A COMPUTATIONAL FRAMEWORK TO SUPPORT

GOVERNMENT DECISION-MAKING

IN REGIONAL HURRICANE RISK MANAGEMENT

by

Dong Wang

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LIST OF NOTATIONS

Notation	Explanation
A	Attachment point in reinsurance treaty
b	Homeowner insurance purchase decision in the utility-based model, one if homeowner purchases insurance, zero if not
$B_{imc'}^{h}$	Loss up to the deductible homeowner need to pay if buys insurance
c	Building resistance level (based on combinations of components)
c’	Building resistance level after retrofit
cc’	Eligible retrofit options
f	Choice situation for the homeowner in mixed logit model of homeowner insurance purchase decision
h	Index of hurricanes
H	Total number of possible hurricane events (H = 97)
i	Geographic area unit or location (e.g., census tract)
j	Indicator for different choice alternatives in mixed logit model of homeowner insurance purchase decision
J	Max number of alternative j
k	User-specified weight of expected total loss
$K_{mc}^{c'}$	Cost to retrofit a building in category m from initial resistance level c to final resistance level c' ($)
L^{h}	Loss in hurricane h, weighted sum of the total loss to uninsured buildings and total loss to insured buildings
L_{imc}^{h}	Loss a building in area unit i, of category m and resistance level c experiences in hurricane h
m	Building category (based on architectural features)

Notation	Explanation
M	Maximum payment in reinsurance treaty
n	Decision-maker indicator in mixed logit model of homeowner insurance purchase decision
N^h	Total loss to *insured* buildings in hurricane h
$P_{imc'v}$	Premium homeowner pay in the utility-based homeowner model
P^h	Annual occurrence probability of hurricane h
q	Binary index indicate the property acquisition accept decision, one if homeowner accepts acquisition, zero if not
r	Likelihood ratio index to evaluate the mixed logit models
R	Max limit of retrofit subsidy for one home ($).*Decision variable in government model.*
s	Scenario defined as a long-term timeline of hurricane occurrence
S	Total number of hurricane scenarios (S = 2000)
t	Time period
T	Total number of time periods (T = 600)
$u_{imcv}^{qbc'}$	Homeowner decision variable. Probability homeowners in area unit i, category m, resistance level c, and risk region v makes insurance choice b, retrofit house from resistance level c to resistance level c', and accept acquisition q
U^h	Total loss to uninsured buildings under hurricane h
v	Risk region, defined as larger geographic region made up of many area units i
V_m	Value of a building in category m
w_{imcv}	Probability homeowners in area unit i, category m, resistance level c, and risk region v buy insurance. *Decision variable in homeowner model*
W	Government decision about how many area units to offer property acquisition. *Decision variable in government model.*

Notation	Explanation
x	Covariate in mixed logit model of homeowner insurance purchase decision
X_{imcv}	Number of buildings in area unit i, category m, resistance level c, and risk region v
z	Percentage of retrofit cost subsidized (0 to 1). *Decision variable in government model.*
α	Coefficients for variables other than premium and deductible in mixed logit model
β	A vector of coefficients of the variables for decision-maker in mixed logit model
γ_U/γ_N	User-specified weight of uninsured/insured loss
δ_{imc}	Percentage of buildings in area unit i, category m, resistance level c will do any retrofit given the grant at z percentage with maximum limit J. *Output from homeowner model*.
ε	A random term that is independent and identically distributed (iid) extreme value and represents the factors that affect utility but are not observed in the mixed logit model
η	Parameters of the distribution (e.g., mean and covariance of β) in mixed logit model
θ_v	Risk attitude for homeowner in risk region v
κ_v	User-specified constant to define homeowner's insurance purchase budget as percentage of building value, may vary for different risk regions v
λ_v	Primary insurance pricing loading factor for risk region v
Λ_v	Maximum allowable profit loading factors from government decision
ν_i	Binary variable that is one if homeowner in area unit i is offered acquisition by government; and zero otherwise. Output from ranking from homeowner risk by different area unit.
ξ	Price government offers for acquisition as fraction of building value. *Decision variable in government model.*

Notation	Explanation
ρ	Minimum premium required for insurance purchase (raw premium in discrete choice model, and premium in utility model)
τ	Primary insurer administrative loading factor
φ	Shrinkage, a measure of the amount of overfitting present
ϕ	User-specified allowable expected loss
χ	Minimum net benefit required for each retrofit (-$300)
ψ_{im}	Percentage of buildings in area unit i, category m that accept acquisition when offered. *Output from homeowner model*.
$\mathit{\Omega}$	Government budget limit for retrofit grant and acquisition. It's a user-specified input.

ABSTRACT

This dissertation introduces a computational framework that can be used to identify hurricane disaster risk management policy solutions based on behavior of the system as a whole, including interactions among multiple types of stakeholders (homeowners, insurers, government, reinsurers) and strategies (insurance, retrofit, property acquisition), Specifically, it supports the following government decisions: (1) how much to spend on mitigation, (2) how to regulate the price of extreme event insurance, (3) how to allocate spending between homeowner retrofit grants and property acquisition, and (4) how to design retrofit grant and acquisition programs. The framework includes four interacting mathematical models—stochastic programming optimization models to represent government and insurer decisions, empirical discrete choice models of individual homeowner decisions, and a regional loss estimation model. It includes a description of how insurers and homeowners are expected to respond to government policies and what the outcomes will be for each. A full-scale application for eastern North Carolina suggests it is possible to identify system-wide win-win solutions that are better both for each stakeholder type individually and for society as a whole. For comparison, another version of the framework that uses a utility-based homeowner decision model is also presented. The comparison shows some similarities and differences between the two frameworks and in particular, suggests the utility-based framework is more sensitive to price changes.

Within this extended framework, understanding the circumstances under which homeowners will purchase insurance is critical to creating an effective insurance market for hurricane wind and flood loss. This dissertation introduces empirical homeowner wind and flood insurance purchase decision models, which contribute to the empirical literature on the subject through an analysis of survey data for homeowners in North Carolina. Separate mixed logit models for flood insurance and wind insurance purchasing decisions are developed. The analysis uses stated preference data on the influence of premium and deductible to address some limitations of revealed preference data in which it is difficult to fully decouple effects of premium, deductible, risk, and coverage limit, and mandatory purchase requirements. The results for flood insurance and wind insurance are similar. There is evidence that the following are all significant and associated with higher probability of purchasing insurance—lower premium, lower deductible, more recent previous hurricane experience, location in a flood- plain or closer to the coast, higher income, and younger homeowners. However, demand is relatively inelastic with respect to premium and deductible, and the willingness to pay for a $1 reduction in deductible varies throughout the population with some willing to pay more than $1, a behavioral anomaly. The recency of the last hurricane experience is more influential for homeowners who experienced damage than for homeowners who did not. Results suggest that insurance purchase and home retrofits are complements, not substitutes. Finally, statistical models that can be used to predict insurance penetration rates for a region under different premium levels are presented to be used in the framework.

Chapter 1

INTRODUCTION

1.1 Introduction

The current government system for managing hurricane risk associated with existing buildings in the U.S. has evolved over time, with periodic developments in response to disaster events or new understanding of the risks. It now includes initiatives to supplement the private insurance market, such as, the National Flood Insurance Program (NFIP) that has covered flood loss since 1968, and state catastrophe insurance programs such as state wind pools (or “beach plans”) that aim to serve residents unable to obtain policies in the private market (Kousky 2011a). It also includes risk reduction initiatives, such as, the Hazard Mitigation Grant Program (HMGP), the Flood Mitigation Assistance (FMA) Program, and the Pre-Disaster Mitigation (PDM) Program, which support property acquisition and other projects, as well as scattered state and local programs to encourage building owners to undertake retrofits, such as the My Safe Florida Home program, which operated from 2007 to 2009, offered homeowners a free vulnerability assessment and the possibility of a $5,000 grant to retrofit (Smith et al. 2016).

Despite these myriad efforts and some successes, however, the current system is not as effective or sustainable as it could be. Most homeowners do not invest in pre-event retrofit activities to reduce damage, nor do they adequately insure, and thus, they are vulnerable to severe disruption in extreme events and often lack sufficient resources to recover. Insurers are concerned about low penetration rates and potential insolvency. The NFIP is deeply in debt, owing $24.6 billion before the major hurricanes of 2017 (U.S. GAO 2017), and many state catastrophe pools lack sufficient funds to cover large-scale disasters (Kousky 2011a). Even with these initiatives, disasters are typically followed by large, unplanned (and thus, often inefficient) government expenditures that create major budget difficulties.

To better understand this challenge and develop solutions, this dissertation focuses on the behavior of the system as a whole to help support government regional hurricane risk management. The system includes interactions among the many types of stakeholders (e.g., homeowners, insurers, government, reinsurers) and among the many strategies (e.g., insurance, retrofit, property acquisition). These interactions are critical because no one stakeholder can solve the problem alone. Each stakeholder acts with its own objectives, available alternatives, perceptions, biases, timelines, constraints, and information about the risk and risk management options. The result can be outcomes that are suboptimal for everyone. While it is in the interest of all of those groups to reduce the vulnerability of the residential inventory, for example, only homeowners have the authority to purchase insurance for their homes or make physical changes through retrofits, and it may be rational for them to choose not to mitigate given their budget constraints and/or relatively short expected tenure. Insurers and government agencies influence homeowners' decisions by modifying pricing, providing incentives, and enforcing regulations; however, they do not physically change the inventory themselves. Further, no one strategy can solve the problem alone. They act in different ways. For an individual homeowner, insurance reduces variability by removing the tail of the loss distribution, while retrofit lowers the mean loss, and property acquisition removes the chance of loss altogether.

1.2 Computational Modeling Framework

With these challenges in mind, a computational framework to examine hurricane risk management from a systems perspective has been developed recently, with different versions described in Kesete et al. (2014), Peng et al. (2014), and Gao et al. (2016). The different versions of the framework together include four interacting mathematical models: (1) a utility model of homeowner decision-making by individual homeowners, (2) a stochastic programming model of decision-making by individual primary insurers, (3) a Cournot-Nash model of insurer competition, and (4) a loss estimation model. The framework has been implemented for hurricane risk, but it could be adapted to other hazards as well.

Table 1.1 summarizes the differences among the versions, including the new one presented in this dissertation. The Kesete et al. (2014) version considers only insurance (not retrofit or property acquisition), uses a utility-based homeowner model of insurance decisions and includes a stochastic programming model of the decisions made by a single primary insurers without competition. The Peng et al. (2014) version is similar to Kesete et al (2014), except that homeowners decisions about retrofit are also included. The Gao et al. (2016) version advances Kesete et al. (2014) by adding a Cournot-Nash model of insurer competition. The version of the framework in this dissertation builds on Peng et al. (2014) by including an empirical discrete choice model (DCM) of homeowner decisions about insurance, retrofit, as well as acquisition, and including a new model of government decision-making (rather than treating the government as an exogenous player). A version with the original utility-based homeowner decision model is also tested for comparison in Chapter 4.

Table 1.1: Different computational framework versions

Paper	Homeowner model	Insurer competition included?	Retrofit included?	Acquisition included?	Government model included?
Kesete et al. 2014	Utility	No	No	No	No
Peng et al. 2014	Utility	No	Yes	No	No
Gao et al. 2016	Utility	Yes	No	No	No
This work	Utility or DCM[a]	No	Yes	Yes	Yes

[a] DCM is short for discrete choice models

The version of the computational framework in this dissertation includes a model of government decision-making, an empirical homeowner decision model with insurance, retrofit, and property acquisition as strategies, a stochastic programming model of decision-making by a single primary insurer, and a loss estimation model (Figure 1.1).

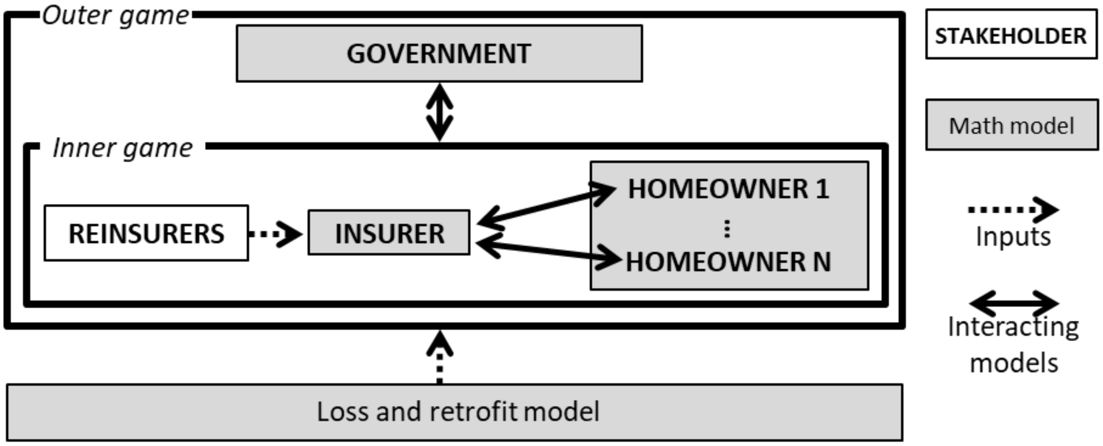

Figure 1.1: Hurricane risk management computational modeling framework

1.3 Case Study Area

The application of the framework is demonstrated for a full-scale case study for hurricane risk to single-family residential buildings in eastern North Carolina (Figure 1.2). It includes Raleigh (the capital) east to the coast. The survey data used to develop the empirical homeowner insurance purchase, retrofit action and acquisition decision models was also collected in the same area. Many devastating hurricanes have affected this area, including Floyd (1999), Isabel (2003), Irene (2011). Sandy (2012), Matthew (2016), Maria (2017) and Florence (2018). This is the same study region used in Kesete et al. (2014), Peng et al. (2014), and Gao et al. (2016).

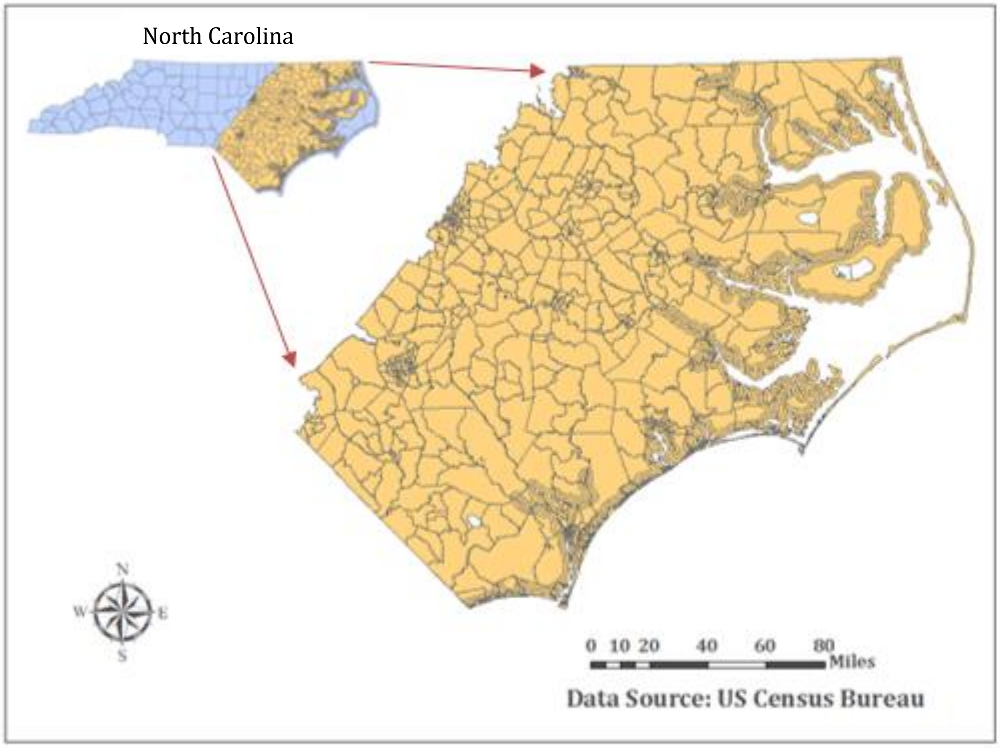

Figure 1.2: Case study area – eastern North Carolina (yellow shaded)

1.4 Contributions

The main contributions in this dissertation are:

(1) To develop the empirical models of how homeowners make insurance purchase decisions for hurricanes and integrate them into the framework. The models are separate mixed logit models for flood insurance and wind insurance purchasing decisions as a function of premium, deductible, and selected attributes of the homeowner and insured property. This work is documented in Chapter 2.

(2) To develop a new version of the computational framework, one that for the first time includes (a) the government as an outer game player that interacts with the insurer and homeowners in the inner game, (b) empirical homeowner models, and (c) acquisition as a strategy (Chapter 3). The government model is formulated as an optimization model aiming to minimize societal loss under a budget constraint. In the optimization model, the government interacts with homeowners by offering acquisition and a retrofit grant and interacts with the primary insurer by imposing a restriction on pricing (Chapter 3).

(3) To implement the computational framework in eastern North Carolina to demonstrate how the interactions among different stakeholders affect the decisions and outcomes for each stakeholder and the whole society (Chapter 3).

(4) To examine the effect of the homeowners model type by comparing the new framework version results with the discrete choice homeowner models to one with the original utility model (Chapter 4).

The empirical homeowner hurricane insurance decision model contributes to the empirical literature on the subject through an analysis of survey data for homeowners in North Carolina. Most of the literature focuses on flood insurance and uses revealed preference data. The data in this dissertation address both wind and flood insurance in parallel, and includes discrete choice experiment questions asking whether homeowners would purchase insurance under different hypothetical premium and deductible combinations. In particular, the work focuses on: (1) developing statistical models that can be used to predict insurance penetration rates for a region under different premium levels, (2) understanding the influence of certain factors on homeowner insurance purchasing decisions— in particular, premium, deductible, previous hazard experience, risk, and previous retrofit actions, and (3) comparing the insurance purchasing decisions for flood and wind perils. Models that could be used in a predictive mode for a region can be helpful in and of themselves to assess the likely effect of rate changes and/or within the framework modeling the larger insurer-homeowner system of managing hurricane risk. Comparison of models for flood and wind perils can help determine if the research findings based on the flood peril are likely to apply to wind as well.

The computational framework in this dissertation helps to identify policy solutions that are better both for each stakeholder type individually and for society as a whole. By recognizing the stakeholders' different perspectives up front as an integral part of the analysis, the modeling framework makes it possible to identify those win-win system-wide solutions that are most likely to be effective and that are easier to build a coalition around instead of finding solutions that are theoretically best but unworkable in practice. This approach complements the traditional method of making incremental changes to the existing system and focusing on how to convince homeowners and other stakeholders to undertake actions considered desirable for community resilience. Specifically, the framework helps address the following questions: (1) How should the government optimize its risk management spending within a realistic context defined by homeowners, insurers, and reinsurers, using an assessment of actual hurricane risk? Specifically, how much should the government spend on risk management, what is the best combination of government interventions—homeowner grants for retrofit, property acquisition, and insurance pricing regulation—given a specified budget, and how should a grant and acquisition programs be designed? How do changes in the societal objectives affect the government's best policies? (2) How will those policies play out within the system? That is, how is each stakeholder type likely to react to different government interventions, and what will the consequences be for each?

The comparison between the new framework version results with the discrete choice homeowner models to one with the original utility model is also a contribution. As utility-based homeowner models have been widely used in the previous research, it is important to understand the effects of different choices of homeowner models in the framework.

1.5 Outline of Dissertation

This dissertation has five chapters. Following the introduction in Chapter 1, Chapter 2 describes the discrete choice models of homeowner hurricane insurance purchase decisions, and how the homeowner decision models fit in the overall computational framework. Chapter 3 introduces the new version of the framework that incorporates the government as an outer game player that interacts with stakeholders in the inner game. A full-scale case study for hurricane risk to single-family residential buildings in eastern North Carolina is conducted to demonstrate application of the framework. Chapter 4 compares the similarities and differences between the utility-based framework and the DCM-based framework using the case study in eastern North Carolina. Key contributions and possible future extensions are summarized in Chapter 5.

Chapter 2

HOMEOWNER PURCHASE OF INSURANCE FOR HURRICANE WIND AND FLOOD PROTECTION

This chapter describes development of empirical homeowner hurricane insurance decision models based on survey data from eastern North Carolina, and integration of these discrete choice models into the computational framework to predict homeowner insurance decisions. Section 2.1 describes how homeowner insurance decisions have been addressed in the previous literature, Section 2.2 introduces the covariates to be included in our discrete choice models, and their hypothesized effects on insurance purchase decisions, Section 2.3 describes the survey data used in developing the models, Section 2.4 introduces the mixed logit model and how the survey data was fitted to produce the mixed logit models, and Section 2.5 explains the results in detail.

2.1 Literature Review

Empirical research across multiple disciplines has addressed insurance purchase for flood and wind perils through surveys, controlled experiments, and analyses of data on policies purchased. Survey-based research includes Baumann and Sims (1978), Pynn and Ljung (1999), Blanchard-Boehm et al. (2001), Kriesel and Landry (2004), Landry and Jahan-Parvar (2011), Petrolia et al. (2013), Petrolia et al. (2015). More recently and most similar to the current study, researchers in the Netherlands have conducted discrete choice and contingent valuation experiments to collect stated preference data since flood insurance is not currently available in that country (Botzen and van den Bergh 2012a, b; Botzen et al. 2013, Brouwer and Schaafsma 2013). Experiment-based studies include Slovic et al. (1977), McClelland et al. (1993), and Ganderton et al. (2000). More recently, researchers have analyzed data on actual insurance policies purchased from the NFIP (Browne and Hoyt 2000, Dixon et al. 2006, Zahran et al. 2009, Michel-Kerjan and Kousky 2010, Kousky 2011b, Atreya et al. 2015, Kousky and Michel-Kerjan 2015). These analyses focus on data from different geographic regions, time periods, and units of analysis (individual policies to states). Grace et al. (2004) analyzes Insurance Services Office (ISO) data for standard homeowner's insurance policies, viewing them as bundled coverage of catastrophe and non-catastrophe coverage and attempts to disaggregate the two. Kunreuther and Michel-Kerjan (2009) presents two similar analyses of standard homeowners' insurance policies—one using data for the entire Florida homeowners' market for 2006, the other using data from seven companies representing 50% of the markets in Florida, South Carolina, New York, and Texas for 2000-2005. Nyce and Maroney (2011) analyze wind insurance data from Citizens Property Insurance Corporation in Florida, but do not model demand.

Most of these studies reported a regression model with the response variable *has insurance or not* (when at the household or policy unit of analysis), *number of policies per 1000 people* (when a larger area is the unit of analysis), or *amount of coverage or claims*. In all except the recent studies from the Netherlands the data are revealed preference data, and in most, it relates to flood insurance, probably because flood insurance is typically purchased separately in the U.S. While revealed preference data describe homeowner behavior within the system as it currently is, stated preference data are not constrained by the features of the current system. The stated preference data in this study thus complement previous research. Although coverage of the wind peril is typically intertwined with standard homeowners' insurance in the U.S., in a stated preference format, it can be separated cleanly, like the flood peril is in the NFIP. Stated preference allows more direct investigation of the sensitivity to premiums and deductibles as well. NFIP premiums are set based on flood zone and a limited set of house attributes (Kousky 2011b), and state pool wind policy premiums are typically set at the state level with differences based only on mitigation activities undertaken (Petrolia et al. 2015). In the revealed preference data, therefore, it is difficult to decouple the effects of premium and risk level (Kousky 2011b; Petrolia et al. 2015, Landry and Jahan-Parvar 2011). Premiums and deductibles are also linked and so the tradeoff between them is determined in the rate setting. The fact that some homes in the 100-year floodplain are required to buy can also complicate the interpretation of results in some studies. Finally, premium data are not available for homeowners who did not purchase insurance, so in previous studies, researchers have had to conduct the analysis at an aggregate scale (e.g., county) rather than an individual policy level (e.g., Kousky 2011b, Atreya et al. 2015), estimate what the premiums would have been for non-purchasers (e.g., Kreisel and Landry 2004, Dixon et al. 2006), or use a response variable other than whether or not insurance was purchased (e.g., claim/coverage purchased in Michel-Kerjan and Kousky 2010).

Collectively, the empirical research has identified many factors that may influence homeowners natural hazard insurance purchase decisions, including: (1) probability and potential magnitude of loss (e.g., hazard proximity, attributes of structure, home value, mortgage); (2) policy attributes (e.g., premium, deductible, coverage limit, contract duration); (3) psychological factors (e.g., risk perception, worry, hazard experience); (4) demographic factors (e.g., wealth, income, age); (5) social influences (e.g., regulations, neighbors' actions, local government mitigation activities); (6) responsibility (e.g., expectation of disaster assistance, expectation of insurer claim payment); and (7) emotion-focused coping strategies (e.g., wishful thinking, fatalism). In Section 2.2, we focus on literature directly related to variables of interest in this study.

2.2 Covariates and Hypotheses

This section discusses each variable in turn, and makes hypotheses based on best understanding from literature. Results of the hypothesis tests are presented in Section 2.6.

2.2.1 Premium and deductible

The effect of a change in premium on the likelihood homeowners will buy flood and wind insurance is of great interest. High premiums reduce penetration rates, leaving more homeowners uninsured and increasing societal risk. Low premiums can impede insurers' ability to build adequate reserves (Kousky 2011b). Finding the best balance requires an understanding of how sensitive homeowners' flood and wind insurance purchase decisions are to premiums, and how that sensitivity varies throughout the population. To date, a clear statement on the subject remains elusive. Most importantly, estimated premium elasticities from all studies relying on revealed preference data are influenced by the correlations between premium and risk, deductible, and coverage limit, and by the effects of regulations such as the mandatory purchase requirement and subsidies (Kousky 2011b, Landry and Jahan-Parvar 2011). Keeping that in mind, empirical studies that have reported premium elasticities for flood or general homeowners' insurance have presented values ranging from -0.1 (inelastic) to about -2.0 (elastic), a range that could lead to different policy decisions (Table 2.1). Some of the variability may be explained by the fact that the studies are not all directly comparable because of differences in the perils covered, the metrics defined for insurance demand and premium, and the aggregation level used in the analysis. Premium can be measured as absolute premium (used in this study), marginal premium (e.g., dollars per $100 coverage), or a measure of the value added per dollar output (e.g., (premium – L)/L, where L is the present value of expected loss). In examining how premium elasticities might vary across the population, Landry and Jahan-Parvar (2011) found evidence that they are more elastic for homeowners that have explicitly subsidized rates and for those that do not hold a mortgage. Grace et al. (2004) found they were much higher for catastrophe coverage than non-catastrophe coverage. Kunreuther and Michel-Kerjan (2009) found they were higher in South Carolina and New York than Florida and in some cases varied with wind risk, although the findings there were not consistent.

Table 2.1: Premium elasticities reported in the literature

Source	Place	Premium elasticity	Note
Flood insurance			
GAO 1983	U.S.	-0.38	
Browne and Hoyt 2000	U.S.	-0.109 -0.997	Depends on demand definition
Krisel and Landry 2004	Coastal counties	-0.259	
Dixon et al. 2006	100 NFIP communities	-0.06	
Landry and Jahan-Parvar 2011	Near coast, Southeast	-0.620; -0.870[a] -1.550; -4.478 -0.133; -0.502	All Subsidized properties Non-subsidized properties
Botzen and van den Bergh 2012a	Netherlands	-1.27	
Botzen et al. 2013	Netherlands	-0.3	
Atreya et al. 2015	GA	-0.156 to -0.302	Depending on model
This study	NC	-0.263	Base model
Homeowners insurance			
Grace et al. 2004[b]	FL	-1.079 -1.915 -0.404	Total Catastrophe Non-catastrophe
	NY	-0.857 -2.064 -0.331	Total Catastrophe Non-catastrophe
Kunreuther and Michel-Kerjan 2009	FL	-0.893	County-level study
	FL	-0.245 (-0.067 to -0.475)	Zip code-level study Average and (range) over 5 years
	SC	-1.241 (-0.949 to -1.637)	
	NY	-0.762 (-0.599 to -1.275)	
Wind insurance			
This study	NC	-0.483	Base model

[a] Values based on High; Low assumptions in determining premium. Authors suggest high value is probably a better estimate.
[b] Views homeowners' insurance as catastrophe and non-catastrophe coverage bundled.

Deductible is not included as a covariate in any of the models based on NFIP data, but Michel-Kerjan and Kousky (2010) and Kousky (2011b) both analyzed deductible choices and found that most people chose a low deductible and the choice varied with flood zone. In 2005 in Florida, for example, almost 80% of policies had the lowest available deductible ($500), 18% the second lowest ($1000), and only 2% had the maximum available ($5000) (Michel-Kerjan 2010). This choice of low deductibles even when it does not make financial sense is consistent with the literature on other lines of insurance (Kunreuther and Pauly 2006). Further, homeowners in the SFHA (special flood hazard area, i.e., 100-year floodplain) tended to choose higher deductibles than those outside the SFHA. The authors suggest that may be because within the SFHA, homeowners are required to buy insurance, so they may then try to minimize cost by increasing deductible. In their analysis of standard homeowners' policies, Grace et al. (2004) discuss two possible conflicting effects of a higher wind deductible—reducing the premium (making it desirable), and increasing the risk the homeowner bears (making it undesirable). They find that on balance, the first effect dominates for catastrophe coverage, but the latter dominates for non-catastrophe coverage. Botzen et al. (2013), which used the stated preference data for flood insurance in the Netherlands, included deductible (in euros) in their model of the insurance purchase decision and found an elasticity of -0.18, meaning a 1% increase in deductible decreases the probability of buying insurance by 0.18%.

