to low risk perception (Fothergill et al. 1999, Botzen et al. 2009, Ge et al. 2011), but some have found no significant relationship (e.g., Bubeck et al. 2012).

Browne and Hoyt (2000) found that property owners with higher incomes are more likely to buy insurance and to choose higher coverage. Similarly, Landry and Jahan-Parvar (2011) found that residents with higher incomes insure more than do those with lower incomes, although the results are not monotonic and significant over the entire range. Bubeck et al. (2012) found that income only marginally influences mitigation decisions.

Although a higher income seems to encourage protective action, it is not always necessarily positively correlated with high risk perception. For example, Botzen et al. (2009) and

Ge et al. (2011) found that high income is associated with low risk perception. Based on these studies, we state the following four hypotheses:

H6. A white-male indicator is negatively associated with flood risk perception.

H7. Age is positively associated with flood risk perception.

H8. Education is negatively associated with flood risk perception.

H9. Higher income is positively associated with flood insurance purchase decision-making.

2.3.4. Proximity to Hazard

Proximity to hazard affects both insurance purchase decisions and risk perception (Landry and Jahan-Parvar 2011, Brilly and Polic 2005). Landry and Jahan-Parvar (2011) found that distance from a coast is negatively related to insurance purchases. Brilly and Polic (2005) found that location is highly related to risk perception. The level of risk perception, however, might not necessarily be equivalent to an expert's assessment of risk (Botzen et al. 2009). Similarly, Lindell and Earle (1983) found that people believe that risk from environmental hazards decreases with distance. Using these studies, we hypothesize as follows:

H10. Proximity to hazard is positively associated with flood insurance purchase decision-making.

2.3.5. Government Aid

Expectation of government aid could lead to low mitigation or protective action (Bubeck et al. 2012). Fatalism seems to have the same effect as the expectation of government aid. For example, respondents who believe that flooding is beyond human control seem to have lower perceptions of flood risk (Brilly and Polic 2005). Brilly and Polic (2005) also provide a theoretical explanation for how these two attitudes affect insurance purchase decisions. In contrast, Bubeck et al. (2012) explain that these attitudes serve as coping mechanisms that modify risk perception and link it to protective action. Their review of risk perception and other factors influencing flood mitigation found no theoretical or empirical evidence to support a direct relationship between risk perception and mitigation. They argue that the interaction of risk perception with coping mechanisms explains the protective actions that people take. In this study, we hypothesize as follows:

H11. Expectation of government aid is negatively associated with flood insurance purchase decision-making.

2.3.6. Tenure

Past tenure length has been found to influence both risk perception and flood insurance purchase decisions. For example, past tenure is associated with exposure to hazard, which, in turn, affects both risk perception and protective action (Ge et al. 2011). Future expected tenure also affects protective action. Studies have found that people who intend to live for a long time in a particular house are more likely to invest in expensive mitigation measures (Lindell and Hwang 2008). Nonetheless, other studies found both past and future tenure to be non-significant (Bubeck et al. 2012). In this study, we hypothesize as follows:

H12. Past tenure is positively associated with hurricane experience.

H13. Future tenure is positively associated with flood insurance purchase decision-making.

2.4. METHOD

2.4.1. Data Collection

This analysis was developed by using a quantitative dataset created at the University of Delaware, Disaster Research Center (DRC), as part of the National Institute of Standards and

Technology (NIST)-funded project, “Modeling Natural Disaster Risk Management: A Stakeholder Perspective,” during the fall of 2012 and spring of 2013. The data were collected by telephone interviews, with an instrument that aimed to better understand household decisions regarding hurricane insurance and mitigation. The instrument included questions based on current social science, engineering, and economics insights on these hazard adjustments. The survey’s major topics include 1) prior hazard experience; 2) information about the location and structure of the respondents’ homes; 3) information on length of residence and attachment to place; 4) an inventory of prior insurance and retrofit decisions regarding wind and flood; 5) an assessment of hurricane risk perception; 6) data on prior experiences with and impacts from hurricanes; 7) a set of randomly assigned scenarios that explored the impact of different premium and deductible combinations on insurance purchases; 8) a set of randomly assigned scenarios that explored the impact of different potential incentives on the likelihood of adopting mitigation measures; 9) demographic and socioeconomic variables. The final instrument included just over 100 possible questions, but skip patterns insured that respondents answered only questions relevant to their own specific experience. With these skips in place, the mean time to completion for this survey was 27 minutes.

Our sample for the survey included 50% listed household numbers, 25% random digit dial (RDD) landline numbers, and 25% RDD cellphone numbers. The numbers came from 49 counties[1] in the eastern half of North Carolina. During the initial moments of the survey, we screened for home ownership and included only homeowners in our sample, given the nature of the topic. Given the nature of the retrofits being explored, we also screened for home type.

[1] Beaufort, Bertie, Bladen, Brunswick, Camden, Carteret, Chowan, Columbus, Craven, Cumberland, Currituck, Dare, Duplin, Edgecombe, Franklin, Gates, Granville, Greene, Halifax, Harnett, Hertford, Hoke, Hyde, Johnston, Jones, Lee, Lenoir, Martin, Moore, Nash, New Hanover, Northampton, Onslow, Pamlico, Pasquotank, Pender, Perquimans, Pitt, Richmond, Robeson, Sampson, Scotland, Tyrrell, Vance, Wake, Warren, Washington, Wayne, Wilson.

Residents with single family homes, manufactured homes, and duplexes were eligible to take the survey, whereas those with townhouses, apartments, and condominiums were excluded because of the significant structural differences. We also asked for the person who makes insurance and home-repair or improvement decisions to answer the survey questions. If an adult or a decision-maker was not available, appointments were made to complete the survey at another time. We purchased the sample from *Genesys,* a third-party sample provider. The listed numbers came from a database of the listed telephone directory. For RDD numbers, the *Genesys* system uses RDD procedures to generate random phone numbers based on a set of all telephone exchanges using the area codes and zip-code combinations matching the counties identified above. After obtaining the initial numbers, we had *Genesys* purge business and disconnected numbers from the initial sample. To purge the business numbers, a database composed of non-residential yellow-page businesses was utilized. The distinction of *non-residential* is important because over one million households nationwide use their residential phone number for business purposes as well. The generated sample was compared to this database, and any matching telephone numbers were purged from the sample. The remaining numbers not purged from the sample were then examined to determine if they were disconnected.

The survey was administered by using a computer-assisted telephone interviewing (CATI) system in operation at the DRC, with paid graduate and undergraduate students providing the labor for the project. All students were trained on both the system and the instrument to ensure that they understood both the questions and the underlying concepts that each question was intended to tap. Our call center was activated at different times of the day, with a focus on calling between 2:00 pm and 8:45 pm Monday through Thursday and on Saturdays from noon to 4:00 pm. Each phone number was called up to ten times to make contact with the residence and to attempt the interview. Special attention was given to training the interviewers to convert soft refusals. In addition, an incentive was offered: the participants who completed the survey were entered into a drawing with a one in 100 chance of winning an iPad Mini. The final number of observations, after ineligible respondents were removed, was 358, and our cooperation rate for the sample overall was 23%.

The data were then cleaned to remove the respondents who failed to answer all hurricane- and flood risk perception and flood insurance purchase questions. Moreover, only respondents whose primary residence is in the area were included in the analysis, given that there could be significant variation in risk perception when the home is a secondary home or a rental property. The final data that were used in the analysis include 318 observations. Nonetheless, these data also had missing values, as shown in Tables 2-1 and 2-2. With regard to the most common type of data-handling methodologies, listwise and pairwise deletions do not use the full data set and are ineffective, given the limited dataset available in this study. In addition, the listwise deletion methodology is known to result in larger standard error estimates, which in turn lower the power of hypotheses tests (Allison 2003). Although the pairwise deletion methodology uses more data, compared with the listwise, the standard error estimates are not consistent, which creates doubt regarding the validity of confidence intervals and hypotheses tests (Allison 2003). Hence, the data were multiple imputed in order to use the full data set. As recommended by Schafer and Olsen (1998), a total of five imputations were carried out in Amelia II, a program for missing data, in R (Honaker et al. 2011). Amelia uses a bootstrapping based algorithm to impute data. Figure 2-1 shows the geographic distribution of the 83% of the survey respondents in eastern North Carolina who gave their full address.

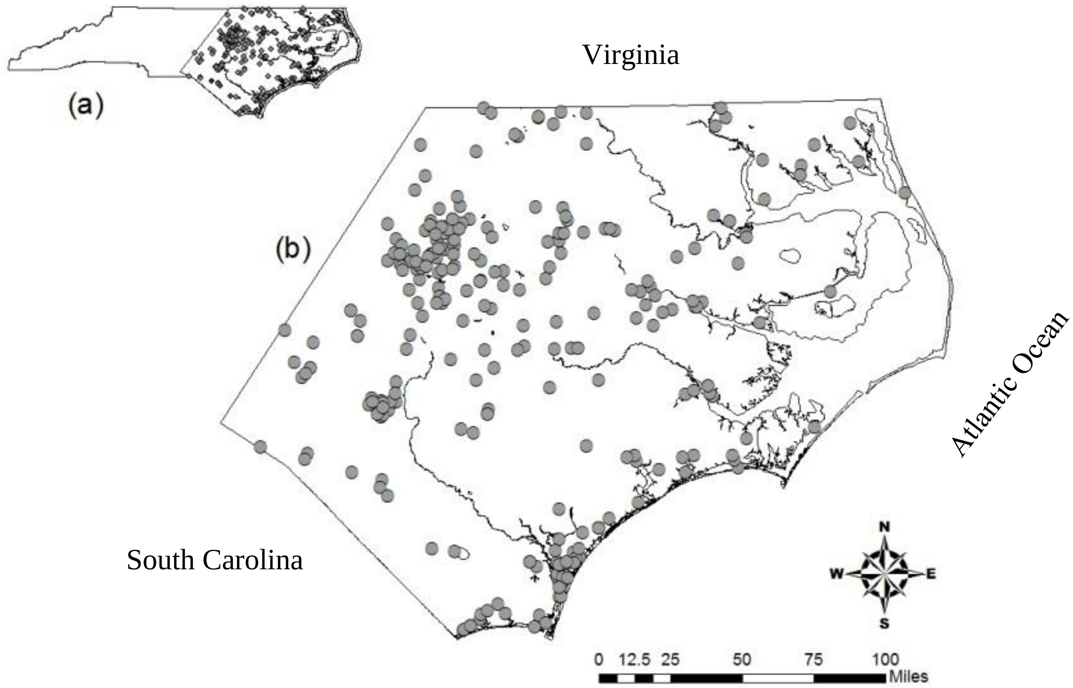

Figure 2-1. (a) Study area comprising the eastern half of the state, and (b) geographic distribution of the survey respondents who gave their address

2.4.2. Variables

This section describes the variables used in this analysis and the transformations applied. It is sub-divided into sections on prior hazard experience, risk perception, socio-demographic characteristics, proximity to hazard, government aid, tenure, and flood insurance purchase variables. Tables 2-1 and 2-2 provide the descriptive statistics of the categorical and continuous variables used in this analysis, respectively.

