Market Insurance and Self-Insurance through Retrofit:

Analysis for Hurricane Risk in North Carolina

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Abstract

Insurance and retrofit are potentially effective but currently underutilized mechanisms to manage natural disaster risk. We use an empirical analysis of hurricane risk to residential buildings in North Carolina that includes a detailed, empirically-based representation of the building inventory, risk, insurance and retrofit strategies to examine voluntary choices between insuring, retrofitting, or doing nothing. Using an expected utility framework, we investigate how decisions change with changes in retrofit cost, risk-based insurance premiums, and risk attitudes. Individual loss distribution functions that are specific to location and structural characteristics influence the choice to insure and/or retrofit. We find that subsidizing retrofit has the potential to move the uninsured towards some form of risk reduction and is potentially cost effective. The analysis is novel in linking homeowner decisions regionally to detailed hurricane loss and retrofit modeling.

Keywords: Homeowner, retrofit, hurricane, expected utility, self- insurance, market insurance

1. Introduction

Natural disaster losses represent a major and growing concern from the perspective of public decision-makers, private industry, and households. Estimates of average annual direct natural disaster costs are $110 billion worldwide, $12.3 billion for the US with $6.7 billion attributed to hurricanes (Kousky 2012). While disaster losses can be measured on a societal scale, choices at the household level have a significant impact on regional vulnerability. In this study we focus on household risk management choices of hurricane insurance and retrofit to reduce expected losses due to hurricanes. Retrofit and insurance are two accepted methods to manage natural disaster risk to residential buildings. A retrofit is a physical change to a building designed to reduce its vulnerability to damage, such as, installing hurricane shutters on openings or adding structural adhesive to roof sheathing to reduce wind damage, or elevating a building to reduce flood damage (e.g., IBHS 2010, Datin et al. 2011). Insurance is a mechanism to spread risk, and is feasible for private insurers given some level of loss aversion on the part of homeowners. While there seems to be general agreement that retrofit and insurance are underutilized in the U.S., there remains a need to understand better what combination of insurance and retrofit would be most cost-effective for homeowners. The answer depends on baseline risk; risk attitudes; and the complex interaction of location, characteristics of the structures, and insurance policies and specific retrofit strategies available, each with different costs and effects on the risk. This paper addresses the following related questions:

- What combination of insurance and retrofit strategies would be most cost-effective at reducing the risk for different homeowners under different conditions?

- How do insurance and retrofit interact? As examples of market insurance and self-insurance, are they substitutes or complements? How does the decision to insure influence the retrofit decision and vice versa?
- How much do these strategies reduce the risk for different homeowners? What characteristics of the individuals and the loss distributions of the properties influence choices? How do the individual decisions affect the overall regional costs of disasters?

We explore and address these questions using a computational model rich in detail that allows the interaction between the insurance and retrofit decision to be coupled and complex. The analysis is applied to the case of hurricane risk to residential structures in North Carolina. Specifically, we examine the optimal insurance and retrofit decisions of a region populated with utility-maximizing homeowners, given a detailed, empirically-based representation of the building inventory, hurricane wind and storm surge risk, available insurance policies, and menu of retrofit strategies. We also explore individual and collective response to changes in the cost of retrofits, price of insurance, and risk attitudes. The study is novel in linking the analysis of homeowner decisions at a regional scale to a detailed, state-of-the-art hurricane loss model and realistic representation of a wide range of retrofits options. After a review of related theoretical and empirical literature in Section 2, we present the analytical approach in Section 3. Results are presented and discussed in Section 4, and the paper concludes with a summary of findings and their implications.

2. Literature review

This study draws from the theory of consumer choice with respect to risk and insurance, and studies related to mitigation and insurance for natural disaster risk. We rely on an expected utility framework as a benchmark while recognizing that potential biases as cited in the behavioral literature exist.

2.1. Theory of consumer decisions on self-protection, self-insurance and market insurance

A large body of theoretical research largely in the economics literature is founded on a seminal paper by Ehrlich and Becker (1972) (hereafter EB) that explores measures to reduce the probability of a loss and severity of a loss in an Expected Utility framework (EU). EB distinguishes three approaches to risk reduction—*self-protection*, *self-insurance*, and *market insurance*. They defined *self-protection* as a personal action that reduces the probability of an adverse event. The two other approaches reduce the severity of a loss; *self-insurance* is a private investment and *market insurance* is an investment in insurance at an actuary-based market price. EB show that market insurance and self-insurance are substitutes if the price of market insurance is independent of the amount spent on self-insurance. Among the many extensions and refinements to the EB model, research has examined the effect of the consumer risk attitudes (e.g., Dionne and Eeckhoudt 1985, Briys and Schlesinger 1990) and the influence of certainty of the loss reduction effectiveness of self-insurance (e.g., Hiebert 1989, Briys et al. 1991).

