MODELING OF NATURAL DISASTER CATASTROPHE LOSS INSURANCE MARKET

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

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December 2018

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Cornell University 2018

This dissertation consists of three chapters. The first chapter investigates the impact of insurance affordability criteria on uninsured losses. The vehicle for analysis is a model of a catastrophe insurance market with explicit representation of the key stakeholders (homeowners, primary insurers and reinsurers). The theoretical framework is applied in a case study of eastern North Carolina with spatially explicit representation of hurricane damage due to wind and storm surge. We evaluate the effect of an affordability threshold expressed as a percentage of a home value. If the cost of insurance exceeds 1% or 2% of home value the home is uninsured due to the affordability constraint. We find that the homes that fail the affordability test account for a high proportion of expected losses in the high risk region or our study area and subsidization of insurance rates would not be cost effective.

The second chapter investigates the impact of insurance affordability criteria on uninsured natural catastrophe losses and addresses the question of whether a voluntary, affordable catastrophe insurance market is viable. We use the same game theoretic modeling framework and the same study case used in the first paper. Examining affordability thresholds of 1% or 2% of home value, we find that homes that fail the affordability test account for a high proportion of expected losses in the high risk region of our study area, public subsidization of insurance rates would not be cost-effective, and private subsidization would destroy incentives for insurers to participate in the market. We conclude that a combination of insurance, retrofit, and acquisition is necessary to address regional hurricane risk.

The third chapter develops a dynamic modeling framework for the natural catastrophe insurance market. This framework includes (1) discrete choice models for the homeowner insurance purchase decision; (2) discrete choice models for retrofit; (3) explicit modeling of the interaction between competing insurance carriers and a heterogeneous homeowner population; and (4) a probabilistic representation of hurricane occurrences over time.

BIOGRAPHICAL SKETCH

Kecheng Xu attended Tsinghua University (Beijing, China) and received a Bachelor of Science Degree in Automation Science in July 2013. He then started the M.S./Ph.D. degree program in Civil Engineering of Cornell University with emphasis in Transportation Systems Engineering (with minor in Operation Research and Systems Engineering). He has worked as a consultant with the World Bank on a project in Dominica.

ACKNOWLEDGMENTS

I would like to express my deepest appreciation to my committee chair, Professor Linda Nozick, for her fantastic guidance, patience, tolerance, and caring. I would never have been able to finish this dissertation without her guidance and persistent help.

I also want to thank Professor Rachel Davidson, Professor Joe Trainer from University of Delaware, Professor Jamie Kruse from East Carolina University for their guidance and helps during the completion of this dissertation.

In addition, a thank you to Dong Wand from University of Delaware, who helped and encouraged me a lot during my research. Thank you to Doctor Yang Gao (AIR Worldwide), Doctor Yohannes Kesete (World Bank), Doctor Jiazhen Peng (Air Worldwide), who had worked on this project and helped me with their experiences and guidance.

Finally, I want to thank my parents, who provide me with unconditioned love and support throughout my study in the United States. I would not have been able to come to the United States for study without their support.

This research is supported by the National Institute of Standards and Technology, US Department of Commerce Under Award 60NANB10D016; the National Science Foundation under Collaborative Awards #1435298, 1433622, and 1434716; and the US Department of Homeland Security under Grant Award Number 2015-ST-061-ND0001-01. The funding is gratefully acknowledged. Nonetheless, the statements, findings, conclusions are those of the authors and do not necessarily reflect the views of the National Institute of Standards and Technology, the US Department of Commerce, the National Science Foundation, or the US Department of Homeland Security.

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CHAPTER 1

AFFORDABILITY OF NATURAL CATASTROPHE INSURANCE: GAME THEORETIC ANALYSIS AND GEOSPATIALLY EXPLICIT CASE STUDY

1.1 Introduction

In the recent decades, the cost of natural disasters like hurricanes has increased dramatically with the substantial growth in coastal populations (Kunreuther 1998). The two most important and effective ways to manage regional catastrophe risk is natural disaster catastrophe loss insurance and mitigation. However, studies have shown that homeowners do not invest in sufficient pre-event mitigation and often do not fully insure their properties to reduce losses (Kreisel and Landry 2004; Dixon et al. 2006; Kunreuther 2006). As a result, when a damaging hurricane occurs, government financial aid must come in to the affected area to provide relief and fuel community recovery. These large and unanticipated expenditures strain local and state government budgets and represent an additional tax burden for society (Kunreuther and Pauly 2004). In order to encourage flood insurance adoption, the U.S. National Flood Insurance Program (NFIP) has in the past provided flood insurance at highly subsidized rates that do not reflect the true actuarial risk. Offering insurance at rates that do not reflect the true risk is not financially sustainable and consequently, the NFIP had a $24 billion deficit as of 2013 (Atreya et al. 2015). Similarly, many state wind catastrophe pools are also at risk of insolvency (Baker and Moss, 2009).

To place the NFIP on sounder financial footing, the Biggert-Waters Flood Insurance Reform Act of 2012 (BW-12) was passed by Congress and called for flood insurance premiums that more accurately reflected the actual risk to properties from flooding. The move to implement risk-based rates drew a public outcry from property owners that faced insurance rates that could double or more. Hence, public pressures led Congress to reconsider the notion of the full implementation of risk-based premiums passing the Homeowner Flood Insurance Affordability

Act of 2014 (HFIAA 2014). HFIAA 2014 suggests a standard for affordability of 1% of the value of the home. That is, premiums that exceed the 1% threshold are assumed to be not affordable (NRC, 2015). Both BW-12 and HFIAA called on FEMA to provide a framework for considering affordability. For discussions on affordability see GAO (2016), NRC (2015). Two recent papers that examine affordability of coverage for two different areas are Kousky and Kunreuther (2014) for Ocean City, New Jersey and Zhao, Kunreuther, and Czajkowski (2016) that focuses on Charleston County, South Carolina. Both studies concentrate on resolving the challenge to implement risk-based premiums that are also sensitive to affordability issues. The question of insurance affordability is not unique to flood insurance. We examine the effect of affordability criteria on insurance for wind and flood damage caused by hurricanes. This chapter utilizes a framework developed in Gao et al. (2016) to explore the number of households that could be affected by different affordability thresholds and the effect the threshold would have on the price and take up rate of insurance

1.2 Nested Modeling Framework

This section gives a brief description of the modeling framework used in this study. For a more complete description see (Gao et al., 2016). Figure 1 shows the structure of the interacting models. We consider homeowners, primary insurers, reinsurers and the government as the key stakeholders in the natural catastrophe insurance market. We use a Cournot-Nash game theoretic model, to represent the strategic interactions among insurers that compete in a regional insurance market. An expected utility-based homeowner decision model is used to predict homeowner insurance purchase behavior (based on the cost of the policy, expected losses, and homeowner risk attitudes). A stochastic optimization model is used to optimize primary insurers' pricing decisions and how much risk the insurer will retain or transfer to reinsurers. A regional catastrophe loss model that couples the frequency of damaging hurricanes with location and building resistance is used to estimate the loss to each homeowner and primary insurer. We include the impact of the government in the primary insurers' stochastic optimization model by placing requirements on the cash reserves to be held by the primary insurer proportional to the magnitude of their liability. The reinsurer is assumed to offer reinsurance at a formula-based price that depends on the expected loss of the primary insurer and the standard deviation of the loss. The loss model estimates the financial losses in each hurricane event and, based on the cost of insurance and the resultant take-up rate for insurance, these losses are allocated to homeowners, insurers and reinsurance.

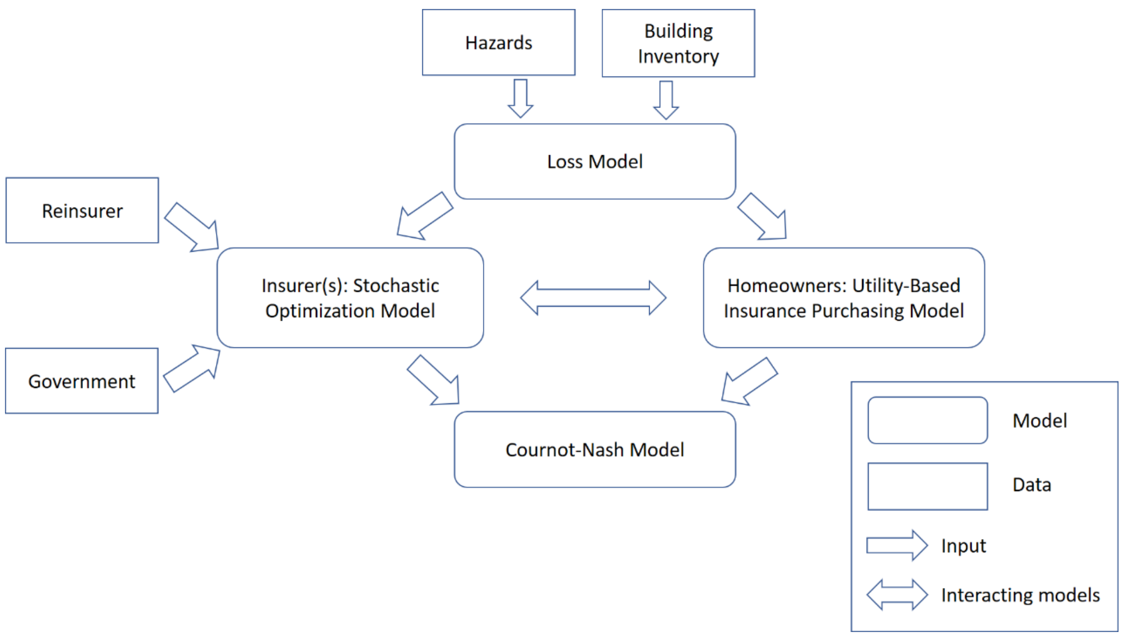

Figure 1.1. Structure of interacting models in nested framework

1.2.1 Loss Model

There are two parts in the loss estimation model. One is the hazards simulation, and the other is loss estimation for each residential building for each hazard. We use as input to the loss model, a set of 97 probabilistic hurricane scenarios developed in Apivatanagul et al. (2011), using the Optimization-based Probabilistic Scenario (OPS) method. In order to include the financial implications of the number and severity of hurricanes experienced over time, we create 2,000 scenarios of a 30-year period developed in Peng (2014). In the hazards simulation, for each scenario, open terrain 3-sec. peak gust wind speeds and surge depths were computed throughout the study region using the storm surge model ADCIRC (Westerink et al. 2008). The loss estimation is a component-based building loss model that relates probabilistic resistances of building components to wind speeds and flood depths, considering the effects of wind pressure, missiles and the internal pressure gradient resulting from a breach of the building envelop. The residential buildings are classified into different groups by their location i, building category m, resistance level c and risk regions $v \in [H, L]$, where H denotes high risk region and L denotes a lower risk region. The number of buildings in each group is identified, denoted as X_{imcv}, and the loss for a specific hurricane hazard h for a specific building of type i, m, c, v, is estimated by the model developed in Peng et al. (2013), denoted as L^h_{imcv}.

1.2.2 Homeowner Model

We assume all the homeowners in the catastrophe insurance market are risk averse rational decision makers that maximize expected utility. Their level of risk aversion differs with their location within regions, v $\in [H, L]$, and x is the expenditures either from catastrophe damage or insurance payments. In the event of a damaging hurricane, the portion of loss that homeowners are assumed to pay, B^h_{imcv}, which is the minimum of the loss experienced and the deductible level d. We also assume each homeowner has an affordability threshold for insurance (and that threshold can vary based on the home's location in either the high or low risk region) where that threshold is a percentage, κ_v, of their home values, V_m.

1.2.3 Insurer Model

Each insurer is assumed to maximize profit using a stochastic optimization procedure that prices insurance coverage given actuarial risk, homeowner demand, the number of competitors, and the cost of reinsurance. Insurers select prices $p_v, v \in [H, L]$ per dollar of expected loss to be covered in each risk region. The price per dollar of coverage is the sum of 1 plus a specified administrative loading factor τ and a profit loading factor λ_v. If the premium is less than a minimum annual cost associated with servicing a policy, then the insurer will not offer the policy, the minimum specified value is r. For the price offer p_v, homeowners choose whether or not to buy the insurance. The premium collected is the price p_v multiplied by the expected insured loss Q_v. In the event of a hurricane h, the loss to an insured building L^h is covered by several parties. Homeowners pay the first portion of the loss up to deductible d, denoted as B^h. Reinsurers pay a specified co-participation percentage, β%, of the loss between the attachment point, A, and the maximum limit, M. Reinsurers require an annual premium r^{sy}, including a base premium b and a reinstatement payment. Primary insurers pay the remaining part of the loss. The optimization model for the primary insurance uses the 2,000 scenarios (each of which gives a unique time series of hurricanes over 30 years) to optimize the price of the policy to the homeowners in each risk region, p_v, and the attachment point A, the maximum limit M for the reinsurance policy. The government requires that primary insurers have cash reserves in order to limit the risk of insolvency. We assume that the primary insurers will start their business with an initial investment C^{s0} that equals a specified constant k multiplied by the annual premiums received in all risk regions. In each year y, they will reallocate the amount of their accumulated surplus C^{sy} larger than C^{s0} into other lines of business. If the accumulated surplus becomes zero or less, the primary insurer becomes insolvent.

1.2.4 Cournot-Nash Model

A Cournot-Nash game theoretic equilibrium model is used to capture the competition between primary insurers. All carriers have the same knowledge of the risk, the market, and only provide full coverage insurance to homeowners. In other words, they face the same cost structure. Gao et al. (2016) discusses the Cournot-Nash game and a collusive joint profit maximization framework to describe the range of possible outcomes of a dynamic game in this context. The homeowner model is used to derive a demand function for each risk region, $Q_v = D_v(p_v), v\epsilon[H,L]$, with its inverse: $p_v = P_v(Q_v) = D_v^{-1}(Q_v), v \in [H,L]$, where Q_v is the total insured loss covered by primary insurers or reinsurers in the entire region v and p_v is the price for that region. If there are n primary insurers (carriers) in the market, by symmetry, we can rewrite the inverse demand function as: $p_v = P_v(Q_v) = D_v^{-1}(Q_v) = D_v^{-1}(nq_v), v \in [H,L]$, where q_v is the expected loss insured by one primary insurer in the region v. From the stochastic optimization insurer model, we can derive a cost function for each primary insurer in terms of the expected loss insured: $cost = C(q_H, q_L)$. So we can derive the net profit for each primary insurer as follows:

$$\pi(q_H, q_L) = \sum_v q_v P_v(nq_v) - C(q_H, q_L)\ \forall v = [H,L]$$

q_{vj}^* is the coverage offered by insurer j that maximizes profit in the region v, given *n* competitors. This model takes into consideration the optimal reaction of competitors to every q_{vj} chosen by insurer *j*.

1.3 CASE STUDY

1.3.1 Inputs

The case study uses 503 census tracts covering eastern North Carolina. The case study area includes low-lying coastal counties and extends westward to include half of Raleigh, the state capital. On average, a tropical storm or hurricane is expected to make landfall on the North Carolina coast every four years (SCONC 2010). Recent hurricanes affecting North Carolina include Floyd (1999), Isabel (2003), Irene (2011) and Mathew (2016). We classify this region into two risk (H, L) zones by distance from the coastline, which yields 731 geographic zones. We defined 8 categories of buildings based on the number of stories, garage, and roof type. For each category, there are 68 building resistance levels. The total inventory reaches 931,902 in two risk zones. We used the component-based loss simulation model to estimate both wind and flood damages for each type of building at each location. The loss calculation process includes 2000 scenarios of (probabilistic event-based, with a set of 97 events) 30 year (with 20 time steps per year) hazard simulation, and a joint probability distribution estimation of annual loss for each type of building under each possible hurricane event. We embed the loss model into individual homeowner and insurer models to derive the insurer's optimal cost function. We repeat the loss estimation with a varying portfolio of insured buildings (as determined by the homeowner decision model) and conduct a stochastic optimization for managing risk for the book of business. In the insurer model, the deductible level $d = \$5000$, co-participation factor $\beta\% = 95\%$, administrative loading factor $\tau = 0.35$, factor defining allowed surplus $k = 3$. We set the minimum premium required by the insurer to offer insurance at $\rho = \$100$.