2.4.2.1. Prior hazard experience

The number of hurricanes experienced (X_1) measures the number of hurricanes that a respondent has personally experienced. To meet the normality assumption, a log transform of this variable is used in the analysis. The highest degree of property damage (X_2) that the respondent has experienced during any prior hurricane event is measured on a Likert scale of 1 to

5. The first and the last scales are verbally anchored, where 1 means “no damage”, and 5 means “complete destruction”. This scale is collapsed into a binary response by combining responses from 1 to 3 together and 4 and 5 together. This is done because of the limited number of observations available for the analysis; by estimating two parameters instead of five for each variable, more relevant factors can be incorporated into the analysis.

2.4.2.2. Risk perception

The levels of worry (X_4) and emotion (X_5) about hurricanes are measured on a Likert scale of 1 to 5, where 1 means “never worry”, whereas 5 means “constantly worry” or “dread”, respectively. Similarly, these variables are collapsed into a binary, with 1 to 3 being in one category and 4 and 5, which represent extreme worry or dread, in another. The level of worry about floods (Y_1) is also measured on a Likert scale of 1 to 5 and is transformed in the same fashion.

2.4.2.3. Socio-demographic characteristics

The role of race and gender are taken into account in combination, by creating a binary indicator for “white male” (X_6), where 1 represents “white male,” and 0 represents all other respondents. Age (X_7) is measured as a continuous variable. Education level is measured in nine categories ranging from elementary school to graduate school. This is transformed into a binary variable (X_8), with those holding an associate’s degree or above grouped together. Income is measured as a categorical variable, with eight non-overlapping ranges, from less than \$15,000 to greater than \$250,000. It is similarly transformed to a dichotomous variable (X_{10}), with \$75,000 as a cutoff. The reason for these transformations is, again, the limited number of observations available to estimate a parameter for each category.

2.4.2.4. Proximity to hazard

Proximity to hazard (X_9) is measured as a binary variable, where 1 represents people who are not eligible for the North Carolina Coastal Property Insurance Pool (CPIP), and 0 represents those who are eligible. This variable measures how close respondents are to the coast.

2.4.2.5. Government aid

The participants were asked if it was likely that they would be eligible for government aid in the event of a hurricane disaster. This variable is measured on a Likert scale of 1 to 3, representing “not at all likely”, “somewhat likely”, and “very likely”, respectively. The result is then transformed into a dichotomous variable (X_{11}) by collapsing 2 and 3 into one response.

2.4.2.6. Tenure

Length of tenure in years (X_3), which represents overall past exposure to hurricanes, is measured as a continuous variable. Length of expected future stay in home (X_{12}) is also measured as a continuous variable.

2.4.2.7. Flood insurance purchase decisions

Each flood insurance purchase question has three choices, of which two represent buying, albeit at different deductible and premium values, and one represents not buying. The respondents were asked a total of four questions, with different combinations of deductible and premium values. Because we are interested in insurance buying decision-making, the responses are combined into a binary of whether a respondent expressed intent to buy or not. One of these repeated questions could be used as the flood purchase decision variable, but to ensure that the effects of variations in premium and deductible levels are accounted for in this analysis, we use two (X_{13} and X_{14}) of the four repeated measures.

Table 2-1. Descriptive statistics of categorical variables used in the model

	Frequency		Frequency
X_9 -Proximity to hazard		**X_{11} -Government aid**	
Eligible for CPIP	92	Not at all likely	139
Not eligible for CPIP	221	Somewhat likely	88
Missing	5	Very likely	61
X_4 -Worry about hurricanes		Missing	30
1 Never worry	67	**X_{13} -Flood insurance purchase Q1**	
2	90	Will not buy	106
3	93	Will buy	173
4	39	Missing	39
5 Constantly worry	26	**X_{14} -Flood insurance purchase Q2**	
Missing	3	Will not buy	102
Y_1 -Worry about floods		Will buy	177
1 Never worry	185	Missing	39
2	72	**X_8 -Education**	
3	37	Elementary school only	3
4	11	Some high school, did not finish	10
5 Constantly worry	12	Completed high school	50
Missing	1	Some college but didn't finish	46
X_5 -Emotion		2-year college degree/A.A/A.S.	33
1 Not worried about hurricanes	69	4-year college degree/B.A./B.S.	79
2	101	Some graduate work	9
3	72	Completed masters or prof. degree	52
4	31	Advanced graduate work or Ph.D.	13
5 Dread hurricanes	41	Missing	23
Missing	4	**X_{10} -Income**	
X_2 -Prior damage level		Less than 15,000	9
No damage	128	15,000 to 35,000	28
2	124	35,000 to 50,000	31
3	28	50,000 to 75,000	49
4	8	75,000 to 100,000	46
Complete destruction	5	100,000 to 150,000	46
Missing	25	150,000 to 250,000	15
X_6 -White male		Over 250,000	13
No	192	Missing	81
Yes	105		
Missing	21		

Table 2-2. Descriptive statistics of continuous variables used in the model

	Mean	Std. Dev	Missing
X_1 -Number of hurricane experiences	6.00	6.22	19
X_3 -Past tenure in home	18.48	12.98	8
X_{12} -Future stay in home	34.31	19.80	20
X_7 -Age	58.73	13.24	29

2.4.3. Analytical and Solution Procedures

We base our analysis on the theoretical and empirical studies discussed in Section 2.2. Using a structural equation model, we test the hypothesized causal relationships, as discussed in Section 2.3, among different factors and their combined effect on flood insurance purchase decisions. The model is built around six factors: (i) prior hazard experience, (ii) risk perception, (iii) socio-demographic characteristics, (iv) proximity to hazard, (v) the role of government aid, and (vi) tenure.

Structural equation models, sometimes also called simultaneous equation models, are multivariate regression models. They are different from regular multivariate regression in that the dependent variable in one equation can be the independent variable in another. This feature allows the variables to simultaneously influence one another either directly or through intermediaries (Fox 2002).

Structural equation models have several advantages compared to single-equation models. First, they allow latent constructs with multiple variables to represent feelings that are hard to measure with a single variable. For example, it is difficult to measure overall hurricane risk perception by using only a single variable. In this analysis, we use both worry and emotion levels to construct this latent variable. Second, structural equation models allow the inclusion of the mediation effect of variables. This is important for analyzing the interrelationship among variables, including indirect effects on one another. The third advantage of using structural equation models is that path diagrams make it convenient to easily illustrate relationships and causal effects.

In this analysis, we use structural equation models because our primary objective is to understand the simultaneous relationship among the different variables described in Section 2.4.2 and their combined effect on flood insurance purchase decisions. In particular, we analyze, through the mediation effect of risk perception, the effect of prior hazard experience on flood insurance purchase decisions. Previous studies have mostly been limited to multivariate analyses (e.g., Peacock 2003, Peacock et al. 2005). Only a few studies have investigated the interrelationship between different factors and mediation effects on people's actions, using multistage, multi-equation models or structural equation models (e.g., Lindell and Hwang 2008, Bubeck et al. 2012, Zaalberg et al. 2009). Lindell et al. (2008) found that hazard experience has both direct and mediated effects (through perceived personal risk) on taking protective measures. Bubeck et al. (2012) found that coping mechanisms, such as fatalism and expectation of receiving government aid, serve as intermediary variables between risk perception and protective action. Zaalberg et al. (2009) found several affect and coping variables that mediated between past hazard experience and the taking of protective action. In this study, we extend this work by separating hurricane and flood risk perception, and test Hypothesis 3, which says that higher hurricane risk perception leads to higher storm related flooding risk perception. Thus, we have two intermediary variables–hurricane risk perception and hurricane-induced flood risk perception–that link past hazard experience and flood insurance purchase decision-making.

Structural equation modeling requires temporal ordering to represent causal relationships; hence, the use of cross-sectional data becomes problematic unless the time sequence of the variables is evident. In this study, we asked about residents' past experience, their current risk perception, and their future mitigation plans to account for the time sequence and satisfy the temporal ordering requirement.

Structural equation models require a large sample size. This is particularly true when one attempts to represent complex relationship and causality effects, such as insurance purchases or mitigation actions. Usually, a typical sample size in studies with a structural equation model analysis is approximately 200 observations, and the minimum recommended sample size-to-parameter ratio is 10 (Kline 2011). In this study, we use 318 observations. Figure 2-2 depicts the hypothesized structural equation model that was built based on the theoretical and empirical discussions in Section 2.2 and the hypotheses in Section 2.3.

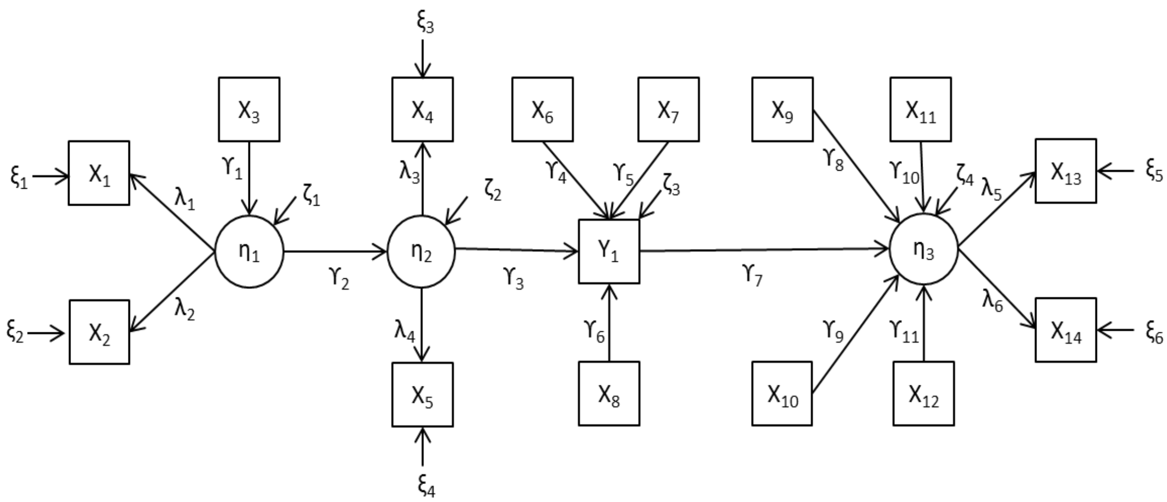

Figure 2-2. Hypothesized structural equation model for flood insurance purchase decision-making

In Figure 2-2, η_1, η_2, and η_3 are latent constructs that represent past hurricane experience appraisal, hurricane risk perception, and flood insurance purchase decision-making, respectively. ξ represents the error terms of the variables that construct the latent variables. Similarly, ζ represents the error terms of the latent and intermediary variables. The λs are parameters to be estimated for the variables that make the latent variables, and the Υs are parameters for the causal relationship among latent and observed variables. The observed variables ($X_{1\text{-}14}$ and Y_1) are defined in Section 2.4.2.