Hypotheses: Lower premium (H_1) and lower deductible (H_2) are associated with higher probability of insurance purchase.

2.2.2 Previous hazard experience

Baumann and Sims (1978), Browne and Hoyt (2000), Zahran et al. (2009), Botzen and van den Bergh (2012a), Petrolia et al. (2013), and Atreya et al. (2015) all provide evidence that prior experience with flood events is associated with an increase in flood insurance purchase. In Florida, from 2004 to 2005 the number of NFIP policies jumped 6%, compared to at most a couple percentage points each year from 2000 to 2004, possibly due to homeowners' experience with the four hurricanes that made landfall in Florida in 2004 (Michel-Kerjan and Kousky 2010).

Since the relationship between insurance purchase and prior experience with hazard events may depend on the specific nature of the experience—number and recency of events, and severity and nature of the overall impact of the event and of the impact to the homeowner personally—it is worth examining the extent to which the literature provides insights into these features of prior experience. Botzen and van den Bergh (2012a), Baumann and Sims (1978), Browne and Hoyt (2000), Zahran et al. (2009), and Atreya et al. (2015) all specify prior experience in a way that requires an impact associated with the experience—evacuation for the first, damage for the others. Baumann and Sims (1978) also provides some evidence that the percentage of people with insurance increased with the perceived severity of the flood damage. Focusing on the number of experiences, Petrolia et al. (2013) found that each additional flood event experienced increases the probability a homeowner holds flood insurance by 11%, and Zahran et al. (2009) found the addition of one flood per year in a county increases the number of NFIP policy holders per 100 households by 27%. Considering the importance of recency, Browne and Hoyt (2000) defined prior experience as the total flood damages in a state ($) from the prior year only, so the effect of damage before that it is not clear. Baumann and Sims (1978) found that the increased rate of insurance purchase following the 1972 floods only lasted about 6 months. Atreya et al. (2015) included covariates for a county's flood damage per capita ($) 1, 2, 3, 4, 5, and 6 years prior and found that they were significant one to three years prior, but not earlier than that.

Hypotheses: More hurricane experiences (H_3) and less time since the last hurricane experience (H_4) are associated with higher probability of insurance purchase. Further, the time since the last hurricane experience is more influential for homeowners who experienced damage (H_5).

2.2.3 Risk/geographic proximity to hazard

One would expect homeowners to be more likely to purchase insurance for homes with a higher hurricane risk. Homeowners are often not fully aware of their home's risk, which depends on the hazard at the location (i.e., probability, intensity of wind speeds and flood depths), exposure (i.e., value at risk), and structural vulnerability (i.e., likelihood of damage given a specified load). Although computer models could be used to estimate a home's risk, for simplicity and perhaps to focus on the aspects of risk a homeowner is most likely to be aware of, studies have concentrated instead on geographic proximity to the hazard, as measured by location in the 100- and/or 500-year floodplain, and distance from the river or coastline. Zahran et al. (2009), Kousky (2011b), Petrolia et al. (2013), Atreya et al. (2015) found increased demand for flood insurance associated with location in the floodplain. This could reflect an effect of the risk and/or the mandatory purchase requirement in the floodplain. Landry and Jahan-Parvar (2011), which focused on a data sample within 1000 ft. of the coast, found coverage increased moving from FEMA flood zone B/C/X (moderate to low risk) to A (high risk) to V (high risk coastal). A larger distance from the main river was associated with a smaller willingness to pay for flood insurance in Botzen and van den Bergh (2012a, b). A larger distance (km) from the shoreline was associated with decreased demand for flood insurance in Kriesel and Landry (2004) and Petrolia et al. (2013) (marginal effects=-0.0011 and -0.002, respectively), and for wind insurance in Petrolia et al. (2015).

Hypotheses: Location in a floodplain (H_6) and smaller distance from the coast (H_7) are associated with higher probability of insurance purchase. The former will be a stronger effect for flood insurance; the latter for wind insurance.

2.2.4 Previous retrofit actions

Although insurance and structural retrofitting are both ways to manage hurricane risk for homes, they have largely been studied separately in the empirical literature and questions remain about the circumstances in which they are substitutes or complements. Using the percentage of policies with the wind protection device credit in Florida as a covariate, Grace et al. (2004) found that more wind protection is associated with lower demand for catastrophe coverage but greater demand for non-catastrophe coverage, suggesting catastrophe insurance and retrofit are substitutes. On the other hand, in an analysis focused directly on the intersection of insurance and mitigation for wind, Petrolia et al. (2015) found that wind insurance purchase and the number of wind mitigations installed (0 to 7, e.g., storm shutters, roof anchors, wind-resistant glass) are positively correlated, suggesting that insurance and retrofit are complements. A large dataset from the My Safe Florida Home program in Florida provided evidence that homeowners who chose a larger deductible were less likely to mitigate, but if they did, spent more on the mitigation (Carson et al. 2013). There is also a theoretical literature on the interactions between insurance and mitigation based on the seminal paper, Ehrlich and Becker (1972) and summarized in Shan et al. (2016), but that is largely based on assumptions of rational behavior and expected utility.

No Hypothesis: The relationship between previous retrofit actions and probability of insurance purchase is unclear.

2.2.5 Income and age

Income has frequently been used as a covariate in empirical studies of demand for homeowner insurance for flood and/or wind. Income tends to be highly correlated with wealth and thus there are multiple possible competing hypotheses of the relationship with demand for insurance (Ganderton et al. 2000, Grace et al. 2004). A higher income and wealth could suggest increased demand for insurance because greater disposable income would make the premium more affordable and the value at risk (i.e., potential loss) increases. On the other hand, it could suggest decreased demand for insurance because the potential losses are a smaller share of wealth, and risk aversion tends to decrease with wealth all leading to a tendency to self-insure. Almost all studies (for flood, wind, and catastrophe coverage) have found that the former effect dominates and income is positively associated with insurance demand, although relatively inelastic (Baumann and Sims 1978; Kunreuther et al. 1978; Browne and Hoyt 2000; Grace et al. 2004; Kriesel and Landry 2004; Landry and Jahan-Parvar 2011; Botzen and van den Bergh 2012a, b; Atreya et al. 2015; and Petrolia et al. 2015). A couple exceptions were Kousky (2011b) and Kunreuther and Michel-Kerjan (2009), both of which had mixed results.

Evidence of a possible relationship between homeowner age and demand for flood or wind insurance is more mixed. Some studies have found insurance demand increases with age (Kunreuther et al. 1978, Atreya et al. 2015), some that it decreases with age (Kousky 2011b, Botzen and van den Bergh 2012a, b), and some did not find evidence either way (Baumann and Sims 1978, Blanchard-Boehm et al. 2001).

Hypotheses: Higher income is associated with higher probability of insurance purchase (H_8). The relationship between homeowner age and probability of insurance purchase is unclear.

2.3 Data Description

This section describes the survey used in this study, including the discrete choice experiment related to the insurance purchase questions. Imputation of missing data is also introduced.

2.3.1 Survey overview

Data were collected through a telephone survey conducted at the University of Delaware, Disaster Research Center (DRC) in the Fall of 2012 through the Spring of 2013. The survey, designed to better understand household hurricane insurance and mitigation decisions, included questions about the respondent's house, hazard event experience, past insurance and home retrofit decisions, hypothetical future insurance and home retrofit decisions, and socio-demographic characteristics (details in Appendix A). The sample included 50% listed household numbers, 25% random digit dial landline numbers, and 25% random digit dial cellphone numbers, all from the Eastern half of North Carolina, including Raleigh east to the coast. Telephone numbers were purchased from *Genesys*, a third party provider. Business and disconnected numbers were purged, and screening questions were used to ensure the house was single-family or duplex, and the respondent was the homeowner and one of the people who makes insurance purchase decisions for the house. A computer-assisted telephone interviewing (CATI) system was used to administer the survey, which required 27 minutes on average to complete. Each phone number was called up to ten times, and as an incentive, participants who completed the survey were entered in to a drawing with a 1 in 100 chance of winning an iPad. After ineligible respondents are removed, the dataset includes 357 respondents with a cooperation rate of 23%. Where possible, for each variable, we compared the distribution of the sample to that for all homeowners in the Eastern half of North Carolina. The comparison suggests that the sample is reasonably representative of the population, although it is slightly older (mean age is 59 years for sample vs. 53 years for population), very slightly farther from the coast (mean is 103 km for sample vs. 94 km for population), and more likely to be in a floodplain (mean is 0.11 for sample vs. 0.03 for population). The population distribution of income was not available for homeowners, but based on an estimate using the income distribution for the population and national rates of homeownership by income bracket, the sample is likely somewhat higher income than the population. Distributions of the prior damage and retrofit variables were not available for the population.

2.3.2 Discrete choice experiment

A discrete choice experiment was included in the survey to collect stated preference information on hypothetical future household insurance purchase decisions. This provided data for the response variable. Respondents were asked to assume that wind damage from hurricanes is NOT covered by their homeowners' policy and if they want that coverage they have to buy a separate kind of policy. They were then presented with two hypothetical insurance policies that would protect against hurricane-caused wind damage only. The only differences between the alternatives in each pair were the premium and deductible. They were exactly the same in every other way. For example, "Policy A has a $250 deductible and an annual premium of $2000. Policy B has a $1000 deductible and an annual premium of $1000" (Figure. 2.1). They were asked if they would buy Policy A, buy Policy B, or not buy either policy. The question was repeated four times with different combinations of policies (i.e., deductible and premium levels) each time. A similar set of four questions was asked later in the survey but for hurricane-caused *flood* damage.

Question: Would you buy Policy A, buy Policy B, or not buy either policy?

	Policy 1	Policy 2	Neither
Deductible	$250	$1000	
Annual premium	$2000	$1000	

Figure 2.1: Example question in discrete choice experiment

The hypothetical insurance policies and choice sets were developed systematically to create an efficient design (Louviere et al. 2000). To capture the range of values considered possible in practice, four levels of deductible were defined ($250, $500, $1000, and $5000), and four levels of premium were defined ($500, $1000, $2000, and $5000). The full factorial design includes $4^2 = 16$ policies (i.e., deductible-premium combinations). After removing the two that would be dominant or dominated (i.e., best or worst, respectively, in terms of both premium and deductible), 14 candidate policies remained, which were then used to generate a fractional factorial design with eight policies. Federov's algorithm (Federov 1972), which seeks to maximize information about the parameters, was used to create the fractional factorial design. It was implemented using the *optFederov* function in the R package {AlgDesign} with a cubic model, maximizing the D criterion (Wheeler 2004, 2014). Shifts and swaps were employed to create the choice sets (Huber and Zwerina 1996). Shifting the level of each variable up one created a second set of eight policies which were then paired with the first to create an initial eight choice sets of two policies each. To ensure that no choice set included a dominant alternative (i.e., a policy that was preferred over the other in terms of both deductible and premium), a few attribute levels were swapped manually, producing the final design. The design is efficient based on the level balance, orthogonality, and minimal level overlap defined in Huber and Zwerina (1996). The order of the eight choice sets was randomized for each respondent. The first four were used in the questions related to wind damage; the second four in questions related to flood damage.

When the choice sets were developed, unfortunately an error was made in which a higher deductible was considered to be preferable to a lower deductible. As a result, all pairs of policies included one that dominated the other, i.e., was better in terms of both deductible and premium. When the error was discovered, the same process described above was repeated to create new choice sets that fixed the problem. Since some surveys had already been conducted, those respondents were called back and when possible respondents were asked the eight insurance purchase questions again, this time with the corrected choice sets. In the end, there were 106 respondents who were asked only the original questions that included a dominant policy, 95 were asked both the original and corrected questions, and 133 were asked only the corrected questions. All observations were included in the analysis for a few reasons. First, although not efficient for collecting information on the premium-deductible tradeoff, the original questions were still valid questions. Second, in preliminary analyses when we included a dummy variable to identify which of the three groups a respondent was in, it was not significant. Third, the questions do still contain valuable information about the respondent's preference for insurance with the dominant policy versus no insurance. They also provide an indication of how well respondents understood the questions. For the questions that contained a dominant policy, 81% of responses chose the dominant policy or *Neither*. This suggests that most respondents did understand the question in most cases. The 19% of questions in which the dominated policy was selected were distributed across respondents suggesting that the respondents may not have heard or understood the questions properly in those cases (as opposed to a few people fundamentally misunderstanding how premiums and deductibles work).[1]

2.3.3 Covariates

The candidate covariates were selected based on goals of: (1) including those most likely to predict the insurance purchase decision based on the literature, (2) focusing on those that would be possible to use in a predictive mode (i.e., for which data can be collected for a region), (3) limiting the total number to avoid overfitting too many parameters to too little data thus producing overly optimistic models that

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[1] As a check, we fitted the base models (a) after dropping all observations in which a dominated alternative was selected and separately (b) keeping only the corrected observations for the 95 who were asked both original and corrected. In both cases, results were quite similar in terms of sign, magnitude, and statistical significance of the coefficients, except that in case (b), x_{dist} was no longer significant in the flood model and x_{fp} was no longer significant in the wind model.

will not replicate in other data samples (Babyak 2004, Harrell 2015, Hutcheson 2011), and (4) avoiding highly correlated variables and those with narrow distributions (Table 2.2). Due to the desire to use the model for prediction at the regional level, some variables known to be potentially important were not included, such as subjective risk perception, risk preference, and others listed at the end of Section 2.1.

Table 2.2: Descriptive statistics

	Variable	Hypothesized effect[a]	Num. observations[b]	Mean	Standard deviation
y_f	Buy flood insurance (Yes/No), 1/0	---	1571	0.64	0.48
y_w	Buy wind insurance (Yes/No), 1/0	---	1620	0.78	0.42
x_p	Premium, $/year	Negative	321	1414	1743
x_d	Deductible, $/year	Negative	321	1132	1774
x_{time}	Time since last hurricane, years	Negative	295	8.04	9.05
x_{num}	Number of hurricanes experienced	Positive	318	5.94	6.10
x_{exp}	Hurricane experience, 1/0	Positive	318	0.94	0.24
x_{dam}	Prior damage, 1/0	Positive	316	0.15	0.36
x_{fp}	Location in floodplain, 1/0	Positive	292	0.11	0.31
x_{dist}	Distance to coastline, km	Negative	294	102.9	69.4
x_{ret}	House had previous wind retrofit, 1/0	Unclear	346	0.68	0.47
x_{inc}	Income[c], $/year	Positive	253	94,447	70,760
x_{age}	Age, years	Unclear	309	58.89	13.37

[a] Positive means increase in variable is associated with an increase in probability of purchasing insurance

[b] There are a total of 321 respondents and 3191 observations since each respondent answered multiple questions. (1571 observations for flood and 1620 observations for wind)

[c] Income was asked as an interval variable but was coded as a continuous variable with the values in parentheses for each interval: less than $15k ($7.5k), $15k-$35k ($25k), $35k-$50k ($42.5k), $50k-$75k ($62.5k), $75k-$100k ($87.5k), $100k-$150k ($125k), $150k-$250k ($200k), more than $250k ($300k).

Location in a floodplain (x_{fp}), a binary variable, and straight-line nearest *Distance to the coastline, km* (x_{dist}) were computed in a geographic information system (GIS) based on the address or nearest cross-streets provided. In the survey, respondents were asked "How many hurricane events have you personally experienced?" which provided *Number of hurricanes experienced* (x_{num}). If they answered more than zero to that question, they were asked for the year of their last hurricane experience to get *Time since last hurricane* (x_{time}), and for the highest degree of property damage their home has experienced during any prior hurricane event using a scale from 1 to 5, where one means no damage and five means complete destruction to get *Prior damage* (x_{dam}). Because of the small counts for levels 4 and 5, *Prior damage* (x_{dam}) was collapsed into a binary variable with 1 and 2 coded as zero, 3, 4, and 5 coded as one. Since the *Time since last hurricane* (x_{time}) and *Prior damage* (x_{dam}) variables only apply to responses with a positive number of hurricanes experienced ($x_{num}>0$), we defined the binary *Hurricane experience* (x_{exp}) variable as one when $x_{num}>0$ and zero otherwise so that $x_{exp}*x_{time}$ and $x_{exp}*x_{dam}$ could be used in the models. In the survey, respondents were asked one by one if, to the best of their knowledge, the home had any of the following features to protect against wind damage—high wind shingles and synthetic water barrier on the roof, spray adhesive applied to the underside of the roof in the attic, hurricane straps to improve connection between roof and wall, hurricane shutters, or impact resistant windows and doors. If they answered Yes to any of the five questions, the variable *Previous wind retrofit* (x_{ret}) was coded as a Yes; otherwise, it was a No. For respondents living in a mobile home, the five retrofit choices were replaced with two—extra tie downs to improve the anchorage, and improved structural resistance to high winds. Note that x_{ret}=1 for houses that have features that protect against wind damage whether the homeowner deliberately undertook a retrofit to obtain the feature or the house happened to have the features.

2.3.4 Imputation

After removing the 37 respondents who either did not answer at least one discrete choice question or who answered no more than a couple covariate questions, we had 321 respondents with a total of 3191 observations. The data, however, still included missing values (Table 2.2) in a patchwork, not monotone, pattern. The most common methods of handling missing data—listwise and pairwise deletion—are inefficient since they discard useful data and result in coefficient estimates that are potentially biased (Harrell 2015). Those limitations and the availability of new software have made it increasingly common to use imputation instead to handle missing data. In this analysis, we used multiple imputation because it avoids the problems of deletion methods and unlike single imputation, accounts for the uncertainty introduced by the fact that missing values are being imputed and so does not underestimate the p-values (van Buuren 2012; Harrell 2015). In multiple imputation the dataset is imputed multiple times creating *m* "complete" datasets, the analysis is conducted separately on each, and then the results are combined (van Buuren 2012). Specifically, we used the {mice} package in R, which implements the multiple imputation using chained equations (MICE) algorithm (van Buuren and Groothuis-Oudshoorn 2011, van Buuren 2012). We generated *m*=10 imputed datasets, consistent with approximate guidelines in van Buuren (2012) and Harrell (2015). As recommended in Harrell (2015) and Moons et al. (2006), and White et al. (2011), all variables in Table 2.2 were included as predictors for the imputation, and the algorithm was set for 20 iterations. The cart method was used for *Time since last* *hurricane* (x_{time}) since it provided the best results for that variable's bi-modal distribution. Otherwise, default settings were used—logistic regression for binary variables and predictive mean matching for all others.

Two main types of checks were conducted to ensure the distributions of the observed and imputed datasets were sufficiently similar. First, distributions of observed and imputed datasets were compared using kernel densities for continuous variables, and histograms for binary variables. Second, for each variable x_j, we duplicate the entire dataset, but in the duplicated observations, we set all values of x_j to missing. We then impute values for the missing values of x_j and compare the distribution of the imputed values for the originally non-missing observations to the original values (He and Zaslabsky 2012, Harrell 2015). Results of all checks suggest that the imputed datasets match the observed data well in terms of distributions of variables[2]. Results from the imputed datasets were combined using Rubin's rules (van Buuren 2012, White et al. 2011, Miles 2015).

2.4 Model Description

2.4.1 Mixed logit model

Mixed logit (also known as random parameter logit) models were used to analyze the data described in Section 2.3. Each household decision-maker *n* is assumed to choose a single alternative from among a finite set of discrete alternatives in each of *F* choice sets (i.e., collection of alternatives offered). Person *n* chooses the

[2] As a final check, fitting the base models using listwise deletion instead of imputation produced results that were quite similar in terms of sign, magnitude, and statistical significance of the coefficients, except that age was no longer significant in either model, and income was no longer significant in the flood model.

alternative within the choice set that provides the highest utility. The utility he derives from each alternative *j* in choice situation *f* is:

$$U_{njf} = \beta_n^T x_{njf} + \varepsilon_{njf} \quad (2.1)$$

where x_{njf} is a vector of observed covariates for alternative *j* faced by person *n* in choice set *f*, β_n is a vector of coefficients of those variables for person *n*, and ε_{njf} is a random term that is independent and identically distributed (iid) extreme value and represents the factors that affect utility but are not observed (Train 2009). Covariates may include attributes of the alternative *j* and/or the person *n*. This specification is the same as for the standard multinomial logit, except that the β varies over decision-makers *n*. Since it would be extremely difficult and not of real interest to estimate the coefficient for every individual in the sample, instead the coefficients are considered random variables with joint density $f(\beta|\eta)$, where η are the parameters of the distribution (e.g., mean and covariance of β) (Train 2009).

If the value of β_n was known for a person *n*, the choice probability for a single choice situation would be the same as a standard logit, so the probability person *n* chooses alternative *j* conditional on β_n is as in Equation 2.2. Now consider that in panel data each respondent chooses an alternative in each of a sequence of choice situations *f*. Conditional on β_n, the probability that person *n* chooses a sequence of alternatives $\vec{j} = \{j_1, \dots, j_F\}$ is the product of the logit formulas (Train 2009) (Eq. 2.3). To get the unconditional choice probability requires integrating over all possible values of β_n (Eq. 2.4).

$$(P_{nj}|\beta_n) = \frac{e^{\beta_n^T x_{nj}}}{\sum_l e^{\beta_n^T x_{nl}}} \quad (2.2)$$

$$(P_{n\vec{j}}|\beta_n) = \prod_{j=1}^{J}\left[\frac{e^{\beta_n^T x_{nj_f f}}}{\sum_l e^{\beta_n^T x_{nlf}}}\right] \tag{2.3}$$

$$P_{n\vec{j}} = \int (P_{n\vec{j}}|\beta_n)\ f(\beta|\eta)d\beta = \int \left(\prod_{f=1}^{F}\left[\frac{e^{\beta_n^T x_{nj_f f}}}{\sum_l e^{\beta_n^T x_{nlf}}}\right]\right) f(\beta|\eta)d\beta \tag{2.4}$$

To solve for the choice probabilities, we specify the functional form of the distributions of β and estimate the parameters η. Equation 2.4 is typically solved by simulation (Train 2009). A value of β is randomly sampled from $f(\beta|\eta)$ and then used to compute the product of the conditional probabilities $(P_{d\vec{j}}|\beta_d)$. This is repeated Γ times, where Γ is a large number. The results are averaged to give the simulated probabilities, which are then used to compute a simulated log likelihood. The process is iterated until the maximum simulated likelihood is found. The values of the parameters θ that maximize the simulated likelihood are the estimates used.

The mixed logit was chosen over other possible discrete choice models due to its flexibility. Most importantly, we are using panel data, in which each respondent was asked multiple choice questions. Unlike a multinomial logit, a mixed logit can handle the correlation between unobserved factors over the repeated choices by a single respondent. Unlike the multinomial logit, a mixed logit can also represent random taste variation (i.e., different people assigning different value to each alternative attribute) and avoids the assumption of proportional substitution across alternatives (i.e., independence from irrelevant alternatives) which we suspect does not hold in this case. While a probit assumes unobserved factors have a jointly normal distribution, a mixed logit does not (Train 2009).

Marginal effects and elasticities were computed to compare the effects of the covariates (Train 2009), since they are more easily interpreted than the coefficients (β). The marginal effect is the change in the probability of choosing insurance given a unit increase in the variable and the elasticity is the percentage change in the probability of choosing insurance given a 1% increase in the variable. Both vary by observation, so we compute them for each observation, then take the average (Train 2009). Since the data include three choices and our goal is to estimate the elasticities for purchasing insurance (without regard to Policy A or B), we set the covariates for Policy B equal to the sample mean for all observations and only increment values for Policy A. Recognizing that marginal effects and elasticities are not constant with the value of the covariate, for premium and deductible, we also computed them at a range of values to see how they vary.

2.4.2 Model specification

For the insurance purchase models specifically, we define the utilities for each person *n* for the three alternatives *j* in choice set *f* as Equation 2.5a for j = Insurance (A or B), and Equation 2.5b for j=No insurance:

$$U_{njf} = \beta_0 + \beta_{P,}x_{P,njf} + \beta_{D,n}x_{D,njf} + \overrightarrow{\alpha_n^T}\overrightarrow{x} + \varepsilon_{njf} \qquad (2.5a)$$

$$U_{njf} = \varepsilon_{njf} \qquad (2.5b)$$

The parameter β_0 is the alternative-specific constant. The variables $x_{P,njf}$ and $x_{D,njf}$ are the premium and deductible of the insurance policy, respectively, and thus have different values for each alternative j. The x_n variables are those that are related to the household decision-makers and their homes (listed in Table 2.2). They vary with person *n* but not alternative. The coefficients $\beta_{P,n}$, $\beta_{D,n}$, and α_n are the coefficients to be estimated for the premium, deductible, and the vector of individual-specific variables, respectively. For alternative-specific constants and individual-specific variables, only differences between alternatives are relevant, not their absolute values, so with *J* alternatives, at most *J*-1 can enter the model. For these, therefore, we normalize the values for *j=Neither* to zero. The value of β_0 can be considered the average effect of all factors not in the model on the utility of buying insurance relative to not buying it. Similarly, the values of α_n can be considered the effect of each associated x variable on the utility of buying insurance relative to not buying it. The ε_{njf} represent the factors that are not observed and are iid extreme value. Note that we defined the alternative-specific constants and coefficients for the individual-specific variables to be the same for the Policy A and Policy B alternatives, resulting in a single utility equation for the two policies, called Insurance, as is common practice (e.g., Botzen and van den Bergh 2012a). This was done because what is defined as Policy A is different for every question and likewise for Policy B, so there is no meaningful difference between the two policies that would explain different utility equations. Further, preliminary analyses that allowed those coefficients to differ between Policies A and B suggested that the values were similar as expected.

In this model, we assume the premium and deductible coefficients $\beta_{P,n}$ and $\beta_{D,n}$ are each lognormally distributed and use the negative of the corresponding variable values in the equation. Since lognormal variables are always positive, this ensures an increase in premium and deductible always results in a decrease in the utility of the policy. We assume the constant β_0 is normally distributed and all other coefficients, α_n, are fixed. Further, we allow correlation among the three random variables. These modeling decisions together represent the assumptions that the influence of premium and deductible on the utility of purchasing insurance may vary across the population and the way they vary may be correlated. That is, someone who is heavily influenced by deductible may be more influenced by premium as well. The models were all fitted using the mlogit package in R (Croissant 2013).

2.5 Results

Three alternative models are presented for each peril (flood and wind):

(1) the Base model, which includes all covariates in Table 2.2 except *Prior damage* (x_{dam}) and *House had previous wind retrofit* (x_{ret});

(2) the Prior damage model, which is the Base model but with the addition of *Prior damage* (x_{dam}) and interactions between *Time since last hurricane*, *Prior damage*, and *Hurricane experience* (x_{time}*x_{dam}* x_{exp}) and *Number of hurricanes experienced*, *Prior damage*, and *Hurricane experience* (x_{num}*x_{dam}* x_{exp}), and

(3) the Retrofit model, which is the Base model, but with the addition of *House had previous wind retrofit* (x_{ret}) (Table 2.3).

Since a primary goal of this analysis was development of models that could be used for prediction, the Base models include only variables that could be reasonably estimated for a region to use in prediction at the regional scale. The Prior damage models are included to examine the effect of prior hazard experience in more depth, and the Retrofit models are included to examine the relationship between previous retrofit and insurance purchase. In Section 2.5.1 to 2.5.3, the overall goodness-of-fit of the models, the effects of the covariates, and a comparison of the flood and wind models are discussed, respectively.

2.5.1 Overall model goodness-of-fit

The models' goodness-of-fit are evaluated based on a Wald test, the p-values of the individual coefficients, likelihood ratio index r, Akaike's Information Criterion

(*AIC*), and shrinkage parameter. The pooled Wald test, which tests the null hypothesis that all coefficients are zero, was implemented as in van Buuren (2012, Section 6.3.1). For all six models, the p-values were $p<10^{-10}$ suggesting we reject the null hypothesis. The likelihood ratio index, $0 \leq r \leq 1$, also known as McFadden's pseudo R^2, is often used as a goodness-of-fit measure for discrete choice models. It is defined as: $r = 1 - \left(LL(\hat{\beta})/LL(0)\right)$, where $LL(\hat{\beta})$ and $LL(0)$ are the log-likelihood values at the estimated parameters and when all parameters are set equal to zero, respectively (Train 2009). The *AIC* is defined as $AIC = -2LL(\hat{\beta}) + 2q$, where q is the number of independent parameters. Shrinkage, a measure of the amount of overfitting present, is defined as (Harrell 2015, Section 4.5): $\varphi = (LR - p)/LR)$, where $LR = -2(LL(0) - LL\left(\hat{\beta}\right))$ and p is the total degrees of freedom for the predictors. Higher r, smaller *AIC*, and higher φ are preferred.

The models likelihood ratio index values are 0.34 and 0.29 for the flood and wind models, respectively, indicating very good fit for both models. For comparison, similar mixed logit flood insurance models with panel data had values of 0.18, 0.28, and 0.46 (Brouwer and Schaafsma 2013, Botzen et al. 2013, and Botzen and van den Bergh 2012a). According to Louviere et al. (2000, p55), "between 0.2 and 0.4 are considered to be indicative of extremely good model fits." Following the Harrell (2015) suggestion that a shrinkage value less than 0.9 suggests concern about overfitting and lack of fit with new data, there is no concern about overfitting in these models.