1.3.2 Results

First, strictly in terms of expected loss, are there homes with expected loss that exceeds 1% of home value? The shaded areas in Tables 1.1 and 1.2 identify homes with expected loss of more than 1% of the home value. Table 1.1 shows the count of households that fit categories of expected loss as a percentage of home value that range from below 0.5% to 6.0%. In the low risk region there are 4,608 (0.7%) of the 649,012 homes in the risk region whose expected loss exceeds 1% of the home value. In the high risk region 81,577 (28.8%) of the 282,890 homes in the area within 2 miles of the coast have expected losses that exceed 1 % of the home value. Table 1.2 provides the total expected loss associated with each of categories. When we examine the total expected losses for each region that fall past the 1% threshold, we find expected loss of \$13,036,610 and

$338,026,398 for the low and high risk regions respectively. Using information from the loss model alone, we find that 9.2% of the homes account for roughly 59% of total expected loss.

Table 1.1. Number and Proportion of Households as a Function of the Expected Loss Expressed as a Percentage of the Home Value for Low and High Risk Regions

Region		Low Risk		High Risk	
Number of Households		649,012	100.00%	282,890	100.00%
Expected Loss/Home Value	[0,0.5%]	584,335	90.03%	159,847	56.51%
	(0.5%, 1%]	60,069	9.26%	41,466	14.66%
	(1%, 2%]	3,794	0.58%	34,484	12.19%
	(2%,3%]	83	0.01%	26,154	9.25%
	(3%,4%]	731	0.11%	15,721	5.56%
	(4%,5%]	0	0.00%	4,589	1.62%
	(5%,6%]	0	0.00%	629	0.22%
	(6%,+∞)	0	0.00%	0	0.00%

Table 1.2. Proportion of Total Expected Loss Assigned to Homes that Exceed 1% of Home Value for Low and High Risk Regions

Region		Low Risk		High Risk	
Total Expected Loss ($)		148,610,960	100.00%	445,686,656	100.00%
Expected Loss/Home Value	[0,0.5%]	112,736,200	75.86%	63,886,828	14.33%
	(0.5%, 1%]	22,838,570	15.37%	43,772,532	9.82%
	(1%, 2%]	8,127,765	5.47%	88,921,568	19.95%
	(2%,3%]	332,270	0.22%	117,121,040	26.28%
	(3%,4%]	4,576,575	3.08%	91,312,312	20.49%
	(4%,5%]	0	0.00%	35,565,316	7.98%
	(5%,6%]	0	0.00%	5,106,162	1.15%
	(6%,+∞)	0	0.00%	0	0.00%

The remainder of our analysis moves beyond the loss model to incorporate the effect of the interaction of all stakeholders in the nested model. The system equilibrium price of insurance and hence the cost of insurance to homeowners depends on the expected value of the loss, homeowner risk attitudes, the number of insurance carriers in the market, the cost of reinsurance, and government imposed reserve requirements. All insurers offer insurance in both markets though, potentially at different prices per dollar of expected loss. We will focus on affordability thresholds of the cost of insurance as a percentage of home value of 1% and 2%. If a home falls below the affordability threshold, it will not be insured.

The equilibrium prices for one through five insurers for both the low and high risk region and 1% and 2% thresholds are shown in Figure 1. As expected, when we step away from a single monopoly insurer, insurance prices in equilibrium will decline as the number of competitors increases. The affordability threshold takes potential buyers out of the market when the price of insurance exceeds either 1% or 2% of the home value. The buyers left out due to affordability have either lower home values or the higher risk or both. The extreme case would be the monopolist that would find it most profitable to "cherry pick" and serve only the lower risk/highest home value clients in both the high risk and low risk regions.

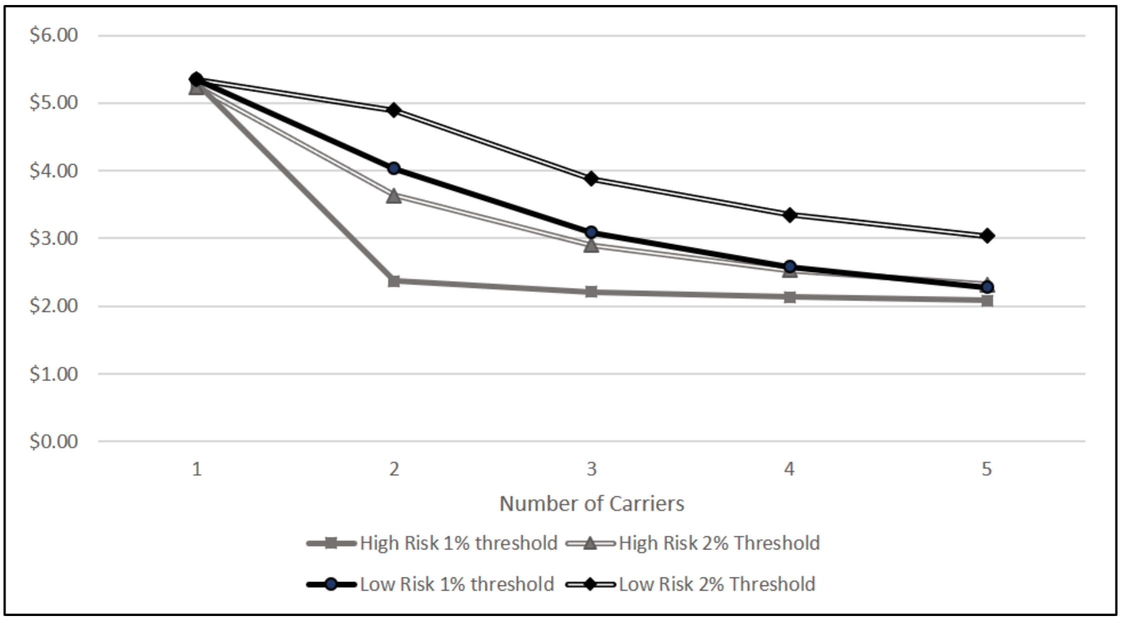

Figure 1.2. Equilibrium Prices for 1 through 5 Carriers for Each Affordability Threshold

The effect of the 1% and 2% affordability thresholds on the number of uninsured households and the proportion of total expected loss covered is summarized in the four-panel Figures 1.3 and 1.4 for the low and high risk regions respectively. In Figure 1.3 a and b, the solid black portion represents the proportion of the 649,012 homes in the low risk region that would exceed the affordability threshold. The left portion of each bar represents the homes that would choose to insure and the right hand portion of each bar represents homes that would be uninsured due to reasons other than the affordability constraint. Other reasons include expected utility optimizing homeowner choice not to insure or the minimum premium required by the insurer to offer insurance is not met. Under fairly competitive conditions with five firms in the market, roughly one half of the homeowners are predicted to insure. Panels c and d of Figure 3 present the proportion of $148,610,488 total expected loss that would be covered by insurance. Using the five-firm case, focusing on the homes uninsured due to the affordability threshold, although they represent around 2-4% of the number of homes in the low risk region, they potentially account for approximately 18% to 27% of total expected losses for the two affordability thresholds.

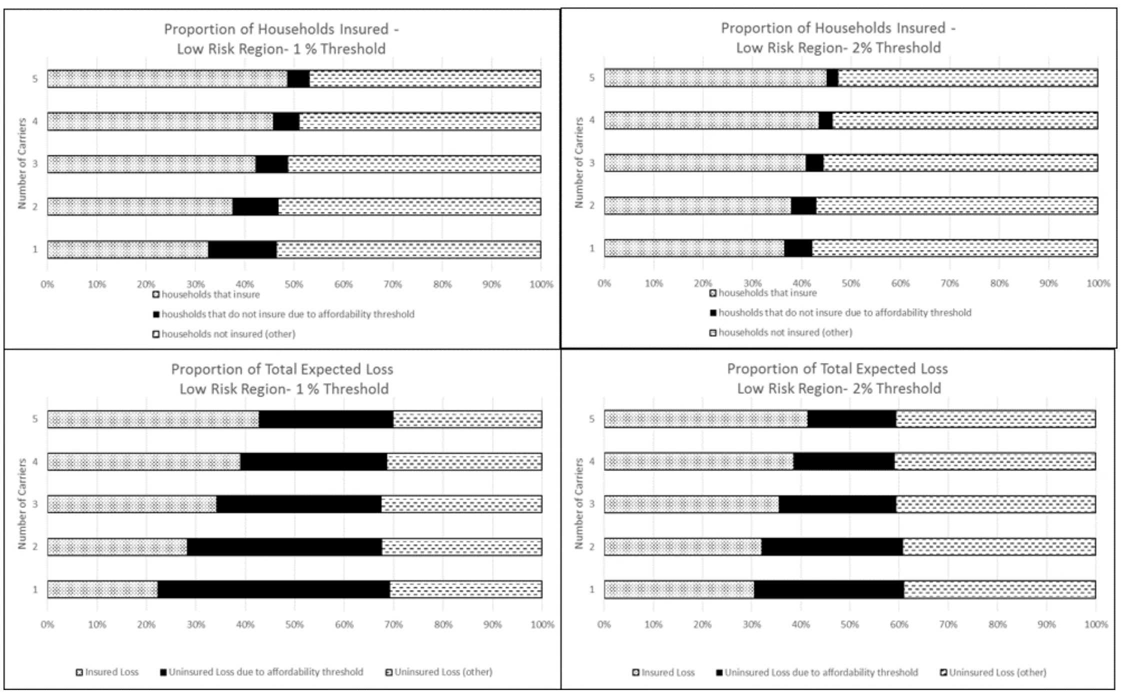

Figure 1.3. (a, b) Proportion of Households that do and do not Insure (c, d) Proportion of Total Insured and Uninsured Expected Losses in Low Risk Region

Moving to the high risk region summarized in Figure 1.4, results indicate an even more dramatic impact of the affordability thresholds. Of the 282,890 homes in the high risk region, 31% to 43% would be uninsured due to the affordability threshold for the five-firm case. At the 1%

(2%) threshold, 86% (78%) of the total expected losses would be uninsured due to the affordability constraint. The affordability constraint affects a considerable proportion of the expected losses in both risk regions.

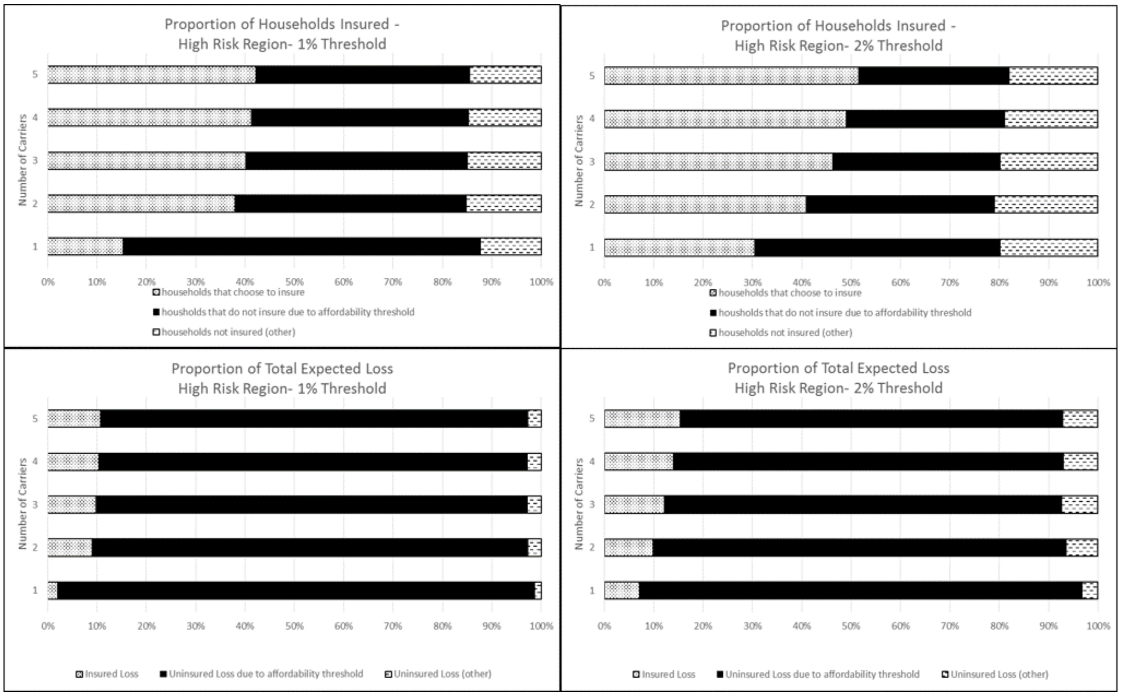

Figure 1.4. (a, b) Proportion of Households that do and do not Insure (c, d) Proportion of Total Insured and Uninsured Expected Losses in High Risk Region

Figure 1.5 provides a summary of the total insurance premiums that would be collected and total primary insurance industry profit predicted for the case study area. Raising the threshold from 1% to 2% qualifies more homes to purchase insurance and thus increases the number of homes insured and the total premiums collected. The five-firm and 2% affordability scenario at the more competitive range of the industry would collect a total of $165,032,330 in premiums and produce $62,927,880 in profit divided between five firms.

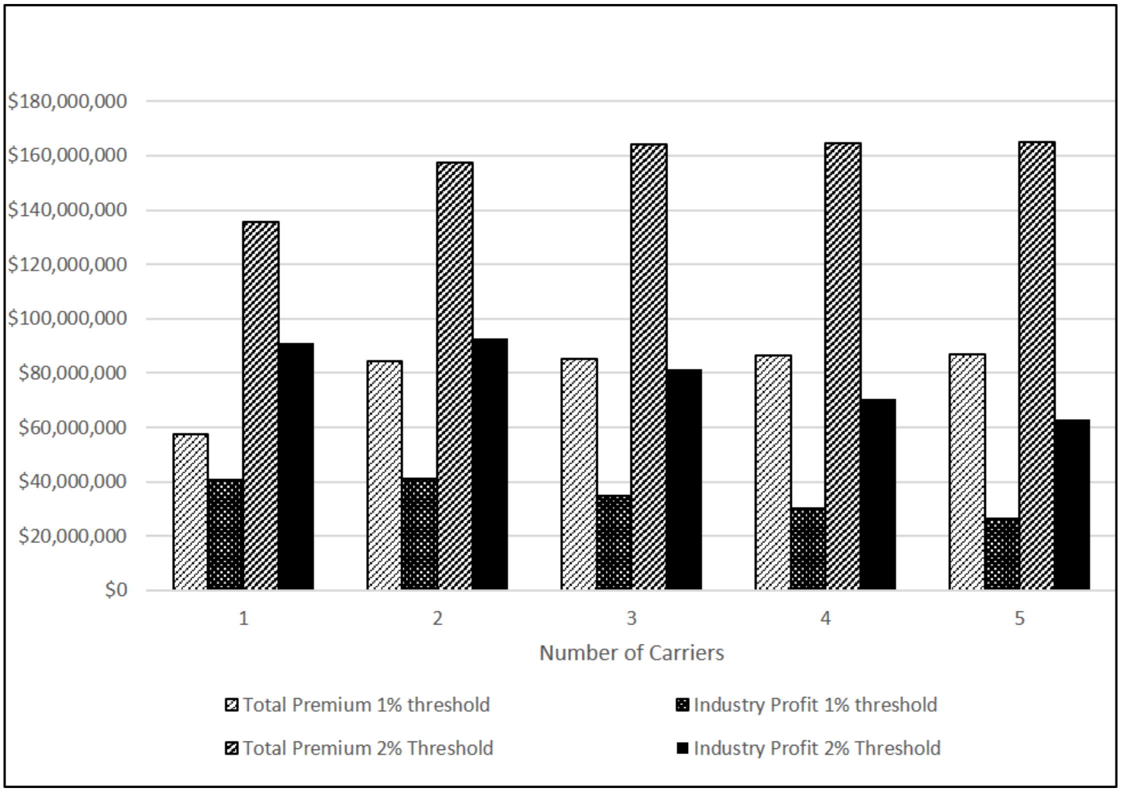

Figure 1.5. Total Premium Collected and Industry Profit at 1% and 2% Threshold

Lastly we ask the question, "How much subsidy would be required to make insurance affordable under the 1% and 2% threshold rule?" Figure 1.6 illustrates the total cost of a subsidy for the high risk and low risk regions. The total budget necessary to fully subsidize insurance premiums to meet a 1% or 2% threshold is high. For the five-firm case and 2% affordability threshold it would still require a $417,520,192 expenditure for the high risk region and $9,919,247 for the low risk region with all other cases requiring an even larger expenditure of public funds.