The core theory of economics has traditionally built upon a simple model of rational behavior. For the case of choice under risk, this has been EU theory that assigns value to a prospect that is linear in probabilities and nonlinear in wealth. However, EU as a theory of decision-making under risk fails to explain behavioral biases as demonstrated in the lab (Kahneman and Tversky 1979). Laboratory research in Behavioral Economics indicates that individuals deviate from the standard models in three respects: non-standard preferences, non-standard beliefs, and non-standard decision-making (DellaVigna 2009). DellaVigna (2009) surveys field experiments and summarizes the existence, strengths, and weaknesses of field evidence of deviations from the standard EU model. As pointed out by Sydnor (2010), there is very little nonlaboratory field research on behavioral biases in real insurance markets. Sydnor (2010) examines the choice of deductibles in home insurance and finds anomalous over-insurance of modest risks characterized by the choice of higher premiums for modest decreases in the size of a deductible. Kunreuther and Pauly (2005) provide a systematic discussion of the effect of behavioral anomalies on the demand side and the supply side of a market for insurance. Both Kunreuther and Pauly (2005) and Kunreuther et al. (2013) utilize the EU framework as a normative benchmark model. In the same spirit, we represent risk-sensitive expected utility maximizing homeowners to explore a benchmark model of loss reduction through market insurance and retrofit. Appealing to the EB context we examine market insurance and self-insurance (retrofit). We explore the case where the market price of insurance is related to the amount invested in retrofit and use an approach similar to Briys et al. (1991) and Courbage (2001) who showed that market insurance and self-insurance could be complementary. Our model considers a richer array of losses than the dichotomous EB Bernoulli distribution of loss/no loss. Our numerical analysis is similar in spirit to the Lee (2010) theoretical model that provides conditions under which an increase in risk aversion leads to more (or less) self-insurance. Our study, with multiple loss states drawn from empirical evidence, addresses the basic question about risk-averse homeowners' market insurance/self-insurance tradeoff, with a regional case study. We consider multiple retrofit options at a menu of prices and the availability of insurance on a parcel-by-parcel basis with location- and structure-specific loss distributions.

2.2. Mitigation and insurance for natural disasters

For the case of natural disaster risk, Kleffner and Kelly (2001) show in an EB framework, if premiums are not risk-based, insured homeowners will invest less in self-insurance. Menegatti and Rebessi (2011) adopt Mengatti's (2009) two-period framework to evaluate the tradeoff between loss prevention and savings. Kousky and Cook (2012) demonstrate that a utility-maximizing homeowner may optimally choose not to insure at the premiums sufficient to support a solvency-constrained insurer if the loss distribution is characterized by fat tails, micro-correlations, or tail dependence. Using empirically-based cases of earthquake risk in Oakland and hurricane risk in Miami, Kleindorfer and Kunreuther (1999) show that mitigation can be beneficial in reducing losses to both insurers and homeowners. They consider one mitigation measure for each city, use loss data from leading engineering loss modeling firms, and assume hypothetical but realistic large and small insurers, each with an assumed portfolio of residential structures. Kleindorfer and Kunreuther (1999) compare the results of three alternate scenarios in which 0%, 50%, or 100% of homeowners adopt mitigation. Kunreuther (2001) presents a similar analysis for a hypothetical insurance company serving Oakland, but addresses building codes, reinsurance, and catastrophe bonds as well. Kunreuther and Michel-Kerjan (2009, Ch. 13) uses large-scale empirical analyses to describe how hurricane losses to residential buildings might be shared among stakeholders under different market environments. The analyses were conducted for Florida, New York, South Carolina, and Texas, and use residential loss estimates from a leading catastrophe risk modeling firm. The analyses were conducted assuming a hurricane with a return period of 100, 250, or 500 years, with either no or full adoption of mitigation by all residential homes. Similar to previous work, we use modeled loss and retrofit data to develop a regional case study analysis. In this study, however, we allow the homeowner decision to purchase market insurance and the level of retrofit to be endogenously determined and dependent on risk attitudes, structural characteristics, and location-specific wind and flood risk probability distributions and numerous retrofit options.

Two recent papers present empirical analyses based on data from the windstorm mitigation credits and My Safe Florida Home (MSFH) programs in Florida (www.mysafefloridahome.com). Using data on the insured value, wind premium, deductible, structural characteristics, mitigation expenditures, and mitigation subsidy for 173,000 MSFH program participants, Carson et al. (2013) provide empirical evidence to support the hypotheses that more risk aversion leads to more mitigation; that self-insurance and market insurance are indeed substitutes; and that the likelihood of self-insurance is positively related to the home's vulnerability and the homeowner's ability to reduce insurance premiums. Young et al. (2012) evaluate the effectiveness of the program by assuming each homeowner undertakes the retrofit with the highest net annual value (as estimated with a loss model), or does not retrofit if none are positive. They estimate that in the current system only 4% would voluntarily retrofit, but an alternative credit system and longer loan period could increase the proportion of the population to 50%.