Table 2.3: Summary results for mixed logit models for flood and wind insurance purchase

	Variable		Flood			Wind		
			Base model	Prior damage model	Retrofit model	Base model	Prior damage model	Retrofit model
x_p	Premium[a]	mean	0.0031***	0.0026***	0.0023***	0.0013***	0.0026***	0.0014***
		s.d.	0.0229***	0.0216***	0.0144***	0.0043***	0.0169***	0.0051***
x_d	Deductible[a]	mean	0.0016***	0.0013***	0.0013***	0.0008***	0.0017***	0.0008***
		s.d.	0.0101***	0.0071***	0.0093***	0.0031***	0.0121***	0.0029***
	Correlation between premium, deductible		0.3234***	0.3515***	0.4059***	0.2516***	0.2506**	0.3682**
	Constant		8.9264***	8.1190***	6.4045***	9.6673***	9.7293***	8.4219***
$x_{time} \times x_{exp}$	Time since last hurricane × Hurricane experience		-0.1381***	-0.1123***	-0.1080***	-0.0195	-0.0272	-0.0120
x_{num}	Number of hurricanes experienced		-0.0952***	-0.1784**	-0.0876***	0.0480	0.0071	0.0377
x_{exp}	Hurricane experience		0.2746	0.4715	-0.8369	-0.2840	-0.1445	-0.5242
x_{dam}	Prior damage			2.3805			0.2917	
$x_{dam} \times x_{num} \times x_{exp}$	Prior damage × Num. hurricanes experienced × Hurricane experience			0.0874			0.0938	
$x_{dam} \times x_{time} \times x_{exp}$	Prior damage × Time since last hurricane × Hurricane experience			-0.2208**			0.0252	
x_{fp}	Location in floodplain		2.0133**	1.5625	1.7493	1.5661**	1.4524*	1.5715*
x_{dist}	Distance to coastline		-0.0085*	-0.0080	-0.0042	-0.0119***	-0.0118***	-0.0097**
x_{ret}	House had previous wind retrofit				2.8837***			1.3972***
x_{inc}	Income		8.56E-06**	8.27E-06**	8.44E-06**	9.76E-06**	9.06E-06**	9.53E-06***
x_{age}	Age		-0.0519***	-0.0406*	-0.0442**	-0.0675***	-0.0665***	-0.0651***

Table 2.3 continued

Variable		Flood: Base model	Flood: Prior damage model	Flood: Retrofit model	Wind: Base model	Wind: Prior damage model	Wind: Retrofit model
Goodness-of-fit measures							
AIC		2223	2226	2220	2392	2397	2399
Log-likelihood		-1096	-1094	-1093	-1180	-1179	-1182
Likelihood ratio index		0.335	0.336	0.337	0.287	0.288	0.286
Shrinkage		0.986	0.984	0.986	0.984	0.981	0.983
Willingness to pay	median	0.565	0.652	0.545	0.598	0.607	0.641
	P(WTP<1)	0.583	0.566	0.596	0.592	0.575	0.581

Notes: *, **, *** indicate, respectively, significance at the 10%, 5%, and 1% level.

[a] To ensure lower premiums and deductibles are considered preferred over higher ones, the premium and deductible coefficients were assumed to be lognormally distributed (and therefore nonnegative), and the negatives of the corresponding variable values were used. Positive coefficients in this table, therefore, correspond to an inverse relationship between premium (or deductible) and utility of insurance. The mean and standard deviation values presented are for premium and deductible, not ln(premium) and ln(deductible).

2.5.2 Covariates

2.5.2.1 Premium and deductible

The coefficients for premium and deductible were modeled as correlated, lognormally distributed random variables. The standard deviations were significant, and likelihood ratio tests comparing models with and without correlation suggest that it was appropriate to consider them random and correlated. The p-values for likelihood ratio tests comparing models with and without correlation were 0.0004 and 0.008 for the flood and wind Base models, respectively, and similarly significant for the other four models. The models all indicate moderate correlation (0.25 to 0.41) between the coefficients for premium and deductible, suggesting that people who are more influenced by changes in premium are likely to also be more influenced by changes in deductible.

Since the coefficients of deductible and premium were both modeled as lognormal random variables, the willingness to pay to reduce the deductible, defined as the ratio of β_d/β_p, is also a lognormal random variable (Train 2009, p.150). The medians of those distributions (Table 2.3) suggest that the median homeowner would be willing to pay about $0.55 to $0.65 in additional premium to reduce the deductible by $1, depending on the specific model. For approximately 60% of homeowners, WTP<1 (Table 2.3). Since the cost of a higher premium is certain while the benefit of a lower deductible is uncertain, the observation that this WTP would be less than $1 is consistent with rational behavior in most cases. On the other hand, the observation in Michel-Kerjan and Kousky (2010) and Kousky (2011b) that most people chose low deductibles even when it did not make financial sense represents a behavioral bias and is consistent with people reporting that they would pay more than $1 in additional premium to reduce the deductible by $1. Note that the lognormal was an appealing distribution choice for premium and deductible because it is restricted to nonnegative values and thus allowed us to ensure that the lower premiums and deductibles would always be preferred. However, one known disadvantage of the lognormal in this application is that it has a long right-hand tail, which can lead to unreasonable values for WTP (Hensher and Greene 2003). The long tail of the WTP distribution may be truncated to remove those unreasonable values if desired (Hensher and Greene 2003).

The average elasticities of premium for the flood and wind Base models are -0.26 and -0.48, respectively, both indicating relatively inelastic behavior (Table 2.4). The elasticities of deductible for the Base flood and wind models are -0.09 and -0.22, respectively, also indicating relatively inelastic behavior and consistent with Botzen et al. (2013). For this type of model, the elasticities are not constant. Figure 2.2a and 2.2b show how the elasticities for the flood and wind Base models, respectively, change with the premium or deductible value. They suggest that premium and deductible become more elastic as they increase, but remain relatively inelastic within the range considered.

Table 2.4: Marginal effects and elasticities for Base models for flood and wind insurance purchase

	Variable	Flood		Wind	
		Marginal effect	Elasticity	Marginal effect	Elasticity
x_p	Premium	-5.95E-05	-0.263	-7.68E-05	-0.483
x_d	Deductible	-4.08E-05	-0.093	-5.81E-05	-0.220
x_{time}	Time since last hurricane	-7.18E-03	-0.148	-1.99E-03[a]	-0.053[a]
x_{num}	Number of hurricanes experienced	-5.25E-03	-0.072	5.23E-03[a]	0.103[a]
x_{fp}	Location in floodplain	0.105	---	0.175	---
x_{dist}	Distance to coastline	-4.73E-04	-0.124	-1.31E-03	-0.610
x_{inc}	Income	4.71E-07	0.090	1.08E-06	0.326
x_{age}	Age	-2.85E-03	-0.389	-7.43E-03	-1.704

[a] Variable not significant at 10% level in Base model (see Table 2.3).

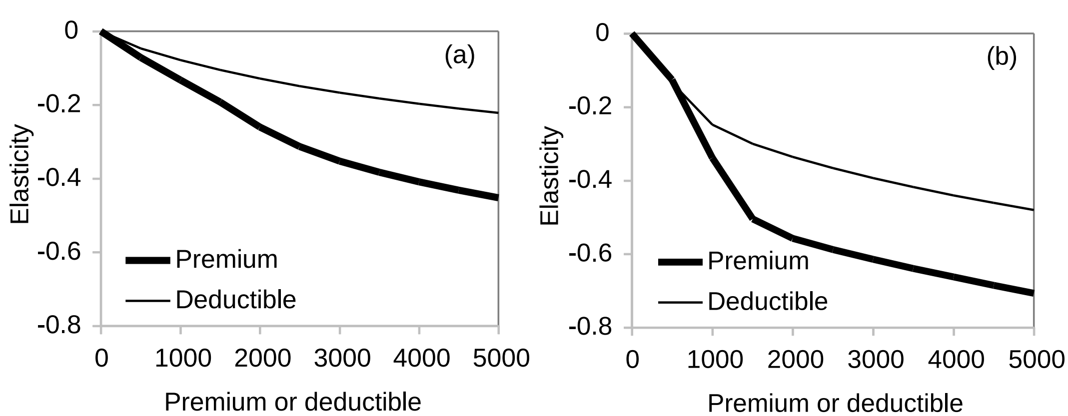

Figure 2.2: Elasticity vs. policy attributes for the (a) Flood base model, and (b) Wind base model

Figure 2.3 provides another way to examine the effect of premium and deductible, showing the market penetration rate (%) vs premium for different deductible levels. To generate a point on these curves, using the sample data, we set both Policy A and B to have the same specified premium and deductible values, determined the probability of buying insurance as the sum of the choice probabilities for Policy A and B, and took the average over all observations. We generated the curves by repeating the process for multiple specified premium and deductible values. As expected, the penetration rates decrease as deductibles and premiums increase. Within the reasonable ranges examined, the penetration rates for the Base flood model vary from 38% when both premium and deductible are $5000 to 71% when they are both $500. The premium has a slightly greater effect, with the penetration rate varying approximately 20% over the range of premium values when deductible is held constant, and 15% over the range of deductible values when premium is held constant. The pattern is similar for the wind model, though the penetration rates are shifted approximately 10% higher. These results are quite similar to those in Botzen et al. (2013) for flood insurance in the Netherlands.

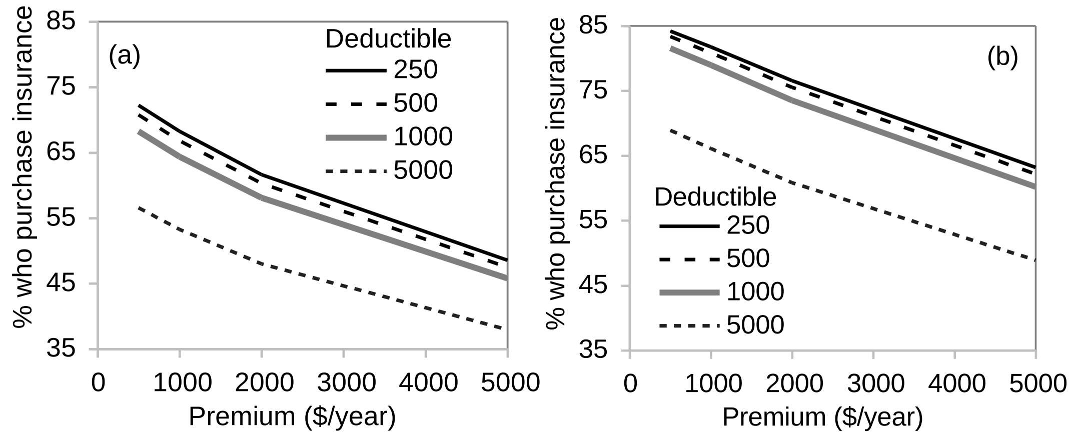

Figure 2.3: Penetration rate (%) vs. premium for different deductible levels for the (a) Flood base model and (b) Wind base model

2.5.2.2 Previous hazard experience

Two variables were used to represent previous experience with hurricanes in the Base models—*Number of hurricanes experienced* (x_{num}) and *Time since last hurricane* (x_{time}). (The latter is multiplied by *Hurricane experience* (x_{exp}) because it only applies when there is at least one hurricane experience.) Both were significant for the flood model at the 1% significance level, but neither were for the wind model. For the flood model, as expected, the longer time since the last hurricane, the less likely homeowners are to buy flood insurance. The elasticity is relatively small though at -0.148 (Table 2.4). This model assumes a linear relationship between x_{time} and utility, however, and x_{time} varies from one to 28 years. Some of the literature suggests that the relationship might be more nonlinear, having a much larger effect within just a few years since the last hurricane. Contrary to expectations, the coefficient of *Number of hurricanes experienced* (x_{num}) is negative in the Base flood model, indicating that more hurricane experiences is associated with a lower probability of purchasing flood insurance. At least a few explanations are possible. A numbing effect may occur, through which experiencing multiple hurricanes makes a homeowner more confident he can handle a future one without insurance. Homeowners who have experienced multiple events may have undertaken more retrofits to substitute for insurance. It is also possible that is the result of an interaction between proximity to hazard and number of hurricanes experienced, although proximity to hazard is measured by the *Location in floodplain* (x_{fp}) and *Distance* (x_{dist}) variables.

To examine the difference between previous hurricane experience that involved personal damage and experience that did not, we compare the flood Base model and Prior damage model results. In the Prior damage model, we include *Prior damage* (x_{dam}) as well as the interaction of *Prior damage* with *Number of hurricanes experienced* (x_{dam}*x_{num}*x_{exp}) and *Time since last hurricane* (x_{dam}*x_{time}*x_{exp}). For wind, still none of the previous hazard experience terms are significant. For flood, in addition to the main effects of *Number of hurricanes experienced* (x_{num}) and *Time since last hurricane* (x_{time}), the interaction term for *Time since last hurricane* and *Prior damage* is significant (x_{dam}*x_{time}*x_{exp}). If there is no prior damage (x_{dam}=0), then $\beta_{time} = -0.1123$ represents the effect of time. If there is prior damage (x_{dam}=1), then $\beta_{time} + \beta_{dam,time,exp} = -0.1123 - 0.2208$=-0.3331 represents the effect of time (Table 2.3). This suggests that the recency of the last hurricane experience is more influential for homeowners who experienced prior damage than for homeowners who did not.

Overall, questions remain about the complex effect of prior hazard experience. For example, the nature of the recency effect, the difference between the effect of experience on flood insurance purchase and wind insurance purchase, and the difference between general experience and experience involving a personal impact all remain unclear. Future research would be useful to further explore the effects of the multiple characteristics of an experience, their interactions, and their effects on insurance purchase.

2.5.2.3 Risk/geographic proximity to hazard

Two variables were used to represent the risk or more precisely, proximity to the hazard in these models—*Location in floodplain* (x_{fp}) and *Distance to coastline* (x_{dist}). Both were significant for both the flood and wind Base models. The signs were as expected, with location in the floodplain and closer to the coastline both associated with an increased likelihood of buying insurance. The marginal effects for *Location in floodplain* (x_{fp}) indicate that being in the floodplain results in a probability of buying insurance that is higher by 0.105 or 0.175 for flood and wind Base models, respectively, compared to not being in the floodplain (Table 2.4). Petrolia (2013) similarly found a marginal effect on flood insurance purchase of 0.232 for being in the SFHA. The marginal effects for *Distance to coastline* (x_{dist}) are -0.0005 and -0.0013 for the flood and wind Base models, respectively (Table 2.4). These are similar to those from Kreisel and Landry (2004) and Petrolia et al. (2013) which were -0.0011 and -0.002, respectively, for flood insurance.

2.5.2.4 Previous retrofit actions

To examine the relationship between previous retrofit actions and insurance purchase, we examined the Retrofit models, which were similar to the Base models, but with the inclusion of the *House had previous wind retrofit* (x_{ret}) variable (Table

2.3). In both the flood and wind models, the *House had previous wind retrofit* (x_{ret}) variable is highly significant ($p<0.001$) and the coefficient is positive, indicating that homeowners whose house has had previous retrofits is more likely to purchase insurance. For the wind model, this suggests that insurance and retrofits are complements not substitutes, as Petrolia et al. (2015) similarly concluded for wind insurance and mitigation. A possible explanation for this is that individuals that are more aware and sensitive to the hazard will undertake retrofit and purchase insurance to manage the risk. For the flood model, it is possible that *House had previous wind retrofit* (x_{ret}) can be interpreted as a proxy for risk awareness and interest in undertaking preparedness in general. Inclusion of the retrofit variable also reduced the significance of the *Location in floodplain* (x_{fp}) and *Distance to coastline* (x_{dist}) variables in both cases, to the point that they are no longer significant in the flood Retrofit model.

2.5.2.5 Income and age

Consistent with the majority of the literature, *Income* (x_{inc}) was significant and positive for all flood and wind models, indicating that higher incomes are associated with increased likelihood of purchasing insurance. The effect was relatively inelastic, as in previous studies as well. Previous studies have had mixed findings related to the relationship between age and catastrophe insurance purchase. In all our models, age was significant and had a negative sign, suggesting that younger homeowners are more likely to purchase both flood and wind insurance.

2.5.3 Compare flood and wind

Overall, the flood and wind models are quite similar, providing evidence that the conclusions from the many flood insurance studies in the literature might apply to a wind only insurance as well. Looking at the Base models, the same coefficients are significant at at least the 10% level in both, with the exception of the prior experience variables—*Number of hurricanes experienced* (x_{num}) and *Time since last hurricane* (x_{time})—which were significant in the flood Base model, but not the wind Base model. The coefficient values are similar as well.

2.6 Conclusions

The societal benefit of wind and flood risk management through insurance and retrofit has been demonstrated in Kesete et al. (2014), Peng et al. (2014), and Gao et al. (2016). It is imperative that we understand better the drivers that prompt insurance purchase and the structure of policy pricing that homeowners find most attractive. Both flood insurance and wind insurance face major challenges in the future. The Biggert-Waters Flood Insurance Reform Act of 2012 (BW12) extended the National Flood Insurance Program (NFIP) for five years and promised sweeping changes toward risk-based flood insurance rates. However, when full realization of the dramatic rate increases needed to meet the requirements of BW12 public outcry prompted the Homeowner Flood Insurance Affordability Act of 2014 that delayed or repealed sections of BW12. While most agree that the NFIP as currently structured is not sustainable with an estimated deficit of $24.6 billion, the future of flood insurance is not clear. The move toward risk-based premiums has the potential to make insurance provided by private companies a potentially feasible alternative to the publically administered NFIP (Thrasher, 2016). If the NFIP continues to be the primary underwriter of flood insurance, structuring policies correctly to reduce the current deficit will become a mandate. If flood insurance is provided privately, its feasibility will depend on an understanding of homeowner demand. Wind insurance pools face some of the same challenges as the NFIP (Moss and Cistenino, 2009). As new options for providing flood and wind insurance must be considered an understanding of the actuarial risk and kinds of policies that homeowners are most likely to purchase is a must.

This Chapter contributes to the empirical literature on homeowner purchase of insurance for hurricanes by introducing separate mixed logit models for flood insurance and wind insurance purchasing decisions. The results for flood insurance and wind insurance are similar, except for the effects of prior hazard event experience. We find evidence that the following are all significant and associated with higher probability of purchasing insurance—lower premium, lower deductible, more recent previous hurricane experience, location in a floodplain or closer to the coast, higher income, and younger homeowners. The analysis suggests that premium and deductible are relatively inelastic effects, and that there is substantial variability in the population in the willingness to pay for a $1 reduction in deductible. The recency of the last hurricane experience is more influential for homeowners who experienced damage than for homeowners who did not. More research is necessary to further explore the effects of the multiple characteristics of a prior hurricane experience (e.g., quantity, recency, intensity), their interactions, their effects on insurance purchase, and how those effects differ between flood and wind insurance. Results suggest that insurance purchase and home retrofits are complements, not substitutes, although this also is an area that could benefit from additional research. The generalizability of these findings could also be tested by collecting data from additional geographical regions. Finally, the statistical models presented in this chapter have been used in the larger computational framework in Chapter 3 to predict insurance penetration rates for a region under different premium levels.

Table 2.5 shows the comparison between the hypotheses from the literature (Section 2.2) and the results from this study. It shows that most of the covariate effects are the same as in the hypotheses. However, in contrast to the hypothesis for *Number of hurricanes experienced* (x_{num}), the results of this study suggest that homeowners are less likely to buy flood insurance when they experienced more hurricanes. Two unclear effects about *House had previous wind retrofit* (x_{ret}) and *Income* (x_{inc}) become clear in this as well.

Table 2.5: Comparison between the hypotheses and this study

	Variable	Hypothesized effect[a]	Effects in this study
x_p	Premium, \$/year	Negative (H_1)	Negative[b]
x_d	Deductible, \$/year	Negative (H_2)	Negative[b]
x_{time}	Time since last hurricane, years	Negative (H_4)	Negative[b] (flood) Not significant (wind)
x_{num}	Number of hurricanes experienced	Positive (H_3)	Negative[b] (flood) Not significant (wind)
x_{exp}	Hurricane experience, 1/0	Positive	Not significant
x_{dam}	Prior damage, 1/0	Positive (H_5)	Not significant
x_{fp}	Location in floodplain, 1/0	Positive (H_6)	Positive[c]
x_{dist}	Distance to coastline, km	Negative (H_7)	Negative[bd]
x_{ret}	House had previous wind retrofit, 1/0	Unclear	Positive[b]
x_{inc}	Income[c], \$/year	Positive (H_8)	Positive[c]
x_{age}	Age, years	Unclear	Negative[b]

[a] Positive means increase in variable is associated with an increase in probability of purchasing insurance
[b] Significant at 1% level
[c] Significant at 5% level
[d] Significant at 10% level

Chapter 3

NEW VERSION OF THE COMPUTATIONAL FRAMEWORK

This chapter introduces a new version of the computational framework that expands and improves the existing framework described in Peng et al. (2014) by including a government optimization model, empirical homeowner models, and acquisition as a strategy. Section 3.1 describes the overall computational framework. Section 3.2 introduces building inventories, hazard, and stakeholders in the computational framework. Section 3.3 presents the government model formulation, in which the interventions, government model objective function, and constraints are discussed. Section 3.4 and 3.5, respectively, summarize the primary insurer model, and the empirical homeowner decision models for insurance, retrofit, and acquisition. The solution procedure is described in Section 3.6. Sections 3.7 and 3.8 discuss the case study inputs and results.

3.1 Overall Framework

The new version of the computational framework includes four mathematical models (shaded boxes) and represents four stakeholders (bold capitals) involved in a nested dynamic Stackelberg game[3] (Figure 3.1). In the outer game, the government is

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[3] A Stackelberg game is a strategic game in economics whose original concept was of a leader firm with first-mover advantage and follower firms that move sequentially (von Stackelberg 1934). The term has evolved to be a framework in which there is a first-mover player with knowledge of the equilibrium response of subsequent-move players.

the leader. With knowledge of how the inner game will respond, it determines what property acquisition offers to make, what retrofit grants to offer homeowners to encourage retrofit, and how to regulate insurance pricing—all to help manage societal risk. A stochastic programming optimization represents the government decisions because it explicitly captures the uncertainty in loss that is fundamental to the challenge. With those government policies in place, in the inner game, the primary insurer and homeowners play a Stackelberg game in which the insurer determines what premiums to charge for policies at a specified deductible (within the government regulatory constraints), and what reinsurance to purchase. Each homeowner responds by choosing from a menu of available insurance, retrofit, and/or property acquisition options. We assume homeowner decisions are described by recently developed discrete choice models of the acquisition acceptance, retrofit, and insurance purchase decisions (Frimpong et al. working paper described in Appendix C, Chiew et al. working paper described in Appendix B, Chapter 2). A stochastic program represents the primary insurer's pricing and risk transfer decisions, with the objective of maximizing total profit over time and constraints on insolvency rate and minimum yearly profitability and capacity. The loss model is a simulation combining hazard, inventory, and damage modules to compute a probability distribution of losses for each group of buildings (defined by location, building type, and homeowner type) and each possible hazard event *h* (e.g., hurricane) in the study area, with and without retrofits of various types. It is similar to regional loss estimation models, such as, HAZUS-MH 2.1 (FEMA 2012) or the Florida Public Hurricane Loss Model (FPHLM 2005). The reinsurer offers reinsurance at a given price as an input.

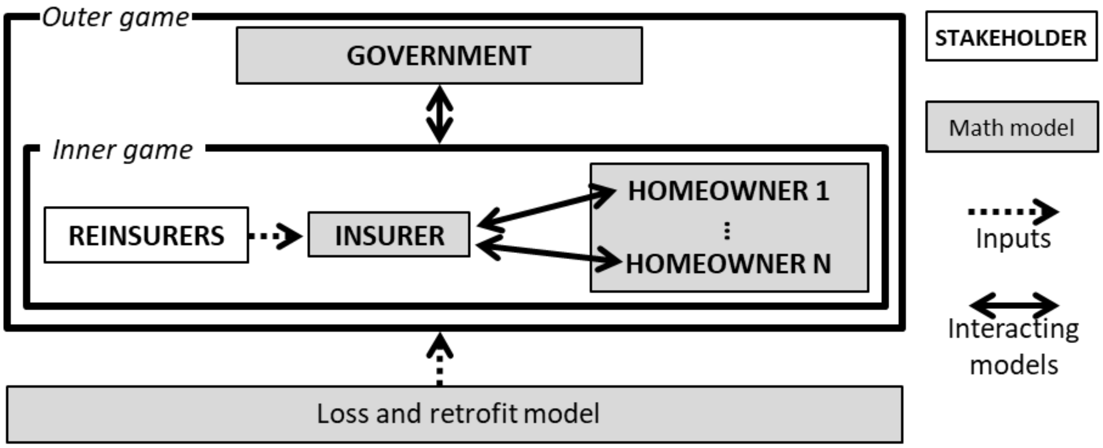

Figure 3.1: Hurricane risk management computational modeling framework (repeated from Figure 1.1 for convenience)

This framework is the same as the one described in Peng et al. (2014), but with the government decisions represented explicitly rather than as exogenous variables; with discrete choice homeowner decision models rather than utility-based homeowner models; and with property acquisition as an additional strategy in addition to retrofit and insurance purchase (Section 1.2). In addition, the retrofit options allowed are a subset of those allowed in Peng et al. (2014) so that they follow the recommendations associated with the Insurance Institute for Business and Home Safety (IBHS) FORTIFIED Home program designation. There are three levels of IBHS FORTIFIED Home designation, which are Bronze, Silver and Gold, and each level has stricter requirements than the previous one. The retrofits description associated with each level are shown in Table 3.1 (Peng 2013). The IBHS rules require that a house should achieve Bronze level first, then Silver, then Gold.. To be more explicit, the IBHS FORTIFIED program requires the roof should be adequate (IBHS Bronze) before the openings (IBHS Silver) or roof-to-wall connections (IBHS Gold) are strengthened, and the openings (IBHS Silver) should be strengthened before roof-to-wall connections (IBHS Gold) are strengthened.

Table 3.1: Summary of retrofit alternatives in each IBHS FORTIFIED level

IBHS FORTIFIED level	Retrofit
Bronze	1. Strengthen roof sheathing attachment and provide secondary water barrier with roof covering replacement
	2. Strengthen roof sheathing attachment and provide secondary water barrier for roof from within attic
Silver	1. Reinforce gable end
	2. Protect openings (impact resistant)
	3. Protect openings (shutters)
Gold	1. Reinforce roof-to-wall connections

3.2 Scope, Definitions, and Main Assumptions

3.2.1 Building inventory

The inventory of single-family residential buildings is divided into groups, where each is defined by its geographic area unit i (e.g., census tract), building category m, resistance level c, and risk region v. Building categories m are defined based on architectural features and are assumed to perform similarly and have similar value (e.g., one-story home with a garage and hip roof). Each building is defined as a collection of *components* to be represented explicitly in the damage and loss modeling (e.g., roof covering, openings). Each component in turn is made of many *component units* (e.g., a single window or section of roof covering). For each component, a few possible physical *configurations* are defined, each with an associated *component resistance*, treated as a random variable. The *building resistance c* of each building is then defined by the vector of resistances of its components, and a *retrofitting alternative cc'* is defined as changing a building from building resistance *c* to a better building resistance *c'*. Risk regions v are larger geographic regions made up of many area units i. They are defined to allow insurer premiums and homeowner risk attitudes to vary geographically, but at greater aggregation than area units. The initial building inventory is defined as X_{imcv}, the number of buildings of type i, m, c, v. We assume the building inventory is constant with time.

3.2.2 Hazard

The model considers hurricane-related wind and storm surge flooding only (although it could be extended to other hazards). The hurricane hazard is represented by an efficient set of probabilistic hurricane events $h \in (1, \dots, H, H+1)$, where $H+1$ represents the case of no hurricane. The first H members of the set (referred to simply as *hurricanes*) are defined as tracks with along-track parameters that determine the intensity, including central pressure deficit and radius to maximum winds. Each hurricane has an associated hazard-adjusted annual occurrence probability P^h such that when probabilistically combined, the set of hurricanes represents the regional hazard (Apivatanagul et al. 2011). In a sense, each hurricane represents all hurricanes that would produce similar wind speeds and surge depths in the study area. For each hurricane, wind speeds and surge depths are estimated throughout the study area. The durations of the time steps *t* vary (a few days to a few weeks). They are defined so that the one-period occurrence probability is constant through the year and so they are short enough to reasonably assume no two hurricanes occur in same time period.

Since a series of hurricanes in quick succession can create very different outcomes for an insurer than the same hurricanes evenly spread over a long time period, we define a long-term (say, 30-year) timeline of hurricanes as a *scenario* $s \in (1, \dots, S)$. Each scenario as a $1 \times T$ vector, where T is total number of time periods in one scenario. For each time period t, either one of the possible hurricanes h occurs, or no hurricane occurs. Each scenario has an occurrence probability P^s, such that $\sum_s P^s = 1$. The complete set of scenarios is defined so that it has the same key characteristics as the full set of $(H + 1)^T$ scenarios that is theoretically possible (Peng et al. 2014).

3.2.3 Stakeholders

The collection of homeowners in the study area is partitioned based on their homes' location i, building category m, building resistance level c, and risk region v. Since homeowners differ based on their i, m, c, v type (and therefore risk), and possibly their risk attitude, the models do not assume they will all make the same decisions but instead captures the heterogeneous behavior of homeowners. We assume one primary insurer and one single layer of catastrophe risk excess of loss reinsurance. We do not distinguish between local, state, and federal government, referring to them collectively as the government, which in our formulation, may offer to subsidize retrofits, may offer to purchase a home through a property acquisition program, and/or may regulate insurance pricing, but it is not an insurer or reinsurer. The effect of capital markets is not considered.