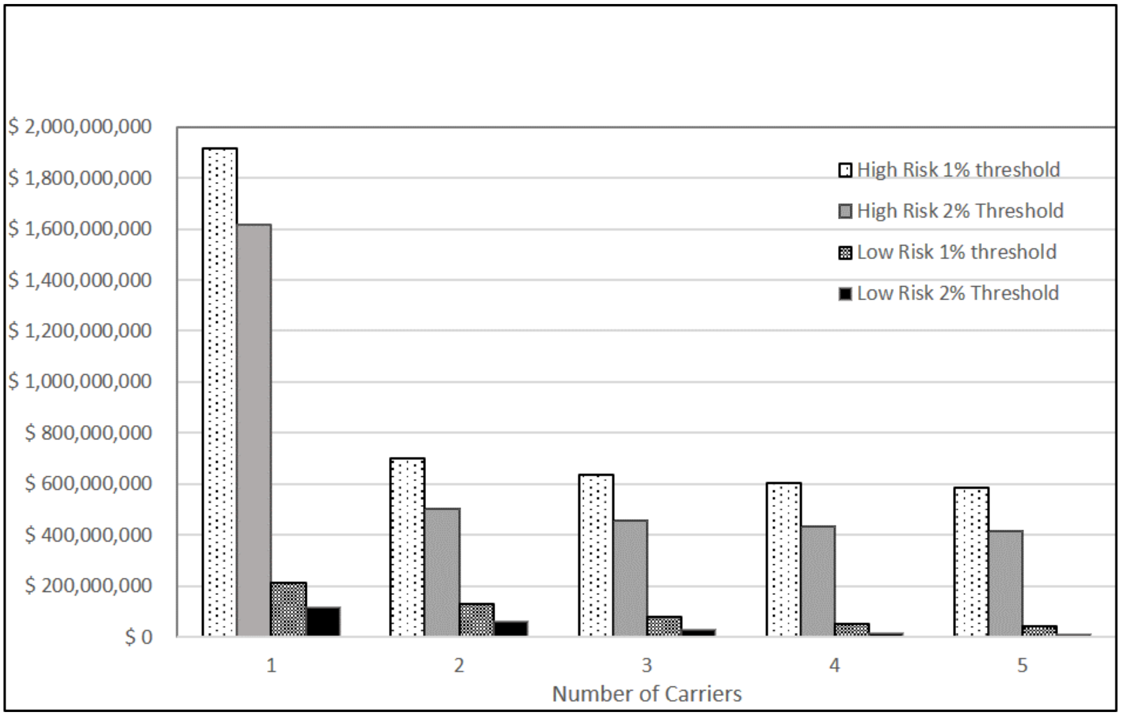

Figure 1.6. Total Subsidy Required to Bring Cost of Insurance to 1% and 2% Affordability Threshold

1.4 Conclusions

This study explores the effect of two levels of affordability criteria in a nested model that takes account of the interaction of homeowners, primary insurers, reinsurance, and the government in a region that is vulnerable to flooding and wind damage due to hurricanes. This study focuses on the current stock of homes in a study area of eastern North Carolina and their level of resistance to hurricane damage. Resistance depends on location of the buildings and their structural characteristics. Insurance decisions are assumed to be made by risk averse expected utility maximizing homeowners. Homeowners face insurance prices determined by an insurance industry comprised of one to five carriers that interact within a noncooperative Cournot-Nash game theoretic framework. All stakeholders have knowledge of the loss distribution due to hurricane damage. We find that a relatively low percentage of homes in the region account for a considerable percentage of the expected losses. When the affordability criteria that cost of insurance cannot exceed 1% or 2% of the home value, we find that about 80% of total expected losses would represent homes that fail to meet this criteria in a high risk region within two miles of the coastline. This study does not take into account any retrofit strategies to mitigate the risk and make homes more resistant to hurricane damage. We estimate the total amount of public funds necessary to subsidize insurance for the homes that do not meet the affordability thresholds. Without coupling the subsidy with strategies to encourage homeowners to mitigate the risk, the required subsidy is excessive relative to the total expected losses for the study area. Our conclusions, based on this study are similar to those given by Zhao, Kunreuther, and Czajkowski (2015) that recommends against subsidized premiums. Rather, accurately priced insurance premiums that communicate the true risk of hazardous locations should be coupled with assistance for low income homeowners and approaches that encourage individual and community-wide hazard mitigation will be more effective policy instruments for mitigating risk.

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CHAPTER 2

PUBLIC AND PRIVATE FINANCING OF NATURAL CATASTROPHE INSURANCE TO MEET AFFORDABILITY CRITERIA

2.1 Introduction

This paper utilizes an integrated computational framework to assess the effect of different financing options for natural catastrophe insurance that satisfy an insurance affordability criterion limiting the insurance burden on individual homeowners. Our integrated model represents a range of stakeholders in this industry including homeowners, primary insurers, reinsurers, and government. A case study for the region of eastern North Carolina is presented as an application of the integrated model.

Affordability of natural catastrophe insurance came to the forefront when the Congress passed the Biggert-Waters Flood Insurance Reform Act of 2012 (BW-12) that reauthorized the National Flood Insurance Program (NFIP). To place the NFIP on sounder financial footing, BW-12 called for flood insurance premiums that accurately reflected the actual risk to properties from flooding. The move to implement risk-based rates drew a public outcry from property owners that faced insurance rate increases.[1] In fact, Mississippi, joined by Alabama, Florida, and Louisiana filed suit against the Department of Homeland Security and the Federal Emergency Management Agency (FEMA) to block implementation of BW-12.[2] Hence, public pressure led Congress to reconsider implementation of risk-based premiums, passing the Homeowner Flood Insurance Affordability Act of 2014 (HFIAA 2014). HFIAA suggests a standard for affordability of 1% of the value of the home. That is, premiums that exceed the 1% threshold are assumed to be unaffordable.[3]

Both BW-12 and HFIAA called on FEMA to “propose an affordability framework.” For discussions on affordability of the NFIP see [4] and [5]. Kousky and Kunreuther (2014) and Zhao, et al. (2016) examine affordability of coverage in Ocean City, New Jersey and Charleston County, South Carolina, respectively. Both studies specify a percentage of household income for an affordability test where an annual insurance premium greater than 5% of household income would require some form of assistance.[6,7] They make the case that discounted premiums should not be used to address the affordability issue promoting a voucher program coupled with mitigation loans. Kousky and Kunrether (2014) demonstrate that for a hypothetical homeowner in a high wave velocity 100-year return interval (V zone) or 100-year return interval (A zone), the cost to the federal government for a voucher coupled with mitigation requirement would be less than half of a voucher-only program.[6] Zhao et al. (2016) examine a voucher plus home elevation mitigation requirement and finds that government expenditures on a combined program would be less than half of a voucher-only program.7] Under BW-12, premiums were intended to adjust to the point that they reflect the full flood risk of a building as determined by its structural characteristics and location. BW-12 was an attempt to address the insolvency issues for the NFIP. Those insolvency issues have become even more compelling with the 2017 hurricane season and associated flooding. Before the 2017 hurricane season, the U.S. Government Accountability Office (GAO) reported that the NFIP owed the Department of Treasury $24.6 billion as of March 2017.[4]

In a report on comprehensive reform of the NFIP the GAO addressed issues pertaining to solvency and resilience.[4] The GAO identified six key interrelated challenges to flood insurance reform:

1) Outstanding debt of the program;

2) Premium rates that do not reflect the full risk of loss;

3) Affordability of insurance premiums that ensure consumers will purchase flood insurance to protect themselves;

4) Low consumer participation in insurance purchase;

5) Barriers to private-sector involvement; and

6) Reduced funding for community flood resilience efforts.

The challenges identified by the GAO for the NFIP are challenges for all natural catastrophe insurance programs in the US and worldwide. For example, many state wind catastrophe pools are also at risk of insolvency.[8] Internationally, the World Bank Disaster Risk Financing and Insurance (DRFI) Program was established in 2010 to "improve the financial resilience of governments, businesses and households against natural disasters.".[9] This research addresses four (2,3,4, and 5) of the six challenges described above in the context of wind and flood damage caused by hurricanes within an integrated model and case study. It utilizes the framework developed in [10] to examine a **private-sector insurance industry** with **voluntary consumer participation**. **Risk-based premium rates** are evaluated within a model based on consumer demand and the level of competition in the industry. We examine the financial burden of achieving an **affordability** target in a case study of eastern North Carolina. Xu et al. (2017) uses the Gao et al. framework to examine the number of households that fall into the tail of the distribution with expected losses that exceed 1% or 2% of home value.[11] They find a relatively small number of homes is responsible for a disproportionately large share of expected losses. In this paper we look at the impact of an affordability constraint that limits the number of households that can purchase insurance, the effect on insurance pricing, insurer profitability, and uninsured losses. We examine policies that subsidize insurance rates to meet an affordability target, and the stakeholders affected by the subsidy burden.

Section 2.2 summarizes the modeling framework developed in [10]. After presenting the results of a case study for North Carolina in Section 2.3, the conclusions are presented in Section

2.4.

2.2 Integrated Modeling Framework

This section briefly describes the modeling framework used in this study (Figure 2.1). For a more complete description see [10]. We consider homeowners, primary insurers, reinsurers, and the government as the key stakeholders in the natural catastrophe insurance market. We use a Cournot-Nash equilibrium game to represent the strategic interaction among insurers that compete in a regional insurance market. An expected utility-based homeowner decision model is used to predict individually optimal homeowner insurance purchase behavior (based on the price of insurance, expected losses, and homeowner risk attitudes). A stochastic optimization model is used to optimize primary insurers' pricing decisions and to determine firm level risk retention and risk transfer choices. A regional catastrophe loss model couples the hurricane hazard modeling with building locations and resistances to compute probabilistic estimates of loss to each home over a specified number of years. We include the impact of the government in the primary insurers' stochastic optimization model by placing requirements on the cash reserves to be held by the primary insurer proportional to the magnitude of their liability. A reinsurer is assumed to offer a single layer of catastrophe risk excess of loss reinsurance at a formula-based price that depends on the expected loss of the primary insurer and the standard deviation of the loss. Based on the cost of insurance and the resultant take-up rate for insurance, the financial losses in each hurricane event are allocated to homeowners, insurers, and reinsurers. The analysis incorporates an affordability constraint on the household purchase decision and examines the impact on all stakeholders. That is, if the premium exceeds this threshold, we assume the homeowner will not purchase the insurance. The affordability threshold is specified as the cost of insurance (i.e., premium) that exceeds $\beta\%$ of the value of a home. Using the modeling framework, we examine the implication of hypothetical situations in which the insurance industry or the government assumes the burden of subsidizing the insurance premium to ensure affordability.

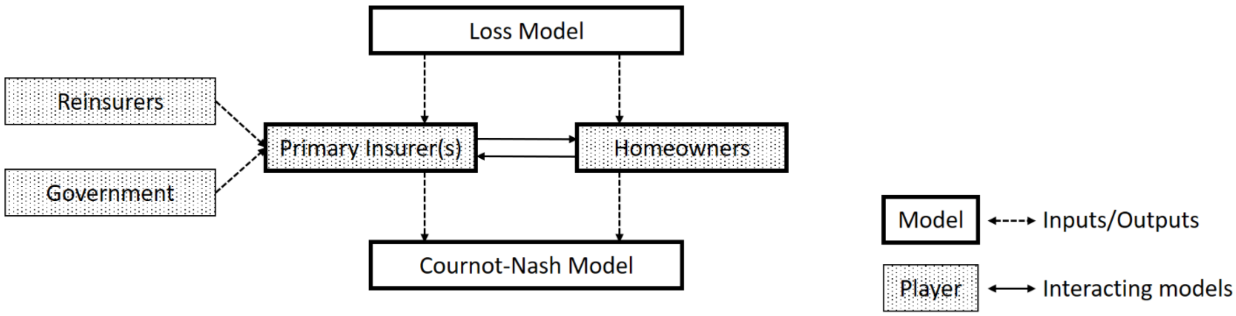

Figure 2.1. Structure of Interacting Models in Computational Framework

2.2.1 Loss Model

There are two parts in the loss estimation model. One is the hazard simulation, and the other is loss estimation for each residential building for each hurricane. We use as input to the loss model, a relatively small (≈100) set of probabilistic hurricane scenarios developed in [12], using the Optimization-based Probabilistic Scenario (OPS) method. In the hazard simulation, for each hurricane scenario, open terrain 3-sec. peak gust wind speeds and storm surge inundation depths were computed throughout the study region using the storm surge model ADCIRC.[13] In order to include the financial implications of the number and severity of hurricanes experienced over time, we used the S=2,000 scenarios s of a T=30-year period developed in [14]. The loss estimation is a component-based building loss model that relates probabilistic resistances of building components to wind speeds and flood depths, considering the effects of wind pressure, missiles and the internal pressure gradient resulting from a breach of the building envelop. The residential buildings are classified into different groups by their location i, building category m, resistance level c and risk regions $v \in [H, L]$, where H denotes high risk region and L denotes a lower risk region. The number of buildings in each group is identified, denoted as X_{imcv}, and the loss for a specific hurricane hazard event h for a specific building of type i, m, c, v, is determined by the model developed in [15], denoted as L_{imcv}^h.

2.2.2 Homeowner Model

We assume all the homeowners in the catastrophe insurance market are risk averse rational decision makers that maximize expected utility. The distribution of their level of risk aversion differs with their location by region, $v \in [H, L]$. In the event of a damaging hurricane, the portion of loss that homeowners are assumed to pay, B_{imcv}^h, is the minimum of the loss experienced and the deductible level d. We also assume each homeowner has an affordability threshold for insurance (and that threshold can vary based on the home's location in either the high or low risk region) where that threshold is a percentage, κ_v, of their home value, V_m.

2.2.3 Insurer Model

Each insurer seeks to maximize profit using a stochastic optimization procedure that determines the price of insurance coverage given actuarial risk, homeowner demand, the number of competitors, and the cost of reinsurance. Insurers select prices $p_v, v \in [H, L]$ per dollar of expected loss to be covered in each risk region. The price is the sum of one plus a specified administrative loading factor τ and a profit loading factor λ_v. If the total annual premium is less than a minimum annual cost associated with servicing a policy, then the insurer will not offer the policy. For the offered price, p_v, homeowners choose whether or not to buy full insurance. The premium collected is the price p_v multiplied by the total expected insured loss Q_v. In the event of a hurricane h, the loss across all insured buildings L^h is shared by several stakeholders. Homeowners pay the first portion of the loss through the payment of their individual deductibles d, denoted as B^h. Reinsurers pay a specified co-participation percentage, β%, of the loss between the attachment point, A, and the maximum limit, M. Reinsurers require an annual premium a reinstatement payment after a claim is made by the primary insurer. Primary insurers pay the remaining part of the loss. The optimization model for the primary insurance uses the 2,000 scenarios (each of which gives a unique time series of hurricanes over 30 years) to optimize the price of the policy, p_v, the attachment point A, and the maximum limit M for the reinsurance policy. The government requires that primary insurers have cash reserves in order to limit the risk of insolvency. We assume that the primary insurers will start their business with an initial investment C^{s0} that equals a specified constant multiplied by the annual premiums received in all risk regions. In each year y, they reallocate the amount of their accumulated surplus C^{sy} larger than C^{s0} into other lines of business. If the accumulated surplus becomes zero or less, the primary insurer is considered insolvent.