Prior overall hurricane experience (η_1) is measured by the number of hurricane hazard experiences (X_1) and the prior level of damage (X_2), as hypothesized in H1. We use both variables because experiencing a natural disaster without incurring any damage sometimes causes a false sense of security (Ge et al. 2011). Length of tenure (X_3), which could serve as a surrogate for exposure to hurricane hazard, is expected to influence the overall hurricane experience (η_1), as hypothesized in H12. Prior hazard experience (η_1), in turn, is expected to determine residents' hurricane-risk perception (η_2), as stated in Hypothesis 2. Hurricane-risk perception (η_2) is measured by levels of worry (X_4) and emotion (X_5) (Hypothesis 1) and is expected to be positively associated with storm related flood risk perception (Y_1) (Hypothesis 4). Storm related flood risk perception is expected to be associated with socio-demographic characteristics, such as the "white-male" indicator (X_6), age (X_7), and education level (X_8), as hypothesized in H6, H7, and H8, respectively. Finally, flood risk perception (Y_1), proximity to hazard (X_9), income (X_{10}), likelihood of receiving government aid (X_{11}), and expected future stay in the home (X_{12}) are expected to affect flood insurance purchase decision-making (η_3) (hypotheses H5, H10, H9, H11 and H13, respectively), which is measured by repeated stated flood insurance choice preferences (X_{13} and X_{14}). This flood insurance purchase decision-making latent construct is similar to a latent growth curve, except that there is no time lapse because it is simply a repeated measure; hence, the slope is zero, but the mean measures the stated preference toward flood insurance purchases. Equations 2-1 to 2-10 represent these relationships.

$$X_1=\lambda_1\eta_1+ \xi_1 \tag{2-1}$$

$$X_2=\lambda_2\eta_1+ \xi_2 \tag{2-2}$$

$$\eta_1 = \Upsilon_1 X_3 + \zeta_1 \tag{2-3}$$

$$X_4 = \lambda_3 \eta_2 + \xi_3 \tag{2-4}$$

$$X_5 = \lambda_4 \eta_2 + \xi_4 \tag{2-5}$$

$$\eta_2 = \Upsilon_2 \eta_1 + \zeta_2 \tag{2-6}$$

$$Y_1 = \Upsilon_3 \eta_2 + \Upsilon_4 X_6 + \Upsilon_5 X_7 + \Upsilon_6 X_8 + \zeta_3 \tag{2-7}$$

$$X_{13} = \lambda_5 \eta_3 + \xi_5 \tag{2-8}$$

$$X_{14} = \lambda_6 \eta_3 + \xi_6 \tag{2-9}$$

$$\eta_3 = \Upsilon_7 Y_1 + \Upsilon_8 X_9 + \Upsilon_9 X_{10} + \Upsilon_{10} X_{11} + \Upsilon_{11} X_{12} + \zeta_4 \tag{2-10}$$

The model fitting is run in lavaan 0.5-17, an R package for structural equation modeling (Rosseel 2012). The package is free and works on continuous, ordered, and binary variables. For categorical variables, which are used in this study, lavaan uses the weighted least square mean and variance adjusted (WLSMV) estimator. A package called semTools (Contributors 2014) is used to pool the parameters and standard errors of the imputed data set, by using Rubin's method (Rubin 1987). Chi square of the model fit is computed according to the methodology of Li et al. (1991).

2.5. RESULTS

This section discusses the results of the analysis and the subsequent modification of the initial specification, and it presents an equivalent model that can equally represent the hypotheses stated in Section 2.3.

The model shown in Figure 2-2 has a robust chi square p-value of 0.362, which is significant. Nonetheless, some of the parameter estimates, as shown in Table 2-3, are not significant. The table shows four types of parameter estimates: latent variables, regressors, intercepts, and thresholds. The estimated parameters for the observed variables that construct latent variables are given in the first category. The effect of the observed variables on latent or other observed variables is given by the estimated parameters under the second category: regressors. The intercept category applies only to continuous variables that construct latent variables; in our case, the only such variable is the number of hurricane experiences. Finally, the thresholds give the cutoffs for categorical variables that construct latent variables and serve as intermediary variables.

The results show that the prior hurricane experience appraisal construct (η_1) is significant: the prior damage level parameter (λ_1) is fixed to 1 for identification, and the number of hurricane experiences parameter (λ_2) is significant at the 10% level (p-value of 0.07). The parameter for tenure length in home (Υ_1) is significant at a p-value of 0.078. The hurricane risk perception construct (η_2) is also significant; the parameter for worry (λ_3) is fixed to 1, and the parameter for emotion (λ_4) is significant at a p-value of 0. The effect of prior hazard experience (η_1) on hurricane risk perception (η_2) is significant at a p-value of 0.023.

The effect of being a white male (Υ_4) is barely significant at the 10% level (p-value 0.097) but, as expected, reduces flood risk perception (Y_1). Nonetheless, the effect of hurricane risk perception (Υ_3) on flood risk perception (Y_1) is highly significant at a p-value of 0. Age and education were found to be not significant. It should be noted that this does not mean that these factors do not influence flood protection decisions, but it simply means that they were not significant in these data and the hypothesized structural equation model. Additionally, it is important to note that structural equation modeling is an empirical tool. Although 318 observations are sufficient for the model shown, the actual flood insurance decision processes might require a more complex structure, perhaps by including more data points and additional information on important factors such as information acquisition, processing, and media effect (Kano 2009).

The flood insurance purchase construct (η_3) is significant at a p-value of 0. This result is perhaps not surprising given that it is made from repeated measurements. The parameters for flood risk perception, proximity to hazard, and income are all significant at a p-value of 0.009, 0.001, and 0.022, respectively. The sign of all the parameters also supports the hypotheses stated in Section 2.3. Nonetheless, two factors, government aid and future tenure, are not significant. Moreover, the thresholds for prior damage level, one of the two stated flood insurance purchase decisions and flood risk perceptions, are not significant, which indicates that the model needs to be modified. Table 2-3 summarizes the results.

Table 2-3. Initial structural equation model results

	Estimate	Std.err	Z-value	P(>|z|)
Latent variables:				
η_1: Past hurricane experience appraisal				
λ_1: X_1-Number of hurricane experiences	0.255	0.141	1.815	0.07*
λ_2: X_2-Prior damage level	1			
η_2: Hurricane risk perception				
λ_3: X_4-Worry about hurricane	1			
λ_4: X_5-Emotion	1.139	0.174	6.527	0***
η_3: Flood insurance purchase decision				
λ_5: X_{13}-Stated flood insurance purchase decision	1			
λ_6: X_{14}-Stated flood insurance purchase decision	0.997	0.183	5.456	0***
Regressions:				
η_1: Past hurricane experience appraisal				
Υ_1: X_3-Time in home	0.013	0.007	1.764	0.078*
η_2: Hurricane risk perception				
Υ_2: η_1-Past hurricane experience appraisal	0.829	0.364	2.278	0.023**
Y_1: Worry about flood				
Υ_3: η_2-Hurricane risk perception	0.706	0.109	6.496	0***
Υ_4: X_6-White Male	-0.334	0.201	-1.659	0.097*
Υ_5: X_7-Age	-0.004	0.008	-0.484	0.629
Υ_6: X_8-Education	0.088	0.228	0.388	0.698
η_3: Flood insurance purchase decision				
Υ_7: Y_1-Worry about flood	0.247	0.095	2.609	0.009***

Υ_8: X_9-Proximity to hazard	-0.564	0.167	-3.378	0.001***
Υ_9: X_{10}-Income	0.501	0.22	2.284	0.022**
Υ_{10}: X_{11}-Government aid	0.057	0.088	0.644	0.52
Υ_{11}: X_{12}-Future stay in home	-0.002	0.004	-0.549	0.583
Intercepts:				
X_1-Number of hurricane experiences	0.519	0.124	4.199	0
Thresholds:				
X_2-Prior damage level	0.975	0.921	1.059	0.29
X_4-Worry about hurricane	1.198	0.556	2.154	0.031**
X_5-Emotion	1.215	0.595	2.044	0.041**
X_{13}-Stated flood insurance purchase decision	-0.926	0.497	-1.862	0.063*
X_{14}-Stated flood insurance purchase decision	-0.524	0.485	-1.08	0.28
Y_1-Worry about flood	0.609	0.578	1.053	0.292

* Significant at 0.1; ** Significant at 0.05; *** Significant at 0.01

The structural equation model was modified by removing the parameters that were not significant, namely, age (X_7), education (X_8), likelihood of receiving government aid (X_{11}), and expected future tenure (X_{12}). This is a minor modification and does not significantly change the underlying theory of how prior hazard experience, risk perception, socio-demographic characteristics, proximity to hazard, and tenure influence flood insurance decision-making. The modified diagram is shown in Figure 2-3. The resulting model fit is chi square p-value of 0.72, which is a significant increase from the initial model. Additionally, all the parameters are significant and have the expected signs. All the intercepts and thresholds are also significant. Table 2-4 shows the unstandardized parameter estimates and the standardized errors, along with the p-value for each estimated parameter.