3.3 Government Formulation

A stochastic programming model represents the government decision to allocate a specified budget among possible property acquisition and homeowner retrofit grant investments so as to minimize a measure of societal loss. The analysis is conducted on an annual basis, with shorter time steps *t* that allow for the possibility of multiple hurricanes in a year. The interventions considered, objectives, and budget constraint are described in turn.

3.3.1 Interventions

Three government interventions are considered here—property acquisition, retrofit grant, and insurance pricing regulation. Variations could be incorporated into the computational framework, but these are arguably the most common types of risk management interventions and represent a range of approaches.

In property acquisition, the government offers to buy particularly high risk properties. They are then demolished and the land is repurposed for open space or another use more appropriate to the site (Robinson et al. 2018). While in the past property acquisition typically has been offered only after a disaster when homes are already damaged, in this formulation, we do not include that constraint. Consistent with the way projects typically specify neighborhood areas for acquisition rather than scattered individual homes, we assume that a property acquisition offer would have to be made to all homes within a geographic area unit *i* or none. The geographic area units *i* can be rank ordered from high to low risk, and one government property acquisition decision then is to determine, W, the number of area units *i* to offer property acquisition. We rank order the area units based on an average of the: (1) ranking based on the expected loss per home in dollars, and (2) ranking based on number of times it is expected to be damaged in the next 30 years. Figure 3.2 shows the ranking in detail. The definition of repetitive loss properties that are the main target of FEMA property acquisition programs is similarly a combination of frequency and amount of loss (U.S. GAO 2004). Past acquisition programs typically have offered homeowners 100% of pre-event market value for their homes, although the price could as low as 75% of market value if the local or state government does not supplement the 75% paid by the HMGP and it could be as high as 125% of market value if the homeowner receives extra incentives, such as those offered after Hurricane Sandy for high risk areas, group buyouts, and staying in the county (Robinson et al. 2018). We thus consider the price offered, ξ, as a percentage of home value to be a second government property acquisition decision.

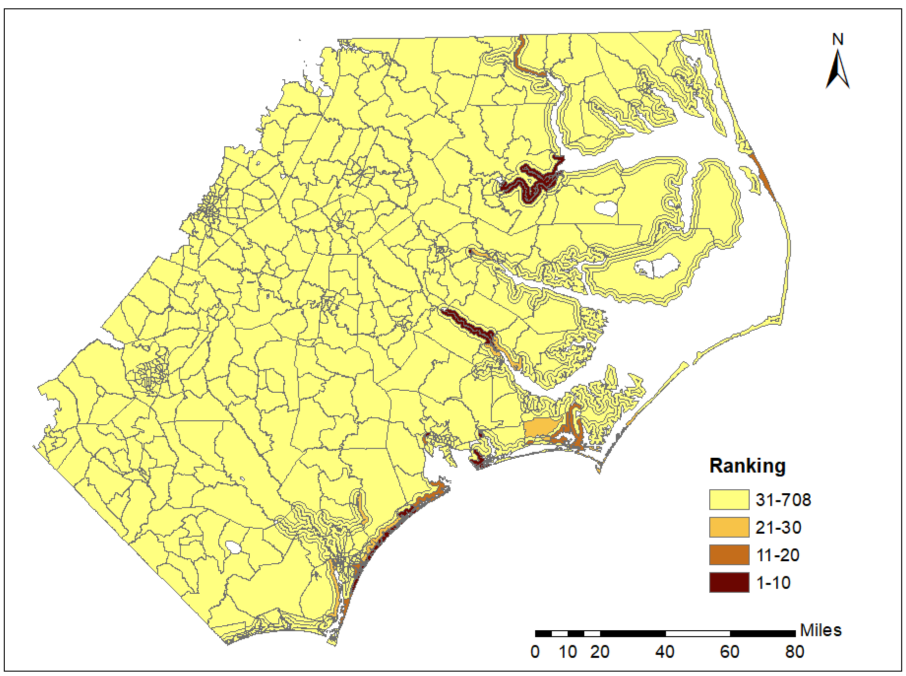

Figure 3.2: Average ranking of number of times expected to be damaged in 30 years and expected loss per home

An increasing number of programs are offering incentives to encourage homeowners to undertake retrofits to reduce future damage (Rollins and Kinghorn 2013). The incentives come in different forms (e.g., grants, low interest loans, insurance premium reductions, and income tax deductions) and with different specifications. Jasour et al. (2018) suggests that a grant is the most effective of these forms of economic incentive, and thus, using a typical structure here, we assume the government offers each homeowner a grant to pay some or all of the costs of a retrofit, and the grant does not have to be repaid. Thus, this dissertation defines retrofit grants based on: (1) the percentage of the retrofit cost the government offers to subsidize, z, and (2) the maximum amount it will pay a homeowner for a retrofit in dollars, R. In modeling implementation of a public grant program, we seek a fair scheme that targets the homes that can benefit the most from retrofits and is reasonably practical to implement. For fairness, we assume any if the government budget is insufficient to allow all homeowners who want to use the grant to get it, then they receive it on a first come first served basis, which is represented by randomly selecting among eligible homes.

Finally, assuming the single insurer operates within a regulated environment, the government may regulate the premiums. The annual homeowner premium charged for each homeowner of type i, m, c, v is assumed to be risk-based, computed as the expected value of the loss to insured buildings of type i, m, c, v less the deductible, multiplied by one plus τ plus λ_v (Peng et al. 2014). The loading factors τ and λ_v represent the primary insurer's administrative cost and profit margin for risk region v, respectively. We assume, therefore, that the government can establish maximum allowable profit loading factors Λ_v that insurers may charge.

Therefore, overall a single government policy is defined by six variables—the number of zones in which acquisition offers are made, W, and at what price, ξ, as a percentage of building value; the percentage of the retrofit cost the government offers to subsidize, z, and the maximum amount it will pay a homeowner for a retrofit in dollars, R; and the maximum profit loading factor allowed in the low and high risk regions, Λ_L and Λ_H.

3.3.2 Objective function

The government objective is to minimize societal loss. The full range of typically unreported losses (in addition to direct repair costs) are too important to ignore, but too difficult to model explicitly. These include losses associated with business interruption, emergency services, environmental damage, disruption, and stress (Heinz 2000). In this formulation, we use a simplified method to represent societal loss. First, we consider the true societal loss to be proportional to total direct loss, which in our loss model includes both insured and uninsured loss associated with damage to structural, nonstructural, interior, electrical, mechanical, and plumbing components. Second, as in Xu et al. (2007), in addition to minimizing losses on an annual expected value basis, we seek to minimize hurricanes with particularly large losses, those that are beyond the normal regional capacity to manage. Third, we consider both uninsured and insured loss to be important. While it is certainly preferable for losses to be insured than uninsured, it is still more preferable to avoid loss altogether since even insured homeowners may be underinsured, and making an insurance claim and repairing damage—especially in a post-disaster environment where they were not planned and demand for contractors is high—can involve a great deal of time, energy, disruption, and stress. Following the 2010-11 Canterbury earthquake sequence in Christchurch, New Zealand, for example, perhaps the most well-insured earthquake ever, 37% of residents reported that dealing with property insurance issues had a moderate or major negative impact on their everyday lives (CERA 2012).

With these ideas in mind, we define the objective function in general terms as a weighted sum of expected loss and expected loss above a user-specified allowable loss, ϕ (Expression 3.1). Loss in hurricane h, L^h, is defined as a weighted sum of the total loss to uninsured buildings, U^h, and total loss to insured buildings, N^h (Equations 3.2 to 3.4), where L^h_{imc} is the loss to a building of type i, m, c in hurricane h (from the loss model); X_{imcv} is the number of buildings of type i, m, c, v, after any retrofit has been implemented; and w_{imcv} are decision variables from zero to one output from the homeowner models (Section 3.5) that equal the percentage of homeowners of type i, m, c, v that buy insurance. The user-specified threshold, ϕ, and weights k, γ_U, and γ_N can be varied to examine the effect of different assumptions, as in Section 3.7.

$$\text{Min. } k[\textstyle\sum_h P^h L^h] + (1-k)\cdot[\textstyle\sum_h P^h max\{L^h - \phi, 0\}] \tag{3.1}$$

$$L^h = \gamma_U U^h + \gamma_N N^h \quad \forall h \tag{3.2}$$

$$U^h = \textstyle\sum_{imcv} L^h_{imc} X_{imcv}(1 - w_{imcv}) \quad \forall h \tag{3.3}$$

$$N^h = \textstyle\sum_{imcv} L^h_{imc} X_{imcv} w_{imcv} \quad \forall h \tag{3.4}$$

3.3.3 Budget

The government decisions are subject only to a budget constraint. Assuming a single budget for both acquisition and retrofit grants allows the model to examine the tradeoff between the two types of interventions. We let $K^{c'}_{mc}$ be the cost to retrofit a building of category *m* from building resistance *c* to building resistance *c'*. Then Constraint (3.5) defines the amount the government spends on a retrofit grant to one building of category *m* being retrofit from building resistance *c* to *c'* as either $K_{mc}^{c'}z$ or R, whichever is less. The number of zones offered acquisition, W, is presented in Constraint (3.6), where ν_i is a binary that is one if area unit *i* is offered acquisition and zero otherwise. Constraint (3.7) defines the total amount the government spends on both retrofit grants (first term) and acquisition (second term), where δ_{imc} is the percentage of buildings in area unit *i*, building category *m*, and resistance level *c* that will do a retrofit when the grant offered is defined by subsidy percentage z and maximum amount R, ξ is the price paid for each acquired building as a percentage of building value, V_m, and ψ_{im} is the percentage of buildings in area unit *i* of type *m* that accept an acquisition offer. The percentage of buildings that accept a grant and that accept an acquisition offer, δ_{imc} and ψ_{im}, respectively are output by the homeowner models (Section 3.5). Constraint (3.8) ensures that the total amount spent on acquisition and retrofit grants does not exceed a user-specified amount, Ω. By varying the value of the total government budget for interventions Ω, we can determine the best amount to spend (Section 3.8.1).

$$G_{mcc'} = \min\{R,\ K_{mc}^{c'}z\} \quad \forall\, m,\ c,\ c' \tag{3.5}$$

$$W = \sum_i \nu_i \tag{3.6}$$

$$G = \sum_{imcc'}(G_{mcc'}X_{imc}\delta_{imc} + \xi V_m X_{imc}\psi_{im}\nu_i) \tag{3.7}$$

$$G \leq \Omega \tag{3.8}$$

3.4 Insurer Decision Model

The primary insurer decision model is the same as that described in Peng et al. (2014), with the minor change that profit loading factors λ_v are now subject to maximum values, Λ_v, set by the government policy. The insured decision model is a stochastic program that seeks to maximize the total profit over the full time horizon, averaged over all scenarios *S*. It chooses decision variables defining the policy premiums (specifically, profit loading factors λ_v for each risk region v) and reinsurance purchase (specifically, attachment point *A* and maximum limit *M*), subject to the constraints that ensure the probability of insolvency and capacity ratio do not exceed specified values, and the return on equity is at least a specified value. It is solved using a genetic algorithm.

Note that while hurricane-related wind and flood damage are currently insured separately in the United States—wind as part of regular homeowner's policies and flood through the National Flood Insurance Program, in this analysis we consider both to assess how they might be managed together. The framework is flexible enough, however, that one could run it with only wind or only flood coverage as well.

3.5 Homeowner Decision Models

For a specified government policy (defined by acquisition offer zones v_i and price ξ; retrofit grant percentage z, and maximum amount R; and maximum allowable profit loading factors Λ_v and for a specified insurance pricing decision (defined by profit loading factors λ_v, which in turn determine premiums), each homeowner decides which, if any, risk management action to take. A homeowner can accept an acquisition offer if presented. If he does not accept an acquisition offer, he can decide whether to retrofit (and if so, how), buy insurance, both, or neither. These homeowner decisions are simulated using a set of discrete choice models recently developed for this purpose. Full models are summarized in Appendix B and C. They are discussed here briefly.

Acquisition is captured by a pooled probit model that predicts the probability household will accept an acquisition offer as a function of price offered (as percentage of building value), whether it is in a 100-year floodplain, straight line distance to the coastline (km), number of years the household has lived in the home, and incomes ($1,000s) (Frimpong et al. working paper, detail in Appendix C). Retrofit is captured by five different mixed logit models, one each to predict the probability a household will retrofit to protect against wind damage to the roof, wind damage to the openings, wind damage to the roof-to-wall connections, flood damage to the appliances, sidings and insulation, and flood damage to the house (by elevating it) (Chiew et al. working paper, detail in Appendix B). The variables used in the retrofit models include alternative specific constants of revealed preference variables, retrofit grant percentage, maximum grant amount, number of hurricanes previously experienced, straight line distance to the coastline (km), and unemployment status (employed, unemployed, or retired). The acquisition and retrofit models were developed using data from a mail survey of homeowners conducted in 2017 in the study area, the eastern half of North Carolina (Figure 1.2). Finally, insurance purchase is captured by two mixed logit models that predict the probability a household will purchase flood insurance or wind insurance (assuming their standard homeowner's policy does not already cover it), respectively, Chapter 2). The insurance models are functions of premium, deductible, location in a 100-year floodplain, straight line distance to the coastline (km), income, age, and in the case of flood, time since last hurricane experienced, number of hurricanes experienced as well (Chapter 2). Note that in applying these discrete choice homeowner decision-making models for prediction at the regional level, for simplicity and because it would not affect results, some additional variables that were not significant at the 0.1 level were not considered. Further, acquisition price, grant percentage paid and maximum offered, and premium and deductible were taken from the government and insurance decision models (Sections 3.3 and 3.4). Data for the explanatory variables were obtained from the U.S. Census, computed using GIS (e.g., straight line distance to coastline), or estimated using the hazard model data (i.e., time since last hurricane). Details are available in Section 3.7.

The homeowner decisions are implemented in four main steps (Figure 3.3). First, for each home in a zone in which acquisition is offered, we apply the acquisition model to determine the probability the homeowner will accept the offer, then simulate to determine if they do. Any homes that are acquired are removed from the building inventory. Second, for each home that is not acquired, we apply the five retrofit models in turn to determine the probability the homeowner will undertake each retrofit type, then simulate to determine if they do. Some retrofits are prohibited for some building types m and resistance levels c so as to ensure that retrofits always reduce vulnerability, follow the guidelines outlined in the IBHS FORTIFIED home program (IBHS 2017), and offer at least a minimum user-specified expected net benefit χ. For example, IBHS FORTIFIED program requires the roof must be adequate before roof-to-wall connections are strengthened. The requirement to satisfy IBHS guidelines was not included in Peng et al. (2014). In addition, if a homeowner wants to retrofit and is offered a grant, we assume he will always accept it because there is no downside to do so.

Third, for each home not acquired, we apply the insurance models to determine the probability the homeowner will buy flood and/or wind insurance, then simulate to determine if they do. We assume retrofit decisions are implemented first, so the insurance policy applies to the building after any retrofit. We assume that if a home is in a location that may experience flood damage (i.e., it has nonzero flood loss in at least one T-period scenario s), then if the homeowner buys flood insurance, they must buy wind insurance as well; and if the home is not flood-prone, the homeowner will not buy flood insurance but may buy wind insurance or not. In simulating insurance purchase, we assume each homeowner has a maximum budget for insurance equal to a specified percentage κ_v of his total home value V_m, where κ_v may vary for different risk regions v. Further, an insurer will not offer insurance if the raw premium (i.e., without the loading factors) is less than a minimum threshold, ρ.

Finally, the outputs of the model are collected. Homeowner decisions are aggregated to determine for each building type i, m, c, v, how many homeowners made each combination of acquisition acceptance, retrofit, and insurance purchase decision. They can then be summed to determine ψ_{im}, δ_{imc}, and w_{imcv}, the percentage of buildings in area unit i, building category m, and resistance level c that will accept an acquisition offer, that will do a retrofit, and that will buy insurance, respectively. All three quantities are used within the government decision model; the last also within the insurer decision model.

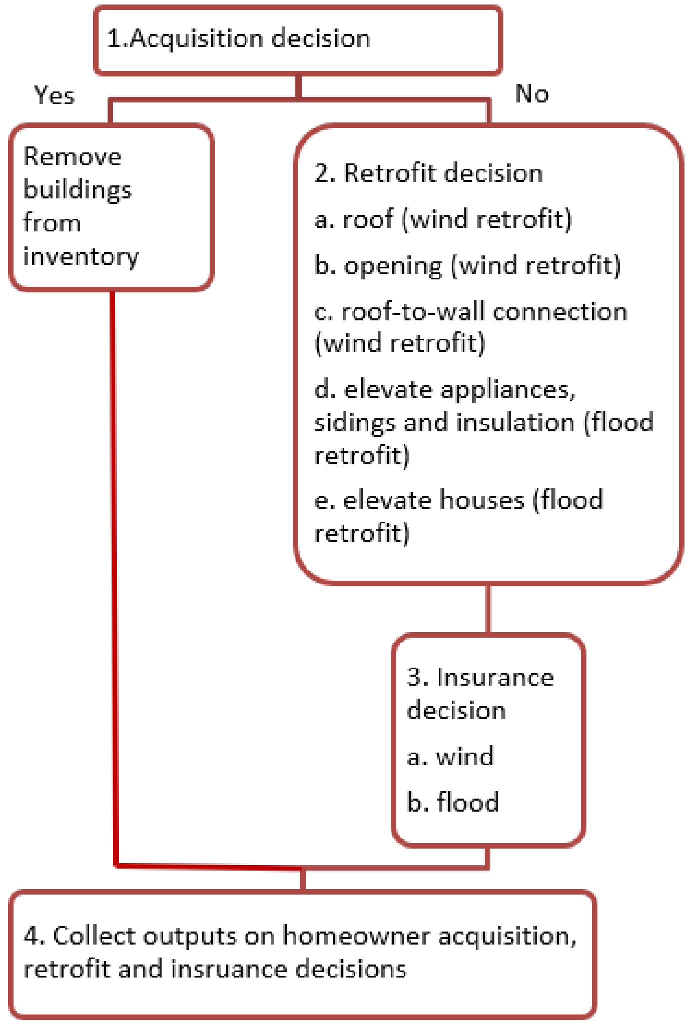

Figure 3.3: Flowchart of homeowner decision steps

3.6 Solution Procedure

The government decision model was solved using a simple enumeration approach. A set of possible government policies (i.e., values of the government decision variables W, ξ, R, z, Λ_L, and Λ_H) are specified to cover the likely decision space. We first identify the values of maximum allowable profit loading factors, Λ_L and Λ_H, assuming the government will select the minimum values for which the insurer can satisfy its insolvency, return on equity, and capacity constraints. With the selected values of Λ_L and Λ_H, the objective function value is determined for each remaining solution (i.e., combinations of W, ξ, R, z), and the set of policies with the best objective function value is selected. This approach was selected for a few reasons. It is computationally tractable, which is important since the interacting insurer-homeowner models must be solved for each government policy tested. To be implemented, the government decision variables should have round values (e.g., a retrofit grant of $5,000 rather than $4,952), so it was reasonable to focus on a relatively small number of solutions. It is also straightforward to implement. To be more attractive, simulated annealing, tabu search or other metaheuristic methods could be examined in the future.

The solution algorithm proceeded as follows. For each specified possible government solution (W, ξ, R, z, Λ_L, and Λ_H) and for each possible combination of insurer profit loading decision variables (λ_v, which determine the premiums), the decisions made by each homeowner are simulated using the homeowner discrete choice models (Section 3.5). Specifically, homeowner acquisition acceptance decisions are simulated, then for homes that are not acquired, retrofit decisions and then insurance purchase decisions are determined. Using those homeowner decisions computed for each possible set of insurer profit loading decision variables, the insurer optimization is run to determine the optimal insurer solution (profit loading factors λ_v, and reinsurance decisions A and M). The results are then collected, providing: (1) the optimal government decisions and expected resulting homeowner and insurer decisions, and (2) outcomes for each stakeholder type (government expenditures, resulting insured and uninsured loss distributions; insurer profit, probability of insolvency, and return on equity; and expenditures for different groups of homeowners).

The solution algorithm was implemented in Matlab and run in parallel on Unix-based high performance computing cluster. Each possible solution (i.e., for one set of government decision variables) took approximately three hours to run.

3.7 Case Study Inputs

A case study application of the computational framework was conducted for the eastern half of North Carolina, focusing on single-family wood-frame homes. The main inputs are summarized here. Additional inputs are as described in Peng et al. (2014) unless otherwise noted.

The 2010 census tracts are the basic area unit of study i, but each of the 143 census tracts that touch the coast was divided into three zones—within one mile of the coastline; one to two miles from the coastline; and the remainder of the census tract. We define just two risk regions v based on location less than two miles from the coast (high risk) or not (low risk). Eight building categories m were defined to represent all combinations of number of stories (one or two), garage (yes or no), and roof shape (hip or gable). Building values V_m were estimated using R.S. Means as in Legg (2011).

To define the component resistances c and retrofits cc' in the case study, we began with a set of six physically realistic, component-focused wind retrofit strategies based on those promoted as part of the IBHS FORTIFIED for Existing Homes™ program and three permanent flood retrofit strategies in Taggart (2007). The wind retrofit strategies are: Strengthen roof sheathing attachment and provide secondary water barrier (1) with roof cover replacement or (2) from within attic, (3) reinforce gable ends, (4) reinforce roof-to-wall connections, and protect openings with (5) impact resistant glass or (6) shutters. The flood retrofit strategies are: (1) elevate appliances and electrical, (2) upgrade siding and insulation, and (3) elevate the entire house. We assume each retrofit will last for thirty years and divide the retrofit cost by thirty so that the costs and benefits of the retrofits and insurance are normalized to constant basis. To allow representation of the retrofit alternatives, we defined six components: roof cover, roof sheathing, roof-to-wall connections, openings (i.e., windows, doors, garage doors), walls, and flood susceptibility. For each component, the two to four possible configurations were identified so that each is a common physical configuration before or after a typical retrofit. With 2 to 4 configurations for each of the 6 components, there are 192 possible building resistance levels c, and up to 143 possible retrofits cc', depending on the initial building resistance. The total initial (pre-retrofit) building inventory X_{imcv} by census tract was estimated using census data and building ages relative to building code changes. The final building inventory included 931,902 buildings in 708 area units. There are 441 zones with 649,012 (70%) buildings in the low risk region and 267 zones with 282,890 buildings (30%) in the high risk region.

Described more fully in Peng et al. (2014) and Peng (2013), the component-based building loss model that generates losses L_{imc}^{h} is an extended and modified version of the Florida Public Hurricane Loss Model from the Florida Office of Insurance Regulation (FPHLM 2005) combined with the flood damage simulation model in Taggart and van de Lindt (2009) and van de Lindt and Taggart (2009). It relates probabilistic resistances of building components to wind speeds and flood depths, considering the effects of wind pressure and missiles and the increase in internal pressure that results when the building envelop is breached. The model includes losses due to damage to structural, non-structural, interior, electrical, mechanical, and plumbing components. Damage to home contents, relocation expenses, disruption to occupants' lives, public expenses associated with providing emergency relief, or other indirect costs are not included.

We used the set of $H = 97$ probabilistic hurricane scenarios developed in Apivatanagul et al. (2011) using the Optimization-based Probabilistic Scenario (OPS) method. For each hurricane, open terrain 3-sec. peak gust wind speeds and surge depths were computed throughout the study region using the storm surge and tidal model ADCIRC (Westerink et al. 2008). We reevaluated the flood depths at more coastal locations than in Apivatanagul et al. (2011) to improve the geographic resolution. Using those hurricanes, we developed a set of $S = 2{,}000$ thirty-year scenarios that represent the full set of possible scenarios with minimal error (Peng 2013). With 20 time steps per year, there are $T = 600$ time steps per scenario s.

Data for the explanatory variables used in the discrete choice models of homeowner acquisition, insurance and retrofit decisions were collected from various sources. Household income, homeowner age, employment status and number of years the household has lived in the home were obtained from the U.S. Census. Straight line distance to coastline and whether the houses were in floodplain were computed using footprint data in GIS. Time since last hurricane and number of hurricane experienced was estimated using the hazard model data. With this data, a population of homeowners was simulated so that it reflected the correct distribution of values for each variable. For example, the employment rate is 55%, then generate random number from 0 to 1 to each homeowner to compare with 0.55, if less than 0.55, then this homeowner is employed, otherwise not.

Finally, other input parameter values include minimum raw premium required to offer insurance of $\rho = \$100$; homeowner insurance budgets of $\kappa_H = 5\%$ and $\kappa_L = 2.5\%$ of building value for high and low risk homeowners, respectively; and minimum net benefit required for each retrofit, $\chi = -\$300$ assuming a modestly negative net benefit may still be acceptable due to risk aversion; deductible is assumed to be $2,500 for all cases and can be variated if needed

The following government model user-specified parameters were used as base case values: threshold that defines the tail of the annual loss distribution $\phi = \$6.25$ billion, weight of expected loss vs. loss distribution tail $k = 1/8.5$, weight of uninsured and insured loss, respectively, and $\gamma_N = 1$ and $\gamma_L = 1$. Values of k, γ_N, γ_L, and annual government budget Ω were varied to examine their effects. In solving the framework, the 273 combinations of the following government decision variable values were considered as possible solutions: Retrofit grant amount R=\$0, \$5,000, \$7,500, \$10,000; percentage retrofit subsidized by government z=0, 50%, 100%; number of zones offered acquisition W=0, 5, 10, 15, 20; acquisition price offered as percentage of home value ξ=75%, 100%, 125%; maximum allowable profit loading factor Λ=0.7, 0.8, 0.9 (assuming $\Lambda_H = \Lambda_L$).

3.8 Case Study Results

Revisiting the questions posed in the Section 1.4, we examine the results provided by the computational framework in this case study application by considering each stakeholder type in turn. We first examine what the model recommends the government do and what the resulting government/societal outcomes would be (Section 3.8.1). In Section 3.8.2, we then similarly examine the primary insurer's likely responses to the government policies and the resulting consequences for the insurer. Finally, we examine the homeowner actions expected in response to the government policies and insurer decisions, and the resulting consequences for those homeowners in Section 3.8.3.

3.8.1 Government

3.8.1.1 Recommended government policies

The government faces multiple decisions in setting a risk management policy. The ones addressed in the current framework are: (1) how much money to spend on mitigation, (2) how to allocate the spending between retrofit grants and property acquisition, and (3) how to design the retrofit grant and acquisition programs.

Mitigation budget. We first examine the question of how much to spend on mitigation by comparing results for multiple annual government budget levels ($0, $20M, $60M, $100M, and unlimited). Table 3.2 presents the resulting recommended government policies and outcomes. For comparison, we also present results for a run in which homeowners are artificially not allowed to take any protective action (buying insurance, retrofitting, or being acquired). While spending more money always results in better objective function values, the marginal benefit declines above $60M (Figure 3.4). When voluntary retrofit and insurance are allowed but with no government budget, the total uninsured loss decreases by $134M, but 94% of that ($127M) becomes insured loss (Table 3.2). The objective function value, therefore, decreases by 2%. As the government budget increases to $20M, $60M, and $100M, the objective function decreases by 7%, 15%, and 21% respectively, relative to when no homeowner action is allowed, due to reductions in both uninsured and tail loss (Figure 3.4). The decision of how much to spend on mitigation in real life will depend on available funds and competing government priorities, but this type of analysis can support decision-making about an appropriate government budget for mitigation. For this case study, we assume $\Omega = \$60M$ is taken to be the best budget and use that as the base case in the remainder of the analyses.

Table 3.2: Government: Recommended decisions and annual expected outcomes

Govt. budget ($M)	Government Decisions							Government Outcomes ($M)				
	Insurance	Retrofit grant		Acquisition offers		Amount spent on						
	Max. profit loading Λ	% subsized z	Max grant paid ($) R	Num. zones[b] W	Price[c] x	Acq ($M).	Retrofit grants ($M)	Obj. fn	Total loss	Unins. loss	Insured loss	Tail loss
No action[a]		-	-	-	-	-	-	141	585	585	-	82
0	0.8	0	0	0	0	0	0	138	578	451	127	80
20	0.8	50	10,000	15	0.75	7.9	12.1	131	553	428	125	75
60[d]	0.8	50	10,000	15	1	38.6	21.4	120	514	390	123	67
100	0.8	50	10,000	20	1	73.0	24.8	111	486	368	117	61
Unlimited	0.8	100	10,000	20	1.25	142.0	64.6	99	443	333	111	53

[a] Homeowners are not allowed to take any protective action (insure, retrofit, or be acquired) in this run.
[b] Maximum of W=20 zones were considered as possible solutions.
[c] Price offered for acquisition as a percentage of building value.
[d] The $60M government budget run is the base case.