2.2.4 Cournot-Nash Model

A Cournot-Nash game theoretic equilibrium model is used to capture the competition among primary insurers. All carriers have the same information on the risk, the market, and only provide full coverage insurance to homeowners. In other words, they face the same cost structure. Gao et al. (2016) discusses the possible outcomes to the dynamic game that range from the single shot Cournot-Nash equilibrium to a collusive joint profit maximum. The homeowner model is used to derive a demand function that gives the relationship between the total expected loss covered and the price of insurance in each risk zone. For each risk region, $Q_v = D_v(p_v), v \epsilon [H, L]$, and its inverse: $p_v = P_v(Q_v) = D_v^{-1}(Q_v), v \in [H, L]$, where Q_v $(D_v(.))$ is the total expected insured loss covered by primary insurers (total demand) or reinsurers in the entire region v and p_v is the price for that region. If there are n primary insurers (carriers) in the market, by symmetry, we can rewrite the inverse demand function as: $p_v = P_v(Q_v) = D_v^{-1}(Q_v) = D_v^{-1}(nq_v), v \in [H, L]$, where q_v is the expected loss insured by one primary insurer in the region v. From the stochastic optimization insurer model, we derive a cost function, $C(q_H, q_L)$, for each primary insurer in terms of the expected loss insured, so we can derive the net profit $\pi(q_H, q_L)$ for each primary insurer as follows:

$$\pi(q_H, q_L) = \sum_v q_v P_v(nq_v) - C(q_H, q_L) \qquad \forall v = [H, L]$$

where q_{vj}^* is the coverage offered by insurer j that maximizes profit in the region v, given *n* competitors. This model takes into consideration the optimal reaction of competitors to every q_{vj} chosen by insurer *j*.

2.3 Case Study

2.3.1 Inputs

The case study area is the eastern half of North Carolina, including the low-lying coastal counties and extending westward to include half of Raleigh, the state capital (Figure 2.2). On average, a tropical storm or hurricane is expected to make landfall on the North Carolina coast every two years.[16] Recent hurricanes affecting North Carolina include Floyd (1999), Isabel (2003), Irene (2011), and Matthew (2016). We divide the region into 731 census tract-based geographic zones for analysis. We also group these small zones into two larger risk zones, where all homes within 2 miles of the coast are located in the high risk zone, *H*, and those located beyond this distance are assumed to be in the low risk zone, L. We defined eight categories of buildings based on the number of stories, garage, and roof type and one building value for each. For each category, there are up to 68 building resistance levels. There are 931,902 homes across both risk zones, with 282,890 and 649,012 homes in the high and low risk zones, respectively. We used the component-based loss simulation model to estimate both wind and storm surge flood damages for each type of building at each location. The loss calculation process includes S=2000 scenarios of (probabilistic event-based, with a set of 97 events) 30 years (with 20 time steps per year) hazard simulation. It also includes a joint probability distribution estimation of annual loss for each type of building under each possible hurricane event. We embed the loss model into individual homeowner and insurer models to derive the insurer's optimal cost function. We repeat the loss estimation with a varying portfolio of insured buildings (as determined by the homeowner decision model which is influenced by the cost of the premiums charged) and conduct a stochastic optimization for managing risk for the book of business. In the insurer model, the deductible level $d = \$5000$, co-participation factor $\beta = 95\%$, administrative loading factor $\tau = 0.35$, and factor defining allowed surplus $k = 3$. We set the minimum premium required by the insurer to offer insurance at $\$100$. We use lognormal distributions for the risk aversion parameter in the utility model for the homeowners and specify the parameters for those distributions so that they are consistent with the penetrations in the low and high risk zones given in [17]. For further details see [10]. We bound the total premium that may be charged for insurance to be $5.35 per dollar of expected loss covered in both risk zones. For example, a $150,000 home with expected annual loss of $2,000 would face a maximum annual premium of $10,700. We experiment with a single monopoly insurer and an oligopolistic market with 4 carriers for comparison.

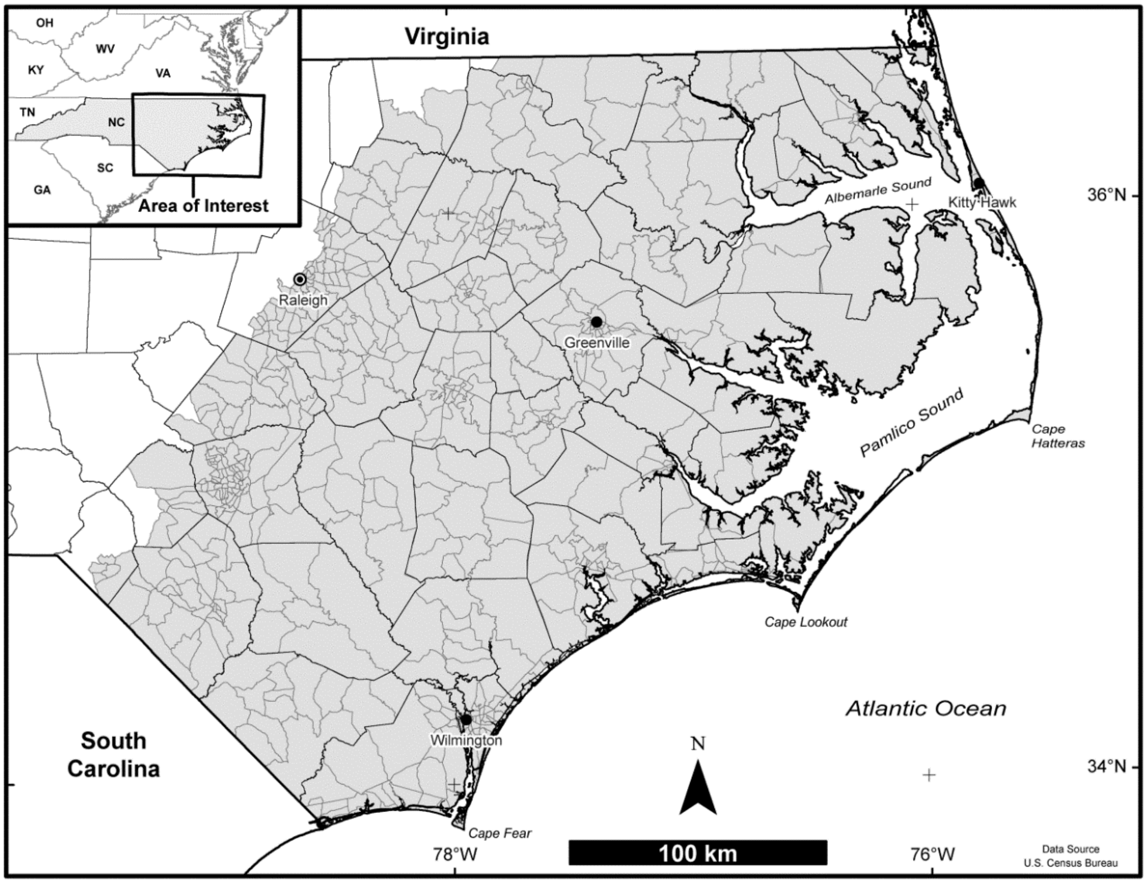

Figure 2.2. Study Area (Source: Xu et al., 2018[11])

Figure 2.3 shows the vulnerability of the homes using the ratio of the expected annual loss to the value of the home expressed as a percentage. For almost 90,000 of the more than 930,000 homes in the region, expected loss exceeds 1% of the home value. For the homes that are above the 1% threshold, we find that more than $351 million of the almost $600 million or about 60% of total expected loss can be attributed to about 9% of the homes in the region. As illustrated in Figure 3, the average annual loss of homes for which that loss is at least 4% of the value of the home is almost $7 thousand. Clearly, a relatively small proportion of homes account for a relatively large proportion of expected losses.

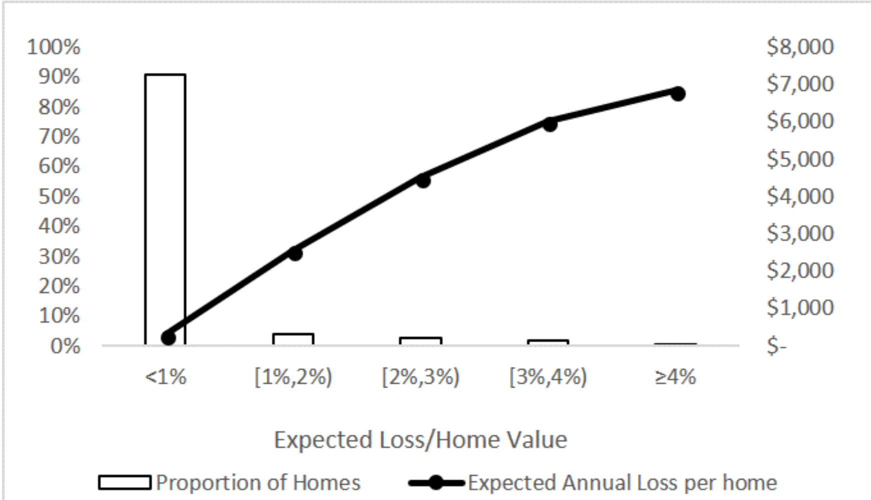

Figure 2.3. Number of Homes and Average Value of the Loss Categorized by Expected Loss as a Percentage of Home Value.

2.3.2 Results

Table 2 compares (1) premium costs; (2) expected uninsured loss; (3) proportion of households insured; and (4) amount of loss uninsured due to affordability limitations across seven alternative cases when there are either one or four carriers in the insurance market. Table 3 compares (1) carrier profit; (2) probability of carrier insolvency; and (3) government or industry subsidy required for the same seven cases. Each of the seven cases is defined by an affordability threshold in the high and low risk regions, whether or not homeowners can receive a subsidy for the amount of the premium beyond the affordability threshold, and if that subsidy is available, the source of the subsidy (insurance carriers or government).

Table 2.2. Market Characterization for Seven Scenarios

Case	Affordability threshold		Subsidy paid by	Premium per dollar loss ($)				Uninsured loss ($M)			
				1 carrier		4 carriers		1 carrier		4 carriers	
	High Risk	Low Risk		High Risk	Low Risk	High Risk	Low Risk	High Risk	Low Risk	High Risk	Low Risk
1	5%	2.50%	n/a	4.89	5.35	2.09	3.46	354	99	204	91
2	1%	1%	n/a	5.29	5.35	2.13	2.58	417	111	377	100
3	2%	2%	n/a	5.24	5.35	2.53	3.35	394	104	326	96
4	1%	1%	Govt.	5.35	5.35	5.35	5.35	31	76	31	76
5	1%	1%	Carriers	5.35	5.35	-	-	-	-	-	-
6	2%	2%	Govt.	5.35	5.35	5.35	5.35	45	81	45	81
7	2%	2%	Carriers	5.35	5.35	-	-	45	81	-	-

Case	Affordability threshold		Subsidy paid by	Proportion of households insured (%)				Total expected loss uninsured due to affordability			
				1 carrier		4 carriers		1 carrier		4 carriers	
	High Risk	Low Risk		High Risk	Low Risk	High Risk	Low Risk	High Risk	Low Risk	High Risk	Low Risk
1	5%	2.50%	n/a	44%	27%	59%	26%	298	47	135	26
2	1%	1%	n/a	26%	25%	39%	23%	397	46	352	28
3	2%	2%	n/a	35%	26%	43%	25%	365	28	326	16
4	1%	1%	Govt.	71%	28%	71%	28%	0	0	0	0
5	1%	1%	Carriers	-	-	-	-	-	-	-	-
6	2%	2%	Govt.	68%	28%	68%	28%	0	0	0	0
7	2%	2%	Carriers	68%	28%	-	-	-	-	-	-

Assume 5.35 is maximum insurers are allowed to charge.

Table 2.3 Annual Industry Performance Across Seven Scenarios

	Affordability threshold		Subsidy paid by	Profit ($M)		Probability of insolvency		Total subsidy ($M)	
Case	High risk	Low risk		1 carrier	4 carriers	1 carrier	4 carriers	1 carrier	4 carriers
1	5%	2.50%	n/a	206	110	0.61%	1.35%	-	-
2	1%	1%	n/a	80	21	0.57%	1.43%	-	-
3	2%	2%	n/a	126	49	0.66%	1.32%	-	-
4	1%	1%	Govt.	1,361	1,361	0.12%	0.15%	1,475	1,475
5	1%	1%	Carriers	-	-	100.00%	-	-	-
6	2%	2%	Govt.	1,314	1,314	0.09%	0.13%	1,214	1,214
7	2%	2%	Carriers	-	-	100.00%	-	-	-

We consider thresholds of 5% and 2.5% of the value of the home to be the affordability thresholds in the high and low risk zones, respectively for a "base case" analysis (Case 1). This case forms a point of comparison for the remaining six cases. The thresholds of 5% in the high risk zone and 2.5% in the low risk zone cover almost all the homes (>99%) in both the low and high risk area and these homes represent about 99% and 97% of the expected loss in the high risk and low risk zones, respectively if the cost of insurance were exactly the expected loss. Of course the cost of insurance always exceeds the expected loss due to an administrative fee and a profit loading factor.

Under the base case, with one insurer the insurance premium is $4.89 and $5.35 per dollar of expected loss in the high and low risk zones, respectively (Table 2.2). When there are four insurers, the premiums drop to $2.09 and $3.46 in the high and low risk zones, respectively. The decline in prices translates into a drop in uninsured losses to $204 and $91 million in the high and low risk zones, respectively; hence about 50% of the expected loss is covered by insurance when there are four carriers (in comparison 24% when there is a single monopoly carrier). Of the expected losses not covered, $135 and $26 million are not covered as a result of affordability issues. It is important to remember that in this model, homeowners also may not purchase insurance even if they can afford to, either because they are sufficiently risk tolerant based on maximizing expected utility (that is, it is not worth it to them to purchase the insurance), or their premium would not exceed the $100 threshold for the carriers to be willing to sell the insurance to them. With four carriers, the profit is lower than in the monopoly situation reaching $110 million profit with four carriers and an annual insolvency rate of about 1.35% (Table 2.3).

If we assume that affordability concerns on the part of homeowners imply that the maximum amount of a policy they can purchase is limited to 1% of the value of their homes (Case

2), the market performance, as measured by the amount of expected loss that is insured with four carriers, drops to about $\left(1 - {}^{277K + 100K}/_{600K}\right) * 100\% = 37\%$ from $\left(1 - {}^{204K + 91K}/_{600K}\right) * 100\% = 50\%$. Also, the insurance carriers' profit drops from \$110 million to about \$21 million (Table 3). With a 2% affordability constraint (Case 3) and the same four carriers, the amount of expected loss that is insured rises to about $\left(1 - {}^{326K + 96K}/_{600K}\right) * 100\% = 30\%$. Notice that prices very marginally increase with the decrease in the affordability threshold but more people are able to purchase insurance as we now assume they can afford to do so.

With these lower affordability thresholds of 1% or 2%, many homeowners simply cannot afford to purchase insurance though there is a functional, even if somewhat limited, market for insurance. Suppose the government were to pay for insurance beyond the affordability threshold. In that situation (Cases 4 and 6 in Table 2), the prices increase to \$5.35 in both regions and the insured loss reaches 82% and 79% when the affordability threshold is 1% and 2%, respectively. The uninsured loss increases when the affordability threshold is 2% because more homeowners are not willing to purchase as their portion of the cost for insurance rises beyond 1% of the value of the home (Case 4 vs. Case 6). Prices increase because homeowners do not experience the costs that are charged by the carriers once they cross the affordability threshold. Of course this increase in insured loss comes at a substantial expense. The subsidy reaches about \$1,475 M/930K homes which is about \$1600 per home in the study area regardless of whether they purchase or need insurance or about \$10,000 per home that actually purchases insurance and received a subsidy (Case 4). When the affordability threshold is 2%, the subsidy is almost \$12,000 per home that purchases insurance and receives a subsidy (Case 6). The per home average subsidy increases when the threshold rises to 2% for affordability because fewer homes qualify for a subsidy and those homes experience relatively higher expected losses in comparison to the pool of homes that qualify with a 1% affordability threshold. From Table 3, it is important to notice that the profitability of the carriers increases dramatically when there is a government subsidy (Cases 4 and 6). Effectively that subsidy flows to the insurers as profit. If industry is required to bear the burden of risk by providing full insurance while collecting premiums capped by the affordability threshold, there is effectively no market (i.e., no households are insured) regardless of the whether the affordability criteria is 1 or 2%. Potential carriers simply cannot earn sufficient profit to attract them to the market under these conditions.