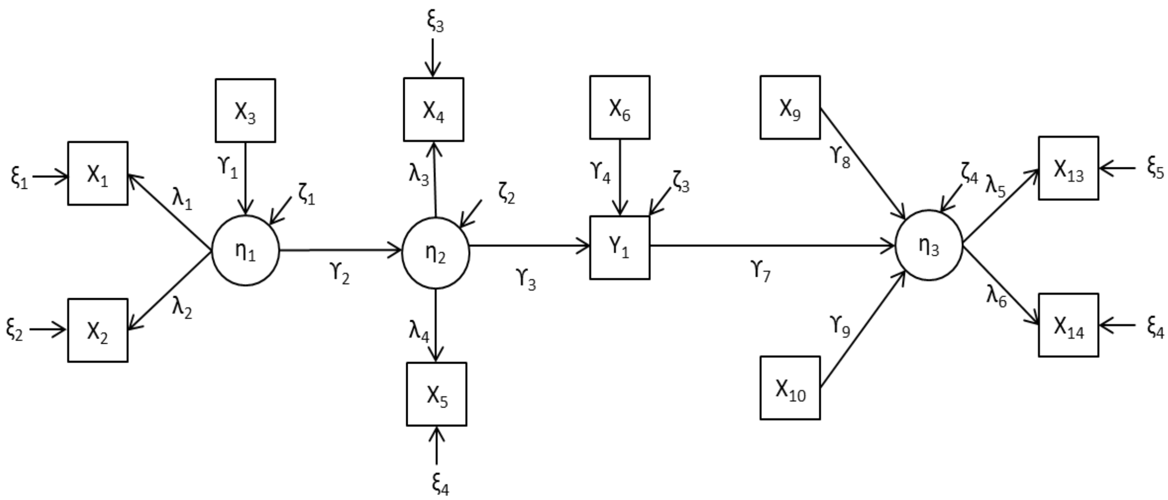

Figure 2-3. Modified hypothesized structural equation model for flood insurance purchase decision-making

Table 2-4. Modified structural equation model results

	Estimate	**Std.err**	**Z-value**	**P(>|z|)**
Latent variables:				
η_1: Past hurricane experience appraisal				
λ_1: X_1- Number of hurricane experiences	0.259	0.139	1.866	0.062*
λ_2: X_2- Prior damage level	1			
η_2: Hurricane risk perception				
λ_3: X_4-Worry about hurricane	1			
λ_4: X_5-Emotion	1.09	0.158	6.894	0***
η_3: Flood insurance purchase decision				
λ_5: X_{13}- Stated flood insurance purchase decision	1			
λ_6: X_{14}-Stated flood insurance purchase decision	1.019	0.213	4.787	0***
Regressions:				
η_1: Past hurricane experience appraisal				
Υ_1: X_3- Time in home	0.012	0.006	1.916	0.055*
η_2: Hurricane risk perception				
Υ_2: η_1-Past hurricane experience appraisal	0.959	0.453	2.115	0.034**
Y_1: Worry about flood				
Υ_3: η_2-Hurricane risk perception	0.679	0.105	6.442	0***
Υ_4: X_6-White Male	-0.384	0.192	-1.996	0.046**
η_3: Flood insurance purchase decision				
Υ_7: Y_1- Worry about flood	0.243	0.091	2.655	0.008***
Υ_8: X_9-Proximity to hazard	-0.567	0.161	-3.525	0***
Υ_9: X_{10}-Income	0.377	0.151	2.505	0.012**

Intercepts:				
X_1: Number of hurricane experiences	0.729	0.048	15.312	0***
Thresholds:				
X_2: Prior damage level	0.876	0.227	3.864	0***
X_4: Worry about hurricane	0.826	0.234	3.524	0***
X_5: Emotion	1.573	0.406	3.871	0***
X_{13}: Stated flood insurance purchase decision	-0.855	0.222	-3.845	0***
X_{14}: Stated flood insurance purchase decision	-0.808	0.208	-3.884	0***
Y_1: Worry about flood	0.461	0.209	2.203	0.028**

* Significant at 0.1; ** Significant at 0.05; *** Significant at 0.01

This structural equation model is one of many plausible ways to represent the relationship between different factors that affect flood insurance purchase decision-making. Alternative structural equation models can be developed to represent the fundamental theory tested in this study, i.e., that prior hurricane hazard experience affects flood insurance purchase decision-making through the mediation effect of both hurricanes and hurricane-induced flood risk perceptions. One such model is shown in Figure 2-4. In this model, the number of hurricane hazards experienced (X_1), the level of prior damage (X_2), and past tenure (X_3) are directly regressed to hurricane-risk perception (η_2), instead of these variables constructing an overall prior hurricane hazard experience latent variable. Although the number of hurricane experiences (X_1) and prior damage level (X_2) were significant, past tenure (X_3) was not; hence, the model was re-specified by removing past tenure (X_3). The final alternative model is significant, with a chi square p-value of 0.16. This construct is equally valid compared to the model given in Figure 2-3 but does not account for how the length of exposure to a hurricane hazard might influence risk perception. The chi square p-value for the alternative model is also lower than the p-value of the model shown in Figure 2-3. Presenting equivalent models such as the one in Figure 2-4 allows us to acknowledge that there are other alternative explanations of the data and helps us to avoid confirmatory bias (Kline 2011).

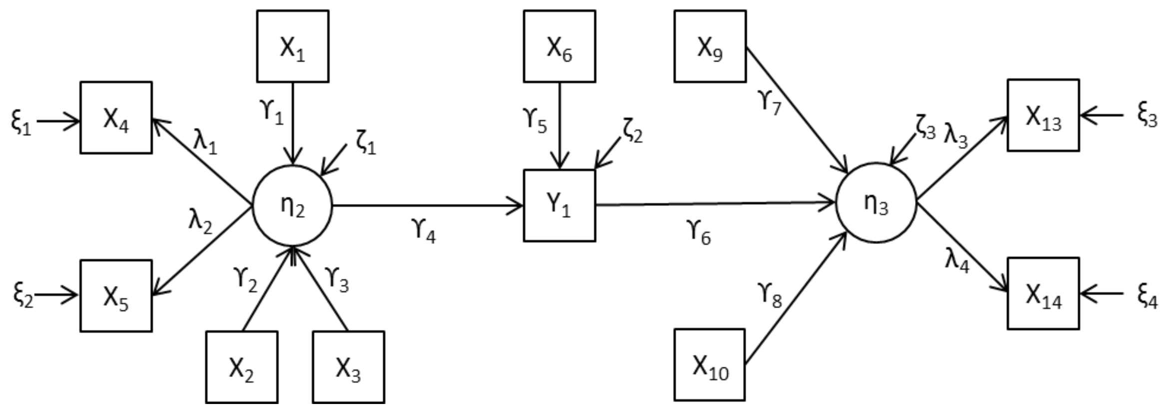

Figure 2-4. Alternative structural equation model for flood insurance purchase decision-making

2.6. DISCUSSION

The results of this analysis support past theoretical and empirical findings on the effects of prior hazard experience, length of tenure, race, gender, income, and proximity to hazard on flood insurance purchase decision-making. The results also show that prior hurricane hazard experience affects flood insurance purchase decision-making through the mediation effect of both hurricanes and hurricane-induced flood risk perceptions.

The role of prior hurricane hazard experience is in line with several studies that determined that past experience raises risk perception (Hypothesis 2) and the likelihood of taking protective measures (Baumann et al. 1978, Zaleskiewicz et al. 2002, Lindell and Hwang 2008, Zaalberg et al. 2009). Past tenure length is significant in the model and, as expected, is positively associated with overall hazard experience (Hypothesis 12). This is because tenure length increases the probability of exposure to natural hazards, as suggested by Ge et al. (2011).

Past experience alone, however, does not necessarily directly influence insurance purchase or any other protective action. Slovic et al. (2004) argue that although past experience makes it easy to recall or imagine the damage, it is the affect tagged with it that leads to protective action. Similarly, Siegrist et al. (2008), conducting face-to-face interviews with 201 people who had never experienced a flood hazard, found that the people could imagine their house being destroyed by a flood but could not imagine the negative affect associated with it. The study found that negative affects such as fear and helplessness were underestimated by this group. Zaalberg et al. (2009), using a structural equation model, found a strong mediation effect of affect variables in linking prior hazard experience and protective action. The results of this analysis are aligned with this evidence concerning the mediation effect of affect variables in linking prior experience and flood insurance purchase decision-making (hypotheses H2, H4, and H5).

Not everyone who has previously experienced a hurricane or a hurricane related flood hazard event takes protective measures. Negative emotion is a necessary but not a sufficient factor, and there are other factors at play, such as doubt about the effectiveness of measures and their high costs (Siegrist and Gutscher 2008). In this study, doubt about the effectiveness of flood insurance translates to doubt about the NFIP, as flood insurance is not provided by private insurers. Several studies investigate the effects of race and gender on people's trust of institutions and risk perceptions. Almost all studies find white males to be different in terms of risk perception (Slovic 2000). Flynn et al. (1994) and Finucane et al. (2000) attribute the low risk perception attitude of white males to their trust of experts, institutions, and authorities. This finding could be explained by white males' greater involvement in managing institutions, compared to women and non-white men. In our model, the white-male effect on flood risk perception (Hypothesis 6) is negative compared to the rest of the respondents, in line with previous studies.

In this analysis, we find that an income cutoff of $75,000 is significant, with the higher income positively influencing flood insurance purchase decisions (Hypothesis 9). This corroborates other studies that found income to have an important role in insurance purchase decision-making (e.g., Browne and Hoyt 2000, Michel-Kerjan and Kousky 2010). This result is not surprising, as the cost of protective measures is an important factor that influences insurance purchase decisions (Siegrist and Gutscher 2008).

Proximity to hazard, measured by whether people lived in the counties in which the CPIP is offered or not, was significant in this study (Hypothesis 10). People on the coast are evidently more exposed to hurricane-induced floods, and the results of this analysis suggest that the respondents' appraisal of the risk is correlated with experts' risk assessment, which is in line with Siegrist and Gutscher's (2006) findings.

2.7. CONCLUSION

This article explores the factors that influence flood insurance purchase decisions. The structural equation model reveals a plausible relationship among different factors and shows how, in combination, they affect flood insurance purchase decision-making. Past experience of hurricane hazard (both frequency and level of damage) and tenure length are strong factors that affect flood insurance purchase decisions, through the mediation effect of hurricane and hurricane-induced flood risk perceptions, which are measured by levels of fear and worry.

The implication of this relationship is enormous in terms of both designing an effective risk communication system and the strategic timing of risk awareness campaigns. People who have experienced hurricanes can recall the associated anxiety and worry, but those with no experience cannot. Hence, the biggest question in risk communication is how to raise the awareness and risk perception of people who have never experienced natural disaster so that they can protect themselves through insurance or other protective measures.

Based on the mediation effect of the affect variables revealed in this analysis, it is recommended that risk communication strategies invoke negative affects to be successful. Other studies have reached similar conclusions, such as Keller et al. (2006) and Siegrist et al. (2008). This strategy can be achieved by using graphics and pictures to communicate risk (Stone et al. 2003) or by using more advanced 3D risk communication technologies that target numerous senses, as suggested by Zaalberg and Midden (2010). Effective risk communication is especially important for people who have never experienced floods, as it is difficult for them to predict future affects resulting from severe events (Siegrist and Gutcher 2008).

The results of this analysis also have policy implications for the strategic timing of risk awareness campaigns. Numerous studies have found that people take more protective action in the immediate aftermath of a disaster (e.g., Kunreuther 1978, Browne and Hoyt 2000), suggesting that the negative affect associated with a hazard experience fades with time. Based on the findings of this study on the role of affect variables on flood insurance purchase decision-making, we recommend that risk awareness campaigns be conducted in the period immediately following a flood event. Burn (1999) makes a similar recommendation based on a flood risk perception study of the Red River flood of 1997.