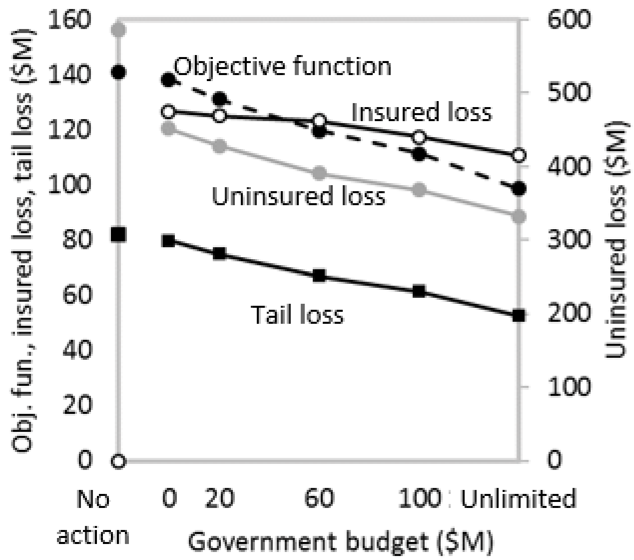

Figure 3.4: Objective function value, uninsured loss, insured loss, and tail loss ($M) versus government budget ($M)

Regulation of insurance pricing. For the base case run (and in fact, for all runs), the case study results suggest that the maximum insurer profit loading factor should be set at $\Lambda = \Lambda_H = \Lambda_L = 0.8$ (Table 3.2). That means that for every dollar of expected loss the insurer covers, they will make 80 cents profit (in addition to 35 cents for administrative costs). When $\Lambda = 0.7$, the insurer constraints are not satisfied. In particular, the average annual return on equity, defined as the profit divided by the average surplus over the last two periods, falls below the minimum allowable value of 0.05 if $\Lambda = 0.7$. Thus, $\Lambda = 0.8$ is the lowest value considered for which insurer solvency, capacity ratio, and return on equity constraints are satisfied, and that is the recommended solution.

Acquisition-retrofit grant tradeoff. The solution suggests spending \$38.6M (64%) of the \$60M budgeted on acquisition and \$21.4M (36%) on the retrofit grant program (Table 3.2). This strategy involves reducing expected loss as much as possible through acquisition, then spending the remainder of the budget on the retrofit grants. Acquisition is preferred because it is more cost-effective at reducing the objective function value, at least for these most at risk properties. The \$38.6M spent on acquisition in this solution reduces the expected annual total loss by \$45.2M; the \$21.4M spent on the retrofit grants reduces it by an additional \$18.8M (Table 3.2). Note that the framework does not consider possible government costs associated with maintaining the property after it is acquired, changes in tax revenue as a result of acquisition, or new risk the household might experience if it moves to another location in the same jurisdiction. To the extent that these omitted costs are substantial, the framework may be somewhat biased in favor of acquisition.

Acquisition program. The way to structure the acquisition program—what price to offer, ξ, and in how many zones, W—depends on the effect of price on participation rate, how many homes are in each zone, and the expected loss for a home in each zone, which declines as less risky zones are offered acquisition. According to the Frimpong et al. (working paper, detail in Appendix C), homeowner acquisition decision model embedded in the framework, the acquisition price offered has a substantial effect on homeowner acceptance rates. In the base case study, as the price goes from 75% to 100% to 125% of the home value, acceptance rate increases from approximately 16% to 59% to 92%. However, as the government offers higher prices, the number of houses it can afford to acquire decreases due to the budget constraint. Thus, the model recommends offering acquisition to the $W = 15$ highest risk geographic zones at ξ=100% of the home value (Figure. 3.5). The \$60M budget does not allow offering a higher price in all fifteen zones or offering that price in twenty zones. Offering 125% of the home value in fewer (ten) zones would increase the participation rate, but for a smaller group of homes (7,108 vs. 13,256), resulting in fewer being acquired.

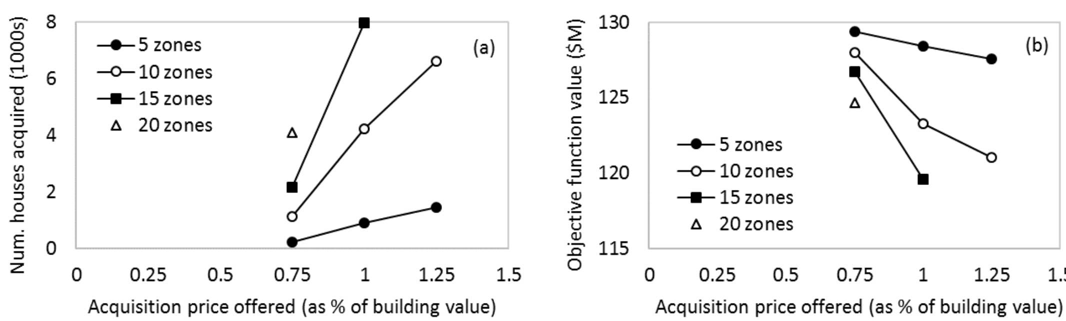

Figure 3.5: Effect of acquisition program structure (number of zones, W, and price offered, ξ) on (a) Number of homes acquired and (b) objective function value (\$M), for optimal retrofit grant solution for $\Omega = \$60M$ base case

Retrofit grant program. Similarly, the way to structure the retrofit grant program—how to specify the maximum retrofit grant amount, *R*, and percentage retrofit to subsidize, *z*—depends on the effect of each on the number of households that retrofit, the types of retrofits that homeowners can afford under the different policies and how much they reduce expected losses, and the government budget available. When available retrofit grant program funds are limited, a tradeoff exists between R and z. The two parameters have different, nonlinear effects on the likelihood a household will retrofit and cost to the government per household, so it is difficult to tell *a priori* what combination is preferred. For the \$60M base case budget, the model recommends a retrofit program that offers to pay $z = 50\%$ of the retrofit cost, up to a maximum of $R = \$10{,}000$ (Table 3.2). With a 50% grant, the government is able to provide a grant to more homeowners than with a 100% grant, and thus more homeowners are able to retrofit (Figure 3.6a). However, the percentage preferred depends on how much money is available for the retrofit program, which in turn, depends on the total government budget and the acquisition solution. For the base \$60M budget, the 100% grants are preferred when acquisition is offered in W =0 or 5 zones, or when it is offered in W =10 or 15 zones but at a price of ξ=75% of the home value (which reduces the offer acceptance rate). In those cases, there is enough money in the retrofit grant program that almost all homeowners who want the grant can get it. When acquisition is offered in W =10 zones at a price of ξ=125%, there is not enough money remaining for all homeowners who want a grant to get one, and thus the 50% grant becomes preferred.

As long as it is at least \$5,000, the maximum grant amount, R, has less of an effect than the percentage, z, in the base case analysis (Figure 3.6). As the maximum grant amount increases from \$5,000 to \$10,000, more homeowners will want to retrofit, but that effect is offset by the fact that the funds are exhausted sooner. In fact, a retrofit program offering 50% grants up to a maximum of \$7,500 each results in an objective function value that is less than 1% larger (worse) than the recommended 50% grant up to \$10,000. Since they are essentially alternative, equally good solutions from the government objective perspective, one might consider other possible objectives to choose between them, such as the effect on homeowners or insurers.

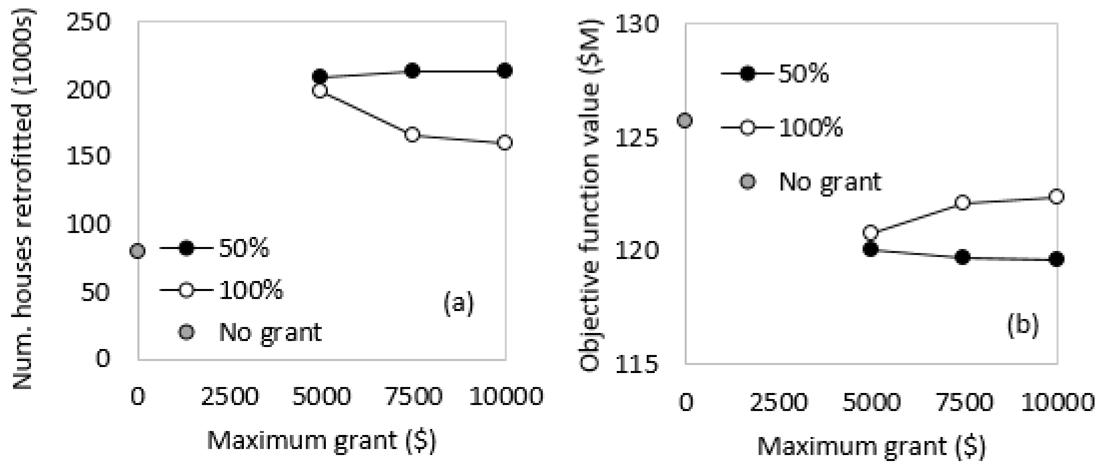

Figure 3.6: Effect of retrofit grant program structure (maximum grant amount, R, and percentage subsidized, z) (a) on Number of homes retrofitted (b) on objective function value ($M) for optimal acquisition solution for $\Omega = \$60M$ base case

3.8.1.2 Expected government outcomes

In addition to providing a recommended set of actions, the framework describes the resulting outcomes of interest for each stakeholder type. The government objective is defined as minimizing the sum of the expected total loss (insured plus uninsured) and the tail loss (i.e., total loss greater than the specified threshold of $6.25 billion), where the two quantities are scaled so that they receive approximately equal importance. This objective function value is of primary importance, but we can also see the effect on the components of it—uninsured, insured, and tail loss. If the government spends the $\Omega = \$60M$ base budget as recommended in Table 3.2, the objective function would be reduced 14% from $138M when there is no government spending to $120M. The expected annual uninsured, insured, and tail loss would be reduced 13%, 3%, and 16%, respectively (Table 3.2). The $64M reduction in expected annual total loss resulting from a $60M annual investment of government dollars suggests the investment is worth it in an expected net benefit sense. In addition, the investment reduces the chance of a large loss. Figure 3.7, which shows the inverse CDF of the loss reduction resulting from the $60M government investment (relative to no government investment), suggests that there is a 0.23 probability the reduction in loss will exceed the $60M invested. Dividing by the 0.32 annual probability of a hurricane, there is a 70% chance that the loss reduction will exceed the $60M if a hurricane does occur. More importantly, the loss reduction might be very large. There is a 1 in 100 chance each year the total loss will be reduced $679M (11.3 times the initial investment). It could be up to $1.5 billion if a catastrophic hurricane occurred. Simulating annual losses, there is a probability of approximately 0.43 that the loss reduction will exceed the amount spent in four years (one political term of office).

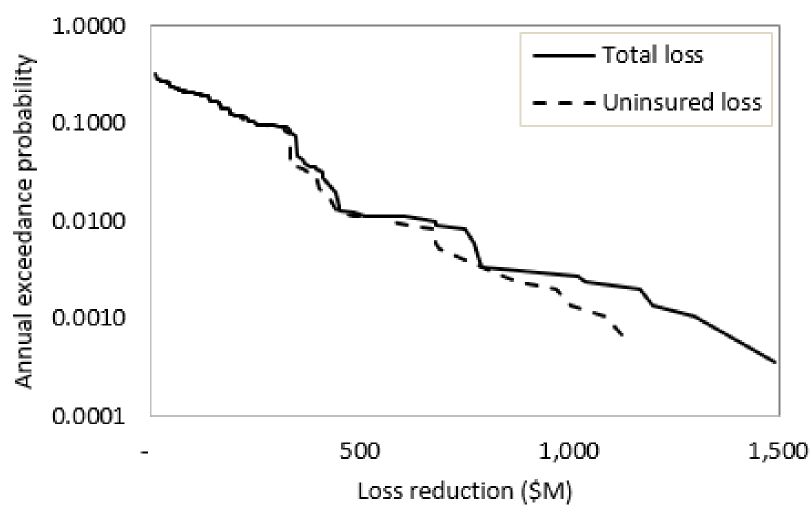

Figure 3.7: Annual probability of exceedance vs. Reduction in total and uninsured loss resulting from $60M government investment

We explored a few alternative government objective functions to see how sensitive the results are to the objective specification. In particular, we tried runs with objectives based on (1) expected total loss only (i.e., $k = 1$), (2) tail loss only (i.e., $k = 0$), and (3) uninsured loss only (i.e., γ_N=1, γ_L=0). In all cases, the recommended solution was the same as the base case. While one could reasonably suggest an alternative objective function and they should be expected to produce different results if they are quite different, it appears that, for this case study at least, the results are not overly sensitive to the specification of government goals.

As noted in Section 3.3.2, we assume in this model that the true societal loss is proportional to total direct loss. If that is true, the recommended government actions should not differ if all components of the true societal loss were included. It is important to note, however, that to the extent that there are additional losses avoided by mitigation investment that are not accounted for in this analysis, the benefit of the investment is even larger than suggested in these results.

3.8.2 Insurers

3.8.2.1 Expected insurer responses

With the government programs in place, and knowing how the homeowner reacts, the primary insurer responds by setting their profit loading factors, λ_H and λ_L, which determine the premium charged for each homeowner, and determining the reinsurance attachment point, *A*, and maximum limit, *M*. For the base case of \$60M budget, the government sets the maximum profit loading factor as 0.8, and the primary insurer is then expected to respond by setting the profit loading factors to that maximum value. It is possible that the insurer may decide to price the insurance lower than the maximum set by the government regulators if a higher price would depress penetration enough to lead to a reduction in profit. In this case, however, that does not occur. The primary insurer is also expected to then transfer some of its risk by purchasing reinsurance that attaches at $424M and has a maximum limit at $3,700M. As the government budget increases, the primary insurer is able to transfer a modestly decreasing amount of risk (lower *A*, *M*) because the increase in retrofits lead to a somewhat reduced portfolio loss distribution.

3.8.2.2 Expected insurer outcomes

In the base case analysis, if the government acts and the primary insurer responds as suggested by the framework, we expect the insurer to earn an expected annual profit of $34.7M and the reinsurer to earn $35.1M (Table 3.3). Note that in all these results, the model constraints ensure that the insurer 30-year probability of insolvency and capacity ratio do not exceed 0.1 and 3, respectively, and the return on equity is at least 5%. The results suggest that insurer and reinsurer profits are relatively insensitive to the government interventions because the profit is regulated and based on the discrete choice models, homeowners insurance purchase decisions are relatively insensitive to their loss distributions. Chapter 4 has more discussions when the utility-based homeowner decision model is used and the effects on insurer and reinsurers profits.

Table 3.3: Insurer: Expected responses and annual expected outcomes

Govt. budget ($M)	Profit loading factors, λ_H and λ_L	Attachment point, A ($M)	Maximum limit, M ($M)	Insurer expected annual profit ($M)	Reinsurer expected annual profit ($M)
	Insurer Decisions			Outcomes	
0	0.8	422	3714	35.6	35.8
20	0.8	431	3744	35.3	35.4
60[a]	0.8	424	3700	34.7	35.1
100	0.8	403	3540	32.3	33.8
Unlimited	0.8	373	3455	29.4	32.7

[a] The $60M government budget run is the base case.

3.8.3 Homeowners

3.8.3.1 Expected homeowner responses

With government programs and insurance premiums set, each homeowner decides if they want to accept an acquisition offer if one has been made. If they do not accept an acquisition offer, they can choose to retrofit (with a grant if offered), purchase insurance at the offered price, do both, or do neither. In the base case, with a $60M government investment, the framework suggests that approximately 8,000 homeowners (0.9%) will accept an acquisition offer, 103,000 will purchase insurance only (11%), and 182,000 (19%) will retrofit only, and 32,000 (3.4%) will insure and retrofit (Table 3.4). Figure 3.8 shows how homeowner decisions change from no government budget to a government budget of $60M. Specifically, there are approximately 134,000 homeowners who do not retrofit without government spending but do with $60M government investment (green layer in the leftmost column labeled

“Nothing” in Figure 3.8). Of those 134,000 homeowners, 83% switched from doing nothing to retrofitting, 13% were insured and then added retrofit, and 4% switched from only being insured to only retrofitting. This suggests that the increased retrofitting does not replace insurance but supplements it.

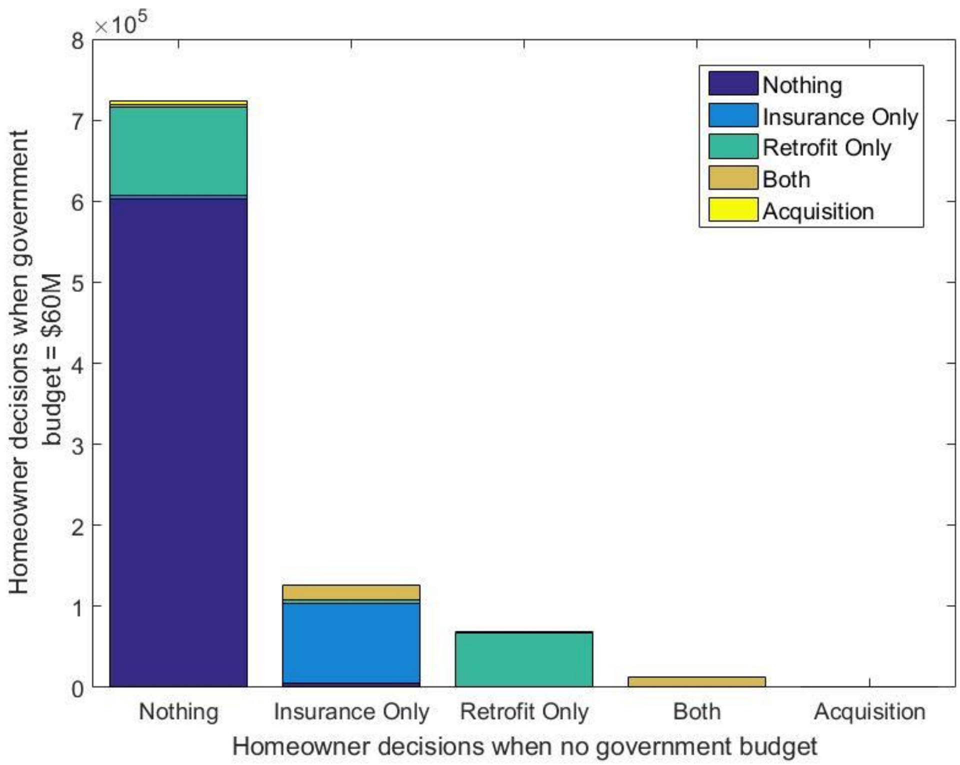

Figure 3.8: Number of buildings making each of the five main choices when government does not offer incentive who switch to each of the five main choices when government offers $60M budget

As the government budget increases, the percentage of homes acquired increases to a maximum of 2.5%, the percentage that insure remains relatively constant, decreasing only slightly from 14.9% to 13.7%, and the percentage that retrofit increases to 34% (Table 3.4). The numbers of homes that retrofit and insure are not zero even with no government investment and are not 100% even with unlimited government investment because for some homes, suggesting that there is a range within which the government can influence homeowner behavior through incentives and voluntary programs. That range may change with region and the types of incentives offered.

Table 3.4: Homeowners: Expected responses and annual expected expenditures

Govt. budget ($M)	Penetration rate [a]			Number of homeowners who do each (1000s)					Average annual expenditures ($)	
	Insurance	Retrofit	Acquisition	Nothing	Insurance only	Retrofit only	Both	Acquisition	High risk region	Low risk region
0	14.9%	8.7%	0.0%	724.2	126.7	68.7	12.4	0.0	1,832	268
20	14.7%	16.7%	0.2%	660.4	113.7	132.5	23.1	2.2	1,778	269
60	14.5%	22.9%	0.9%	607.5	103.1	181.6	31.7	8.0	1,656	270
100	14.2%	25.2%	1.6%	584.2	97.7	200.7	34.2	15.1	1,541	270
Unlimited	13.7%	34.5%	2.5%	504.6	82.6	276.3	45.0	23.4	1,350	242

[a] Penetration rates = number of homeowners that do each strategy divided by total number of homeowners

The framework provides additional detail about what specific type of retrofit homeowners are expected to choose. The selection depends on the pre-retrofit state of the home, the homeowner preferences as captured by the discrete choice models, and for wind-related retrofits, restrictions based on the IBHS FORTIFIED program (Section 3.1). For the base case, for example, the most popular retrofit choices are to strengthen both roof covering and roof sheathing (117,000 homeowners), strengthen roof sheathing (37,000 homeowners), elevate appliances (33,000 homeowners), and strengthen roof covering and roof sheathing, and elevate appliances (6,000 homeowners). The relative popularity of the different retrofit choices are similar across government budget levels, except that some more expensive retrofits (e.g., upgrading siding and insulation to reduce flood damage) become more popular as the budget increases (Table 3.5).

Table 3.5: Most frequently implemented retrofits[a] under different government budgets (approximate average cost, number of homeowner choose this retrofit)

Frequency	Optimal solution ($60M budget)	No govt. intervention
Most common	RC[b], RS[c] ($8k, 117k)	RC, RS ($8k, 40k)
↓	RS ($2k, 37k)	Elevate Appliances ($3k, 21k)
	Elevate Appliances ($3k, 33k)	RS ($2k, 13k)
Least common	RC, RS, Elevate Appliances (10k, 6k)	

[a] Only includes retrofits that are implemented more than 5,000 homeowners
[b] RC means roof covering
[c] RS means roof sheathing

Examining the retrofits in terms of the IBHS FORTIFIED home categories, the results suggest that for the base case, of the approximately 213,000 homes that are retrofitted, 77% (16,400) change from no designation to Bronze, 19% (4,000) do not change category because they are retrofitted for flood not wind, 3% (639) go from no designation to Gold, and 1% go from Silver to Gold (Table 3.6). These results reflect the restrictions modeled that require homes to follow the IBHS guidelines. Alternative guidelines could be used if desired.

Table 3.6: Number of homes making each IBHS level change for different government budget levels

Government budget /$M	Null to Bronze	Null to Silver	Null to Gold	Bronze to Silver	Bronze to Gold	Silver to Gold	Total number change in each level		
							Bronze	Silver	Gold
0	54,784	249	415	71	6	726	54,784	320	1,147
20	116,365	449	3,270	121	26	1,838	116,365	570	5,134
60	164,616	610	5,500	147	47	2,702	164,616	757	8,249
100	182,974	626	6,216	164	51	3,039	182,974	790	9,306
Unlimited	242,815	498	11,749	232	85	4,216	242,815	730	16,050

3.8.3.2 Expected homeowner outcomes

If the stakeholders all act as recommended and expected by the framework for the $60M base case, the average homeowner in the high risk region (within 2 miles of the coast) would pay $1,656 per year for all expenses, including any insurance premiums or deductibles if they insure, any retrofit cost if they retrofit, and any residual hurricane loss they are responsible for (Table 3.4). This is 10% less than the $1,832 they would pay with no government intervention. For the low risk region, average annual expenditures are a much lower $270, about the same as with no government intervention because all the acquisition and most of the retrofit grants are used in the high risk area. In general, as the government budget increases from zero to unlimited, the average high risk homeowner expenditures decrease 18% from $1,832 to $1,350 (Table 3.4).

What makes hurricanes problematic for homeowners is the uncertainty in expenditures and the chance that they could be larger than the household's ability to pay. Figure 3.9 shows the inverse CDF of annual homeowner expenditures for the case with no government budget and the base case $60M government budget, for both high and low risk regions. To highlight the effect of the $60M of government spending, Figure 3.9 includes only the 83,000 (29%) and 137,000 (21%) of high and low risk area homeowners, respectively, for whom the expenditures change between government budgets of $0 and $60M. While the effect for the low risk region is small, for the high risk region, the tail of the loss distribution is substantially reduced. Considering the tail below an exceedance probability of 0.005, for example, the average annual loss is reduced by approximately $6,400 (25%) for high risk region, and $500 (5%) for low risk region. This suggests that the policies are effective from the average homeowner's perspective as well, helping reduce their expected expenditures and the possibility they have especially large expenditures one year.

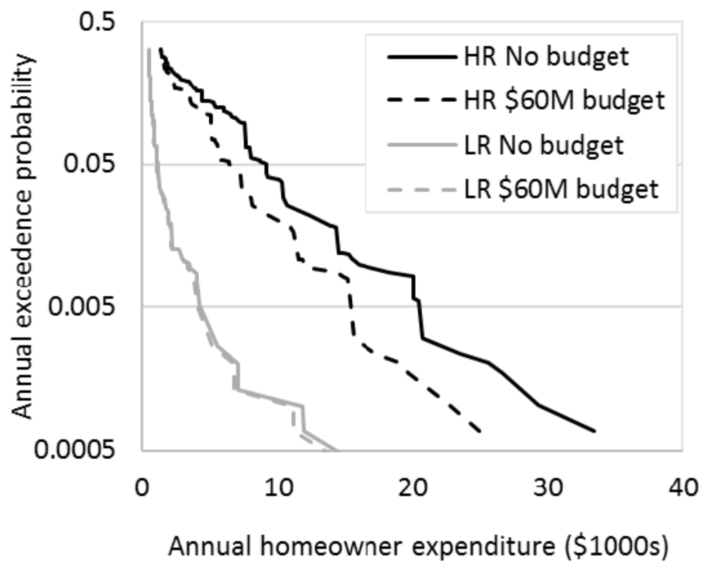

Figure 3.9: Distribution of average annual homeowner expenditure in high and low risk regions, with annual government budget of $0 or $60M, considering only homeowners whose expenditures differ between the two budget levels

3.8.4 Conclusions

This chapter introduces an improved computational framework that can be used to identify hurricane disaster risk management policy solutions that are better both for each stakeholder type individually and for society as a whole. Specifically, the framework can help determine how much the government should spend on hurricane risk management, what combination of interventions to implement, and how to design them. Despite the vast literature on disaster risk assessment and management, this type of systems level decision support that considers interactions among multiple stakeholder types (homeowners, insurers, government, reinsurers) and multiple intervention types (insurance, retrofit, and property acquisition) is new. Analyses that focus on a single stakeholder are likely to create solutions that are unappealing from other perspectives, making them impractical to implement. Similarly, analyses that consider a single intervention (e.g., insurance) are unlikely to manage the risk effectively and efficiently, since each strategy has different strengths and weaknesses. Further, the updated computational framework is grounded in state-of-the-art engineering-based regional loss estimation and empirically-based understanding of homeowner decision-making, making it more realistic than analyses based on simpler assumptions.

The full-scale case study application for the Eastern North Carolina demonstrates that it is possible to identify system-wide win-win solutions that are attractive from all stakeholder perspectives. The solution recommended in the case study meets the government objectives of reducing societal risk (defined in terms of both expected value and tail of the distribution), the insurer and reinsurer goals of making profit while achieving a minimum allowable return on equity and maximum allowable probability of insolvency, and homeowner aims to reduce their annual expenditures (defined in terms of both expected value and tail of the distribution). The framework should help both design such policies and make the business case for them by specifying the outcomes for each stakeholder.

The updated framework offers multiple opportunities for future improvement and expansion. Implementation of the discrete choice models to represent homeowner decision-making represents an advance toward more realistically capturing the way homeowners make these decisions. Nevertheless, their predictive power can surely be improved through additional data collection, examination of additional explanatory variables, and linking the retrofit and insurance decisions. This version of the framework assumes a single primary insurer; future work can incorporate representation of the insurance market as in Gao et al. (2016). While the solution method adopted in this analysis is adequate to demonstrate the framework future work should develop more efficient and improved solution algorithm.

Chapter 4

EFFECT OF HOMEOWNER DECISION MODEL ON THE NEW VERSION OF THE FRAMEWORK

Chapter 4 describes a version of the computational framework that is the same as that in Chapter 3 except that instead of using discrete choice models to represent homeowner acquisition, retrofit, and insurance decisions, homeowner decisions are represented with an expected utility model. The comparison between these two frameworks is discussed in this chapter. Since the utility homeowner model has been widely used (e.g. Kelly and Kleffner 2003) including in previous framework versions in Kesete et al. (2014) and Peng et al. (2014), it is important to understand the implications of each homeowner model choice, and the extent to which conclusions are consistent across types of homeowner model. For convenience, the framework version in this chapter is referred to as the utility-based framework, and the one in Chapter 3 is referred to as the DCM-based framework.

Section 4.1 describes the main differences in these two frameworks, including differences in each stakeholder decision model and the solution procedure. Section 4.2 introduces the case study inputs and Section 4.3 discusses the case study results.

4.1 Differences in Computational Framework Versions

While most of the framework formulation is the same for Chapters 3 and 4, a few changes were required to enable implementation of a utility-based homeowner model. They are described in this section.

4.1.1 Government model

Only two government interventions are considered in this version of the framework—property acquisition and retrofit grant. Insurance pricing regulation is not included because in the utility-based framework, premium does not end up being too high because homeowners are very sensitive to price change.

The government still makes property acquisition offers to homeowners in the same ranked order as in Chapter 3, and the government still needs to determine, W, the number of area units i to offer property acquisition to. Though the price offered, ξ, is an important government property acquisition decision, it could not be used in the utility model. Instead, the percentage of buildings of type m in area unit i who accept an acquisition offer, ψ_{im}, is specified and assumed to be constant within an area unit. The acceptance rate can be varied to examine its effect. The reason for using acquisition acceptance rate instead of using acquisition price is because while the benefit of accepting an acquisition offer (the money received for selling the house) is easy to include, it is difficult to capture the expenses and other effects, including the cost of buying or renting a new home to live in, disruption to one's life, and other potential positive or negative changes. As a result, if only the price received included, being offered acquisition will always led to a positive utility for the homeowner, which means homeowner will always choose to accept the acquisition offer no matter the price To better reflect the price effect to the acquisition offer and the fact that only some homeowners will choose to accept the acquisition offer based on the price, the acquisition acceptance rate is used.

The retrofit grant remains the same except that one additional restriction is introduced. The grant is only offered to homeowners who buy insurance in order to help keep a healthy insurance market. Without this restriction, the grant crowds out the insurance market as seen in Peng et al. (2014).

As a result of these modifications, a single government policy is defined by three variables instead of six—the number of zones in which acquisition offers are made, W; the percentage of the retrofit cost the government offers to subsidize, z, and the maximum amount it will pay a homeowner for a retrofit in dollars, R.