2.4 Conclusions

This study explores the effect of an affordability criteria in a computational framework that takes account of the interaction of homeowners, primary insurers, reinsurance, and the government in a region that is vulnerable to flooding and wind damage due to hurricanes. The case study focuses on the current stock of homes in a study area of eastern North Carolina and their level of resistance to hurricane damage. Resistance depends on location of the homes and their structural characteristics. Insurance decisions are assumed to be made by risk averse expected utility maximizing homeowners. Homeowners face insurance prices determined by an insurance industry comprised of one or four carriers that interact within a noncooperative Cournot-Nash game theoretic framework. All stakeholders have knowledge of the loss distribution due to hurricane damage. We find that a relatively low percentage of homes in the region account for a considerable proportion of the expected losses. With a relaxed affordability criterion of 5% of home value in high risk areas and 2.5% in low risk area, voluntary purchase of insurance at risk-based rates is sufficient to support a viable private sector insurance industry. When the affordability criteria that cost of insurance cannot exceed a 1% or 2% of the home value, we find that about 80% of total expected losses would represent homes that fail to meet this criterion in a high risk region within two miles of the coastline. This study does not take into account any retrofit strategies to make homes more resistant to hurricane damage thereby mitigating the risk. Further, we explore the possibility of allowing the burden to subsidize insurance rates fall on the insurance industry or the government. With burden fully placed on the insurance industry, the market would simply disappear as profitability from the full insurance buyers is not sufficient to offset the subsidy. The cost of subsidizing from public funds averages about $10,000 per household per year with most of the subsidy transferring to the insurance industry. If the burden is shared between the homeowner and the government, there is a viable insurance market, however, the costs of doing so, do remain large.

Without coupling the subsidy with policies that encourage homeowners to mitigate the risk, the required subsidy is excessive relative to the total expected losses for the study area. Our conclusions, based on this study are similar to those given in [7] that recommends against subsidized premiums. Rather, accurately priced insurance premiums that communicate the true risk of hazardous locations should be coupled with assistance for low income homeowners and approaches that encourage individual and community-wide hazard mitigation will be more effective policy instruments for mitigating risk. In addition, a thoughtful acquisition program for the properties at highest risk of hurricane damage is likely a better solution than a *carte blanche* approach of insurance subsidies than hide the ability of insurance premiums to communicate risk. For areas vulnerable to hurricane damage, a three pronged approach that includes risk-based insurance rates, complemented by grants for retrofit to reduce damage and acquisition program for the few highest risk properties is likely to be most effective in promoting risk reduction and resilience. Future work will focus on finding the balance of these three strategies as opposed to reliance on insurance alone to manage hurricane risk.

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CHAPTER 3

DYNAMIC MODELING OF COMPETITION IN THE NATURAL HAZARD CATASTROPHE LOSS INSURANCE MARKET WITH EXPLICIT CONSIDERATION OF HOMEOWNER FINANCED MITIGATION

3.1 Introduction

The consequences of natural disasters are rapidly escalating. U.S. Losses from Hurricanes Harvey and Irma are estimated at between $150 and $200 billion (Horowitz 2017). Natural disaster catastrophe loss insurance is currently the most important and effective way to manage regional catastrophe risk. However, there exist problems on both the demand and supply side of the insurance market. Kunreuther (1996) observes that on the demand side, property owners in hazard-prone areas usually do not fully insure their properties nor invest sufficiently in mitigations against losses from natural disasters. On the supply side, the insurance industry is not willing to promote or offer coverage against these events. This has led to the creation of the National Flood Insurance Program (NFIP) which offers flood insurance at rates that do not cover the full cost of the insurance. For this reason, as of March 2017, the NFIP has a $24.6 billion deficit (Gao 2017). Even at these reduced rates, homeowners are underinsured and therefore, the government often must come to the rescue when severe events occur with disaster assistance, which results in large and unexpected expenditures on government (Kunreuther and Pauly 2004).

Insurance for natural hazard loss is complicated because the carriers receive a steady stream of premiums and this income stream must match against infrequent but potentially very large claims. There are other important dynamics at play as well since the interactions between key stakeholders in the insurance market (i.e., homeowners, insurers, reinsurers, and government) evolve over time. For example, homeowner attitudes evolve over time as their hurricane experience accumulates, which can cause evolutions in their insurance purchase decisions impacting aggregate demand for insurance. Evolution in homeowner price sensitivity impacts the insurance industry through variability in take up rates and the amount of risk in their portfolio, which they adaptively control through pricing and the purchase of reinsurance. Also, the building inventory evolves through new building and as homeowners undertake mitigation to reduce losses which further impacts the homeowner insurance purchase decision.

There is a wide array of research focused on the dynamics of individual aspects of this problem, but there is little research that comprehensively models the range of dynamics that impact the evolving market for natural catastrophe loss insurance. For instance, many researchers develop statistical models of the household insurance purchase decision and conclude that previous hazard experience (Browne and Hoyt 2000; Zahran et al. 2009; Botzen and van den Bergh 2012b; Petrolia et al. 2011; Atreya et al. 2015), homeowner characteristics like income and age (Landry and Jahan-Parvar 2011; Botzen and van den Bergh 2012a, b; Atreya et al. 2015; Petrolia et al. 2015) and/or previous retrofit actions (Petrolia et al. 2015) have a significant influence on the insurance purchase decision. Dumm et al. (2011, 2012) focus on the building codes and conclude that effective building codes in hazard-prone areas help decrease hazard losses and insurance premiums. Kunreuther (2008) discusses the influence of long-term insurance on homeowners and insurers. Kleindorfer et al. (2012) examine the demand and supply of annual and multi-year insurance with respect to protection against a catastrophe risk in a competitive insurance market. Hence, there is an urgent need for establishing a comprehensive tool for researchers, insurance industry, and government officers so that effective methods to restructure the natural hazards insurance market can be identified.

Closely related to this research Gao et al. (2016) proposed a game theoretic modeling framework to capture the strategic relationship between the homeowners, insurers, and reinsurers in the market in a static context. They applied this framework to analyze the market for insurance against hurricane-induced loss in (flood and wind combined) in Eastern North Carolina. Their framework is a static, perfect information, Cournot-Nash noncooperative game which integrated (1) a utility-based homeowner decision model for insurance purchase; (2) a stochastic optimization model of the premium and reinsurance decisions by the primary insurers; and (3) a state-of-the-art regional catastrophe loss estimation model.

Since the framework developed in Gao et al. (2016) has many of the elements needed to model the evolving market for natural hazard catastrophe loss, we extend this framework in three important ways. First, we replace the utility model for the homeowner insurance purchase decision with discrete choice models fitted to survey data (Wang et al. 2017). This allows homeowner preferences for insurance to vary based on the socio-economic characteristics of the homeowners and with evolving hurricane experience of the household. Second, we extend the framework to include opportunities for homeowners to invest in retrofit using Jasour et al. (2018) to allow the building inventory to evolve over time. Third, given the evolving tastes of the homeowner and the evolving building characteristics via retrofit, we extend the modeling to explicitly represent the ability of insurers to vary their pricing decisions as well as their reinsurance practices annually.

Section 3.2 describes the dynamic framework developed for modeling the insurance market. Section 3.3 gives the results of a case study conducted in eastern North Carolina. Section 3.4 summarizes the key insights from the modeling and analysis and suggests opportunities for future research.

3.2 Modeling Framework

Figure 3.1 gives the modeling framework including the interactions between the models and the required data. This framework considers homeowners, insurers, reinsurers, and the government as the key stakeholders in the natural catastrophe insurance market. The core of the model is interacting models that describe the competition between the insurance carriers and the price equilibrium that is reached between the carriers and the homeowners. Through these interactions, the evolving characteristics of the homeowners and the building stock are explicitly integrated in the analysis.

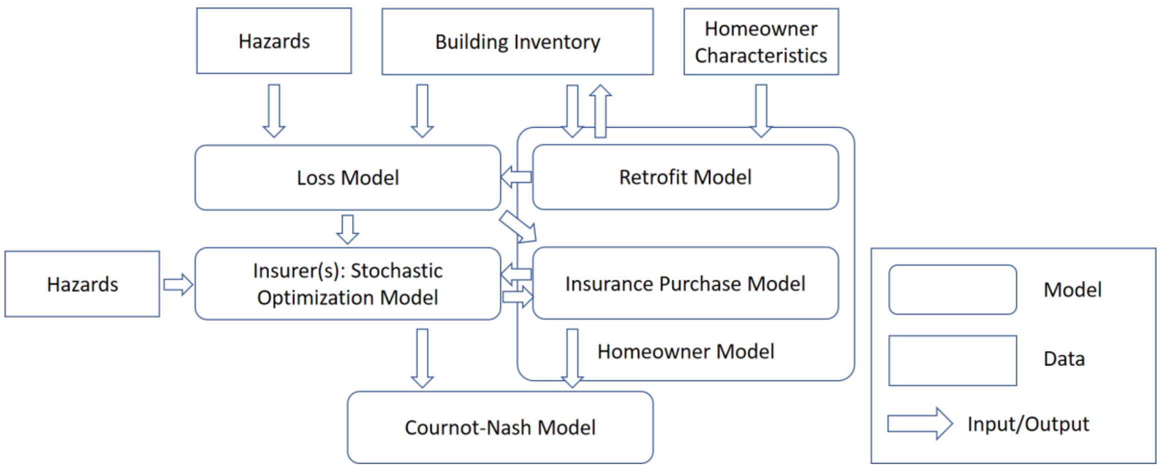


Figure 3.1. Structure of Interacting Models

Reinsurers and the government are not explicitly presented in Figure 3.1 because we assume that their decisions are made outside the framework and form constraints on the actions of the carriers. Reinsurers are assumed to offer reinsurance at a cost defined by the mean expected insured loss and the standard deviation of that loss. The impact of expected mean insured loss and the standard deviation of the loss on the cost of the reinsurance are assumed to be known values. We assume that for a given price for insurance in the low and the high risk regions, a stochastic optimization model is used by each carrier to optimize their decisions as to how much risk the insurer will transfer to reinsurers. The impact of the government on the primary insurers' is represented in the stochastic optimization model by placing requirements on the cash reserves to be held by the primary insurer proportional to the magnitude of their liabilities. Similarly, we assume that the government requires a fixed multiple of the premiums written to be available as a cash surplus. This multiple is assumed to be given. Hence, these two stakeholders are included via input data in the insurers' stochastic optimization model.

A regional catastrophe loss model is used to estimate the loss to each homeowner and primary insurer after a hurricane. The loss estimation model estimates the financial losses in each hurricane event and these losses are allocated to homeowners and insurers based on the insurance deductible and the insurance purchase decisions made by each homeowner. A perfect information Cournot-Nash model is used to represent the interactions among the homeowners and insurance carriers annually. As the characteristics of the homeowners and properties evolve, new equilibrium prices for insurance are computed. We assume that carriers have a long term understanding of the regional hazard that is updated through the retrofit actions of the homeowners but that hazard representation does not include forecasts of the evolving hazard. Rather, that hazard is re-estimated annually based on mitigation actions already take so as to set prices for the next policy year.

3.2.1 Loss Model

The residential buildings are classified into different groups based on their location i, building category m, resistance level c, and risk regions $v \in [H, L]$, where H denotes a high risk region and L denotes a low risk region. The number of buildings in each group is identified, denoted as X_{imcv}. The hurricane hazard is represented by an efficient set of probabilistic hurricane scenarios $h \in (1, \ldots, H)$. Each hurricane scenario has an associated hazard-adjusted annual occurrence probability Ph such that when probabilistically combined, the set of hurricane scenarios represents the regional hazard (Apivatanagul et al. 2011). The loss for a specific hurricane hazard h for a specific building of type i, m, c, v, is estimated by a combination of a modified version of Florida Public Hurricane Loss Model (FPHLM 2005) for the wind-related loss and Taggart and van de Lindt (2009) and van de Lindt and Taggart (2009) for the flood-related loss, denoted as L^h_{imcv}.

3.2.2 Homeowner Model

When hurricane occurs, the homeowners are assumed to pay, B^h_{imcv}, denotes the minimum of the loss experienced and the deductible level d. We also assume each homeowner has an affordability threshold for insurance (that threshold can vary based on the home's location in either the high or low risk region) where that threshold is a percentage, κ_v, of their home values, V_m. Finally, the primary insurers will not provide homeowners with insurance if the premium is less than a specified level ρ.

3.2.2.1 Insurance Purchasing Model

Gao et al. (2016) used a utility model to represent the homeowner insurance decision making preferences. We make use of models developed in Wang et al. (2017). Based on data collected from a telephone survey conducted from the fall of 2012 through the spring of 2013 in eastern North Carolina, they develop several mixed logit models of insurance purchase behavior.

The utilities for each homeowner n and for each alternative j as:

$$U_{nj} = \beta_0 + \beta_{P,n} x_{P,nj} + \beta_{D,n} x_{D,nj} + \alpha_n^T z_n + \varepsilon_{nj} \text{ for } j = \text{Purchase insurance}$$

$$U_{nj} = \varepsilon_{nj} \text{ for } j = \text{No insurance}$$

where β_0 is the alternative-specific constant, $x_{P,nj}$ and $x_{D,nj}$ are the premium and deductible of the insurance policy, respectively, z_n are variables related to the homeowners and their homes, $\beta_{P,n}$ and $\beta_{D,n}$ are the coefficients estimated for the premium and deductible, respectively, α_n are the coefficients estimated for the individual-specific variables, ε_{nj} are the factors not observed and are assumed to be iid extreme values. Note that $\beta_{P,n}$ and $\beta_{D,n}$ are assumed to be lognormally distributed. Since lognormal variables are always positive and an increase in premium and deductible always results in a decrease in the utility of the policy hence they use the negative of the corresponding variable values in the equation.

3.2.2.2 Retrofit Decision Models

We integrate mitigation decision models developed by Jasour et al. (2018) into the current modeling framework to include the effect of pre-event mitigation to reduce losses from hazards. Jasour et al. (2018) develops their models from the same survey used by Wang et al. (2017) and the loss model developed by Peng et al. (2013). In the survey, nine different retrofit decisions were asked. Among these retrofits, six are for the wind hazard and the rest three are for the flood hazard.

As mentioned previously, the model explicitly represents the different resistance levels for each home type and it now includes decisions about structurally specific retrofits. Clearly homeowners will only mitigate to higher resistance levels. There are other restrictions as well. For example, for roof retrofits, either the roof sheathing is upgraded or the roof covering and the sheathing are upgraded at the same time. Also, given the benefit of roof upgrades, homeowners will do that before upgrading openings. As a final example, for roof-to-wall retrofits, these are only selected if they accompany upgrades to openings or the openings have already been upgraded (Malik et al. 2013).

Jasour et al. (2018) estimates four mixed logit models to reflect decision-making with respect to four kinds of retrofits, among which three models are wind-related and one is flood-related. It is important to note that the statistical models give the impact of making grants available. We do not make use of this option in the case study described below, rather, we assume that all upgraders are at the homeowners' expense only.

It is also true that not all homeowners will consider investment in each retrofit that is feasible for each year. Based on the survey described in Wang et al. (2017), about 35% of home buyers consider retrofit at the time of home purchase. About 37% of homeowners, after a hurricane event they experience, will consider retrofit. Finally, about 48% of homeowners consider retrofit annually for other reasons (e.g. when renovating their home, hearing about a hurricane elsewhere, etc.). We use these statistics to govern when homeowners are given the opportunity to consider retrofit.