Finally, because income is a significant factor, the issue of affordability must be addressed. The NFIP provides subsidies, but this alone has not helped to increase the insurance market penetration rate, and many who are eligible go uninsured (Aerts et al. 2014). In the past, there have been proposals to redesign the flood insurance market by introducing risk based premiums and a subsidy in the form of vouchers for low income households, to address the issue of affordability without necessarily encouraging risky behaviors (Michel-Kerjan and Kunreuther 2011), but so far, improvement in this regard has been slow. In light of this, we recommend that the issue of affordability be addressed not only through subsidies but also through a comprehensive evaluation of the current flood insurance market.

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CHAPTER 3

HURRICANE RISK MANAGEMENT THROUGH SELF-INSURANCE AND MARKET INSURANCE

ABSTRACT

People tend to hold low deductible policies from market insurance (insurance from an insurance company) by paying *actuarially unfair* premiums, and they underinvest in self-insurance (an *ex ante* structural retrofit measure that reduces the severity of loss). Such decisions can be suboptimal, and given limited budgets for undertaking protective action, it is important that homeowners optimally invest in retrofit and insurance. Using phone-survey data (n=140), this article investigates the relationship between self-insurance and market insurance decisions. We built an ordered logistic model by using revealed preferences about structural retrofit measures and standard homeowners' insurance deductible choices, to understand the effect of physical mitigation on the insurance market. We found that self-insurance and market insurance are substitutes, and factors such as the number of adults in the household, race, the number of prior hurricane experiences, and education level have significant effects on deductible choices. Finally, we discuss the implications of these results in terms of setting appropriate standard homeowners' premium and deductible values.

3.1. INTRODUCTION

The relationship among market insurance, self-insurance, and self-protection has been of great interest to economists. Ehrlich and Becker (1972), in their seminal work, define self-insurance as a mitigation measure that reduces the severity of loss, whereas self-protection is viewed as a measure that reduces the probability of loss. For example, raising a structure to protect it from flooding would be considered self-protection, whereas installing shutters to protect it from hurricanes would be considered self-insurance. Market insurance is an insurance policy offered by a private insurance company. Within the realms of market insurance, there has also been an effort to understand peoples' risk appetite based on the policy or deductible level they choose (e.g., Cohen and Einav 2005, Sydnor 2006). This article investigates the relationship between self-insurance and market insurance decisions, using revealed preferences about structural retrofit measures and standard homeowners' insurance deductible choices.

In the United States, standard homeowners insurance is available through private companies. To qualify for mortgages, most people must purchase standard homeowners insurance, but homeowners have the option of choosing deductible levels and/or coverage limits. Deductibles serve as a protection against moral hazard (Kunreuther 1998) by ensuring that homeowners are liable for a fraction of losses, and hence discourage risky behavior. Many studies have consistently found that people choose lower deductibles, in spite of being required to pay *actuarially unfair* premiums for the additional coverage (e.g., Cohen and Einav 2005, Sydnor 2006, Barseghyan et al. 2013). Such choices are suboptimal and have important policy implications.

Given budget limitations for protective action, it is important that homeowners optimally invest in structural retrofit measures and insurance. Whereas most studies examine the relationship between mitigation and insurance purchase from a mitigation decision-making point of view, by investigating the effect of deductible choice (independent variable) on the decision to mitigate (dependent variable) (e.g., Carson et al. 2013, Burrus et al. 2008), we focus on the effect of having a retrofitted structural feature (independent variable) on the deductible choice (dependent variable). The motivation is to investigate the role of physical mitigation, beyond reducing the severity of loss, in order to improve the insurance market.

In this study, we specifically investigate the role of five structural retrofit measures on homeowner insurance deductible choices, using survey data from the eastern half of North Carolina. These measures are (i) high-wind shingles and synthetic water barriers on the roof, (ii) spray adhesive to the underside of the roof in the attic, (iii) hurricane straps to improve the connection between roof and walls, (iv) hurricane shutters, and (v) impact-resistant windows and doors. In addition, we also test the effects of prior hurricane experience, level of worry about hurricanes, proximity to hazard, education, race, income, and number of adults and children in the household.

The rest of the article is organized as follows: Section 3.2 covers the literature review. Section 3.3 then details the different hypotheses tested. After Section 3.4 presents the survey instrument, the variables used, and the analytical and solution approaches adopted, the results are presented in Section 3.5. Finally, Sections 3.6 and 3.7 provide the discussion and conclusion, respectively.

3.2. BACKGROUND

Researchers have been interested in understanding consumers' deductible choices across different industries, including the automobile (e.g., Cohen and Einav 2005, Barseghyan et al. 2013), flood (e.g., Michel-Kerjan and Kousky 2010), and standard homeowners insurance markets (e.g., Sydnor 2006, Barseghyan et al. 2013). For example, Sydnor (2006), using homeowners insurance data, found that 83% of consumers chose a deductible lower than the maximum allowed and that they paid 400% to 500% of the expected value for the additional coverage provided by the lower deductible. Cohen and Einav (2005), using a data set from an auto-insurance company, analyzed choices made from an individual-specific menu of four deductible-premium combinations. They found that people held lower deductible values and paid *actuarially unfair* premiums. Michel-Kerjan and Kousky (2010) analyzed purchase decisions of flood insurance in Florida and found that 97% of customers chose a deductible lower than the maximum, with 80% actually choosing the lowest deductible.

Schindler (1994) argues that the tendency to choose low deductibles has undesirable consequences for both the individual consumer and society as a whole. From the consumer side, choosing a low deductible means overpaying, as the premium associated with low deductibles is *actuarially unfair*. He explains that this is equivalent to buying something you do not need. From the insurer side, low deductibles increase administrative costs because small-amount claims require the same investigative and paperwork operations as large claims do, and this cost is eventually passed to the consumer, which in turn affects the whole market.

In addition, people have limited resources and budgets for protective measures. For example, evidence shows that immediately after flooding, people increased their standard homeowner policy deductible level and used the savings to buy flood insurance (Asservatham et al. 2014), which suggests that people allocate an overall budget to protective actions. Our study is similar to that of Asservatham et al. (2014), which investigates the effect of a flood event on standard homeowners' deductible choices, except that instead of examining a flood event, we look at the effect of structural retrofit measures on homeowners' deductible choices.

Schindler (1994) offers four potential reasons for consumers' tendency to choose low-deductible insurance. The first is the desire for flat-rate payments, i.e., people prefer a sure outcome over a gamble. The second is lack of information, which is lack of awareness of potential savings from choosing higher deductibles. The third is desire for a good deal, which might underestimate the recurring nature of the premium payment, and the fourth is the desire to make mandatory insurance more palatable. The argument here is that when insurance is required by law, perhaps the low deductible and the small claims help to reassure consumers that the insurer will live up to its promises. This is similar to the argument by Michel-Kerjan and Kunreuther (2011) that people think insurance is a bad investment unless they reap its benefits.

The role of deductible choice in mitigation decision-making has been widely studied (e.g., Carson et al. 2013, Burrus et al. 2008). Nonetheless, the role of mitigation in deductible choice has not been adequately addressed. We argue that this is important, beyond the need to understand the effect of undertaking mitigation on the insurance market, because it accounts for the temporal sequencing of activities. In most cross-sectional stated-preference data such as ours, the actual timing of the structural retrofit measure and of the insurance decision is unclear, which makes it difficult to infer the causal relationship between these measures. Nonetheless, because mitigation efforts are typically undertaken infrequently and insurance contracts are renewed yearly, it is reasonable to assume that the deductible level choices revealed are the respondents' choices in the year in which the survey was conducted, whereas the mitigation measures were performed in the past. Bubeck et al. (2012) discuss the importance of using panel data to fully capture the temporal variation of risk aversion and the relationship between different protective actions. By using the deductible choice as a dependent variable, we indirectly account for the temporal ordering of events.

3.3. HYPOTHESES

This section expands the background literature in Section 3.2 by discussing specific concepts related to deductible choice and develops a set of hypotheses.

3.3.1. Mitigation and Risk Aversion

Ehrlich and Becker (1972) studied the interactions among market insurance, self-insurance, and self-protection. They found that market insurance, which is a policy from an insurance company, and self-insurance are always substitutes, whereas market insurance and self-protection are complements. They argue that optimal decisions about market insurance should be viewed in the context of the interaction among these three types of insurance and protective measures. Dionne and Eeckhoudt (1985) extend this work by examining the role of risk aversion in how consumers make optimal choices among market insurance, self-insurance, and self-protection. They found that an increase in risk aversion leads to an increase in the level of self-insurance, but this is not always true for self-protection. Briys and Schlesinger (1990), examining the interaction among risk aversion, self-insurance, and self-protection, concluded that self-insurance reduces risk, whereas self-protection does not.

Several empirical studies have used deductible level choices in market insurance as a way to infer the risk appetite of individuals (e.g., Cohen and Einav 2005, Sydnor 2006). These studies have concluded that the higher the risk aversion, the lower is the deductible value chosen. As suggested by Dionne and Eeckhoudt (1985), it is reasonable to state that people who have high risk aversion would invest in self-insurance, and as a result, their risk would be reduced, as determined by Briys and Schlesinger (1990). This reduction in risk would then be revealed by higher market insurance deductible levels that these people hold, as argued by Sydnor (2006). Following this deductive reasoning, we hypothesize that

> H1: People who live in a retrofitted home hold higher market insurance deductible levels. That is, these two risk management measures are substitutes (this hypothesis is used an underlying logic for some of the remainder of the hypotheses)

H2: People who worry more about hurricanes hold a lower market insurance deductible level.

3.3.2. Prior Hazard Experience

Using data from individuals whose standard homeowners insurance excludes wind, Petrolia et al. (2013) found that past wind damage experience leads to a higher likelihood of buying wind insurance. Baumann and Sims (1978) found that people who had previously experienced flood damage were more likely to buy flood insurance. Krantz and Kunreuther (2007) and Siegrist and Gutscher (2008) determined that prior hazard experience affects risk perception, and the latter attribute this phenomenon to the negative affect that the experience creates.

At least two plausible explanations can be drawn from these findings. The first is that if people with prior hazard experience have high risk perceptions, then they would most likely choose lower deductible values. However, this reasoning does not take into account the role of mitigation. A second logical explanation is that people who have experienced a hazard would have already undertaken mitigation measures to lower their risk. Petrolia et al. (2013) and Peacock (2003), using survey data, found that those who have experienced hurricanes in the past have undertaken more mitigation, which lends support to the second explanation. Following this analysis, we hypothesize that

H3: People who have had more hurricane experience hold higher market insurance deductible levels.