3. Method of analysis

In this paper, the inventory of residential buildings in the case study region is divided into groups with similar risk. Within each group, we assume homeowners individually make insurance purchase and retrofit decisions so as to maximize expected utility, and we examine the aggregated results under different conditions. We conduct the analysis for the region to explore the regional level outcomes that are the result of the aggregation of the decisions made by the many heterogeneous homes that comprise the region. In Sections 3.1, 3.2, and 3.3, we present definitions of key terms, the model formulation, and the case study inputs, respectively.

3.1. Definitions and scope

The inventory of residential buildings in the study region is divided into groups, where each is defined by its geographic area unit or location i (e.g., census tract), building category *m*, and resistance level c (hereafter referred to as buildings of type *i*,*m*,*c*). Building categories *m* are defined based on architectural features and are assumed to perform similarly in hurricanes 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's current resistance *c* to an improved building resistance *c'*. The initial building inventory is defined as X_{imc}, the number of buildings of type i, m, c.

The model considers hurricane damage only and includes both hurricane-related wind and storm surge flooding. The hurricane hazard is represented by an efficient set of probabilistic hurricane scenarios $h \in (1, \dots, H)$, defined as tracks with along-track parameters that determine the intensity, including central pressure deficit and radius to maximum winds. For each hurricane, wind speeds and surge depths are estimated throughout the study area. Each hurricane scenario has an associated annual occurrence probability P^h such that when probabilistically combined, the set of hurricane scenarios represents the regional hazard completely (Apivatanagul et al. 2011). In a sense, each hurricane scenario represents all hurricanes that would produce similar wind speeds and surge depths in the study area. The set is efficient in that it includes a relatively small number of hurricane scenarios, but they are carefully chosen and their probabilities assigned so that they capture the full information about the probabilistic hazard, as detailed in Apivatanagul et al. (2011).

3.2. Model formulation

Homeowners may choose any combination of insurance and retrofit and have full information about the effect on their loss distribution. If a homeowner buys insurance, he pays a premium p_{imc} based on the expected loss for buildings of type i, m, c. We assume coverage of the total home value minus a specified deductible (in dollars), d. It is straightforward to extend the formulation to allow multiple deductibles or coverage levels. We let the binary index n indicate the insurance purchasing choice—one if a homeowner purchases insurance, or zero if not. If he chooses to retrofit, he can choose which retrofit alternative cc' to adopt, each of which represents a physical modification of the building that requires a cost to implement and reduces the vulnerability to damage. We define Δ as the set of resistance levels c' to which a home with resistance c can retrofit, and the case of $c' = c$ corresponds to a situation with no retrofit (the same resistance is maintained). The model provides as output $w_{imc}^{nc\prime}$, a binary decision variable equal to one if a homeowner of type i, m, c makes the insurance choice n and implements a retrofit from building resistance c to resistance c'; and zero otherwise. It is run separately for each group i, m, c, and since the models do not interact, the computation is parallelized. The analysis is conducted on an individual building and annual basis.

For each building in location i, of building category m, and resistance level c, after the owner has retrofitted to resistance level c', expected loss in hurricane scenario h is:

$$L^h_{imc'} = \sum_\delta R^\delta_{mc'} a^{\delta h}_{imc'} \qquad \forall i, m, c' \in \Delta, h \tag{1}$$

where $a^{\delta h}_{imc'}$ is the probability a building in location i of category m and resistance level c' will experience damage state δ in hurricane h; and $R^\delta_{mc'}$ is the cost to reconstruct a building of category m to its post-retrofit building resistance c' after it has been damaged to damage state δ. These values can be obtained from a building loss simulation model, such as, HAZUS-MH 2.1 (FEMA 2012), the Florida Public Hurricane Loss Model (FPHLM 2005), or models used by private firms such as Risk Management Solutions, Inc. or AIR Worldwide.