The retrofit cost varies based on the retrofit and building category (Peng et al. 2013). Some retrofits are not cost beneficial for some buildings based on their configuration and their locations. However, since many homeowners are risk averse, they may still be willing to engage in the retrofit if the amount by which the cost exceeds the benefit is not too large. For this reason, we assume that homeowners will only consider a retrofit when its cost-effectiveness exceeds a certain threshold γ, where γ is the difference between the cost of the retrofit and the expected losses avoided if the retrofit is performed. Notice that since homeowners are generally risk averse, γ, is a negative value.

3.2.3 Insurer Model

The framework assumes each insurer is a net profit maximizer. Given the price of insurance offered, a stochastic optimization model (where the scenarios that encapsulate the uncertainty in regional hurricane risk are a 30-year sequence of spatially specific hurricane events) is used to optimize the primary insurers' reinsurance decisions. In a hurricane hazard h, the loss of an insured building L^h is covered by several parties. Homeowners pay the first portion of the loss up to deductible d, denoted as B^h. Reinsurers pay a specified co-participation percentage, β%, of the loss between the attachment point, A, and the maximum limit, M with the remaining (1- β)% paid by the insures. Reinsurers require an annual premium r^{sy}, including a base premium b and a reinstatement payment.

The government requires that primary insurers have cash reserves to control the risk of insolvency. It is assumed that the primary insurers will start their businesses with an initial investment C^{s0} (under scenario s) that equals a specified constant k multiplied by the annual premiums received. In each year y under scenario s, they will reallocate the amount of their accumulated surplus C^{sy} larger than C^{s0} into other lines of business. When the accumulated surplus becomes zero or less, the primary insurer becomes insolvent. We set the profit F^{sy} and surplus C^{sy} to zero for the remaining years. Additionally, the State insurance regulators require the insurers' capacity ratio (i.e., the leverage ratio) to be less than a given threshold, μ^{sy}, in each year.

3.2.4 Cournot-Nash Model

A static Cournot-Nash model is used to capture the competition between primary insurers on an annual basis. All primary insurers compete annually and make their decisions simultaneously. We assume that they do not consider the dynamic aspects of this competition and treat each year as a single shot game. The carriers are assumed to be homogeneous, have the same knowledge of the market and only provide full coverage insurance to homeowners. This leads to the assumptions that they face the same cost structure and will make the same pricing decisions. Hence, we compute the equilibrium prices in each year for all the insurers, that is, insurers share the same prices in each year, but prices can be different among years.

The homeowner model is used to derive a demand function for each risk region, $Q_v = D_v(p_v), v \epsilon [H, L]$, with its inverse: $p_v = P_v(Q_v) = D_v^{-1}(Q_v), v \in [H, L]$, where Q_v is the total insured loss covered by primary insurers or reinsurers in the entire region v and p_v is the price for that region. If there are n primary insurers in the market, by symmetry, we can rewrite the inverse demand function as: $p_v = P_v(Q_v) = D_v^{-1}(Q_v) = D_v^{-1}(nq_v), v \in [H, L]$, where q_v is the expected loss insured by one primary insurer in the region v. Using the stochastic optimization model for an insurer, a cost function for each primary insurer in terms of the expected loss insured is $cost = C(q_H, q_L)$. Hence the net profit for each primary insurer is derived as follows:

$$\pi(q_H, q_L) = \sum_v q_v P_v(nq_v) - C(q_H, q_L)\ \forall v = [H, L] \tag{1}$$

Since each insurer is a net profit maximizer, if the functions are differentiable, the optimal solution, q_v^*, satisfies the first order conditions as follows:

$$\frac{\partial \pi(q_H, q_L)}{\partial q_v} = P_v(nq_v^*) + q_v^* \frac{\partial P_v(nq_v^*)}{\partial q_v} - \frac{\partial C(q_H^*, q_L^*)}{\partial q_v} = 0\ \forall v = [H, L] \tag{2}$$

This leads to the reaction function for each insurer.

$$R_j(q_{-j}): \begin{cases} \qquad\qquad \cdots \\ q_{vj}^* = \dfrac{\frac{\partial C(q_H^*, q_L^*)}{\partial q_v} - P_v(nq_v^*)}{\frac{\partial P_v(nq_v^*)}{\partial q_v}}\ \forall v = [H, L] \\ \qquad\qquad \cdots \end{cases} \tag{3}$$

where q_{vj}^* is the optimal solution for insurer j in the region v, q_{-j} are the optimal solution for insurer j's competitors. Notice that insurers j's decisions are based on the reactions of other insurers.

3.2.5 Integration of the Dynamic Processes

Figure 3.2 illustrates how these models interact over simulated time. There is an underlying assumption in the framework that the insurance carrier understands the risk of insuring each property given the characteristics of the building. Of course, these characteristics may be modified via retrofit and therefore that knowledge is assumed to be immediately integrated in the carriers pricing decisions. In contrast the homeowners purchase decisions are based on some static attributes, like whether or not the property is in the floodplain and the distance of the property to the coastline, and some attributes that vary over time, like homeowner age, time since the homeowner experienced their last hurricane and the homeowners experience with hurricanes. For this reason, the framework is operationalized by stepping through time for each of a collection of scenarios where each scenario gives a time series of hurricane events over a 30-year period. Take together the collection of scenarios represent the regional hurricane risk.

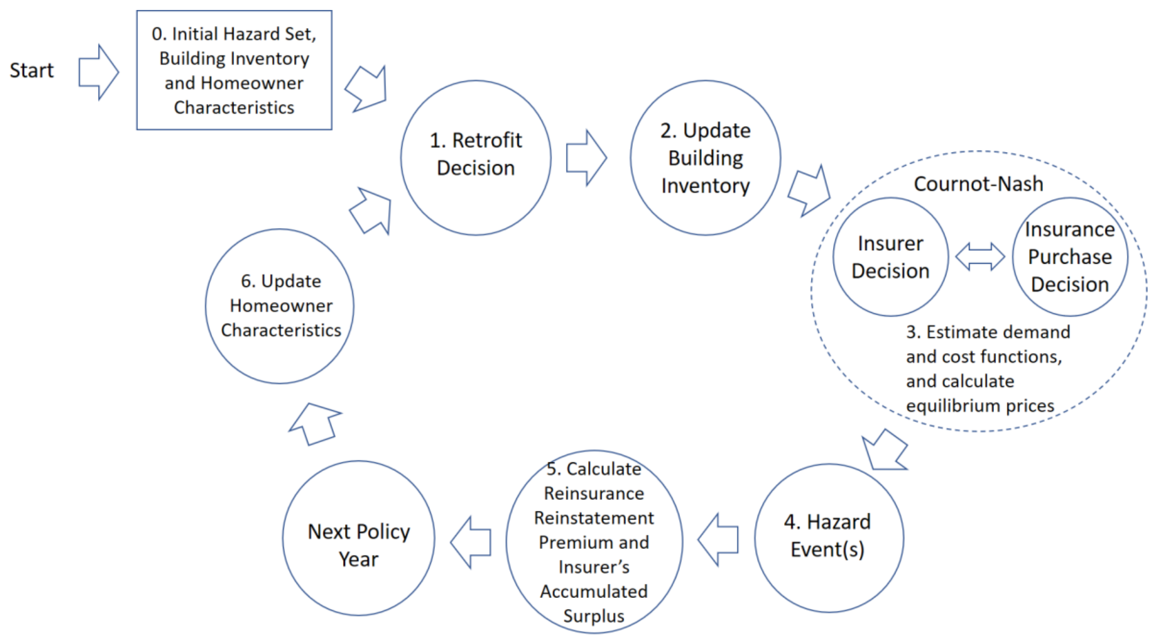


Figure 3.2. Dynamic Modeling Process using the Framework

For each scenario the following computations are performed in this simulation-based framework.

Step 0. First initialize the building inventory and the homeowner characteristics. We initialize homeowners' hurricane experience based on the distribution of experience estimated in the telephone survey;

In each year,

Step 1. Homeowners decide whether or not to retrofit using the retrofit statistical models. Again, homeowners only consider this decision if the benefits of the retrofit exceed the cost by at least γ and other conditions are satisfied as described in Section 3.2.2.2;

Step 2. After mitigation, the expected losses are computed (using all hazard scenarios from the current year to the end of the planning horizon) for each property. The demand as a function of price is computed as is the cost to provide insurance as a function of the price of insurance. These cost and demand functions are done separately in the low and high risk zones;

Step 3. Compute the equilibrium price of insurance for wind and flood in the low and high risk zones. Simultaneously, the insurance carriers make their decisions about reinsurance. Based on those prices, individual homeowners make their wind and flood insurance purchase decisions and the insurance carriers receive those premiums. These decisions, in the aggregate, are consistent with the cost and demand functions used to compute the equilibrium prices;

Step 4. Simulate hazard events in the current year in the hurricane scenario;

Step 5. Record the losses for the homeowners and the carriers as well as the payout from the carriers to the homeowners. Also, based on the losses incurred, the insurers pay a reinsurance reinstatement premium as required by the carrier policies with the reinsurers;

Step 6. Update homeowner characteristics since they evolve from year to year. From 2012 to 2016 about 16.3% of residents in North Carolina moved in each year (U.S. Census Bureau QuickFacts North Carolina 2017). Hence, we assume that about 1/7th of the homes are bought and sold in each year so the age and income of the homeowner is refreshed for these homes consistent with census data. Go back to Step 1 and repeat the procedure until the end of the simulation of the scenario or the insurers become insolvent.

3.3 Case Study

3.3.1 Required Inputs

In total of 503 census tracts in Eastern North Carolina are subdivided into 731 geographic zones, i, based on the distance to the coasts. We defined 8 categories, m, of wood frame residential buildings based on the number of stories, garage, and roof type. For each category, there are up to 68 building resistance levels. Each zone, based on the distance to the coast, is assumed to be in either the low risk or high risk region.

As described in Section 3.2.1, we use the Optimization-based Probabilistic Scenario (OPS) method and use a set of hurricane events, each with an annual occurrence probability that, in the aggregate, represents the regional risk with respect to the spatial distribution of peak wind speeds and flood depths (Apivatanagul et al. 2011). These hazard events are used to develop 2,000 scenarios of 30 years of hurricane histories each in order to compute the financial implications of insurance pricing decisions over time. The hazards include only storm surge flooding, and no effects of precipitation and inland flood are included. Note that these inputs are as same as those used in Peng et al. (2013) and Gao et al. (2016).

In the insurer model, the deductible $d = \$2{,}500$, co-participation factor $\beta\% = 95\%$, administrative loading factor $\tau = 0.35$, factor defining allowed surplus $k = 3$, and the minimum premium $\rho = \$100$. In each year, we bound the maximum price that may be charged for insurance to be \$5.35 per dollar of expected loss covered in both risk zones. In the simulation, we compute demand and cost functions for the range of price (per dollar of expected loss) levels from \$1.35 to \$5.35 with a step size of \$0.001 for the demand function and \$0.1 for the cost function. The value of \$1.35 represents a zero-profit price for the insurer that just covers the transaction costs for the insurer (\$0.35 per dollar expected loss). For retrofit, the threshold of for cost-effectiveness $\gamma = -300$.

We assume that homeowners in the high risk zone can afford insurance if that insurance is no more expensive than $\kappa_H = 5\%$ of the value of the home. In the low risk zone, we assume that insurance is affordable is the cost is no more than $\kappa_L = 2.5\%$ of the value of the home. We adopt these values because, for the wind hazard, for all homes, the expected losses in both high and risk regions is less than 1% of the value of the home. This contrasts with flood hazards. More than 99% of the homes have an expected flood loss of less than 5% of the value of the home in the high risk region and in the low risk region, about 99% of the have an expected flood loss that is less than 2.5% of value of the home. Hence, $\kappa_H = 5\%$ and $\kappa_L = 2.5\%$ allow most properties to be affordable when insurance is priced at the value of the expected loss. Of course, as loading factors rise, homeowners are priced out of the market.

Again, wind losses are generally much less than flood losses. We assume that insurers provide wind and flood insurance as a package. That is, homeowners can only can purchase insurance that covers both hazards. It is important to notice that if their property is not subject to one hazard or the other, their premium will only reflect hazard they actually face because we assume risk-based premiums.

3.3.2 Results of Homeowner Retrofit Model

As mentioned previously, 35% of new home buyers consider retrofit hence we select randomly 35% of new home purchasers in each simulated year and apply the discrete choice models for retrofit to determine which (if any) retrofits they will invest in. Similarly, 37% of homeowners that experience a hurricane event consider retrofit. Finally, ignoring homeowners in the above two categories, 48% of remaining homeowners are randomly selected to consider retrofit. Retrofit will be undertaken only if is “cost-effective” for a threshold $\gamma = -300$. Table 3.1 presents the distribution of the difference between retrofit costs and losses avoided for each retrofit. Notice that setting γ equal to -300 eliminates very few retrofits for wind but does eliminate about 20% of possible retrofits for flood that are very expensive given the costs that would be avoided.

Table 3.1. Distribution of Cost-Effectiveness for Each Retrofit

Cost-Effectiveness	Wind-Related Retrofit						Cost-Effectiveness	Flood-Related Retrofit	
	High			Low				High	Low
	Roof	Openings	Roof-to-wall	Roof	Openings	Roof-to-wall		Flood	Flood
(-500,-400]	0.00%	0.63%	0.00%	0.00%	1.09%	0.00%	(-1500,-1200]	8.51%	1.59%
(-400,-300]	0.00%	0.73%	0.00%	0.00%	0.33%	0.00%	(-1200,-900]	3.64%	0.72%
(-300,-200]	4.68%	0.45%	0.00%	3.92%	0.14%	0.00%	(-900,-600]	1.61%	0.00%
(-200,-100]	0.81%	0.28%	0.13%	0.13%	0.25%	0.17%	(-600,-300]	1.63%	0.00%
(-100,0]	0.46%	0.13%	1.18%	0.43%	0.03%	0.53%	(-300,0]	9.93%	1.32%
(0,100]	94.05%	96.88%	98.60%	95.51%	97.38%	99.29%	(0,300]	74.22%	96.37%
(100,200]	0.00%	0.00%	0.09%	0.00%	0.00%	0.01%	(300,600]	0.38%	0.00%
(200,300]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	(600,900]	0.08%	0.00%
(300,400]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	(900,1200]	0.00%	0.00%

In the initial building inventory data, there are in total 931,902 households in the study area with a total of about $258 million and $360 million expected losses in terms of wind and flood, respectively (Figure 3.3). The average total expected losses decrease by $13 million (5%) and $88 million (24%) by the end of thirty years for wind and flood hazards, respectively. Although the total expected losses decrease in each year, the reduction in that average annual loss declines substantially as the thirty years unfolds. For example, the retrofits done at the beginning of the first year result in about a $19 million (5%) decline in expected losses. The decline in expected annual loss is less than 1% by year six.

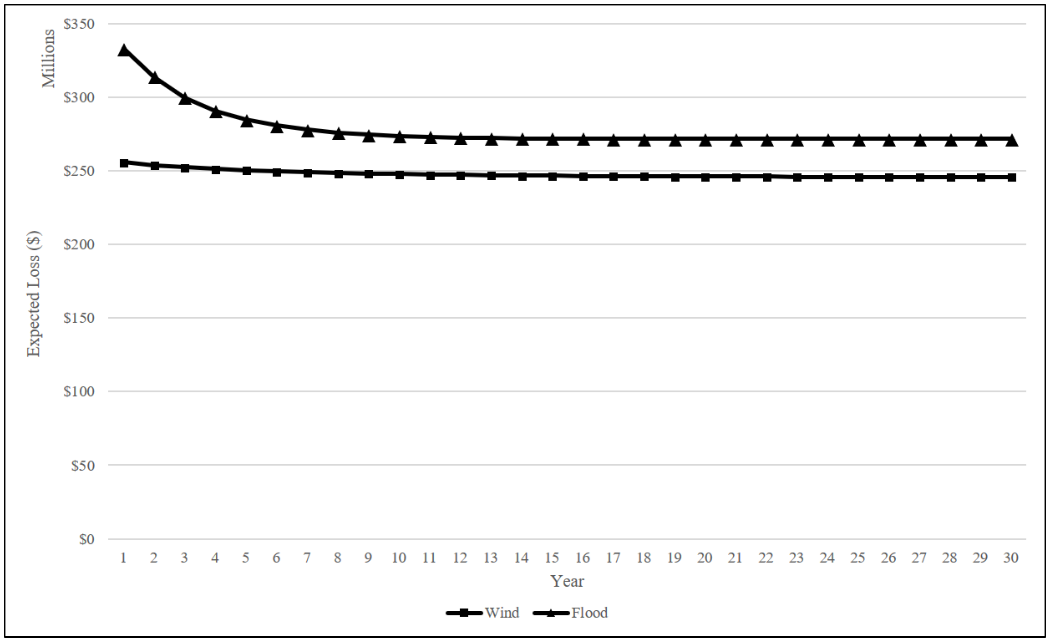


Figure 3.3. Wind and Flood Average Total Expected Losses

Figure 3.4 compares the average and the 5th and 95th percentiles of annual loss using the 2,000 scenarios with and without retrofit. For example, without retrofit, the mean probability that the annual loss exceeds $2.5 B is about 8%. Further, there is about a 5% chance that that probability is actually as high as 13%. With retrofit the mean of the probability that the annual loss will exceed $2.5 B is about 6% and there is a 5% chance that that probability is actually about 9%. Clearly retrofit reduces the mean annual losses but it also reduces the probabilities of very large losses.