3.3.3. Proximity to Hazard

Burrus et al. (2002) argue that if hurricane-strike probabilities increase, a wealth-maximizing homeowner would drop insurance and invest in mitigation, which suggests that as risk increases, there is a shift from market insurance to self-insurance. Michel-Kerjan and Kousky (2010) found that more homeowners in flood-prone areas chose a higher deductible value of flood insurance, even though approximately 80% of all the people who bought flood insurance chose the lowest available level. If we look at this phenomenon solely through a risk-perception prism, it seems an anomaly because it implies that the risk perception of people is lower compared to their risk exposure. Michel-Kerjan and Kousky (2010) suggest that this could be a result of a cost-minimization strategy by homeowners who live in high-risk areas, in response to being required by law to buy flood insurance. This cost-minimization argument can be extended to standard homeowner insurance deductible decision-making, as premiums associated with low deductibles are expensive in high-risk areas, and this insurance is usually required for mortgage purposes. It is also possible that people who live in high-risk areas mitigate more and, hence, would tend to choose higher deductible values. Following this reasoning, we hypothesize that

H4. People who live in high-risk areas hold higher market insurance deductible levels.

3.3.4. Number of Children

Carson et al. (2013) found that the likelihood to mitigate is positively related to the number of children in a household. This is explained by a strong desire to protect young children from harm and is in line with Kunreuther and Kleffner's (1992) argument that people mitigate not only to reduce financial losses but also to prevent injury and death. Using these studies and assuming that market insurance and self-insurance are substitutes (as stated in Hypothesis 1), we hypothesize that

H5. Households with more children hold higher market insurance deductible levels.

3.3.5. Education

Ge et al. (2011), using household survey data from Florida, found that a higher level of education is associated with lower risk perception. Botzen et al. (2009), using survey data on approximately 1,000 homeowners in the Netherlands, came to the same conclusion. Nonetheless, some studies have not found a relationship between education and risk perception (e.g., Bubeck et al. 2012). Burrus et al. (2008) found that highly educated people undertake more mitigation. Again, assuming that market insurance and self-insurance are substitutes (Hypothesis 1), we hypothesize that

H6. People with higher education hold higher market insurance deductible levels.

3.3.6. Income

The effect of income on risk perception seems to be similar to the effect of education. For example, both Ge et al. (2011) and Botzen et al. (2009) found that higher income is associated with lower risk perception. In spite of this inverse relationship between income and risk perception, several studies have found higher income to be associated with mitigation (e.g., Browne and Hoyt 2000, Landry and Jahan-Parvar 2011, Burrus et al. 2008). The reason could be that those with higher income invest in mitigation and, hence, exhibit lower risk aversion, which is in line with Briys and Schlesinger's (1990) explanation of the relationship between mitigation and risk aversion. Both the low risk aversion and the higher probability of undertaking mitigation lead to less dependence on insurance, as explained by Dionne and Eeckhoudt (1985) and Ehrlich and Becker (1972), respectively. Nonetheless, some studies such as that of Burrus et al. (2008) have not found the relationship between income and mitigation to be significant. In this analysis, we hypothesize that

H7. People with higher income hold higher market insurance deductible levels.

3.3.7. Race

Several studies have found that minorities have high risk aversion but that this does not necessarily translate to undertaking mitigating action (Fothergill et al. 1999, Peacock 2003, Lindell and Hwang 2008, Ge et al. 2011). For example, Peacock (2003) found that African Americans/Blacks were less likely to install wind shutters, compared to other races. Ge et al. (2011) argue that ethnic minorities have historically had less access to loans, which can be important for financing expensive mitigation measures. Considering these results and assuming that market insurance and self-insurance are substitutes (Hypothesis 1), we state the following hypothesis:

H8. African Americans/Blacks hold lower market insurance deductible levels.

3.3.8. Number of Adults

Bubeck et al. (2012) discuss how, after weighing the threat they face, people evaluate the benefits of mitigation actions and one's ability to carry them out. The authors refer to one's ability to successfully undertake a protective action as "self-efficacy" and found that high self-efficacy leads to taking more protective action. We argue, based on this, that having more adults in a household increases the probability of the household's self-efficacy and undertaking protective action. Assuming that market insurance and self-insurance are substitutes (Hypothesis 1), we hypothesize that

H9. Households with more adults hold higher market insurance deductible levels.

3.4. METHOD

3.4.1. Data Collection

A survey of households was conducted by the Disaster Research Center (DRC) of the University of Delaware, during the fall of 2012 and spring of 2013. The survey has six modules:

(i) Introduction and screening module, which includes questions that were used to determine eligibility; (ii) Background information module, covering questions about physical characteristics of the building, type of mitigation undertaken, and insurance policy bought; (iii) Risk perception and hazard experience module, which asks residents about their level of worry and emotion towards hurricanes and floods as well as the number of hurricanes and the levels of prior damage that they have experienced; (iv) Protective action module, with questions aimed at understanding people's intentions to insure and/or mitigate in the future; (v) Utility module, with hypothetical lottery questions that help to understand people's risk appetite; and (vi) Socio-demographic module, covering data such as age, income, and education.

The survey was conducted over the phone and took 27 minutes, on average, to complete. Listed household numbers (50%), random digit dial landline numbers (25%), and random digit dial cell phone numbers (25%) were sampled from 49 counties[2] in the eastern half of North Carolina. The samples were purchased from *Genesys*, a third party sample provider, and a computer-assisted telephone interviewing (CATI) system was used to administer the survey. Participants who completed the survey were entered into a drawing, as an incentive, with a 1 in 100 chance of winning an iPad mini. There are 358 observations, with an overall cooperation rate of 23%.

The analysis is limited to single family and duplex homes, as the structural retrofit measures in this analysis are not applicable to mobile or manufactured homes. Renters were removed from the analysis, as they do not make mitigation and insurance related decisions. Similarly, residents who indicated the house as their secondary residence were removed, as they

[2] Beaufort, Bertie, Bladen, Brunswick, Camden, Carteret, Chowan, Columbus, Craven, Cumberland, Currituck, Dare, Duplin, Edgecombe, Franklin, Gates, Granville, Greene, Halifax, Harnett, Hertford, Hoke, Hyde, Johnston, Jones, Lee, Lenoir, Martin, Moore, Nash, New Hanover, Northampton, Onslow, Pamlico, Pasquotank, Pender, Perquimans, Pitt, Richmond, Robeson, Sampson, Scotland, Tyrrell, Vance, Wake, Warren, Washington, Wayne, Wilson.

are not directly affected by hurricane events. In addition, only respondents with standard homeowners insurance were kept in the analysis, as the objective is to look at variation in deductible choices, and it would be difficult to compare results from separate policies, such as the National Coastal Property Insurance Pool (CPIP). The final data comprise 264 observations. Nonetheless, many respondents only partially answered the survey questions, and hence, the final number of valid observations depends on the variables kept in the final model. Figure 3-1 shows the distribution of the survey respondents in the study area who gave their full addresses.

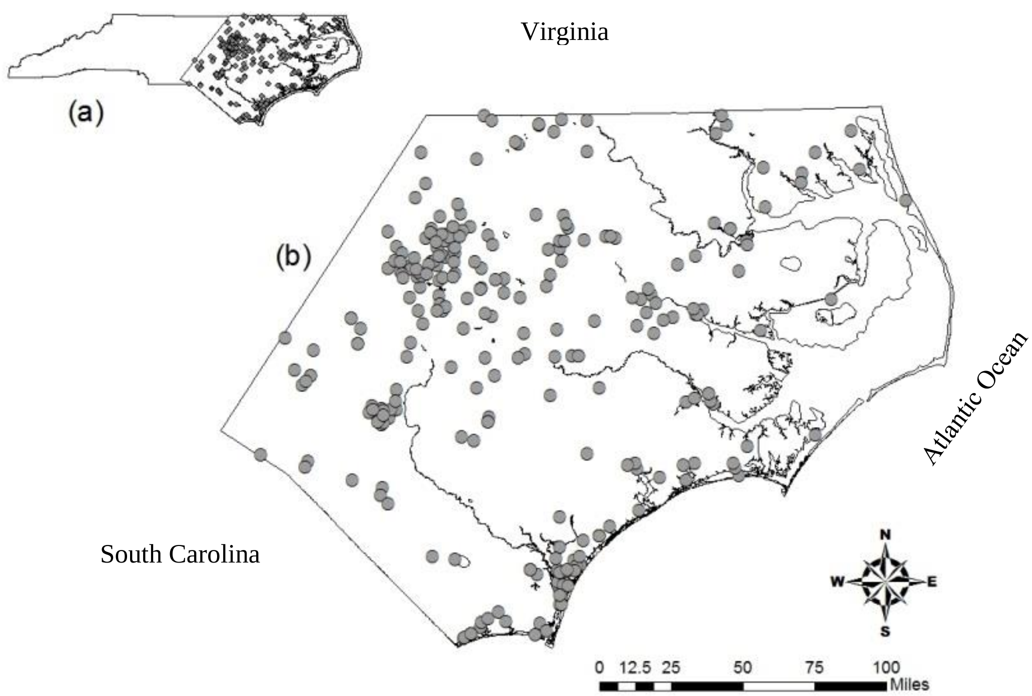

Figure 3-1. (a) Study area comprising the eastern half of the state and (b) geographic distribution of the survey respondents who gave their full addresses.

3.4.2. Variables

In the survey, the deductible values reported by respondents ranged from \$100 to \$5000. A total of 14 deductible levels were reported, and given the limited data set available, it would be impossible to estimate a parameter for each of these levels. For this reason, the deductible levels were grouped into three categories (Y): \$100-\$500, \$1000-\$1500, and \$2000-\$5000.

The respondents were asked if, to the best of their knowledge, their homes had a specific structural retrofit feature that would protect it against wind hazard. The binary variables used in the analysis represent the following five protective features: (i) high-wind shingles and a synthetic water barrier on the roof (X_1), (ii) spray adhesive applied to the underside of the roof in the attic (X_2), (iii) a hurricane strap to improve the connection between the roof and walls (X_3), (iv) hurricane shutters (X_4), and (v) impact-resistant windows and doors (X_5).

The level of worry (X_6) about hurricanes is measured on a Likert scale of 1 to 5, where 1 means "never worry" and 5 means "constantly worry". Due to sample size limitations and the statistical significance of the results, this was collapsed into a binary variable, with responses 1-3 and 4-5 grouped in different categories. Proximity to hazard (X_7) is represented as a binary variable by categorizing respondents based on their eligibility for the CPIP. This variable serves as a proxy to determine how close to the ocean respondents live.