4.1.2 Insurer decision model

The only difference for the insurer decision model in the utility-based framework is that insurer price is not regulated by government policy. In other words, it is the same as the primary insurer decision model described in Peng et al. (2014). The regulation is applied in the DCM-based framework but not the utility-based framework is because in the utility-based framework homeowners are more sensitive to the price change, so insurer could not charge too much from the homeowners if they would like to maintain a relatively high insurance penetration rate. While in the DCM-based framework homeowners are much less sensitive to the price change thus allows insurer to charge way too much from homeowners. It is a stochastic programming model that seeks to maximize the total profit over the full time horizon, averaged over all scenarios *S*. It chooses decision variables defining the premium pricing (specifically, profit loading factors λ_v for each risk region v) and reinsurance purchase (specifically, attachment point *A* and maximum limit *M*), subject to the constraints that ensure the probability of insolvency and capacity ratio do not exceed specified values, and the return on equity is at least a specified value. It is solved using a genetic algorithm.

4.1.3 Homeowner decision model

The homeowner decision model is the most different between Chapters 3 and 4. The homeowner model in Chapter 3 is the same as Peng et al. (2014) with the addition of the acquisition decision. We let the binary index q indicate the property acquisition acceptance decision—one if a homeowner accepts an acquisition offer, or zero if not; and the binary index *n* indicate the insurance purchase choice—one if a homeowner purchases insurance, or zero if not. If he chooses to retrofit, he can choose which retrofit alternative cc' to do, each of which represents a physical modification of the building that requires a cost to implement and reduces the loss distribution. The case of $c' = c$ corresponds to a situation with no retrofit. The model provides as output $u_{imcv}^{qbc\prime}$, a binary decision variable equal to one if a homeowner of type i, m, c, v makes the acquisition acceptance choice *q*, the insurance choice *b*, and implements a retrofit that changes building resistance from *c* to resistance c'; and zero otherwise. It is run separately for each group i, m, c, v, and since the models do not interact, the computation is parallelized. The analysis is conducted on an individual building and annual basis. We assume the decision is made by maximizing utility function $U(x) = 1 - e^{-\theta_v x}$, where $\theta_v > 0$ is the Arrow-Pratt coefficient of risk aversion that is assigned to homeowners in risk region v. This utility function represents risk averse homeowners, which is necessary for a functioning voluntary insurance market given the loading factors on the premiums.

The homeowner decision is implemented in two steps. First, homeowners in area units *i* that are offered property acquisition decide whether or not to accept it. The remaining homeowners then choose some combination of insurance and retrofit that can include neither.

A homeowner's decision to accept a property acquisition offer or not depends on characteristics of the homeowner (e.g., attachment to community, risk perception), the property (e.g., proximity to hazards and amenities), and the acquisition program (e.g., price offered) (Robinson et al. 2018). Further, accepting an offer requires finding alternative housing. It is very difficult to represent the costs and benefits of this decision within a utility maximizing framework, so in this version of the formulation, we simply assume a randomly selected user-specified percentage of homeowners, ψ_{im}, who are offered property acquisition in each area unit i accept the offer.

For homes that are not acquired (and demolished), the homeowner's objective function (Equation 4.1) is to maximize the sum of the expected utilities over all possible hurricanes h if the homeowner buys insurance (first term) and if he does not (second term). In the first case, the homeowner pays the: (1) premium, $p_{imc'v}$; (2) loss up to the deductible, $B_{imc'}^{h}$; and (3) cost to retrofit, $K_{mc}^{c'}$ minus R or $zK_{mc}^{c'}$, whichever is less and satisfies the requirement that only homeowner purchases insurance can get the retrofit grant. In the second case, the homeowner pays the: (1) cost to retrofit; and (2) loss due to building damage, $L_{imc'}^{h}$. We assume the homeowner retrofits first, so that the insurance policy applies to the building after any retrofit. Retrofit requirements are the same as the one in Peng (2013). The insurance decision is not separated into wind related or flood related decision. Homeowner's maximum budget for insurance is still the same as in Chapter 3 which is a specified percentage κ_v of his total home value V_m, where κ_v may vary for different risk regions v , however, the minimum threshold for the insurer, ρ, is defined by the premium instead of raw premium in this case (Equation 4.2-4.3). The inventory is updated after retrofit as in Peng (2013).

The outputs are collected and used in the same way as in Chapter 3.

$$Max \left[\sum_{n=1}\sum_{x=0}\sum_{c\prime} u_{imcv}^{nc\prime q}\left\{\sum_{h} P^h U\left(p_{imc\prime v} + B_{imc\prime}^h + K_{mc}^{c'} - \min\left[R, zK_{mc}^{c'}\right]\right)\right\}\right]$$

$$+\left[\sum_{n=0}\sum_{x=0}\sum_{c\prime} u_{imcv}^{qbc\prime}\left\{\sum_{h} P^h U\left(K_{mc}^{c'} + L_{imc\prime}^h\right)\right\}\right] \quad (4.1)$$

$$p_{imc\prime v} \leq \kappa_v V_m \quad \forall i, m, c', v \quad (4.2)$$

$$p_{imc\prime v} \geq \rho \quad \forall i, m, c', v \quad (4.3)$$

4.1.4 Solution procedure

The government decision model was also solved using an enumeration approach with the difference that government only has three decision variables (i.e., W, R, z) instead of six. The objective function value is determined for each solution (i.e., combinations of W, R, z), and the set of policies with the best objective function value is selected.

The solution algorithm proceeded the same way as in Chapter 3 except that each homeowner's decision is made based on the utility model instead of the discrete choice models. The application is the same as in Chapter 3, and similarly was implemented in Matlab and run in parallel on Unix-based high performance computing cluster.

4.2 Case Study Inputs

A full-scale case study was also demonstrated for hurricane risk to residential buildings in the eastern half of North Carolina. The differences in case study inputs between Chapter 3 (framework with discrete choice models) and Chapter 4 (framework with utility models) are: (1) Explanatory variables are not needed as utility models are used for homeowner decisions; (2) minimum premium required to offer insurance of $\rho = \$100$ instead of raw premium; (3) no minimum net benefit requirement for this framework as risk aversion is already captured by parameter θ_v, the Arrow-Pratt coefficient of risk aversion, in the utility model; (4) weight of expected loss vs. loss distribution tail $k = 1/11$ so that the two objection function terms remain of similar magnitude; and (5) 172 combinations of the following government decision variable values were considered as possible solutions: Retrofit grant amount R=\$0, \$2,500, \$5,000, \$10,000; percentage retrofit subsidized by government z=0, 50%, 100%; number of zones offered acquisition W=0, 5, 10, 20, 30.

4.3 Case Study Results

The case study results are quite different in this Chapter compared to Chapter 3. The results are still summarized based on decisions and outcomes for each stakeholder type. To better understand the differences and similarities between the two frameworks, the Chapter 4 results are compared to those in Chapter 3.

4.3.1 Government

4.3.1.1 Recommended government policies

The types of government decisions in setting a risk management policy are very similar to those in Chapter 3, which are: (1) how much to spend on mitigation, (2) how to trade-off between retrofit grants and property acquisition, and (3) how to design the retrofit grant and acquisition programs, with two decisions to make for retrofit (percentage of grant, z, and maximum limit of grant, R), and one decision to make for acquisition (number of zones to offer acquisition, W).

Mitigation budget. As in Chapter 3, the mitigation budget is examined under multiple annual government budget levels ($0, $20M, $60M, $100M, and unlimited). Recommended government policies and outcomes are shown in Table 4.1 for multiple government budgets, including a run in which homeowners are artificially not allowed to buy insurance, retrofit, or be acquired. Table 4.1 shows that spending more money always results in better (lower) objective function values. Compared to no homeowner action is allowed, the total uninsured loss decreases by $201M, and 39% of that ($79M) becomes insured loss when voluntary risk actions are allowed without government intervention(Table 4.1). In the DCM-based framework, the total uninsured loss decreases by $134M. The objective function value, decreases by 34%, 37%, 42% and 45% respectively relative to no homeowner action run as the government intervention is allowed and the budget increases to $20M, $60M, and $100M (Table 4.1). The similar decreases are 7%, 15% and 21% in the DCM-based framework. It shows the framework is more sensitive to budget change when using utility-based homeowner model compared to using empirical homeowner model. For this case study, we still assume $\Omega = \$60M$ is taken to be the best budget and use that as the base case in the remainder of the analyses because the margin benefit of government investment of $60M is better than $100M and unlimited.

Table 4.1: Government: Recommended decisions and annual expected outcomes

Utility-based framework

	Government Decisions					Government Outcomes ($M)				
	Retrofit grant		Acquisition offers	Amount spent on						
Govt. budget ($M)	% subsidized *z*	Max grant paid ($) *R*	Num. zones[b] *W*	Acq.	Retrofit grants	Obj. fn.	Total loss	Uninsured loss	Insured loss	Tail loss
No action[a]	-	-	-	-	-	128	585	585	-	82
0	0	0	0	0	0	85	463	384	79	47
20	50	5000	10	0	16.2	80	451	364	87	43
60[c]	50	5000	30	42.6	15.9	75	430	339	92	39
100	100	10000	20	29.6	70.5	71	422	327	95	35
Unlimited	100	10000	30	42.6	87.0	67	414	298	116	32

[a] Homeowners are not allowed to take any protective action (insure, retrofit, or be acquired) in this run.
[b] Maximum of W=30 zones were considered as possible solutions.
[c] The $60M government budget run is the base case.

Table 4.1 continued.

DCM-based framework

Govt. budget ($M)	Government Decisions							Government Outcomes ($M)				
	Insurance	Retrofit grant		Acquisition offers		Amount spent on						
	Max. profit loading Λ	% subsidized *z*	Max grant paid ($) *R*	Num. zones[b] *W*	Price[c] x	Acq ($M).	Retrofit grants ($M)	Obj. fn	Total loss	Unins. loss	Insured loss	Tail loss
No action[a]		-	-	-	-	-	-	141	585	585	-	82
0	0.8	0	0	0	0	0	0	138	578	451	127	80
20	0.8	50	10,000	15	0.75	7.9	12.1	131	553	428	125	75
60[d]	0.8	50	10,000	15	1	38.6	21.4	120	514	390	123	67
100	0.8	50	10,000	20	1	73.0	24.8	111	486	368	117	61
Unlimited	0.8	100	10,000	20	1.25	142.0	64.6	99	443	333	111	53

[a] Homeowners are not allowed to take any protective action (insure, retrofit, or be acquired) in this run.
[b] Maximum of *W*=20 zones were considered as possible solutions.
[c] Price offered for acquisition as a percentage of building value.
[d] The $60M government budget run is the base case

Acquisition-retrofit grant tradeoff. In the utility-based framework, the solution suggests spending \$42.6M (73%) of the \$60M budgeted on acquisition and \$15.9M (27%) on the retrofit grant program (Table 4.1), while in the DCM-based framework, the solution suggests spending \$38.6M (64%) on acquisition and \$21.4 (36%) on retrofit grant. This comparison shows both frameworks suggest spending more on acquisition compared to retrofit when given limited budget, though the percentage changes a bit. Acquisition is also preferred in this framework because the objective function is still expressed as weighted loss of total direct loss and tail loss, even though the weight are different, acquisition is still more cost-effective at reducing the objective function value.

Acquisition program. In this utility-based version of framework, there is only one acquisition program decision to make—in how many zones, W—to offer acquisition. For the base case, an acceptance rate of 20% is used. The model recommends offering 30 zones acquisition under the base case (\$60M budget), while it recommends offering 20 zones under the \$100M budget. By contrast, in the DCM-based version of the framework, the model recommends the government spend more and more on acquisition offer as the budget increases. More acquisition acceptance rates (50%, 80%, 100%) were implemented as a parameter to see how acquisition acceptance rates change will affect the results. It shows the highest acquisition offer, which is 100% acceptance rate (indicating a very high price), is preferred.

Retrofit grant program. The way to structure the retrofit grant program is the same as in DCM-based framework, including the maximum retrofit grant amount, R, and percentage retrofit to subsidize, z. There is a tradeoff between R and z. For the base case scenario, the model recommends a retrofit program that offers to pay $z =$

50% of the retrofit cost, up to a maximum of $R = \$5{,}000$ (Table 4.1). Unlike the DCM-based framework, a 100% grant benefits more homeowners than a 50% grant (Figure 4.1a), and the objective function values are very close with a 50% up to \$5,000 grant compared to 100% up to \$5,000 grand (Figure 4.1b). As to whether a 50% grant is preferred or 100% grant is preferred, in both the utility-based and the DCM-based frameworks, 50% is preferred for the \$60M government budget.

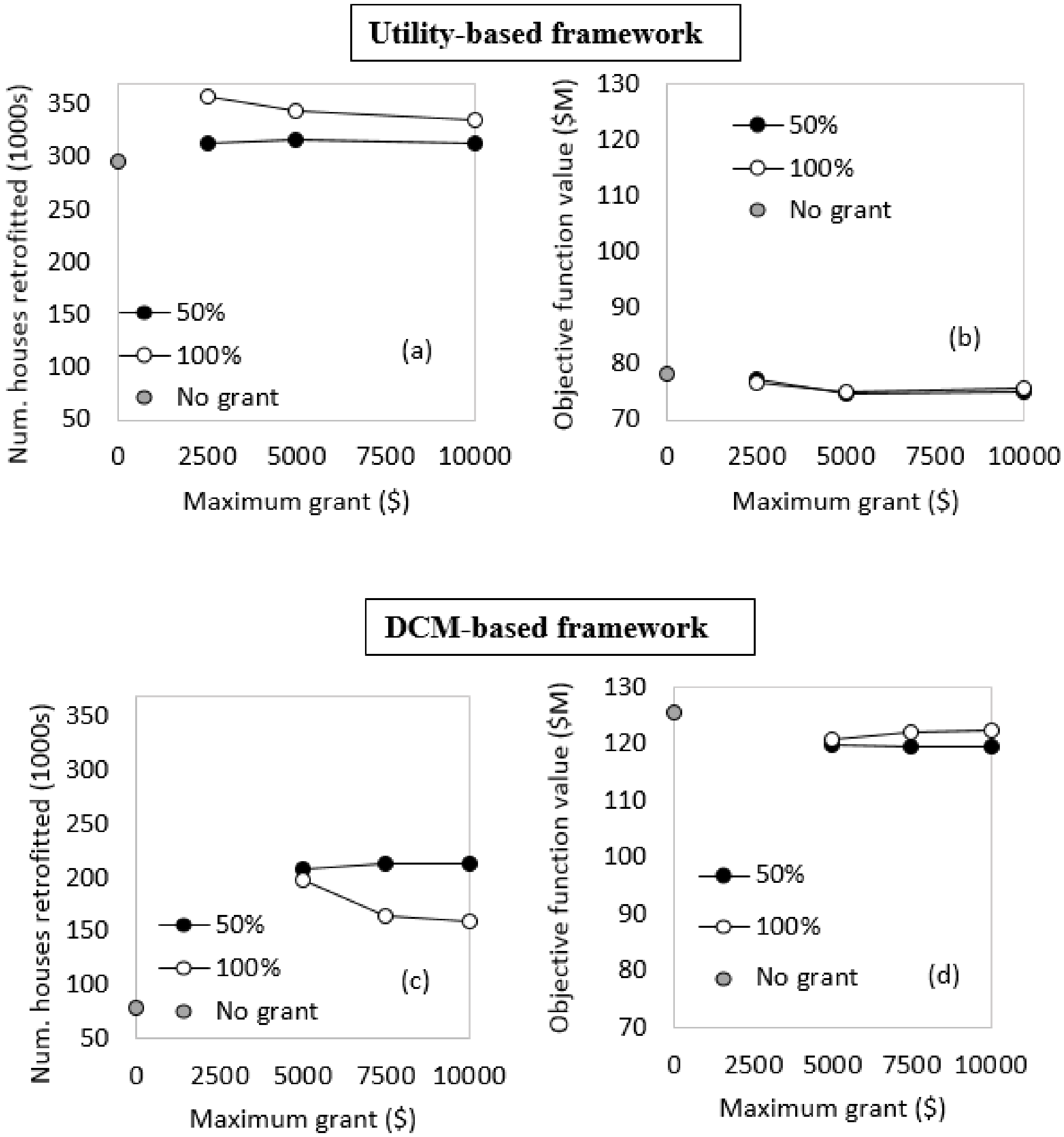

Figure 4.1: Effect of retrofit grant program structure (maximum grant amount, R, and percentage subsidized, z) (a) and (c) on Number of homes retrofitted (b) and (d)on objective function value ($M) for optimal acquisition solution for $\Omega = \$60M$ base case. (a) and (b) are for the utility-based framework, and (c) and (d) are for the DCM-based framework.

As shown in Figure 4.1b, when the maximum grant amount, R, increases from \$2,500 to \$5,000, R has more effect than the percentage, z; when R is more than \$5,000, R and z have a similar effect, and generally speaking, the effect is less than the effect in DCM-based framework. In addition, increasing the maximum grant amount from \$5,000 to \$10,000 does not help reduce the objective function value because more homeowners want to get the grant, which exhausts the budget sooner.

4.3.1.2 Expected government outcomes

The government objective is defined in the same way in the utility-based and DCM-based frameworks. That is, minimizing the sum of the expected total loss (insured plus uninsured) and the tail loss (i.e., total loss greater than the specified threshold of \$6.25 billion), where the two quantities are scaled so that they receive approximately equal importance. In the utility-based framework, when releasing the restriction that no homeowner can take any risk management actions, the objective function value is reduced 34% from \$128M, total loss is reduced 21% from \$585M, uninsured loss is reduced 34% from \$585M, and tail loss is reduced 43% from \$82 (Figure 4.2a). While in the DCM-based framework, the reduction for the objective function value is 2% (from \$141M), for the total loss is 1.2%, for the uninsured loss is 23%, and for the tail loss is 2.4% (Figure 4.2b). The comparison from this perspective shows that the utility-based framework is much more sensitive the government policy change than the DCM-based framework. If the government spends the $\Omega = \$60M$ base budget as recommended in Table 4.1, the objective function would be reduced 12% from \$85M when there is no government spending to \$75M, while the reduction in the DCM-based framework is 13% from \$138M to \$120M. The expected annual uninsured and tail loss would be reduced 12% and 17%, while insured loss would be increased 16% in the utility-based framework, and the expected annual uninsured loss, tail loss and insured loss is reduced 14%, 16%, and 3%. (Table 4.1). The two frameworks are the same in that objective function value, total loss, uninsured loss and tail loss are all reduced when government has more budget, however, the two frameworks are different in that the insured loss increases as government has more budget in the utility-based framework (Figure 4.2a), while it decreases in DCM-based framework (Figure 4.2b). The increasing insured loss makes sense in the utility-based framework because the retrofit grant is linked with insurance purchase requirement, which means with more people retrofitting with grant when the government budgets increases, they are required to buy insurance, thus increase insured loss.

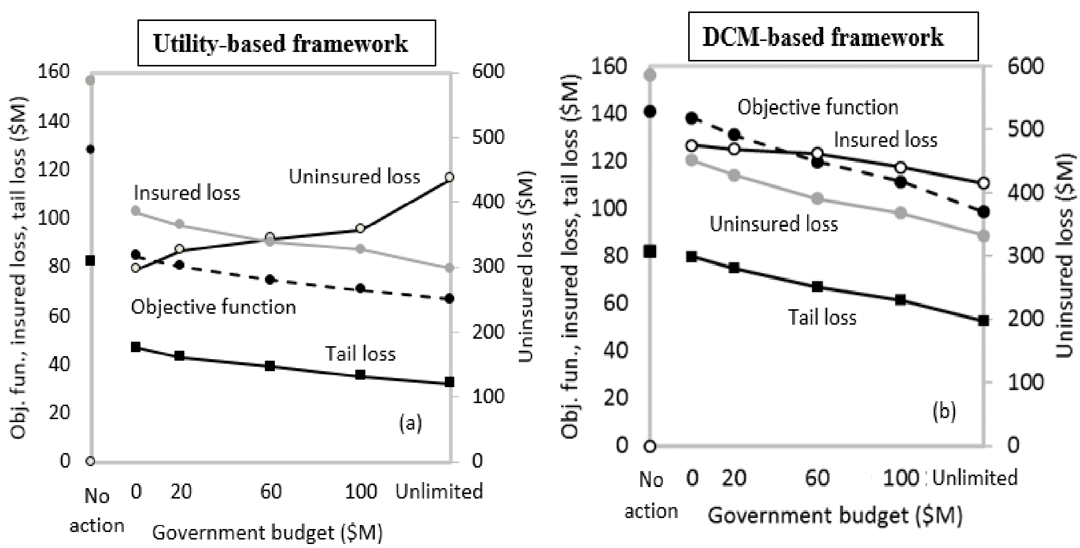

Figure 4.2: Objective function value, uninsured loss, insured loss, and tail loss ($M) versus government budget ($M). (a) is for the utility-based framework, and (b) is for the DCM-based framework.

Unlike in the DCM-based framework in which the government investment is cost effective in terms of total direct loss in base case, i.e., a $60M annual investment from government will reduce $64M total direct loss, in the utility-based framework a $60M annual investment of government dollars only reduced total direct loss by $33M, which suggests the investment is not worth it in an expected net benefit sense. However, the investment does reduce the chance of a large loss, especially for uninsured loss. Analysis shows that $60M budget from the government helps to reduce tail loss a lot. Figure 4.3, which shows the inverse CDF of the loss reduction resulting from the $60M government investment (relative to no government investment), suggests that there is a 0.18 probability the reduction in loss will exceed the $60M invested. Dividing by the 0.32 annual probability of a hurricane, there is a 56% chance that the loss reduction will exceed the $60M if a hurricane does occur. More importantly, the loss reduction might be very large. There is a 1 in 100 chance each year the total loss will be reduced $760M (12.7 times the initial investment). It could be up to $2.9 billion if a catastrophic hurricane occurred. The utility-based framework suggest the government investment helps to reduce very large scale losses better than the DCM-based framework does (e.g. $2.9 billion loss reduction in the utility-based framework vs 1.5 billion in the DCM-based framework). However, the DCM-based framework suggests a better cost benefit (e.g., 18% chance of a loss reduction greater than $60M in the utility-based framework vs 22% in the DCM-based framework). Compare Figure 4.3a and 4.3b, it suggests the total loss reduction in the utility-based framework is almost twice than that in the DCM-based framework. Since insurance can help reduce the very large tail loss, a possible explanation to the difference in Figure 4.3a and 4.3b could be the difference insurance penetration rate in the two versions of framework. The insurance penetration rate changes from 4% to 13% in the utility-based framework when the government budget changes from \$0M to \$60M, while the change in the DCM-based framework is 14.9% to 14.5%.

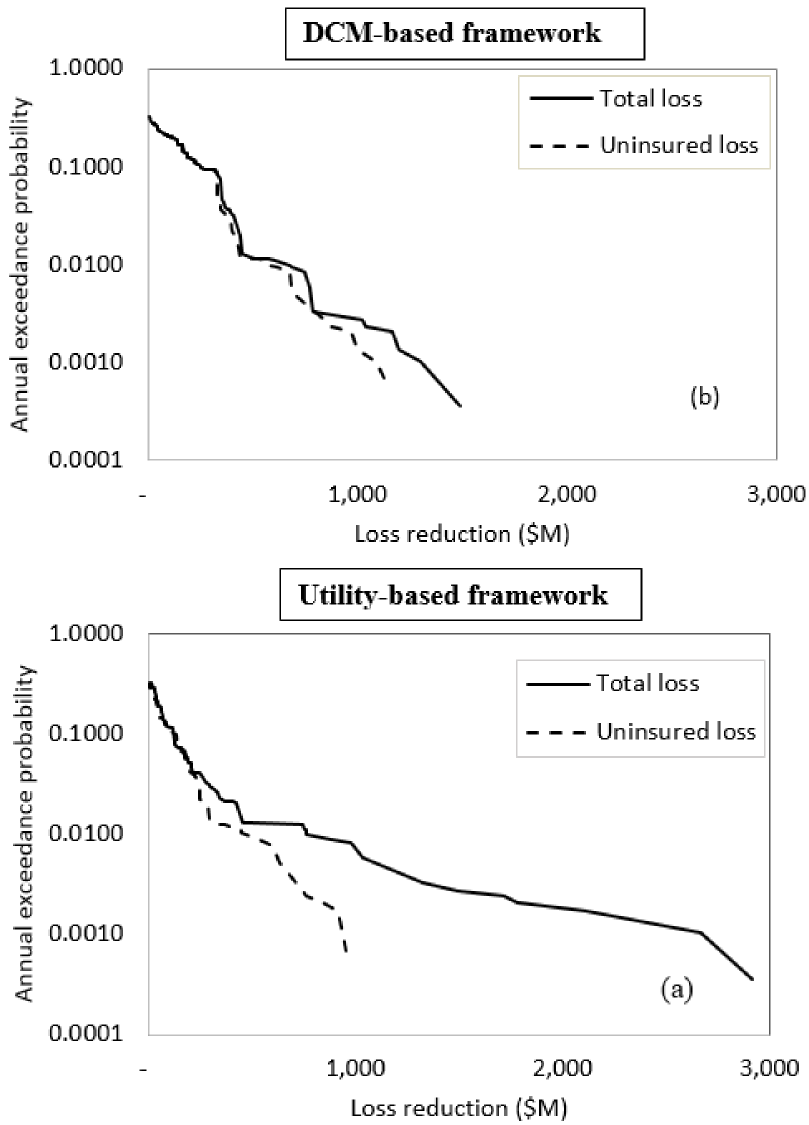

Figure 4.3: Annual probability of exceedance vs. Reduction in total and uninsured loss resulting from \$60M government investment. (a) is for the utility-based framework, and (b) is for the DCM-based framework

As in the DCM-based framework, a few alternative government objective functions were explored to see how sensitive the results are to the objective specification. The results are quite different in the utility-based framework. We tried the runs with objectives based on (1) expected total loss only (i.e., $k = 1$), (2) tail loss only (i.e., $k = 0$), and (3) uninsured loss only (i.e., γ_N=1, γ_L=0). In the first case, the recommended solution was the same as the base case, however, the other two both suggested different solutions than the base case. When we only consider tail loss, the suggested solution is the government offers 100% up to $10,000 retrofit grant, and acquires 10 zones. When only uninsured loss is considered in the objective function, the framework suggests the government offers 100% up to $5,000 retrofit grant and acquires 20 zones. This shows the utility-based framework is more sensitive to changes in the objective function than the DCM-based framework is.

4.3.2 Insurers

4.3.2.1 Expected insurer responses

In the utility-based framework, the insurer responds to the government decisions by making the same types of decisions as in DCM-based framework, choosing the profit loading factors, λ_H and λ_L, and the reinsurance attachment point, *A*, and maximum limit, *M*. The difference between the utility-based and DCM-based frameworks is that in the utility-based framework there are no premium restrictions from the government. The profit loading factors for both high and low risk area remain below 3.0 even without government regulation, and they both increase with an increasing government budget (Table 4.2, Figure 4.4). The value of λ_H takes a similar value in both the utility-based and the DCM-based frameworks, while λ_L is quite different. The reinsurance attachment point is $279M and has a maximum limit at $2,240M. Figure 4.5 shows how the utility-based framework performs differently in reinsurance transfer than that in the DCM-based framework.

Table 4.2: Insurer: Expected responses and annual expected outcomes

Utility-based framework

Govt. budget ($M)	Insurer Decisions				Outcomes	
	Profit loading factors, λ_H	Profit loading factors, λ_L	Attachment point, A ($M)	Maximum limit, M ($M)	Insurer expected annual profit ($M)	Reinsurer expected annual profit ($M)
0	0.79	0.81	192	2062	28.1	23.4
20	0.84	1.06	251	2130	30.8	24.4
60[a]	0.84	1.07	279	2240	31.0	25.2
100	0.89	2.72	352	2426	38.6	26.6
Unlimited	0.90	2.74	404	2758	41.3	28.6

[a] The $60M government budget run is the base case.

DCM-based framework

Govt. budget ($M)	Insurer Decisions			Outcomes	
	Profit loading factors, λ_H and λ_L	Attachment point, A ($M)	Maximum limit, M ($M)	Insurer expected annual profit ($M)	Reinsurer expected annual profit ($M)
0	0.8	422	3714	35.6	35.8
20	0.8	431	3744	35.3	35.4
60[a]	0.8	424	3700	34.7	35.1
100	0.8	403	3540	32.3	33.8
Unlimited	0.8	373	3455	29.4	32.7

[a] The $60M government budget run is the base case.