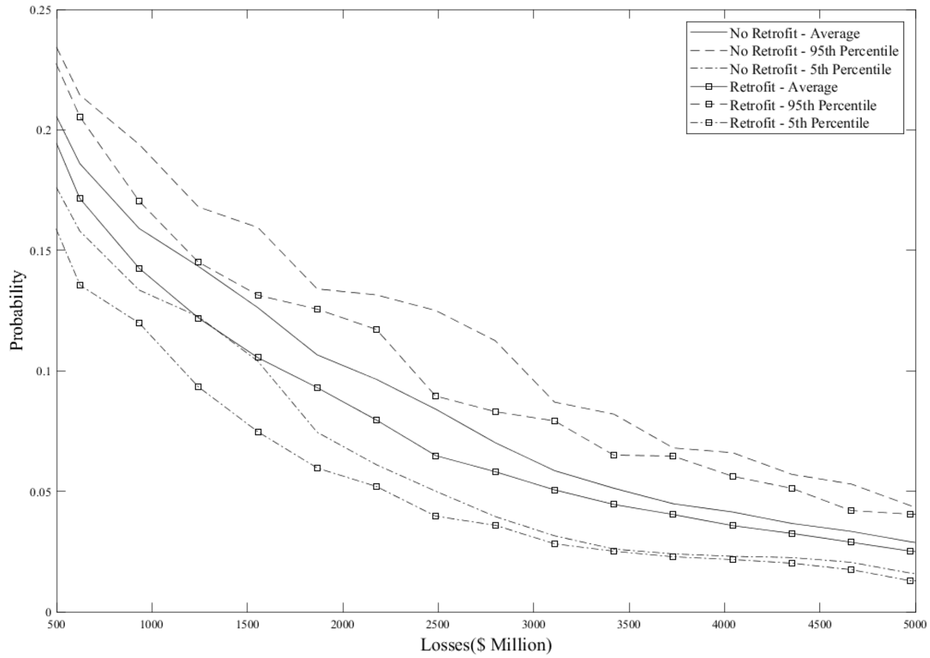


Figure 3.4. Mean, 5th and 95th Percentiles of Losses With and Without Retrofit

Figure 3.5 gives the average retrofit decisions and the penetration rates of each retrofit (i.e., the number of homes undertaking retrofit divided by the number of homes eligible based on the cost-effectiveness criteria) across the 2,000 scenarios over the first five years. For example, on average, about 1,500 (0.50%) elevation retrofits were undertaken in the high risk region in the first year. That number dwindles to about 640 by year five. Average retrofits by type decline over the 30 years because once a home is given a particular retrofit it is ineligible for that retrofit in the future.

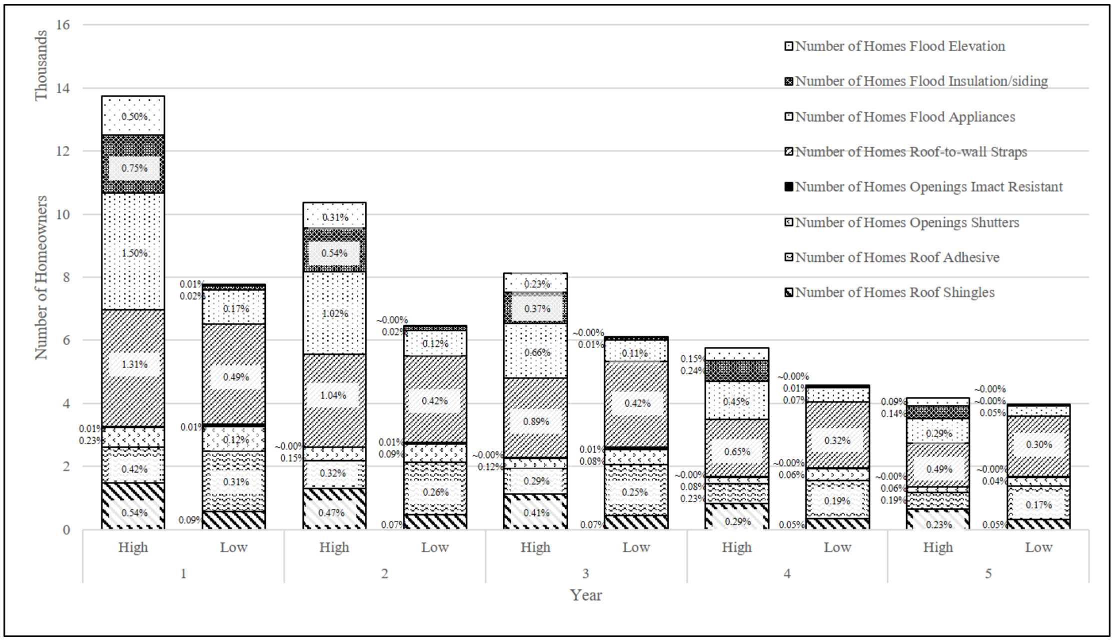
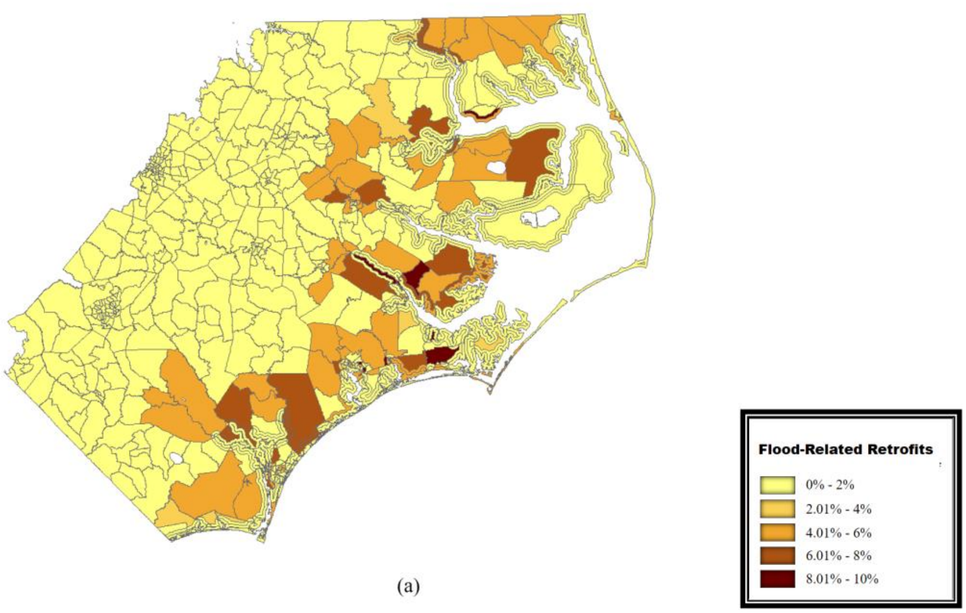


Figure 3.5. Average Retrofit Decisions in the First Five Years

Figure 3.6 shows the spatial distribution of the average percentages of homeowners undertaking flood- and wind-related retrofits over the 30 years across the 2,000 scenarios. As expected, flood-related retrofits are more frequently adopted along the coasts, compared to wind-related retrofits.



(a)

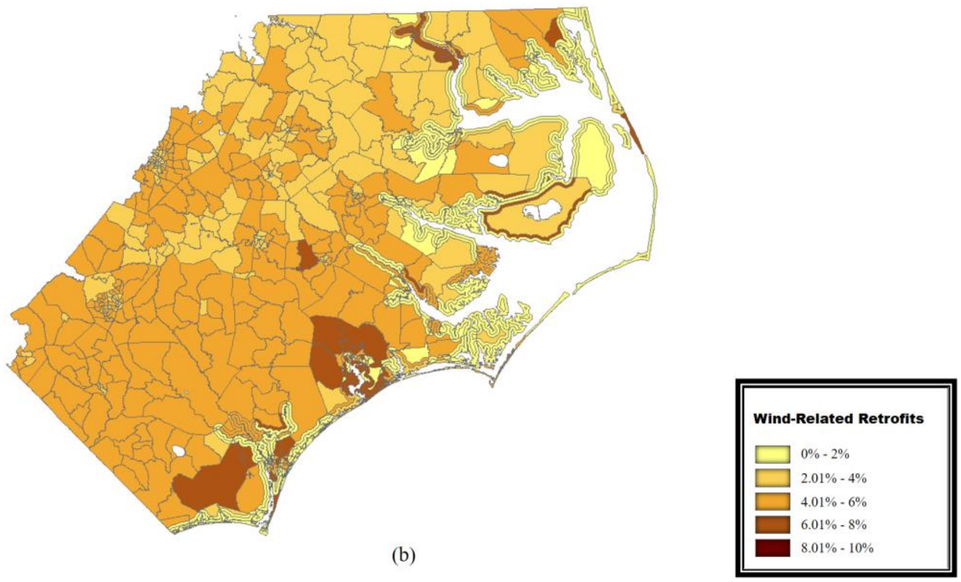


Figure 3.6. Percentages of Homeowners Undertaking (a) Flood- and (b) Wind-Related Retrofits

3.3.3 Results of Cournot-Nash Model

Since the inventory characteristics are changing annually and by scenarios (through the annual retrofit decisions made in each scenario), the cost and demand functions, which are functions of price change annually and by scenarios; hence the equilibrium prices for insurance computed using the Cournot-Nash model change annually and by scenarios. Figure 3.7 gives the demand curves (described in Section 3.2.4) in the high and low risk regions in year one in scenario one for wind and flood. Figure 3.8 gives the cost surface of insurers (described in Section 3.2.5) in year one in scenario one. For computational purposes, polynomial functions are fitted to the inverse demand curves and cost surface. This process is repeated each year for each scenario.

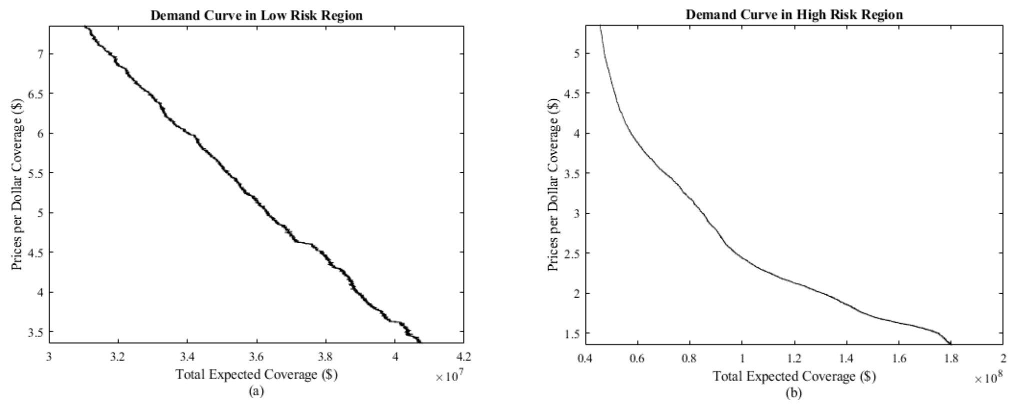


Figure 3.7. Inverse Demand Curves for (a) Low and (b) High Risk Regions

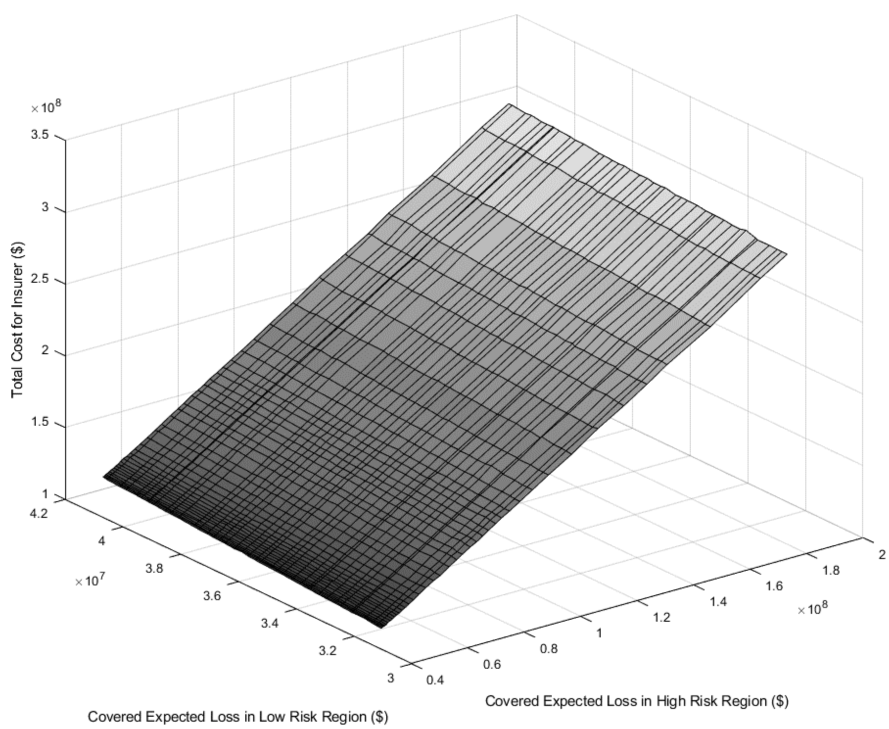


Figure 3.8. Approximated Optimal Cost Surface for Insurer

Figure 3.9 presents the average, minimum and maximum equilibrium prices for high and low risk regions for one to five carriers. We require that prices are no greater than $5.35 per $1 of expected loss. Note that in the high risk region and a single monopoly carrier is not shown in Figure 3.8 because the equilibrium prices in that case are at the cap of $5.35 per dollar of expected loss. This also occurs when there are less than four carriers in the low risk region. Notice that prices in the low risk region are relatively higher than those in the high risk region, which is consistent with the results found in Kunreuther and Michel-Kerjan (2009). Further, notice that prices, in the high risk region increase over the first few years. In the low risk region the prices decline over the first few years. After this period the prices, give the number of carriers in the market are constant. Prices fluctuate at the beginning of the planning horizon because of the retrofit process. As that process tapers off, prices become constant based on the number of carriers in the market.

As mentioned in Section 3.2.2, carriers only provide policies when the premium exceeds $100. Also, homeowners are assumed to be able to afford the policy if the cost of the policy does not exceed 5% of the value of the home in the high risk region and 2.5% in the low risk region. These two constraints produce countervailing pressures in the market. As homes are mitigated, the expected losses decline. In the high risk region, that allows prices to drift up without substantially increasing the number of people that cannot afford insurance. In the low risk region, with falling prices fewer homeowners can purchase as a result of the $100 floor on policies. However, as the prices decline, insurance purchase for those with premiums that exceed $100, are more attractive for the homeowner. It is these complex interactions that cause the shifts in prices as the retrofit process unfolds.