Education (X_8) and income (X_9) were measured in nine and eight categories, respectively. The education categories range from elementary school to advanced graduate work, whereas the income categories range from less than \$15,000 to more than \$250,000. In this analysis, due to data sample size limitations and the nominal nature of the data, we use a cutoff point to see if these variables are significant beyond a certain level. For education, completion of a four-year degree and beyond is considered one category, and income of \$75,000 or more is considered a separate category. Similarly, race is converted into a dichotomous variable representing African Americans/Blacks and others (X_{10}).

Finally, the numbers of prior hurricanes experienced (X_{11}), number of children (X_{12}), and number of adults (X_{13}) were measured as continuous variables. Tables 3-1 and 3-2 show the descriptive statistics of the categorical and continuous variables of the 264 observations, respectively.

Table 3-1. Descriptive statistics of categorical variables

	Freq.	Perc.		Freq.	Perc.
Y - Deductible Choice Category			**X_7 - Proximity to hazard**		
\$100 - \$500	83	31.4%	Eligible for CPIP	59	22.3%
\$1000 - \$1500	74	28.0%	Not eligible for CPIP	205	77.7%
\$2000 - \$5000	26	9.8%	Missing	0	0.0%
Missing	81	30.7%	**X_8 - Education**		
X_1 - High-wind shingles			Elementary school only	1	0.4%
Have	86	32.6%	Some high school, did not finish	8	3.0%
Do not have	99	37.5%	Completed high school	35	13.3%
Do not know	70	26.5%	Some college but didn't finish	35	13.3%
Missing	9	3.4%	2-year college degree/A.A/A.S.	23	8.7%
X_2 - Spray adhesive on roof			4-year college degree/B.A./B.S.	65	24.6%
Have	36	13.6%	Some graduate work	9	3.4%
Do not have	138	52.3%	Completed masters or prof. degree	46	17.4%
Do not know	80	30.3%	Ph.D.	11	4.2%
Missing	10	3.8%	Refused	6	2.3%
X_3 - Hurricane strap			**X_9 - Income**		
Have	49	18.6%	Less than \$15,000	6	2.3%
Do not have	162	61.4%	\$15,000 to \$35,000	16	6.1%
Do not know	43	16.3%	\$35,000 to \$50,000	25	9.5%
Missing	10	3.8%	\$50,000 to \$75,000	40	15.2%
X_4 - Hurricane shutters			\$75,000 to \$100,000	34	12.9%
Have	18	6.8%	\$100,000 to \$150,000	41	15.5%
Do not have	232	87.9%	\$150,000 to \$250,000	12	4.5%
Do not know	4	1.5%	Over \$250,000	12	4.5%
Missing	10	3.8%	Do not know	8	3.0%
X_5 - Impact-resistant windows and doors			Refused	45	17.0%
Have	94	35.6%	Missing	25	9.5%
Do not have	132	50.0%	**X_{10} - Race**		
Do not know	28	10.6%	White	183	69.3%
Missing	10	3.8%	African American/Black	24	9.1%

X_6 - Worry about hurricanes			Asian	2	0.8%
1 Never worry	53	20.1%	American Indian	4	1.5%
2	77	29.2%	Pacific Islander	8	3.0%
3	75	28.4%	Multi-Racial	3	1.1%
4	28	10.6%	Other	15	5.7%
5 Constantly worry	19	7.2%	Refused	25	9.5%
Missing	12	4.5%	Missing	62	23.5%

Table 3-2. Descriptive statistics of continuous variables

	Observation	**Missing**	**Mean**	**Std. Dev.**	**Median**
X_{11} - Number of hurricanes experienced	235	29	5.87	6.25	4
X_{12} - Number of children	233	31	0.48	0.91	0
X_{13} - Number of adults	233	31	2.03	0.81	2

3.4.3. Analytical and Solution Procedures

The hypotheses stated in Section 3.3 are tested using an ordered logistic model in STATA-13, a data analysis and statistical software. Because deductible levels are discrete and ordered, we model the choices as being determined by utility thresholds. The utility U determines a person's opinion and is given as a combination of observed and unobserved components, as in Equation 3-1 (Train 2003). In this equation, x represents the variables, and β and k represent the parameters to be estimated. In our analysis, there are three categories of deductibles: \$100-\$500, \$1000-\$1500, and \$2000-\$5000; hence, there are two cutoff points: k_1 and k_2. The probability of choosing the lowest deductible is shown in Equation 3-2. The probability of choosing the second lowest category of deductible can be calculated by taking the difference in probabilities, as shown in Equation 3-3. The same analogy can be extended to calculate the probability of choosing the other deductible category. The second reason for using an ordered logit model instead of, for example, an ordered probit model is that the ordered logit model allows easy interpretation of the marginal effects of the variables by taking the exponent of the coefficients. The model was built by adding and dropping variables based on p-value. The final model consists of all variables that are significant at a p-value of 0.1.

$$U = \beta' x + \varepsilon \tag{3-1}$$

$$P\,(Lowest\ deductible\ category) = \frac{e^{k_3 - \beta' x}}{1 + e^{k_3 - \beta' x}} \tag{3-2}$$

$$P\,(Second\ lowest\ deductible\ category) = \frac{e^{k_2 - \beta' x}}{1 + e^{k_2 - \beta' x}} - \frac{e^{k_3 - \beta' x}}{1 + e^{k_3 - \beta' x}} \tag{3-3}$$

3.5. RESULTS

Proximity to hazard (X_7), income (X_9), level of worry (X_6), number of children (X_{12}), and the first four structural retrofit features—(i) high-wind shingles and synthetic water barrier on the roof (X_1), (ii) spray adhesive applied to the underside of the roof in the attic (X_2), (iii) hurricane strap to improve the connection between the roof and walls (X_3), and (iv) hurricane shutters (X_4)—were not significant in the analysis. The results of the analysis are shown in Table 3-3. The final model is based on 140 observations, as listwise deletion was employed to handle missing data. The signs of all the coefficients are in line with the hypotheses given in Section 3.3. Residents with impact-resistant windows and doors (X_5) tend to choose higher deductibles, compared to those who live in houses with no such protective features. Similarly, households with more adults (X_{13}), higher education (X_8), and those who have experienced many hurricanes (X_{11}) in the past seem to choose higher deductible values. On the other hand, African Americans/Blacks (X_{10}) preferred lower deductibles. Although the signs give a sense of the general direction of the choices, the marginal effects of these variables on deductible choices actually show the magnitude of these variables' effects on the probability of choosing one of the deductible levels.

Table 3-3. Ordered logit model results

	Coef.	Std. Err.	z	P>|z|
X_5 - Impact-resistant windows and doors	0.79	0.35	2.24	0.025
X_{11} - Number of hurricane experiences	0.06	0.03	2.19	0.029
X_8 - Education (At least 4-year degree)	0.58	0.35	1.67	0.095
X_{13} - Number of adults	0.56	0.23	2.46	0.014
X_{10} - Race (African American/Black)	-1.47	0.67	-2.19	0.028

The marginal effect of having impact-resistant windows and doors is shown in Figure 3-2. The figure shows changes in the probabilities of choosing different deductible levels as a result of having impact-resistant windows and doors, while keeping all other variables at their mean values. The change in probabilities is quite evident, with a drop in the probability of choosing the lowest deductible category and an increase in the probabilities of choosing the two higher deductible categories. With impact-resistant windows and doors, the probability of choosing a deductible level of between \$100 and \$500 drops from 54% to 36%, and the probability of choosing the deductible category of \$1000-\$1500 increases from 35% to 42%. The greatest gain in probability is for the highest deductible category of \$2000-\$5000, which increases from 11% to 21%.

The number of hurricanes experienced seems to have a substantial effect on deductible choice. The results of the analysis show that as people experience more hurricanes, they tend to choose higher deductibles. Figure 3-3 shows the relationship between the number of hurricanes experienced and the probability of deductible choice. The probability of choosing the lowest deductible category continuously decreases as the number of hurricanes experienced increases. For the first 20 hurricane events, the probabilities of choosing the two higher deductible categories increases, but as the number of hurricanes goes beyond 20, the only increasing probability is that of the highest deductible category. For example, if one has experienced 25 hurricanes as opposed to five hurricanes, the probability of choosing a deductible level between

\$100 and \$500 is lower by 24%, whereas the probabilities of holding the \$1000-\$1500 and \$2000-\$5000 deductibles are higher by 5% and 19%, respectively..

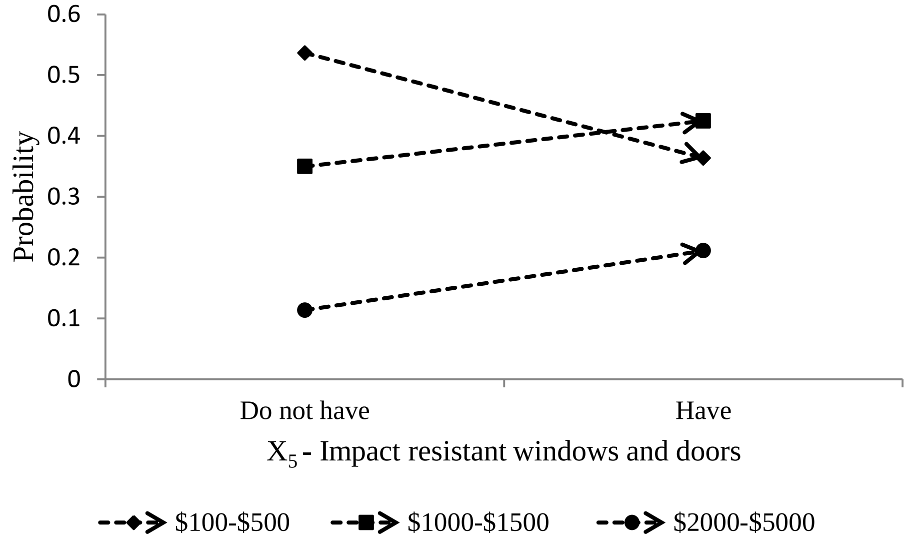

Figure 3-2. Deductible choice probability changes due to having impact-resistant windows and doors

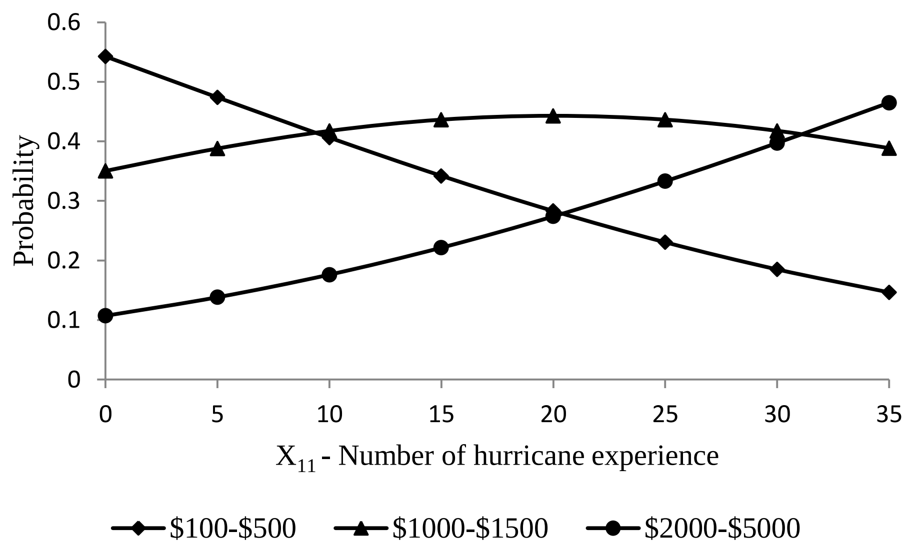

Figure 3-3. The effect of prior hurricane experience on homeowners' insurance deductible choices

The marginal effect of the number of adults was also calculated. The more adults in the household, the more likely it is that higher deductible levels are chosen. For example, for a household with four adults, the probabilities of choosing deductible categories of \$1000-\$1500 and \$2000-\$5000 are 12% and 23% higher, respectively, than those of a household with just one adult. On the other hand, the probability of choosing the \$100-\$500 deductible category is lower by 35%. Figure 3-4 shows the relationship between the number of adults and the probability of choosing different deductible levels.