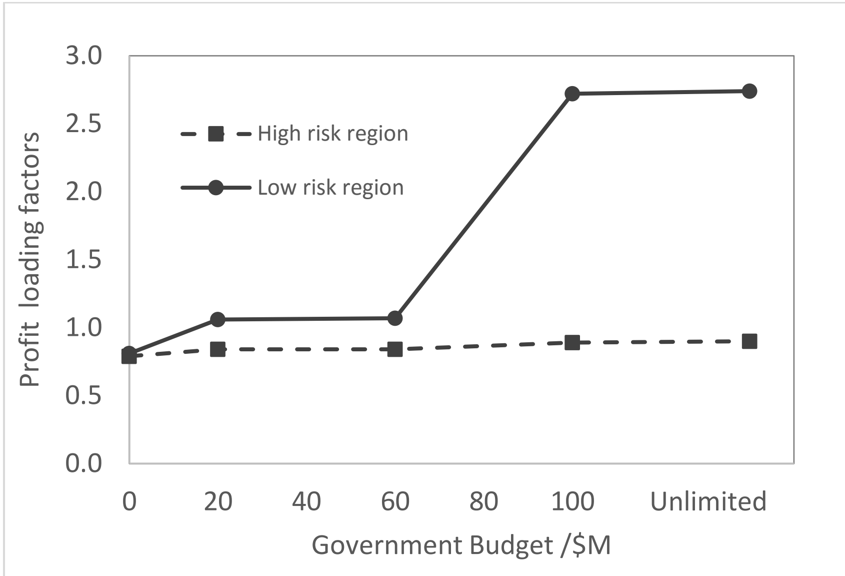

Figure 4.4: Profit loading factors (λ_L, λ_H) versus changing with government budget ($M) in the utility-based framework (Profit loading factors (λ_L, λ_H) are always 0.8 because of the government regulation)

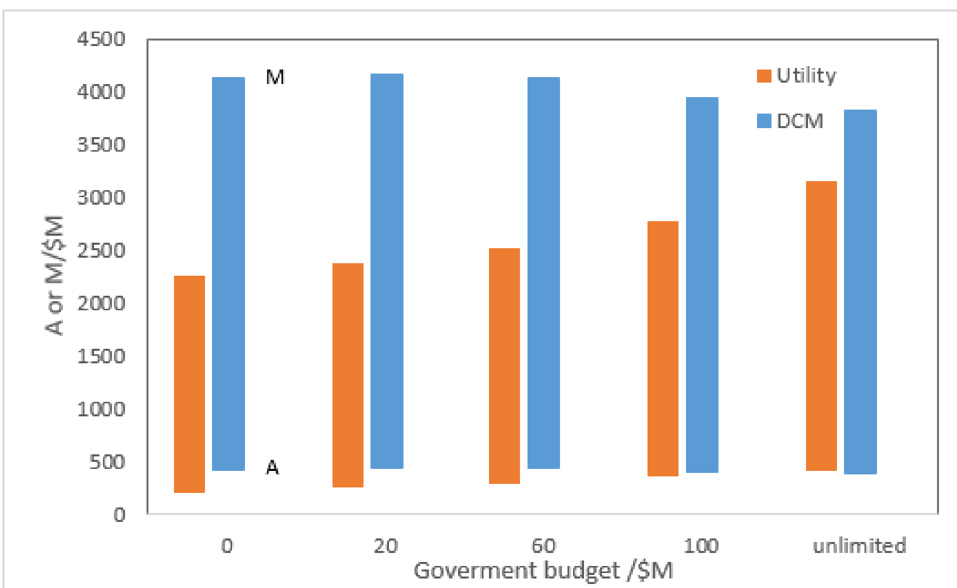

Figure 4.5: Attachment point, A ($M) and Maximum limit, M ($M) under different government budgets in the utility-based and DCM-based framework

4.3.2.2 Expected insurer outcomes

In the base case analysis of a $60M government investment, the insurer is expected to earn an expected annual profit of $31.0M and the reinsurer to earn $25.2M (Table 4.2, Figure 4.6). The constraints remain the same as in the DCM-based framework that the insurer 30-year probability of insolvency and capacity ratio must not exceed 0.1 and 3, respectively, and the return on equity must be at least 5%. Unlike in the DCM-based framework in which both the insurer and the reinsurer make less profit when the government has an increasing budget, in the utility-based framework, the profit of both increases as the government budget increases. This is because the profit is not regulated and based on the utility models, homeowners insurance purchase decisions are sensitive to insurance price, retrofit cost, and the effects of those actions on the homeowner's expected loss.

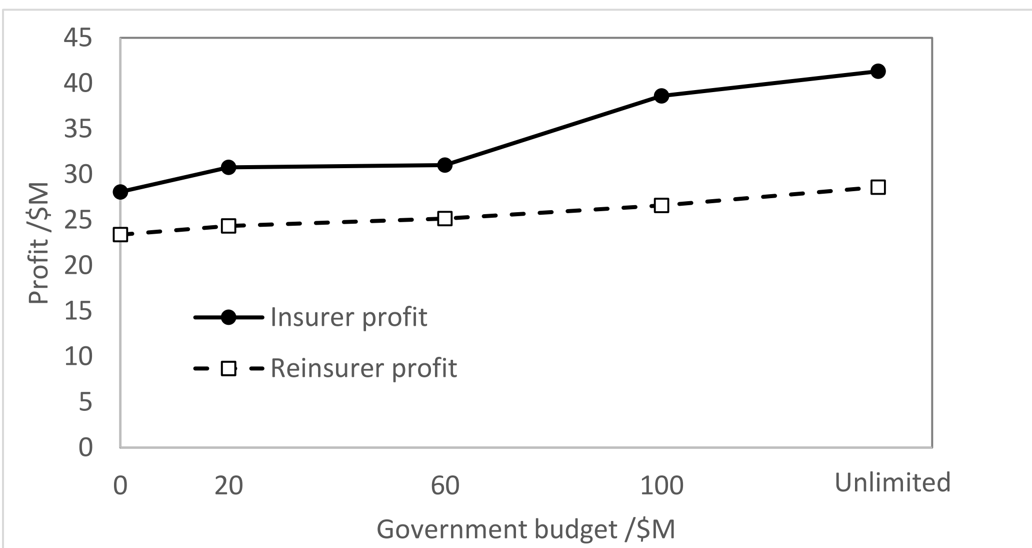

Figure 4.6: Expected annual profit ($M) for insurer and reinsurer as government budget increases

4.3.3 Homeowners

4.3.3.1 Expected homeowner responses

As in the DCM-based framework, homeowners respond to government programs and insurance pricing in the utility-based framework by deciding if they want to accept acquisition offers, and for those who do not accept an acquisition offer, choosing to retrofit (with a grant if offered), purchase insurance at the offered price, do both, or do neither. The differences in the utility-based framework are: (1) homeowners make their decision based on the utility model instead of the discrete choice model, and (2) there is a requirement that retrofit grants are only offered to homeowners who buy insurance to help build a healthy insurance market. The utility-based framework suggests that in the base case, with a $60M government investment, approximately 7,000 homeowners (0.8%) will accept an acquisition offer, 500 (0.05%) will purchase insurance only, 195,000 (21%) will retrofit only, and 121,000 (13%) will insure and retrofit (Table 4.3). In the DCM-based framework, by contrast, approximately 8,000 homeowners (0.9%) will accept an acquisition offer, 103,000 (11%) will purchase insurance only, and 182,000 (19%) will retrofit only, and 32,000 (3.4%) will insure and retrofit. These responses in the utility-based framework show that the requirement of buying insurance to obtain a retrofit grant encourages many more homeowners to take both insurance and retrofit actions and leaves few homeowners buying insurance only. Figure 4.7 shows how homeowner decisions change when the government budget is $60M vs $0M. In the utility-based framework, of approximately 14,000 homeowners who do not retrofit without government spending but do with $60M government investment, 64% switched from doing nothing to retrofitting, 34% were insured and then added retrofit, and 1% switched from only being insured to only retrofitting. This suggests also that retrofit and insurance are supplements. Compared to the DCM-based framework, the number of homeowners do nothing when no government incentive almost stay the same when there are $60M government grant in the utility-based framework, and there are many homeowners adding insurance to the retrofit only decision when government offers an incentive.

Table 4.3: Homeowners: Expected responses and annual expected expenditures

Utility-based framework

Govt. budget ($M)	Penetration rate			Number of homeowners who do each (1000s)					Average annual expenditures ($)	
	Insurance	Retrofit	Acquisition	Nothing	Insurance only	Retrofit only	Both	Acquisition	High risk region	Low risk region
0	4.0%	33.2%	0.0%	617.1	5.9	277.2	31.7	0.0	1,720	212
20	10.4%	34.2%	0.2%	610.9	0.8	222.3	96.5	1.4	1,676	212
60	13.0%	33.9%	0.8%	608.2	0.5	195.1	120.8	7.3	1,600	211
100	26.5%	46.7%	0.5%	490.9	0.4	188.7	246.9	5.1	1,586	208
Unlimited	32.1%	49.8%	0.8%	460.1	0.3	165.1	299.1	7.3	1,557	207

DCM-based framework

Govt. budget ($M)	Penetration rate			Number of homeowners who do each (1000s)					Average annual expenditures ($)	
	Insurance	Retrofit	Acquisition	Nothing	Insurance only	Retrofit only	Both	Acquisition	High risk region	Low risk region
0	14.9%	8.7%	0.0%	724.2	126.7	68.7	12.4	0.0	1,832	268
20	14.7%	16.7%	0.2%	660.4	113.7	132.5	23.1	2.2	1,778	269
60[a]	14.5%	22.9%	0.9%	607.5	103.1	181.6	31.7	8.0	1,656	270
100	14.2%	25.2%	1.6%	584.2	97.7	200.7	34.2	15.1	1,541	270
Unlimited	13.7%	34.5%	2.5%	504.6	82.6	276.3	45.0	23.4	1,350	242

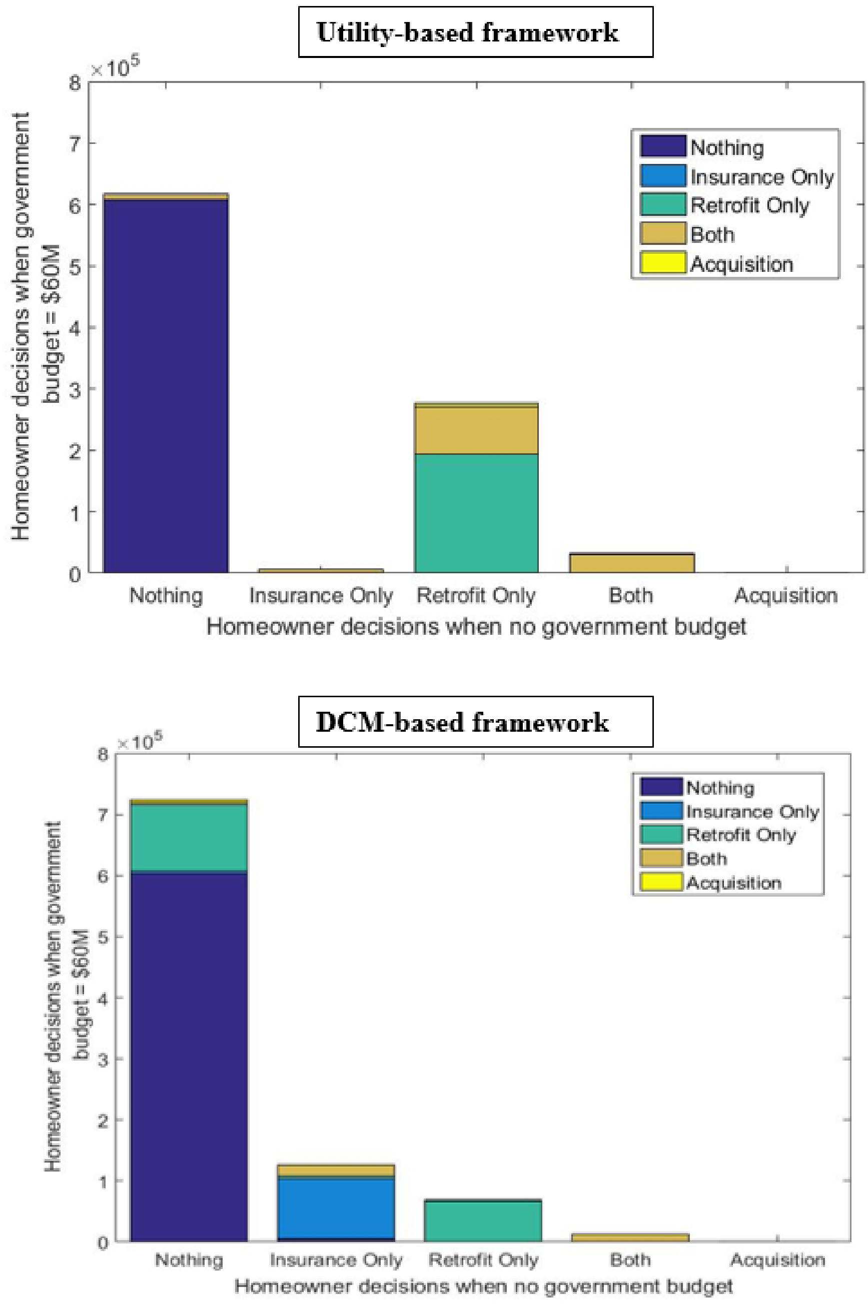

Figure 4.7: Number of buildings making each of the five main choices when government not offer incentive who switch to each of the five main choices when government offers $60M budget

As in the DCM-based framework, fewer homeowners in the utility-based framework do nothing and more homeowners take some risk management actions with government incentives. In particular, more people retrofit their buildings to make them less vulnerable. As the government budget increases, the percentage of homes acquired increases to a maximum of 0.8%, which is lower than that in the DCM-based framework (2.5%). The insurance penetration rate which is relatively constant in the DCM-based framework (14.9% to 13.7%), increases from 4.0% to 32.1% in the utility-based framework. However, the penetration rate for retrofit increases by 16.6 percentage points, which is less than the 25.8 percentage points increase in DCM-based framework (Table 4.3). The comparison between the two frameworks shows that different homeowner decision models as well as the linkage between insurance and retrofit in the utility-based framework make a substantial difference in the framework results. In the utility-based framework there are many more homeowners that both buy insurance and retrofit, and many fewer that buy insurance only.

As the DCM-based framework, the utility-based framework also provides additional detail about what specific type of retrofit homeowners are expected to choose based on the utility model, and for wind-related retrofits, restrictions is also based on the IBHS FORTIFIED program (Section 3.4). For the base case, the most popular retrofit choices are to strengthen roof sheathing (69,000 homeowners), strengthen roof sheathing, reinforce roof-to-wall connection, add shutter and reinforce gable end (41,000 homeowners), strengthen roof sheathing and reinforce gable ends (37,000 homeowners), strengthen roof sheathing and add shutter (36,000 homeowners), elevate appliances (28,000 homeowners), and strengthen roof sheathing, add shutter and elevate appliances (15,000 homeowners). The popular retrofits show a lot diversity in the utility-based framework compared to the DCM-based framework because the characteristics of the discrete choice model. The reason why DCM has less diversity is because in DCM, we break down the 143 retrofits into only 5 retrofits decisions (and without gable), that makes homeowners take very similar retrofits. In addition, more homeowners retrofit in the utility-based framework than in the DCM one. As in the DCM-based framework, the relative popularity of the different retrofit choices are also similar across government budget levels, except that some more expensive retrofits (e.g., strengthening roof sheathing, reinforce roof-to-wall connection, and add shutter to reduce wind damage) become more popular as the budget increases in the utility-based framework (Table 4.4). Examining the retrofits in terms of the IBHS FORTIFIED home categories, the results suggest that for the base case, of the approximately 316,000 homes that are retrofitted, 26% change from no designation to Bronze, 9% do not change category because they are retrofitted for flood not wind, 38% go from no designation or Silver to Gold, and 27% go from Silver to Gold (Figure 4.8 and Table 4.5). The level changes are very different from the DCM-based framework that it is more evenly distributed for Bronze, Silver and Gold level (Figure 4.8), while Bronze level takes up the most of the level changes in the DCM-based framework.

Table 4.4: Most frequently implemented retrofits[a] under different government budgets (approximate average cost, number of homeowner choose this retrofit)

Utility-based framework

Frequency	Optimal solution ($60M budget)	No govt. intervention
Most common	RS[b] ($2k, 69k)	RS ($2k, 87k)
	RS, RTW[c], Shutter, Gable ($15k, 41k)	RS, Gable ($3k, 46k)
	RS, Gable ($3k, 37k)	RS, RTW, Shutter, Gable ($15k, 31k)
Least common	RS, Shutter ($12k, 36k)	Elevate appliances ($3k, 30k)

DCM-based framework

Frequency	Optimal solution ($60M budget)	No govt. intervention
Most common	RC[d], RS ($8k, 117k)	RC, RS ($8k, 40k)
	RS ($2k, 37k)	Elevate Appliances ($3k, 21k)
	Elevate Appliances ($3k, 33k)	RS ($2k, 13k)
Least common	RC, RS, Elevate Appliances (10k, 6k)	

[a] Only includes retrofits that are implemented more than 30,000 homeowners in the utility-based framework, and more than 5,000 homeowners in the DCM-based framework

[b] RS means roof sheathing

[c] Roof-to-wall connection

[d] RC means roof covering

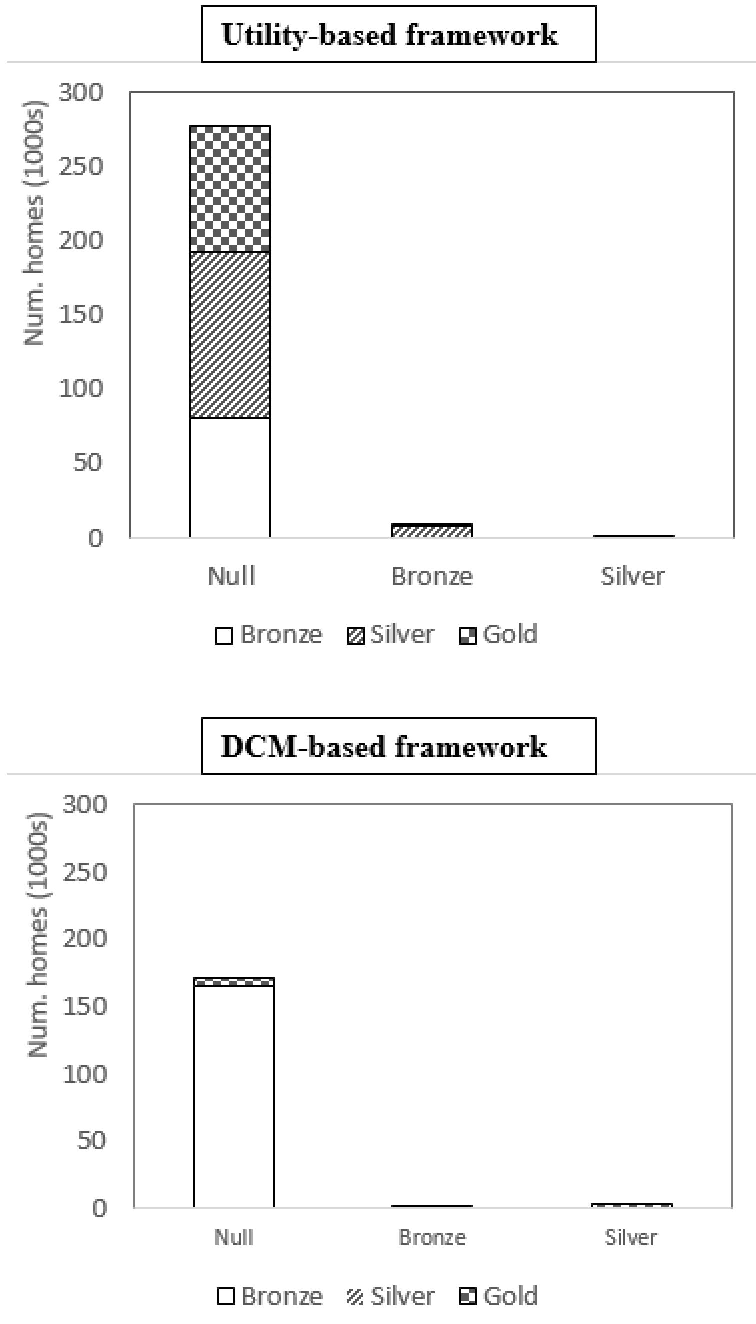

Figure 4.8: Number of homes making each IBHS level change under $60M government budget

Table 4.5: Number of homes making each IBHS level change for different government budget levels

Utility-based framework

Government budget /$M	Null to Bronze	Null to Silver	Null to Gold	Bronze to Silver	Bronze to Gold	Silver to Gold	Total number change in each level		
							Bronze	Silver	Gold
0	99,869	102,079	68,077	6,382	588	762	99,869	108,461	69,427
20	87,158	110,963	81,764	7,362	721	915	87,158	118,325	83,400
60	81,171	111,246	85,096	7,521	761	964	81,171	118,767	86,821
100	76,074	197,330	123,424	13,599	1,439	1,096	76,074	210,929	125,959
Unlimited	70,232	218,897	136,463	15,195	1,643	1,178	70,232	234,092	139,284

DCM-based framework

Government budget /$M	Null to Bronze	Null to Silver	Null to Gold	Bronze to Silver	Bronze to Gold	Silver to Gold	Total number change in each level		
							Bronze	Silver	Gold
0	54,784	249	415	71	6	726	54,784	320	1,147
20	116,365	449	3,270	121	26	1,838	116,365	570	5,134
60	164,616	610	5,500	147	47	2,702	164,616	757	8,249
100	182,974	626	6,216	164	51	3,039	182,974	790	9,306
Unlimited	242,815	498	11,749	232	85	4,216	242,815	730	16,050

4.3.3.2 Expected homeowner outcomes

Homeowner expenditure changes in the utility-based framework results are similar to those in the DCM-based framework results. For the $60M base case, the average homeowner in the high risk region (within 2 miles of the coast) would pay an average of $1,600 ($1,656 in the DCM-based framework) per year for all expenses, including any insurance premiums or deductibles if they insure, any retrofit cost if they retrofit, and any residual hurricane loss they are responsible for (Table 4.3). This is 7% less than the $1,720 they would pay with no government intervention (10% less than $1,832 in the DCM-based framework). For the low risk region, average annual expenditures are a much lower $211 ($270 in the DCM-based framework), about the same as with no government intervention because all the acquisition and most of the retrofit grants are used in the high risk area. In general, as the government budget increases from zero to unlimited, the average high risk homeowner expenditures decrease 9.5% from $1,720 to $1,557 (Table 4.3) (decrease 18% from $1,832 to $1,350 in the DCM-based framework).

The expected expenditures already show the large benefit homeowners receive from government investment, and the analysis of the possibility of extremely large expenditures shows the same thing. Figure 4.9 shows the inverse CDF of annual homeowner expenditures for the case with no government budget and the base case $60M government budget, for both high and low risk regions. To highlight the effect of the $60M of government spending, Figure 4.8 includes only the 124,854 (44%) and 29,426 (5%) of high and low risk area homeowners, respectively, for whom the expenditures change between government budgets of $0 and $60M. The effects for both the low and high risk regions are quite big that the tail of the loss distributions are substantially reduced. Considering the tail below an exceedance probability of 0.005, for example, the average annual loss is reduced by approximately $10,000 or 35% for the high risk region, and 14,500 or 69% for the low risk area (approximately $6,400 or 25% for high risk region, and $500 or 5% for low risk region in the DCM-based framework). This suggests that the policies are not only effective from the average homeowner's perspective, but also helping reduce their expected expenditures and the possibility they have especially large expenditures one year. In addition, the reductions are much bigger in the utility-based framework than in the DCM-based framework, especially for homeowners in the low risk region, suggesting again that the utility-based framework is more sensitive to government policy changes than the DCM-based framework.

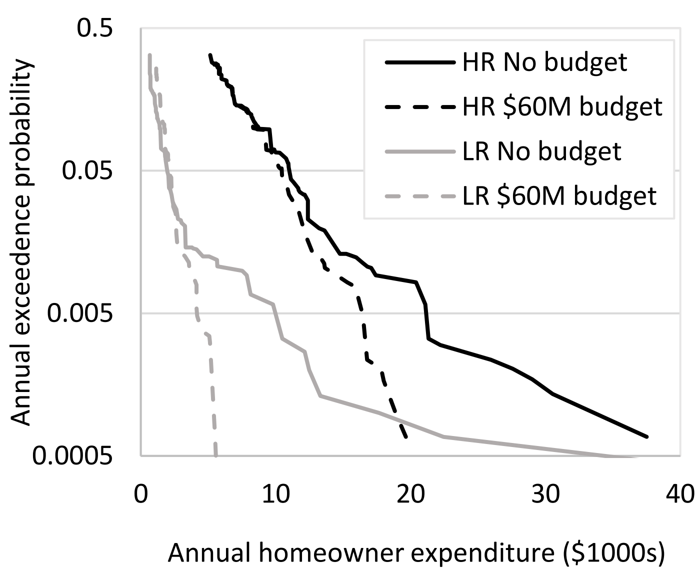

Figure 4.9: Distribution of average annual homeowner expenditure in high and low risk regions, with annual government budget of $0 or $60M, considering only homeowners whose expenditures differ between the two budget levels (LR is short for low risk region, HR is short for high risk region)

4.3.4 Conclusions

Chapter 4 describes a version of the framework similar to that described in Chapter 3, but with utility-based homeowner models. Similarly, the framework can help determine how much the government should spend on hurricane risk management, what combination of interventions to implement, and how to design them. The utility-based framework and the DCM-based framework can both assess disaster risk from a systems level, and suggest decisions that consider interactions among multiple stakeholder types (homeowners, insurers, government, reinsurers) and multiple intervention types (insurance, retrofit, and property acquisition). In addition, both frameworks are linked with a probabilistic regional loss estimation model and demonstrated in a full-scale case study for the Eastern North Carolina. The main differences of these two systematic frameworks are that the DCM-based framework applies discrete choice homeowner decision models for homeowner insurance, retrofit, and property acquisition decisions, and the government interacts directly with both homeowners and the insurer. By contrast, the utility-based framework applies a utility model for these homeowner risk management decisions, and in that utility-based model (and the economic theoretical work in Kelly and Kleffner 2003, for example), retrofit and insurance purchase are more tightly linked and homeowner decisions on acquisition, retrofit and insurance are more sensitive to the changes in insurance price, retrofit cost, and the expected loss. In that case, increased retrofit leads to reduced homeowner loss distributions, and the linkage between retrofit and insurance increases insurance penetration rates, and allows insurers to increase profit loading factors in turn increase insurer profits. The utility-based analysis led Kelly and Kleffner (2003) to conclude that it is not in insurer’s interest to encourage retrofit all else being equal.

The analysis described here in this computational framework based on the utility models suggests otherwise.

The case study demonstrates that in both versions of the framework it is possible to identify system-wide win-win solutions that are attractive from all stakeholder perspectives. The solutions recommended by these two frameworks in the case study both meet the government objectives of reducing societal risk (defined in terms of weighted expected value and tail of the distribution), the insurer and reinsurer goals of making profit while achieving a minimum allowable return on equity and maximum allowable probability of insolvency, and homeowner aims to reduce their annual expenditures. However, these two frameworks do have some differences that suggest how important it is to choose the most appropriate model to represent homeowner behavior. Generally speaking, the utility homeowner model is more sensitive to price changes, thus generates more changes (different homeowner decisions, different losses, etc.) when the government incentive programs change. The discrete choice model is not as sensitive but can capture more empirical homeowner decisions. The framework will perform much better if a better homeowner model is generated. Specifically, the differences are: (1) the DCM-based framework allows the acquisition offer prices to vary, while it will not work in the utility-based framework; (2) both insurer and reinsurer profit are increasing in the utility-based framework as government budget increases, while both decrease in the DCM-based framework; (3) more homeowners take both retrofit and insurance actions in the utility-based framework because of the restriction while it is not the case in the DCM-based framework; (4) homeowners retrofit decision changes the buildings IBHS FORTIFIED level evenly in the utility-based framework while highly skewed in the

DCM-based framework because of the different retrofit decision model. Despite these differences, both frameworks are valuable to help to support government regional hurricane management policies and make the business case for them by specifying the outcomes for each stakeholder. The differences and similarities between the two versions of framework are summarized in Table 5.1.

Table 5.1: Summary of key similarities and differences in the two versions of framework

	the utility-based framework	**the DCM-based framework**
Model assumptions	• Homeowner's decisions on acquisition, insurance and retrofit are captured by utility model (more sensitive to price change) • The government only interacts directly with homeowners, with three decisions to make, which are, z, R, W • Acquisition offer price can not vary • Retrofit and insurance purchase are linked because homeowner must be insured to get retrofit grant	• Homeowner's decisions on acquisition, insurance and retrofit are captured by discrete choice models • The government interacts directly with both homeowners and the insurer, with six decisions to make, which are z, R, W, Λ_L, Λ_H, ξ • Allows the acquisition offer prices to vary • No linkage between retrofit and insurance

Table 5.1 continued.

<table>
<tr><th></th><th>the utility-based framework</th><th>the DCM-based framework</th></tr>
<tr><td>Key similarities</td><td colspan="2">• Help identify system-wide win-win solutions that are attractive from all stakeholder perspectives.
• Assess disaster risk from a systems level, and suggest decisions that consider interactions among multiple stakeholder types (homeowners, insurers, government, reinsurers) and multiple intervention types (insurance, retrofit, and property acquisition)
• Both frameworks are linked with a probabilistic regional loss estimation model and demonstrated in a full-scale case study for the Eastern North Carolina
• Government intervention help to reduce objective function value, total loss, uninsured loss, and especially large tail loss
• More expensive retrofits are more popular when the government budgets increase
• Homeowners spend less when the government budgets increase</td></tr>
<tr><td>Key differences</td><td>• Government has three decisions to make, which are z, R, W
• Insurance penetration rates and insured loss increase with the government budget increase
• Both insurer and reinsurer profit increase as government budget increases
• More homeowners take both retrofit and insurance actions as government budget increases
• Homeowner retrofit decisions change the buildings IBHS FORTIFIED level evenly when the government budget changes</td><td>• Government has 6 decisions to make, which are z, R, W, Λ_L, Λ_H, ξ
• Insurance penetration rates almost remain the same and insured loss decreases with increasing government budget
• Both insurer and reinsurer profit do not change much as government budget increases
• The number of homeowners take both retrofit and insurance actions do not change much as government budget increases
• Most homeowner retrofit decisions change the buildings IBHS FORTIFIED level to Bronze when the government budget changes</td></tr>
</table>

Chapter 5

CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

This dissertation offers four main contributions: (1) introducing empirical-based homeowner insurance decision models, and integrating the models in a computational framework; (2) advancing the computational framework (Kesete et al. 2014, Peng et al. 2014, and Gao et al. 2016) by including a model of government decision making, an empirical rather than utility-based homeowner decision model, and property acquisition as a strategy; (3) demonstrating this improved framework in a full-scale case study for hurricane risk in eastern North Carolina to understand how can different government policies affect decisions and outcomes for each stakeholder type and the whole framework; and (4) comparing the DCM-based framework and the utility-based framework to better understand the effect of different homeowner decision models. These four parts are summarized here:

The separate mixed logit models for flood insurance and wind insurance purchase decisions contribute to the empirical literature on homeowner purchase of insurance for hurricanes. The results for these two types of insurance are similar, indicating that most of the research on flood insurance can be applied to wind insurance. The analysis identifies the significant factors on purchasing insurance. Most importantly, the statistical models can be used to predict insurance penetration rates for a region and thus can be integrated in the computational framework.