When a hurricane h occurs, the actual expenditure $B^h_{imc'}$ by an insured owner of building type i, m retrofitted to resistance level c' is the minimum value between the actual loss the home experiences and the deductible d:

$$B^h_{imc'} = \min\{L^h_{imc'},\ d\} \qquad \forall i, m, c' \in \Delta, h \tag{2}$$

The homeowner premium is based on the expected loss across all possible hurricanes and varies by building type i, m, c'. Thus, the annual premium $p_{imc'}$ for a building in location i, of building category m, and resistance level c' is the expected value of the loss minus the deductible multiplied by $(1 + \tau + \lambda)$, where the loading factors τ and λ represent the primary insurer's administrative cost and profit margin, respectively (Eq. 3):

$$p_{imc'} = (1 + \tau + \lambda) \sum_h P^h \left(L^h_{imc'} - B^h_{imc'}\right) \quad \forall\, i, m, c' \in \Delta \tag{3}$$

We assume each homeowner has a maximum budget for homeowner insurance equal to a specified percentage κ of their home value V_m (Eq. 4). Premiums that exceed the proportion κ of home value are deemed not “affordable.”[1] Further, an insurer will not offer insurance if the premium is less than some specified value ρ that represents a minimum annual cost associated with servicing a policy (Eq. 5). Equation 6 is simply a requirement that any retrofit must improve resistance and each $w_{imc}^{nc\prime}$ must be zero or one (Eq. 7). Finally, each homeowner chooses exactly one combination of insurance-retrofit strategy nc' (Eq. 8), The decision will differ across types i, m, c.

$$p_{imc'} \leq \kappa V_m \quad \forall i, m, c' \in \Delta \tag{4}$$

$$p_{imc\prime} \geq \rho \quad \forall i, m, c' \in \Delta \tag{5}$$

$$w_{imc}^{nc\prime} = 0 \quad \forall i, m, c, n, c' \notin \Delta \tag{6}$$

$$w_{imc}^{nc'} = \{0,1\} \quad \forall i, m, c, n, c' \in \Delta \tag{7}$$

$$\sum_n \sum_{c\prime \in \Delta} w_{imc}^{nc\prime} = 1 \quad \forall i, m, c \tag{8}$$

We adopt a utility function of the form $U(x) = 1 - e^{-\theta x}$ for homeowners where θ is the coefficient of absolute risk aversion. Some level of risk aversion ($\theta > 0$) will assure sufficient demand for insurance at a premium that reflects an actuarially fair price plus loading factors (τ, $\lambda > 0$). The homeowner’s objective (Eq. 9) is to maximize expected utility over all possible hurricane scenarios h if the homeowner buys insurance (first term) and if he does not (second term). The homeowner’s choice variables are the kinds of retrofit and whether or not to purchase insurance. According to the first term, if hurricane h occurs, the homeowner pays: (1) the insurance premium, $p_{imc\prime}$; (2) the loss up to the deductible, $B_{im}^{hc\prime}$; and (3) the cost to retrofit,

[1] Although affordability of insurance premiums is the subject of a National Academy of Science study at this time and an issue of direct relevance to the Homeowner Flood Insurance Affordability Act of 2014, the scholarly literature does not suggest a definitive test for affordability, other than membership of the budget set given prices and income.

$(1-s)K_{mc}^{c\prime}$, where $s \geq 0$ is the percentage of the cost that is subsidized, and $K_{mc}^{c\prime}$ is the cost to retrofit a building of category m from building resistance c to c'. In the second term, the homeowner pays: (1) the cost to retrofit, $(1-s)K_{mc}^{c\prime}$; and (2) the loss due to building damage, $\sum_{\delta} R_{mc\prime}^{\delta} a_{imc\prime}^{\delta h}$. Note that all expenditures are modeled as negative values; and when $h = H+1$, no hurricane occurs, and the loss due to building damage in both cases is zero.

$$Max \ \left[\sum_{n=1}\sum_{c\prime\in\Delta} w_{imc}^{nc\prime}\{\sum_{h} P^{h} U\left(p_{imc\prime} + B_{imc\prime}^{h} + (1-s)K_{mc}^{c'}\right)\}\right] + \left[\sum_{n=0}\sum_{c\prime\in\Delta} w_{imc}^{nc\prime}\left\{\sum_{h} P^{h} U\left((1-s)K_{mc}^{c'} + \sum_{\delta} R_{mc\prime}^{\delta} a_{imc\prime}^{\delta h}\right)\right\}\right] \quad (9)$$

3.3. Case study inputs

The Eastern North Carolina study area includes the low-lying coastal part of the state with the most severe hurricane hazard, and extends westward to include half of Raleigh, the state capital. This area has a long history of destructive hurricanes. On average, a tropical storm or hurricane is expected to make landfall on the North Carolina coast every four years (SCONC 2010). Recent hurricanes affecting North Carolina include Floyd (1999), Isabel (2003), Irene (2011), and Sandy (2012). Further, the state has been active in encouraging retrofitting and insurance purchase. The Beach Plan was created in 1969 as a public/private partnership to provide insurance coverage to the barrier islands. Since 2003, it has offered homeowners policies and windstorm and hail insurance only policies to 18 coastal counties (Lehrer 2008, NCIUA 2013). In June 2010, the North Carolina Department of Insurance announced that qualifying homes on the North Carolina coast would receive insurance premium discounts for wind and hail coverage if they undertake certain mitigation efforts. This study focuses on single-family wood-frame homes, the wind and storm surge flooding hazards (not rainfall-induced flooding), and losses directly due to structural damage (structural, non-structural, interior, mechanical, electrical, and plumbing).