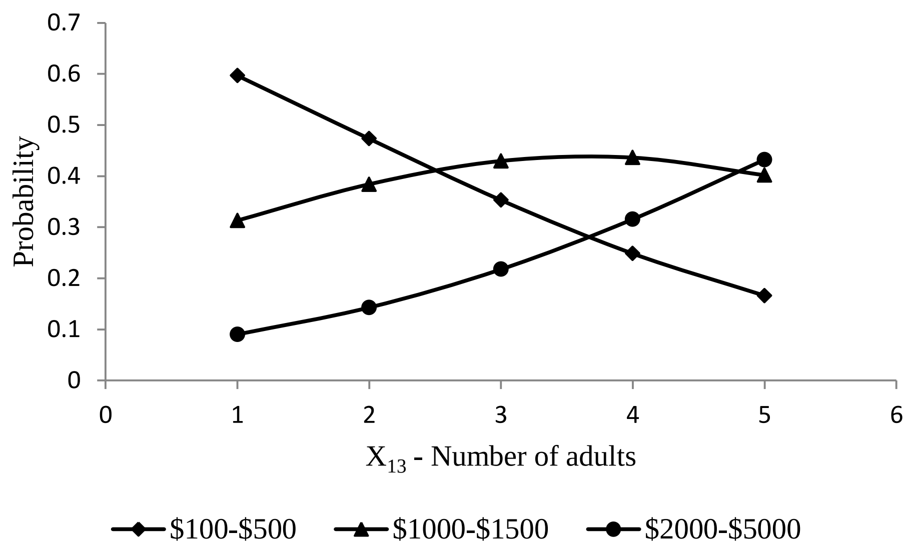

Figure 3-4. The effect of the number of adults in a household on homeowners' insurance deductible choices

The analysis found that higher education leads to choosing higher deductible values. From marginal calculations it was found that, on the one hand, having at least a four-year degree translates to 6% and 7% increases in the probabilities of choosing the \$1000-\$1500 and \$2000-\$5000 deductible categories, respectively. On the other hand, the probability of choosing a deductible level between \$100 and \$500 decreases by 13%. Finally, race was also found to be significant: African Americans/Blacks exhibited 31% more probability of choosing a deductible level between \$100 and \$500, compared with the rest of the respondents. Figures 3-5 and 3-6 show the effects of education and race on homeowners' insurance deductible choices, respectively.

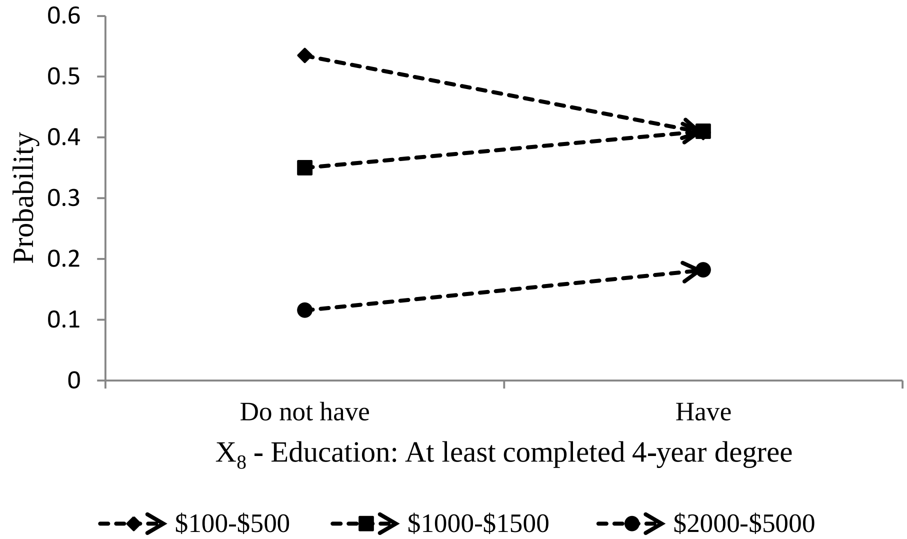

Figure 3-5. The effect of education on homeowners' insurance deductible choices

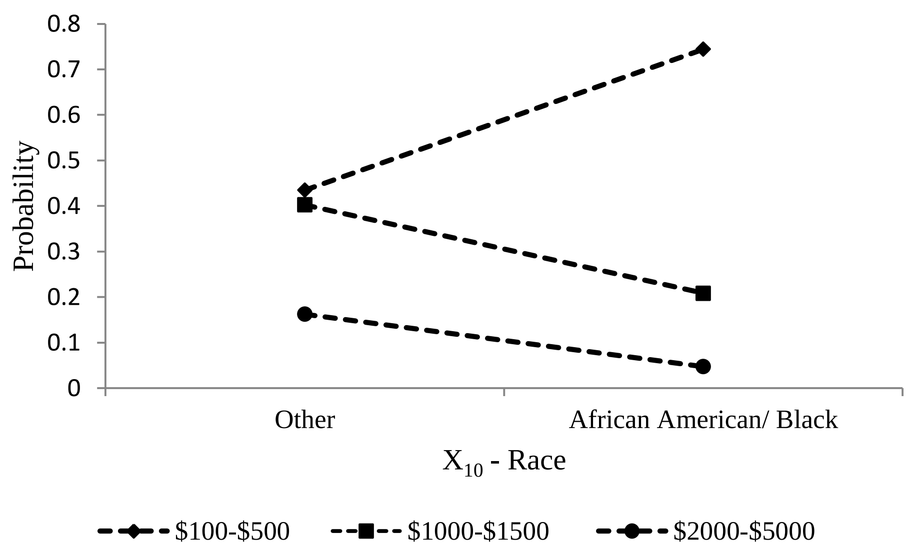

Figure 3-6. The effect of race on homeowners' insurance deductible choices

3.6. DISCUSSION

This analysis reveals that having impact-resistant windows and doors is associated with choosing higher deductible values (Hypothesis 1). This relationship is in line with Ehrlich and Becker’s (1972) finding that self-insurance and market insurance are substitutes.

Installing impact-resistant windows and doors on a typical single-family home could cost on the order of $15,000. Given that this mitigation measure is expensive, our results are in line with those of Carson et al. (2013), who found that people hold high deductibles if they have invested in high expenditure mitigation. Burrus et al. (2008) also found that mitigation increases as homeowners’ deductibles increase.

The substitution between self-insurance and market insurance implies that there is a budget constraint, and spending a substantial amount of money on mitigation would mean that there is less for insurance purchases. For example, Aseervatham et al. (2014), using national and state level data, found that in the aftermath of flood events, people changed their homeowners-insurance deductible to higher levels and used the savings to buy flood insurance.

Several studies, such as those of Krantz and Kunreuther (2007), Hertwig et al. (2004), Brilly and Polic (2005), and Siegrist and Gutscher (2008), have found that the number of hazards experienced leads to an increase in risk aversion, which, along with other factors, might lead to taking protective action. In this analysis, we found that people who have experienced more hurricanes held higher deductible values (Hypothesis 3), which translates to having lower risk aversion. A plausible way of explaining our findings is that people who have experienced hurricanes might actually be the ones who have invested in mitigation (e.g., Petrolia et al. 2013, Peacock 2003) and, hence, have lower risk aversion, which is evident by their high deductible choices. The inability to directly capture this temporal relationship is the major shortfall of using cross-sectional data.

The number of adults in the household was found to have a significant effect on the deductible choice (Hypothesis 9). The findings show that households with more adults feel less need to rely on insurance, which suggests that they are more able to cope with or avoid the risk (Bubeck et al. 2012). Our results show that African Americans/Blacks seem to choose lower deductibles, compared to others (Hypothesis 8). This result signifies the importance of addressing the problem of access to loans for expensive mitigations, which has been discussed in previous studies (e.g., Ge et al. 2011). Finally, having at least a four-year degree is associated with holding a higher deductible value (Hypothesis 6). Several studies have also found education to be positively associated with mitigation (e.g., Burrus et al. 2008). Hence, this result supports the hypothesis that self-insurance and market insurance are substitutes.

In this analysis, proximity to hazard, income, level of worry, number of children, and four of the five structural retrofit measures were not significant. It is important to note that this does not mean that these variables are not influential factors but only shows the limitation of the data set.

3.7. CONCLUSION

The results of this analysis show that certain structural retrofit measures and deductible choices are substitutes, and this has substantial policy implications in terms of setting appropriate premium and deductible values. For example, subsidized premiums reduce the incentive to mitigate because a subsidy allows people to afford low deductible policies, and most mitigation measures do not reduce damage costs to levels below subsidized deductibles (Burrus et al. 2002). Several other studies have found similar results: Kunreuther and Kleffner (1992) show that if homeowners are fully insured, they are less willing to voluntarily reduce their risk; Kleffner and Kelly (2001) show that homeowners invest less in mitigation if premiums are not risk-based. It is important to note that people have a general tendency to choose low deductibles, even in unsubsidized markets (e.g., Cohen and Einav 2005). Underpricing premiums, in addition to this general tendency, leads people to choose low deductible policies and, hence, less mitigation. The results from this article suggest not only premiums should be risk-based but that policies with high deductibles should be readily available so that consumers optimally invest in both self-insurance and market insurance.

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