The DCM-based framework is the most important contribution of this dissertation. It extends and improves the existing versions computational framework by introducing the government decision model. The framework is helpful to identify hurricane disaster risk management policy solutions that are better both for each stakeholder type individually and for society as a whole, and the full-scale case study in the eastern North Carolina proves this point. This type of systems level decision support that considers interactions among multiple stakeholder types (homeowners, insurers, government, reinsurers) and multiple intervention types (insurance, retrofit, and property acquisition) is new. Further, the framework is linked with a state-of-the-art engineering-based regional loss estimation and empirically-based homeowner decision-making models, making it more realistic than analyses based on simpler assumptions.

There are a lot of interesting findings in the comparison between the DCM-based framework and the utility-based framework. These two frameworks both can identify optimal policy solutions, and they both consider multiple stakeholder types (homeowners, insurers, government, reinsurers) and multiple intervention types (insurance, retrofit, and property acquisition). The full-scale case study shows the utility homeowner model is more sensitive to price change (insurance price, retrofit cost, and acquisition offer price), and thus generates more changes in homeowner decisions and different losses when the government incentive programs change. By contrasts, the discrete choice models are not sensitive as sensitive to price but can capture more empirical homeowner decisions. The comparison shows the importance of choosing a good homeowner decision model and understanding the implications of the choice.

5.2 Future Work

The updated framework offers multiple opportunities for future improvement and expansion. Implementation of the discrete choice models to represent homeowner decision-making represents an advance toward more realistically capturing the way homeowners make these decisions. Nevertheless, their predictive power can surely be improved through additional data collection, examination of additional explanatory variables, combining stated preference data with revealed preference data, and linking the retrofit and insurance decisions. Further, other models that represent homeowner decision-making can also be employed to better capture the risk and homeowner decisions. This version of the framework assumes a single primary insurer; future work can incorporate representation of the insurance market as in Gao et al. (2016). While the solution method adopted in this analysis is adequate to demonstrate the framework, future work could develop a more efficient and improved solution algorithm such as simulated annealing. This work assumes homeowner decisions are the same over 30 years. Future work can make the framework more dynamic to anticipate some changes within the time frame considered for the study. Extensions to other perils such as earthquakes could also be applied to further the framework.

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Appendix A

RELATED QUESTIONS IN SURVEY AND CERTIFICATES FOR USING THE DATA

A.1 Related Questions in Survey

This survey was used to better understand homeowner decisions on hurricane-related insurance and retrofit. There are six modules in the survey: (1) Introduction and screening questions, (2) Background, (3) Risk perceptions and hazard experience, (4) Protective action, (5) Utility, and (6) Socio-demographics. The following are the subset of survey questions that were used in modeling homeowner insurance decisions (Chapter 2).

Module 2- Background

These four questions are related to the covariate 'x_{ret} house had previous wind retrofit'. The first three questions were asked if the home is a single family home or a duplex, and the last one was asked if the home is a manufactured home or trailer.

{LASTROOFREPLACE}

About how many years ago was your roof last replaced (that is, for example, all the shingles were removed and new ones installed)?

1 Enter number of years____________________

8 Not sure/Do not know

9 Refused

{ATTICACCESS}

One way to strengthen your roof against hurricane winds requires gaining access to the underside of the roof without removing any finished ceiling or wall. In your house, can you access the underside of the roof?

1 Yes

2 No____________________

8 Not sure/Do not know

9 Refused

{MHWINDRETROFIT}

To the best of your knowledge, does your home have any of the following features that protect against wind damage?

1 Extra tie downs to improve the anchorage

2 Improved structural resistance to high winds

3 Other [Specify: ____________]

8 Not sure/Do not know

9 Refused

Module 3- Risk Perceptions and Hazard Experience

{NUMBER OF HURRICANES EXPERIENCED, x_{num}}

How many hurricane or flooding events have you personally experienced?

1 Enter number___ [Enter zero if NONE]

8 Not sure/Do not know

9 Refused

{TIME SINCE LAST HURRICANE, x_{tim} }

What year was your last hurricane or flood experience?

1 Enter year (YYYY) ___________________

8 Not sure/Do not know

9 Refused

{PRIOR DAMAGE, x_{dam}}

What is the highest degree of property damage your home has experienced during any prior hurricane event? Use a scale from 1 to 5, where one means no damage and five means complete destruction.

1 Enter number ___________________

8 Not sure/Do not know

9 Refused

Module 4- Protective Action

{BUY WIND INSURANCE, y_w}

For the next four questions, I would like you to assume that wind damage from hurricanes is *not* covered by your homeowners' policy and if you want that coverage you have to buy a separate kind of policy.

With that in mind, I am going to tell you the deductible and premium for several pairs of insurance policies that would protect against hurricane-caused wind damage only. The only differences between the alternatives in each pair are the premium and deductible. They are exactly the same in every other way. As I read each pair, please tell me if you would buy policy 1, buy policy 2, or not buy either policy? (Deductible and premium values are fed by the CATI participant database). Table A.1 is an example of one set of questions.

Table A.1: Example of one set of questions for wind insurance

	Policy 1	Policy 2	Choose Policy 1	Choose Policy 2	Choose neither	Not sure	Refused
1	$500 deductible and $1,000 annual premium	$1,000 deductible and $500 annual premium					
2	$250 deductible and $5,000 annual premium	$500 deductible and $500 annual premium					
3	$500 deductible and $2,000 annual premium	$5,000 deductible and $1,000 annual premium					
4	$5,000 deductible and $500 annual premium	$250 deductible and $1,000 annual premium					

{BUY FLOOD INSURANCE, y_f}

Deductible and premium values are fed by FLOODINSUREDATA entries. Table A.2 shows a set of example.

Table A.2: Example of one set of questions for flood insurance

	Policy 1	Policy 2	Choose Policy 1	Choose Policy 2	Choose neither	Not sure	Refused
1	$5,000 deductible and $500 annual premium	$250 deductible and $1,000 annual premium					
2	$500 deductible and $1,000 annual premium	$1,000 deductible and $500 annual premium					
3	$500 deductible and $5,000 annual premium	$1,000 deductible and $2,000 annual premium					
4	$250 deductible and $2,000 annual premium	$1,000 deductible and $1,000 annual premium					

Module 6- Socio-Demographics

This question is used to compute covariate '$x_{age,}$ *Age*'. Age = 2013 - year born

{YRBORN}

In what year were you born?

1 Enter year (YYYY) ____________________

8 Not sure/Do not know

9 Refused

{INCOME, x_{inc}}

I am going to read a list of income ranges. Please stop me when I read the range that best describes your annual household income from all sources. This is before taxes and other deductions.

1	Less than 15 thousand	[$0 -$14,999]
2	15 to 35 thousand	[$15,000 - $34,999]
3	35 to 50 thousand	[$35,000 - $49,999]
4	50 to 75 thousand	[$50,000 - $74,999]
5	75 to 100 thousand	[$75,000 - $99,999]
6	100 thousand to 150 thousand	[$100,000 - $149,999]
7	150 thousand to 250 thousand	[$150,000 - $250,000]
8	Over 250 thousand	[$250,000 +]
9	Not sure/Do not know	
10	Refused	

These questions are used to compute covariate 'x_{fp}, *Location in floodplain' and 'x_{dist}, Distance to coastline'* in ArcGIS. The 'ADDRESS' question was asked first, and the 'LOCATION' question was asked if {ADDRESS} = 8 or 9

{ADDRESS}

As I mentioned at the beginning, as a thank you for participating, one out of every hundred people who complete the survey will win a new iPad. Would you provide your mailing address so that we can mail you the prize if you win?

1 Number

2 Street

3 City

4 State

5 Zip

8 Not sure/Do not know

9 Refused

{LOCATION}

Would you be willing to provide a zip code and the nearest cross street/intersection to your home? That information will help us determine the likelihood that a hurricane will affect your location.

1 Zip

2 Cross street

3 Enter response________

8 Not sure/Do not know

9 Refused

A.2 IRB Letters

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	October 22, 2012
TO:	Rachel Davidson, PhD
FROM:	University of Delaware IRB
STUDY TITLE:	[389944-1] Modeling Natural Disaster Risk Management: A Stakeholder Perspective
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	October 22, 2012
REVIEW CATEGORY:	Exemption category # *2*

Thank you for your submission of New Project materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Jody-Lynn Berg at (302) 831-1119 or jlberg@udel.edu. Please include your study title and reference number in all correspondence with this office.

- 1 -

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UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	October 29, 2018
TO:	Rachel Davidson, PhD
FROM:	University of Delaware IRB
STUDY TITLE:	[389944-4] Modeling Natural Disaster Risk Management: A Stakeholder Perspective
SUBMISSION TYPE:	Continuing Review/Progress Report
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	October 29, 2018
REVIEW CATEGORY:	Exemption category # 2

Thank you for your submission of Continuing Review/Progress Report materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Renee Stewart at (302) 831-2137 or stewartr@udel.edu. Please include your study title and reference number in all correspondence with this office.

cc:

A.3 CITI Certificates

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)
COURSEWORK REQUIREMENTS REPORT*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- **Name:** Dong Wang (ID: 5001805)
- **Email:** derawang@udel.edu
- **Institution Affiliation:** University of Delaware (ID: 1196)
- **Institution Unit:** Civil and Environmental Engineering
- **Phone:** 3025135741

- **Curriculum Group:** Course In The Protection Human Subjects
- **Course Learner Group:** Human Subjects Protections - Social-Behavioral-Educational Focus - All UD Researchers/Faculty/Staff
- **Stage:** Stage 1 - Basic Course

- **Report ID:** 17027748
- **Completion Date:** 08/27/2015
- **Expiration Date:** 08/26/2018
- **Minimum Passing:** 85
- **Reported Score*:** 94

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Belmont Report and CITI Course Introduction (ID: 1127)	08/27/15	3/3 (100%)
Students in Research (ID: 1321)	08/27/15	10/10 (100%)
History and Ethical Principles - SBE (ID: 490)	08/27/15	5/5 (100%)
Defining Research with Human Subjects - SBE (ID: 491)	08/27/15	5/5 (100%)
The Federal Regulations - SBE (ID: 502)	08/27/15	5/5 (100%)
Assessing Risk - SBE (ID: 503)	08/27/15	5/5 (100%)
Informed Consent - SBE (ID: 504)	08/27/15	5/5 (100%)
Privacy and Confidentiality - SBE (ID: 505)	08/27/15	5/5 (100%)
Research with Prisoners - SBE (ID: 506)	08/27/15	5/5 (100%)
Research with Children - SBE (ID: 507)	08/27/15	5/5 (100%)
Research in Public Elementary and Secondary Schools - SBE (ID: 508)	08/27/15	5/5 (100%)
International Research - SBE (ID: 509)	08/27/15	5/5 (100%)
Internet-Based Research - SBE (ID: 510)	08/27/15	5/5 (100%)
Conflicts of Interest in Research Involving Human Subjects (ID: 488)	08/27/15	5/5 (100%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research (ID: 14928)	08/27/15	5/5 (100%)
University of Delaware (ID: 12245)	08/27/15	0/5 (0%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

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COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)
COURSEWORK TRANSCRIPT REPORT**

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- **Name:** Dong Wang (ID: 5001805)
- **Email:** derawang@udel.edu
- **Institution Affiliation:** University of Delaware (ID: 1198)
- **Institution Unit:** Civil and Environmental Engineering
- **Phone:** 3025135741

- **Curriculum Group:** Course In The Protection Human Subjects
- **Course Learner Group:** Human Subjects Protections - Social-Behavioral-Educational Focus - All UD Researchers/Faculty/Staff
- **Stage:** Stage 1 - Basic Course

- **Report ID:** 17027748
- **Report Date:** 08/28/2015
- **Current Score**:** 100

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Students in Research (ID: 1321)	08/27/15	10/10 (100%)
History and Ethical Principles - SBE (ID: 490)	08/27/15	5/5 (100%)
Defining Research with Human Subjects - SBE (ID: 491)	08/27/15	5/5 (100%)
Belmont Report and CITI Course Introduction (ID: 1127)	08/27/15	3/3 (100%)
The Federal Regulations - SBE (ID: 502)	08/27/15	5/5 (100%)
Assessing Risk - SBE (ID: 503)	08/27/15	5/5 (100%)
Informed Consent - SBE (ID: 504)	08/27/15	5/5 (100%)
Privacy and Confidentiality - SBE (ID: 505)	08/27/15	5/5 (100%)
Research with Prisoners - SBE (ID: 506)	08/27/15	5/5 (100%)
Research with Children - SBE (ID: 507)	08/27/15	5/5 (100%)
Research in Public Elementary and Secondary Schools - SBE (ID: 508)	08/27/15	5/5 (100%)
International Research - SBE (ID: 509)	08/27/15	5/5 (100%)
Internet-Based Research - SBE (ID: 510)	08/27/15	5/5 (100%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research (ID: 14928)	08/27/15	5/5 (100%)
Conflicts of Interest in Research Involving Human Subjects (ID: 488)	08/27/15	5/5 (100%)
Avoiding Group Harms - U.S. Research Perspectives (ID: 14080)	08/26/15	3/3 (100%)
Avoiding Group Harms - International Research Perspectives (ID: 14081)	08/26/15	3/3 (100%)
Recognizing and Reporting Unanticipated Problems Involving Risks to Subjects or Others in Biomedical Research (ID: 14777)	08/26/15	No Quiz
University of Delaware (ID: 12245)	08/28/15	5/5 (100%)

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COURSEWORK REQUIREMENTS REPORT*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- **Name:** Dong Wang (ID: 5001805)
- **Email:** derawang@udel.edu
- **Institution Affiliation:** University of Delaware (ID: 1198)
- **Institution Unit:** Civil and Environmental Engineering
- **Phone:** 3025135741

- **Curriculum Group:** Responsible Conduct of Research
- **Course Learner Group:** Social and Behavioral Responsible Conduct of Research Course
- **Stage:** Stage 1 - RCR

- **Report ID:** 18713594
- **Completion Date:** 02/13/2016
- **Expiration Date:** N/A
- **Minimum Passing:** 85
- **Reported Score*:** 91

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Research Misconduct (RCR-Basic) (ID: 16604)	02/13/16	5/5 (100%)
Data Management (RCR-Basic) (ID: 16600)	02/13/16	5/5 (100%)
Authorship (RCR-Basic) (ID: 16597)	02/13/16	5/5 (100%)
Peer Review (RCR-Basic) (ID: 16603)	02/13/16	5/5 (100%)
Conflicts of Interest (RCR-Basic) (ID: 16599)	02/13/16	5/5 (100%)
Collaborative Research (RCR-Basic) (ID: 16598)	02/13/16	2/5 (40%)
University of Delaware (ID: 12245)	08/28/15	5/5 (100%)

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COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COURSEWORK TRANSCRIPT REPORT**

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- **Name:** Dong Wang (ID: 5001805)
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- **Phone:** 3025135741

- **Curriculum Group:** Responsible Conduct of Research
- **Course Learner Group:** Social and Behavioral Responsible Conduct of Research Course
- **Stage:** Stage 1 - RCR

- **Report ID:** 18713594
- **Report Date:** 02/13/2016
- **Current Score**:** 100

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Authorship (RCR-Basic) (ID: 16597)	02/13/16	5/5 (100%)
Collaborative Research (RCR-Basic) (ID: 16598)	02/13/16	5/5 (100%)
Conflicts of Interest (RCR-Basic) (ID: 16599)	02/13/16	5/5 (100%)
Data Management (RCR-Basic) (ID: 16600)	02/13/16	5/5 (100%)
Peer Review (RCR-Basic) (ID: 16603)	02/13/16	5/5 (100%)
Research Misconduct (RCR-Basic) (ID: 16604)	02/13/16	5/5 (100%)
University of Delaware (ID: 12245)	08/28/15	5/5 (100%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

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Appendix B

EMPIRICAL HOMEOWNER DECISION MODEL FOR RETROFIT

The following is from part of

Chiew, E., Davidson, R., Nozick, L., Trainor, J., and Kruse, J. 2018. "The impact of grants on homeowner decisions to retrofit to reduce hurricane-induced wind and flood damage," working paper, Cornell University, Ithaca, New York.

Equations (B.1) and (B.2) are the models for the utility associated with retrofitting against wind damage and flood damage, respectively, for individual i choosing alternative $j =$ Yes in choice situation t. Equations (B.3) and (B.4) show, respectively, the models for the utility associated with retrofitting against wind damage and flood damage, for individual i choosing alternative $j =$ No in choice situation t. Note that the covariate of the location in a floodplain (x_{fp}) appears only in Equation B.2, which accounts for flood damage.

$$U_{ijt}^{wind} = ASC_{ij} + \beta_{GrantPerc}x_{GrantPerc,ijt} + \beta_{MaxGrant}x_{MaxGrant,ijt} + \beta_{dist}x_{dist,ij} + \beta_{inc}x_{inc,ij} + \beta_{num}x_{num,ij} + \beta_{futtenure}x_{futtenure,ij} + \beta_{employ1}x_{employ1,ij} + \beta_{employ2}x_{employ2,ij} + \varphi_i\left[\left(1-\kappa_{RP,it}\right) * \left(\sum_{s=1}^{T_i}\kappa_{RP,is}Y_{ijs}\right)\right] + \varepsilon_{ijt} \quad \text{, for } j = \text{Yes} \quad \text{(B.1)}$$

$$U_{ijt}^{flood} = ASC_{ij} + \beta_{GrantPerc}x_{GrantPerc,ijt} + \beta_{MaxGrant}x_{MaxGrant,ijt} + \beta_{dist}x_{dist,ij} + \beta_{inc}x_{inc,ij} + \beta_{num}x_{num,ij} + \beta_{fp}x_{fp,ij} + \beta_{futtenure}x_{futtenure,ij} + \beta_{employ1}x_{employ1,ij} + \beta_{employ2}x_{employ2,ij} + \varphi_i\left[\left(1-\kappa_{RP,it}\right) * \left(\sum_{s=1}^{T_i}\kappa_{RP,is}Y_{ijs}\right)\right] + \varepsilon_{ijt} \quad \text{, for } j = \text{Yes} \quad \text{(B.2)}$$

$$U_{ijt}^{wind} = \varphi_i\left[\left(1-\kappa_{RP,it}\right) * \left(\sum_{s=1}^{T_i}\kappa_{RP,is}Y_{ijs}\right)\right] + \varepsilon_{ijt} \quad \text{, for } j = \text{No} \quad \text{(B.3)}$$

$$U_{ijt}^{flood} = \varphi_i\left[\left(1-\kappa_{RP,it}\right) * \left(\sum_{s=1}^{T_i} \kappa_{RP,is} Y_{ijs}\right)\right] + \varepsilon_{ijt} \quad \text{, for } j = \text{No} \qquad \text{(B.4)}$$

where: U_{ijt} is the utility of individual i in choice situation t choosing alternative j; ASC_{ij} are alternative-specific constants (ASCs); $x_{GrantPerc,ijt}$ is the percentage of the cost that the government would pay to individual i choosing alternative j in choice situation t; $x_{MaxGrant,ijt}$ is the maximum value of the grant in thousands of dollars that the government would pay to individual i choosing alternative j in choice situation t; φ_i is the individual-specific state-dependence effect that maps the effect of the RP choice of an alternative into the utility evaluation of that alternative in the SP choice situation; T_i is the total number of observed choice situations for individual i; Y_{ijs} is a binary value with value 1 if individual i chooses alternative j in the s^{th} choice situation, and 0 otherwise; and ε_{ijt} is the unobserved random term. State dependence is defined by the term $\varphi\left[\left(1-\kappa_{RP,it}\right) * \left(\sum_{s=1}^{T_i} \kappa_{RP,is} Y_{ijs}\right)\right]$ in equations (B.1) – (B.4). Note that for each RP choice situation, since $\kappa_{RP,it} = 1$, the entire term reduces to zero, and this is what we used in Chapter 3. All other covariates are defined in Table B.1 and Table B.2.

Table B.1: Descriptive statistics for continuous covariates

Variable		Hypothesized effect [a]	Number of respondents	Mean	Standard Deviation
x_{dist}	Distance to coastline, km	Negative	233	99.59	69.62
x_{inc}	Income [b] ($1000s/year)	Positive	196	98.74	74.54

[a] Positive means increase in the covariate is associated with an increase in the probability of carrying out a retrofit.

[b] Income was asked in the survey as an interval variable, but coded in the model as a continuous variable with the values in parentheses for each interval: $0-$15k ($7.5k), $15k - $35k ($25k), $35k - $50k ($42.5k), $50k - $75k ($62.5k), $75k - $100k ($87.5k), $100k - $150k ($125k), $150k - $250k ($200k), more than $250k ($300k).

Table B.2: Descriptive statistics for discrete covariates

Variable		Hypothesized effect [a]	Levels	Number of respondents
x_{num}	Num. hurricanes experienced	Positive	1: two or more 0: zero or one	216 10
x_{fp}	Location in floodplain	Positive	1: In floodplain 0: not in floodplain	24 209
$x_{futtenure}$	Length of time individual expects to stay in their current home	Positive	1: Forever 0: Otherwise	49 165
$x_{employ1}$, $x_{employ2}$ [b]	Employment status	Negative	2: Retired or unable to work 1: Unemployed, homemaker, student 0: Employed full- or part-time	105 14 107

[a] Positive means increase in the covariate is associated with an increase in the probability of carrying out a retrofit.

[b] Level 0 corresponds to $x_{employ1} = 0$ and $x_{employ2} = 0$; level 1 corresponds to $x_{employ1} = 1$ and $x_{employ2} = 0$; and level 2 corresponds to $x_{employ1} = 0$ and $x_{employ2} = 1$

With these utility evaluations, the probability that individual i chooses to retrofit his home against wind damage in choice situation t is:

$$P\left(y_{it}^{wind} = Yes\right) = \frac{\exp\left(U_{i,j=Yes,t}^{wind}\right)}{\exp\left(U_{i,j=Yes,t}^{wind}\right)+\exp\left(U_{i,j=No,t}^{wind}\right)} \quad \text{(B.5)}$$

and similarly for the probability that the individual chooses to retrofit his home against flood damage.

Table B.3 summarizes the results of the retrofit decision model for each of the five damage types. Roof, Openings, and Straps for wind-related retrofits, and appliances and piles are flood-related retrofits. .

Table B.3: Results of retrofit decision models for different damage types

Covariate	Roof		Openings		Straps		Appliances		Piles	
	Coefficient[a]	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
ASC: RP	-0.112	0.727	-1.222***	0.000	0.339	0.406	0.341	0.353	0.552	0.419
Grant Characteristics										
Grant Percentage	2.543***	0.000	2.060***	0.000	3.609***	0.000	1.881***	0.000	4.580***	0.000
Max. Grant Value	0.088***	0.000	0.054**	0.024	0.091***	0.002	0.032	0.222	0.217***	0.000
Other Characteristics										
Number of hurricanes	-1.066***	0.004	-0.107	0.773	-0.955**	0.026	-1.312***	0.003	-2.461***	0.000
Distance from coastline	-0.006***	0.003	-0.006***	0.003	-0.014***	0.000	-0.007***	0.002	-0.016***	0.000
Location in floodplain							-0.017	0.971	0.534	0.437
Income	-0.001	0.619	0.000	0.975	-0.001	0.694	-0.002	0.441	-0.001	0.753
Employment 1	-1.108*	0.089	0.217	0.675	0.698	0.268	-0.194	0.754	0.128	0.900
Employment 2	0.241	0.395	0.184	0.515	-0.011	0.973	-0.016	0.957	-0.672	0.177
Future Tenure	0.509	0.146	0.101	0.758	-0.255	0.517	0.251	0.497	0.346	0.562

[a] The symbols *, ** and *** indicate significance levels of 0.1, 0.05 and 0.01 respectively.

Table B.3 continued

Covariate	Roof		Openings		Straps		Appliances		Piles	
	Coefficient[a]	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
RP-SP Parameters										
State Dependence	0.541^{**}	0.037	1.306^{***}	0.000	1.954^{***}	0.000	0.948^{***}	0.002	3.413^{***}	0.000
Std. Dev. of SP ASC	2.495^{***}	0.000	2.186^{***}	0.000	3.163^{***}	0.000	2.626^{***}	0.000	4.099^{***}	0.000
SP scale relative to RP (calculated from Std. Dev. of SP ASC)	0.514		0.587		0.406		0.488		0.313	

[a] The symbols *, ** and *** indicate significance levels of 0.1, 0.05 and 0.01 respectively.

Appendix C

EMPIRICAL HOMEOWNER DECISION MODEL FOR ACQUISITION OFFER ACCEPTANCE

The following is from part of

Frimpong, E., Kruse, J., Howard, G., Davidson, R., Trainor, J., and Nozick, L. 2018. "Measuring Heterogeneous Price Effects for Home Acquisition Programs in at-risk regions", Working paper, Center for Natural Hazards Research, East Carolina University, Greenville, North Carolina.

Each homeowner makes a total of 10 choices, so we may describe our data as a panel. We specify the econometric model as

$$y_{it} = \boldsymbol{X_i}\boldsymbol{\beta} + \boldsymbol{P_{it}}\boldsymbol{\theta} + \varepsilon_{it}, \qquad \text{(C.1)}$$

where y_{it} is the dependent variable (*choice*); $\boldsymbol{X_i}$ is a vector of respondent- and property-level covariates: *Floodplain, Distance to coastline, Lot size, Tenure in home, Race, Income, and Education*. $\boldsymbol{P_{it}}$ is a vector of choice-specific covariates, which include an indicator for whether the contract is offered before or after the house has sustained damage from a hurricane as well as price variables. $\boldsymbol{X_i}$ and $\boldsymbol{P_{it}}$ are summarized in Table C.1. $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are vectors of parameters to be estimated (summarized in Table C.2); and ε_{it} is the random error component.

Given that our dependent variable is binary, we link the dependent variable to the covariates via the probit link function:

$$(\Phi^{-1}[\Pr(y_{it} = 1 \mid \boldsymbol{x}_i)] = \boldsymbol{X}_i\boldsymbol{\beta} + \mathbf{P_{it}}\boldsymbol{\theta} + \varepsilon_{it}. \qquad \text{(C.2)}$$

Table C.1: Description of each variable in the model

Variable	Description
	Acquisition
Choice (dependent variable)	= 1 if homeowner is willing to accept acquisition at a given pre-damage fair market value of property (Price), and 0 otherwise
Before hurricane event	= 1 if homeowner response of accepting acquisition is observed before hurricane event, and 0 otherwise (after hurricane event)
After hurricane event	= 1 if homeowner response of accepting acquisition is observed after hurricane event, and 0 otherwise (before hurricane event)
Price	percent of home value government is willing to offer to homeowner in exchange for homeowner's house. These are hypothetical and includes 75%, 90%, 100%, 110%, 125%
	Environmental factors
Floodplain	= 1 if property is in floodplain, and 0 otherwise
Distance to Coastline	measured in kilometers as the distance from the North Carolina coastline to the location of homeowner's property
	Property Characteristic
Lot size	homeowners lot size is measured in acres
	Socio-demographics
Tenure in home	number of years a homeowner has lived in the current house
Race	=1 if homeowner is White, and 0 otherwise
Income	Income represents household income and is in three categories. Lower = 1 if income is < \$50,000, and 0 otherwise. Middle = 1 if income > \$49,999 and less than \$100,000, and 0 otherwise. Higher = 1 if income > \$99,999, and 0 otherwise.
Education	=1 if homeowner has at least 2-years college or higher education, and 0 otherwise.

Table C.2: Probit regression results

Variables	Coefficients	Standard Errors	Marginal effects
Before hurricane event	-2.16***	0.42	-0.51
Before hurricane event × price	0.06***	0.004	0.02
After hurricane event × price	0.04***	0.004	0.01
Floodplain	-0.62**	0.29	-0.17
log (Distance)	-0.21**	0.06	-0.04
log (Lot size)	-0.20**	0.08	-0.06
Tenure in home	-0.01*	0.01	-0.003
Race	0.43**	0.22	0.12
Income			
Lower	-0.09	0.19	-0.03
Higher	-0.20	0.34	-0.06
Education	0.28	0.20	0.08
Constant	-3.66***	0.57	
Pseudo R^2	0.29		

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance. Standard errors are robust clustered, and N=1309. For binary variables, marginal effects are calculated as the discrete change from the base. For continuous variables, marginal effects are calculated as a unit change in the variable.

In applying this model in Chapter 3, we assume the property acquisition offer is made before a hurricane, which means the variable 'After hurricane event × price' is always zero.

Appendix D

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