The 2010 census tracts are the basic area unit of study, with each of the 143 census tracts that touch the coast further divided into three areas—a zone 0 to 1 miles from the coastline, a zone 1 to 2 miles from the coastline, and the remainder of the census tract. 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). These account for a large portion of the residential buildings in the study region. Building values V_m were estimated using RSMeans®[2] as in Legg (2011, Appendix G).

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 Institute of Business and Home Safety (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 to new Base Flood Elevation (BFE). Retrofit costs were estimated for each using National Estimator (2012), the Institute of Business and Home Safety Shutter Selection Guide (IBHS 2012), and personal communication with two experts on North Carolina residential construction and hurricane resistance.[3] We assume each retrofit will last for thirty years and annualize the retrofit cost. To allow representation of these retrofit alternatives, we defined six components: roof cover, roof sheathing, roof-to-wall connections,

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[2] RSMeans® provides project and construction cost estimators.

[3] Spencer Rogers, North Carolina Sea Grant and University of North Carolina at Wilmington, and Tom Dugan, Dugan Enterprises, Inc., IBHS Fortified for Existing Homes Evaluator.

openings (i.e., windows, doors, garage doors), walls, and flood susceptibility. The first five, the same as those used in the Florida model, are important for determining wind damage; the last one represents the resistance to flood damage. While not a physical building component in the same sense as the others, for purposes of the loss/retrofit model, flood susceptibility is treated as a component. For each component, two to four possible configurations were identified so that each is a common physical configuration before or after a typical retrofit, and represent the range of typical resistance levels. For each configuration, the corresponding mean and coefficient of variation (COV) of the resistance were defined based on available results in the literature (Peng 2013). For example, roof cover may be regular asphalt or high wind shingles with mean wind resistances of 50 psf and 70 psf, respectively, and COVs of 0.3. With two to four configurations for each of the six components, there are 192 possible building resistance levels *c*, and up to 143 possible retrofits *cc'*, depending on the initial building resistance. Since retrofit alternatives are defined in physical terms (in contrast to hypothetical shifts in fragility curves), associated costs can be estimated, and their effect on losses can be computed by comparing losses estimated with and without their implementation.

The total initial (pre-retrofit) building inventory by census tract was estimated using census data. Buildings were then allocated among the building resistance levels based on location and year built relative to major building code and construction practice changes (based on evaluation of North Carolina building codes since the first state residential code in 1967 and personal communication with experts in North Carolina residential construction and hurricane resistance) (Peng 2013).[4] The final building inventory included 931,902 buildings in 732 area

[4] Spencer Rogers, North Carolina Sea Grant and University of North Carolina at Wilmington, and Barry Gupton, Chief Code consultant/manager, North Carolina Building Code Council.

units (143 within one mile of coast, 135 one to two miles from coast, and 454 more than two miles from coast).

The component-based building loss model used to obtain damage probabilities $a_{imc'}^{\delta h}$ and reconstruction costs $R_{mc'}^{\delta}$ is an extended and slightly modified version of the Florida Public Hurricane Loss Model used by the Florida Office of Insurance Regulation (FPHLM 2005) (Peng et al. 2013, Peng 2013). The loss model 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. Modifications include: (1) addition of a flood damage model based on results from the component-based flood damage simulation model in Taggart and van de Lindt (2009) and van de Lindt and Taggart (2009); (2) Latin hypercube sampling of component resistance values to introduce correlation and improve efficiency; and (3) new component configurations, retrofit strategies (with retrofit costs), and resistance input values. 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. To the extent that the full range of losses is considered, the benefits of insurance and retrofit would increase and the investments would appear increasingly attractive.

We used the set of 97 probabilistic hurricane scenarios developed in Apivatanagul et al. (2011). For each scenario, 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 assume the parameter value $\theta = 3(10^{-5})$ which would yield a similar penetration rate as reported by Dixon et al. (2006) for the National Flood Insurance Program. The homeowners have perfect information about their risk and insurance and retrofit options. The insurer uses risk-based premiums that are lower if loss reducing retrofits are adopted, pricing insurance for each group of homes of category m and resistance level c in location i with perfect information about their risk. Finally, deductible of $d = \$2500$, primary insurer administrative loading factor $\tau = 0.35$, insurer profit loading factor $\lambda = 1$, minimum premium required to allow insurance purchase of $\rho = \$100$, and affordability parameter $\kappa = 5\%$ of the total building value.[5]

The optimization was solved separately for each of the *i*,*m*,*c* combinations that appeared in the study area. Each analysis included 97 hurricane scenarios and up to 288 available alternatives (do nothing, insure only, and 143 retrofit options with or without insurance). The computations were executed in Matlab 8.1 (R2013a) on a Unix-based high performance computing cluster, using 12 cores to evaluate 12 *i*,*m*,*c* combinations simultaneously.