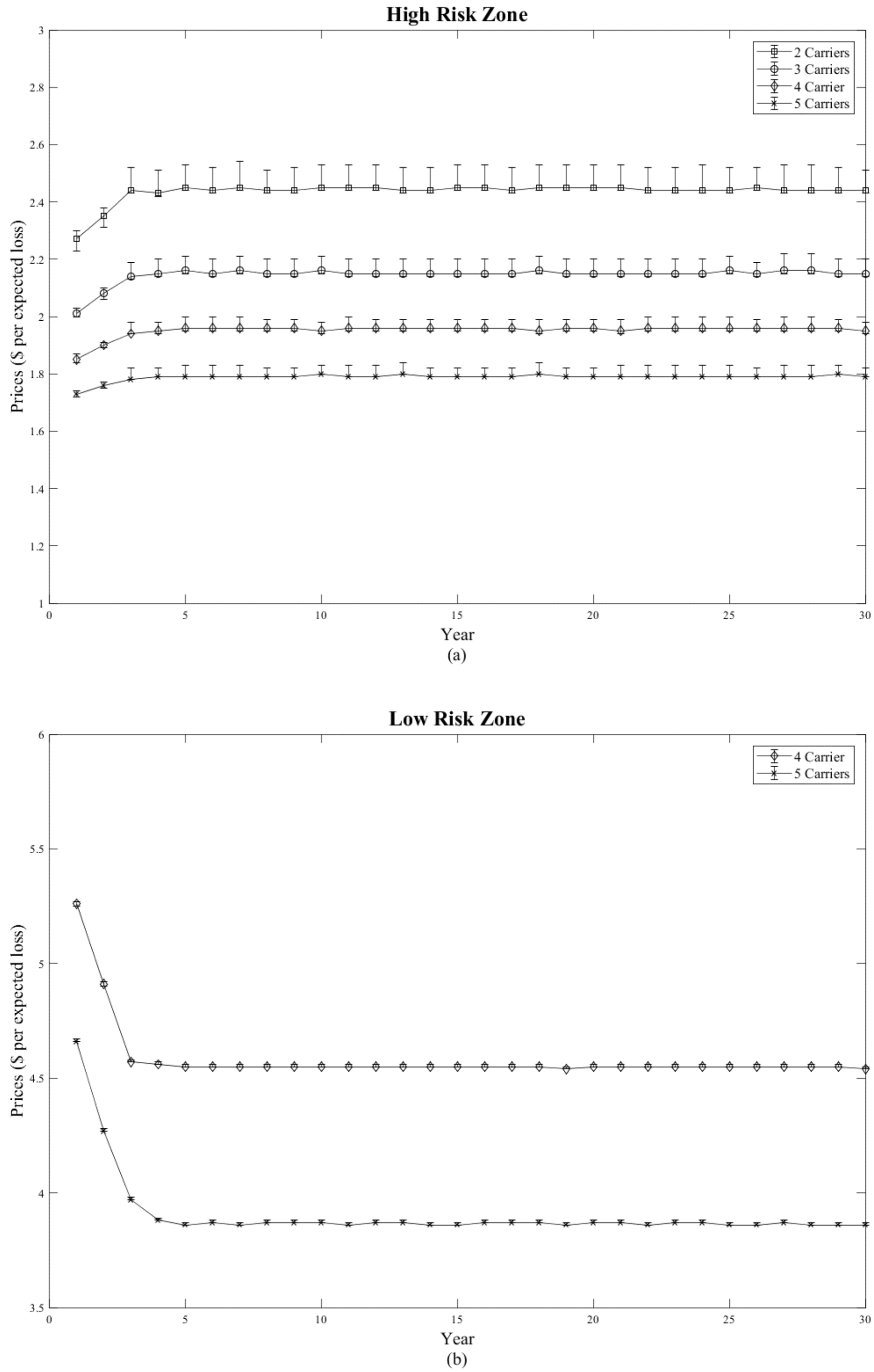


Figure 3.9. Equilibrium Prices in (a) High and (b) Low Risk Regions

Figure 3.9 also presents the range of equilibrium prices across the 2,000 scenarios in both regions. When there is a hurricane event, the equilibrium prices for the following year increases, and the amount of the increase is associated with the severity of the event that occurred. For example, Table 3.2 presents, for the first scenario, (1) the years in which at least one hurricane occurred; and (2) the number and severity of the hurricanes that occurred in each of those years. Table 3.3 presents the equilibrium prices before and after each of those years. In the 23rd year of the scenario, two hurricanes occurred in the first scenario and they caused more damage to residential buildings then were experienced in any other year in that scenario. This led to the biggest increase in the equilibrium prices in the 24th year. This also illustrates why there is a larger range in the equilibrium prices across scenarios in the high risk region than in the low risk region. Also, since in most years there are no events, the average price in a given year is on the lower end of the range.

Table 3.2. Summary of Hurricanes Occurred in the First Scenario

Year	Number of Hurricanes	Flood Losses Caused ($ M)			Wind Losses Caused ($ M)			Total Losses Caused ($ M)		
		High	Low	Total	High	Low	Total	High	Low	Total
5	1	1,008	110	1,117	187	416	603	1,194	526	1,720
7	1	132	~0	132	62	137	199	195	137	331
9	1	880	21	901	73	155	228	953	176	1,129
17	1	880	2	882	261	171	432	1,141	173	1,314
23	2	4,376	268	4,644	338	509	847	4,714	777	5,491

Table 3.3. Equilibrium Prices of Selected Years in the First Scenario

Number of Carriers		1	2	3	4	5
High Risk	Year 5	5.35	2.44	2.15	1.95	1.79
	Year 6	5.35	2.46	2.16	1.96	1.80
Low Risk	Year 5	5.35	5.35	5.35	4.55	3.86
	Year 6	5.35	5.35	5.35	4.56	3.88
High Risk	Year 7	5.35	2.44	2.15	1.95	1.79
	Year 8	5.35	2.44	2.15	1.96	1.79
Low Risk	Year 7	5.35	5.35	5.35	4.55	3.86
	Year 8	5.35	5.35	5.35	4.55	3.87
High Risk	Year 9	5.35	2.43	2.14	1.95	1.79
	Year 10	5.35	2.48	2.18	1.96	1.82
Low Risk	Year 9	5.35	5.35	5.35	4.55	3.87
	Year 10	5.35	5.35	5.35	4.55	3.87
High Risk	Year 17	5.35	2.43	2.14	1.95	1.79
	Year 18	5.35	2.47	2.17	1.95	1.81
Low Risk	Year 17	5.35	5.35	5.35	4.55	3.87
	Year 18	5.35	5.35	5.35	4.55	3.87
High Risk	Year 23	5.35	2.43	2.14	1.95	1.79
	Year 24	5.35	2.50	2.19	1.98	1.82
Low Risk	Year 23	5.35	5.35	5.35	4.55	3.87
	Year 24	5.35	5.35	5.35	4.56	3.88

Although prices in the low risk region are higher than those in the high risk region, the average premiums charged in the low risk region are much lower than those in the high risk region, as shown in Table 3.5. Note that $5.35 in Table 3.4 is artificially capped. This is because of the difference in the magnitude of expected losses between the low and high risk regions. The increase in the level of competition in the market results in a decrease in the equilibrium prices in both regions, as expected, and the average of premiums in both region decline as well. However, the average of penetration rates (i.e., the number of homes purchasing insurance divided by the total number of homes in the region) shows different patterns. Penetrations decrease in the low risk prices even though prices decrease because of the $100 minimum on policies. In the high risk region penetrations increase because more homeowners can afford insurance because of retrofit which has caused premiums to decline because the expected losses have declined.

Table 3.4. Summary of Average Equilibrium Prices, Average Premiums and Average Penetration Rates

Number of Carriers	Avg. Prices		Avg. Premiums		Avg. Penetration Rates	
	High	Low	High	Low	High	Low
1	$5.35	$5.35	$1,663	$578	60.02%	50.14%
2	$2.44	$5.35	$1,499	$578	69.38%	50.13%
3	$2.14	$5.35	$1,511	$578	70.90%	50.13%
4	$1.95	$4.59	$1,501	$554	71.82%	48.00%
5	$1.79	$3.91	$1,447	$520	71.91%	45.32%

Table 3.5 presents the thirty-year average of total, insured and uninsured expected losses in low and high risk regions. In both regions, as the level of competition increases, the prices decrease, which leads to increases in insured losses and therefore decreases in uninsured losses. As prices decline the market for insurance becomes larger because fewer people are closed out of the market due to budget limitations. In addition, as prices decline, more people are no longer eligible for insurance because of the $100 limit however; those homeowners are a small part of the market because these losses are limited. For example, in the high risk zone, the number of households that cannot purchase because of the budget constraint drops to about a quarter with 5 carriers in contrast to the monopoly market. Since many more people can afford insurance with 5 carriers, more people are actually faced with the choice of whether or not to purchase and therefore select not to.

Table 3.5. Summary of Averages of Insured, Uninsured and Total Expected Losses over Thirty Years

Region	# of Carriers	Total Loss ($ M)	Insured Loss ($ M)	Uninsured Loss ($ M)						
				Because of $100 Limit		Because of Budget Constraint		Because of Unwillingness of Purchasing		Total
Low Risk	1	142	$81	$22	37%	$19	31%	$20	32%	$61
	2		$81	$22	37%	$19	31%	$20	32%	$61
	3		$81	$22	37%	$19	31%	$20	32%	$61
	4		$82	$25	42%	$15	25%	$20	34%	$60
	5		$82	$28	47%	$12	20%	$20	33%	$60
High Risk	1	376	$92	$3	1%	$257	90%	$25	9%	$284
	2		$173	$6	3%	$136	67%	$62	30%	$204
	3		$196	$7	4%	$98	55%	$75	42%	$180
	4		$213	$7	4%	$72	44%	$84	51%	$163
	5		$222	$8	5%	$60	39%	$87	56%	$154

Figure 3.10 and Figure 3.11 present the profit per firm and the total insured expected losses over 30 years across the 2,000 scenarios, respectively. As the level of competition increases, the firm profitability drops substantially, however, the total insured losses increase due to the decline in market prices. This decline in profitability as competition increases negatively impacts insolvency rates (Table 3.6). Average profit decreases very marginally in the first several years due to retrofit.

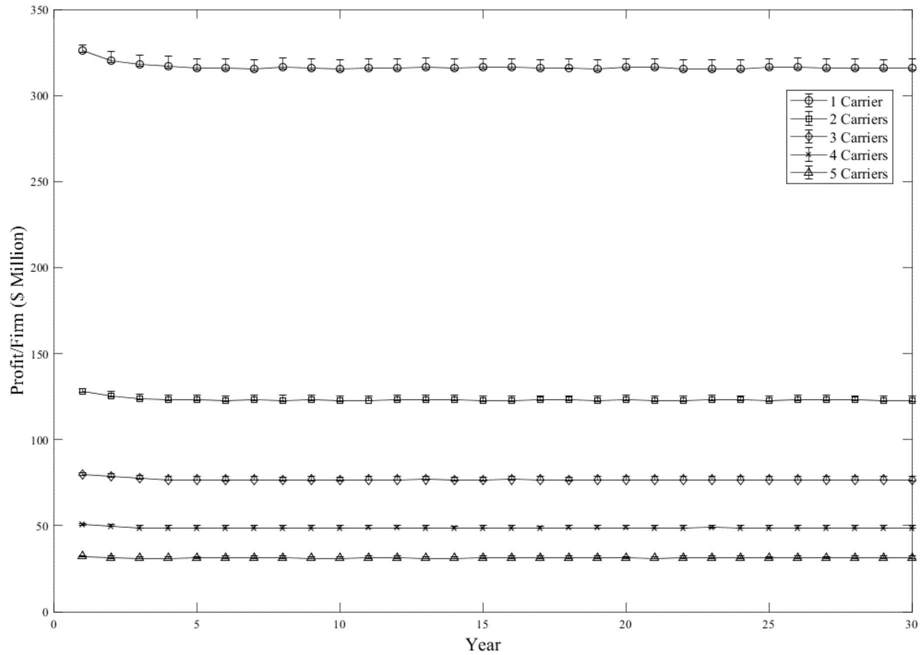


Figure 3.10. Annual Profit per Firm

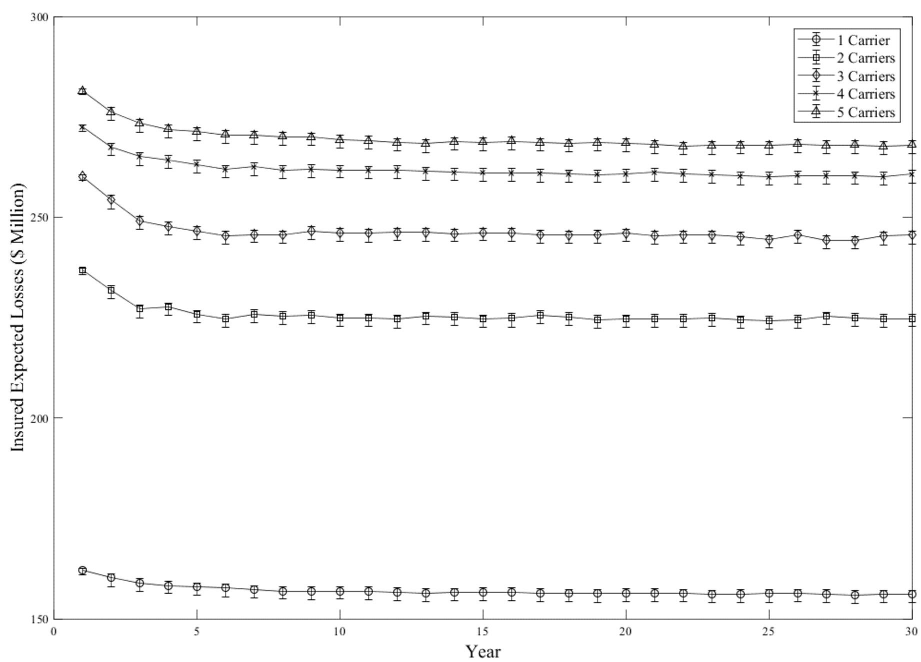


Figure 3.11. Total Insured Expected Losses

Table 3.6. Averages of Insolvency Rates in High and Low Risk Regions

Number of Carriers	Insolvency Rates	
	High	Low
1	1.54%	1.13%
2	1.98%	1.32%
3	2.05%	1.65%
4	2.09%	1.76%
5	2.13%	1.89%

3.4 Conclusions

In this chapter, we presented a dynamic framework for modeling the natural hazard catastrophe loss insurance market. The framework captures the evolving interactions between key stakeholders (home owners, insurers, reinsurers, and the government) in the market, and the competition between insurers. Exercising the model on a case study of eastern North Carolina, as expected, indicate that the level of concentration in the insurance market can lead to significant differences in the operational decisions for insurance firms. As competition in the market increases, there are a substantial decrease in equilibrium prices which is associated with a decrease in the profit for the insurance firms. With a single carrier about 33% of the annual average total loss is insured. At 5 carriers, insured loss reaches almost 60%. Even at 5 carriers, about 14% of the expected loss remains uninsured due to affordability when the threshold for affordability are 5% and 2.5% of the value of the home in the high risk and low risk zones, respectively. It is important to notice that these values are rather high compared to the standards for affordability suggested in the Homeowner Flood Insurance Affordability Act of 2014 (HFIAA 2014). HFIAA suggests a standard for affordability of 1% of the value of the home. That is, premiums that exceed the 1% threshold are assumed to be unaffordable (NRC, 2015).

Retrofit leads to about 16% decrease in expected losses but has a relatively minor impact on insurance prices. Also prices, even with substantial competition, are higher in the low risk region; but, since the hazard is much greater, premiums charged in the high risk region substantial outpace those in the low risk region.

Future research in at least two directions is particularly useful. First, this modeling does not consider any opportunity for the government to acquire repetitive high loss properties. To control escalating costs associated with hurricanes, reducing the number of large dollar repetitive loss properties is likely to be very important. Finally, it is important to extend this work to understand how government programs to support mitigation can be effectively designed and how much risk can be "bought out" via this strategy.

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