4. Analysis results

In this section, we examine the model results and first consider four categories of homeowner choices: (1) do nothing, (2) insure only, (3) retrofit only, and (4) insure and retrofit. We then consider factors that influenced the decisions and the aggregated effects.

4.1. Decision to insure and/or retrofit

In the case study area, 52% of homeowners chose to do nothing, 10% insure only, 30% retrofit only, and 8% both insure and retrofit. Figure 1 illustrates the geographic distribution of

[5] Loading factors were based on personal communication with John Aquino, WillisRe. For comparison with our selection of $\kappa = 5\%$ of the total building value, the Homeowner Flood Insurance Affordability Act of 2014 encourages FEMA to minimize the number of policies with premiums that exceed 1% of the coverage amount (FEMA 2014).

homeowners in each group. The predominant decision by homeowners who are located well inland in the northwestern part of the study area is to do nothing. The homeowners closer to the coast in the southern part of the study area mostly retrofit, and those that are located on the coastline are more likely to do both. The choices vary by building category *m* as well, with more retrofits being undertaken for two-story, gable-roof buildings than for others. Finally, the choices vary by the initial building resistance because some retrofit options are not available for all initial resistances. Buildings with the higher resistance levels have fewer retrofit options. In contrast, structures with the lowest resistance for roof sheathing, for example, are 2.4 times as likely to retrofit as those with the higher roof sheathing resistance.

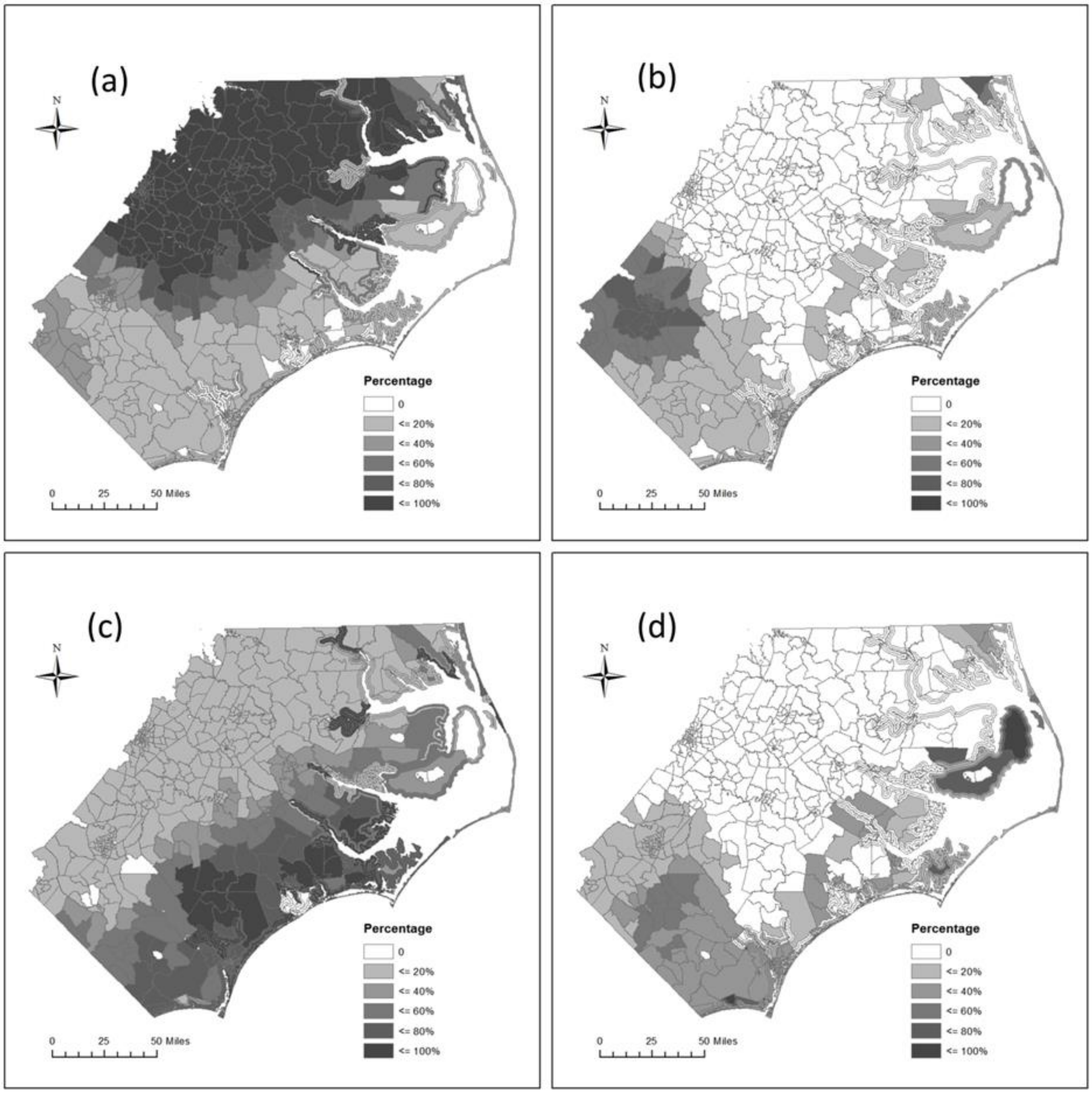

Figure 1. Geographic distribution of the percentages of homes in each area unit *i* that choose to (a) do nothing, (b) insure only, (c) retrofit only, and (d) insure and retrofit

Examining the retrofit choices in more detail, the model recommends a variety of different retrofit strategies for different homeowners, from small to large investments, addressing both wind and flood damage (Peng 2013). Combinations of component retrofits are often the best strategy because a home is only as resilient as its weakest component. However, it is also important to note that homeowners sometimes choose retrofits that are less expensive even if they do not provide the best possible protection from damage.

4.2. Factors affecting insurance and retrofit decisions

To understand why these choices are made, we consider three main factors that determine each homeowner's insurance and/or retrofit decision: (1) their initial loss distribution, (2) the cost to insure and/or retrofit, and (3) risk attitudes.

4.2.1. Initial loss distribution

Figure 2 demonstrates that a home's initial loss distribution is a primary driver of the homeowner's decision. Each home was plotted as a point on one of the four graphs (Figures 2a-2d) based on which choice was made for the home—do nothing, insure only, retrofit only, or both insure and retrofit; and the coefficient of variation (COV) and mean of its initial loss distribution. For clarity, the scatterplots were then translated into the heat maps shown, in which a darker shade indicates a higher density of points. While there is some overlap, homeowners that do nothing tend to have loss distributions that exhibit low means and low COVs. Homeowners with a relatively high COV and low mean loss typically insure only, those with a relatively high mean loss but low COV tend to retrofit only, and those with both a high mean and COV of loss typically do both. Examining similar figures of COV of loss vs. mean loss for portions of the building inventory indicates that the loss distribution largely explains the geographic pattern of choices.

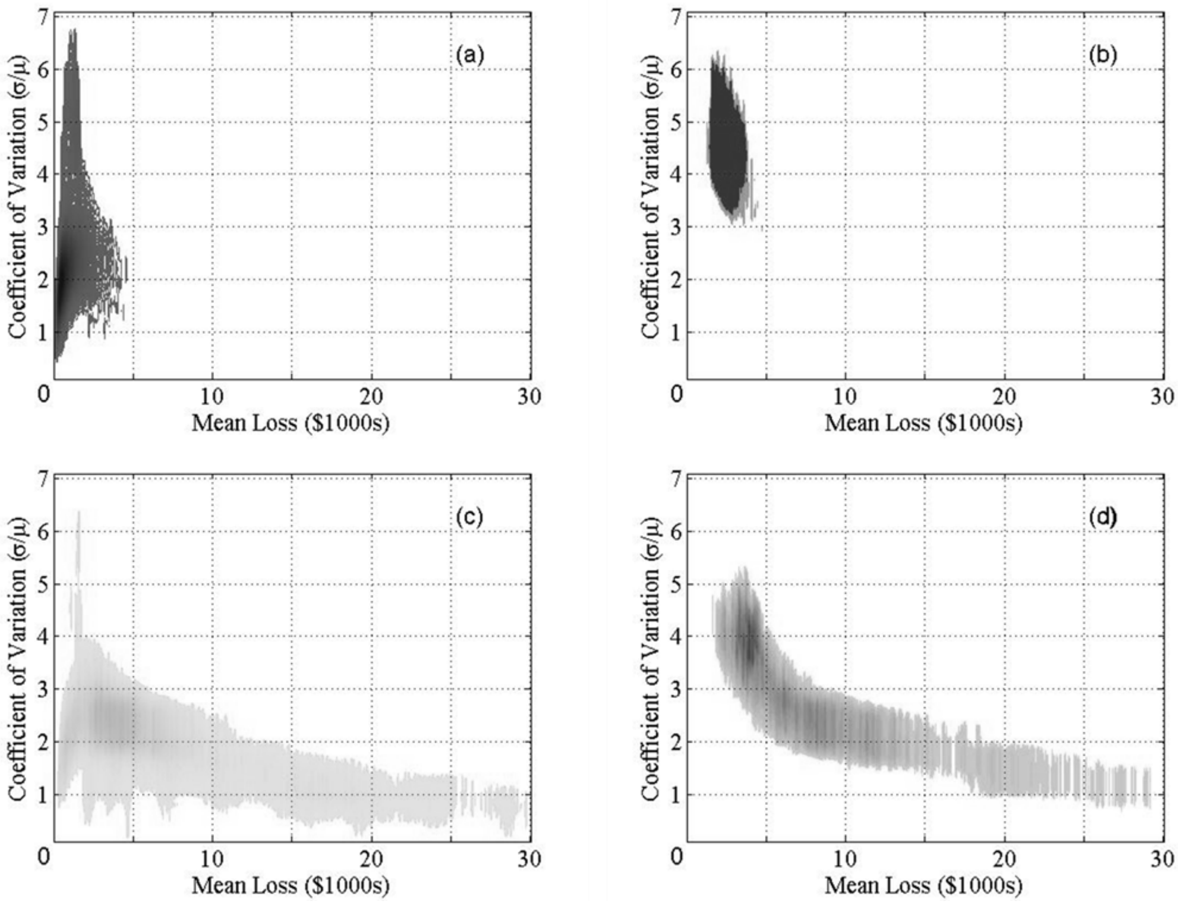

Figure 2. Coefficient of variation of loss vs. mean loss per home, by the four main groups of decisions: (a) do nothing, (b), insure only, (c) retrofit only, and (d) both insure and retrofit

4.2.2. Cost to retrofit and insure

The annualized retrofit cost and insurance premium obviously affect homeowners' insurance and retrofit choices. Recall that the cost of all retrofit options is based on construction cost and independent of the risk. Further since the cost of insurance is risk-based, the cost of insurance adjusts to the reduction in expected losses when a home is retrofitted. The price of insurance therefore depends on retrofit but the price of retrofit is independent of the price of insurance. We will examine the effect of a retrofit subsidy that effectively reduces the cost of retrofit to the homeowner and follow with an analysis of proportional changes in the cost of risk-based insurance.

Retrofit subsidy

We examine the effect of a subsidy on retrofit by starting with the base case of homeowners paying the full cost of retrofit. Figure 3 shows how the proportion of homeowners choosing to do nothing, insure only, retrofit only, and both insure and retrofit changes as the level of subsidization varies from total subsidization (homeowner pays none of the retrofit cost) to no subsidization where the homeowner pays 100% of the retrofit cost. For our study area, almost all (96%) homeowners will optimally choose to retrofit if the action is completely subsidized. The remaining 4% are structures that have the highest resistance level and therefore reap no gains from retrofit. As Figure 3 illustrates, most of the increase in retrofit comes from the ranks of the homeowners that chose neither insurance nor retrofit. Of those 834,000 homeowners who retrofit only when the cost is fully subsidized, 274,000 (33%) would continue to retrofit only if there was no subsidy, 72,900 (9%) would switch to insuring only, and 35,800 (4%) would retrofit at some lower level, but buy insurance as well. The remaining 54% would opt to do nothing. While the percentage of homeowners that both insure and retrofit remains approximately constant at 8% regardless of retrofit cost, the particular homeowners in that group change.

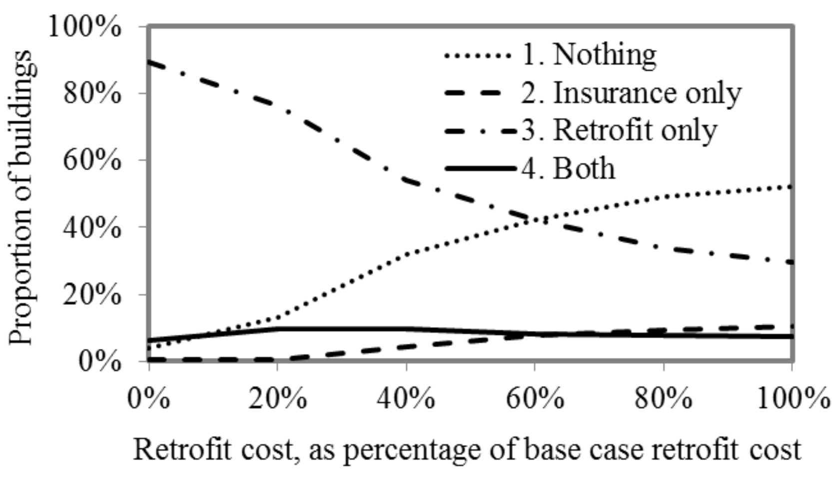

Figure 3. Proportion of buildings making each of the four main choices as a function of retrofit cost

Cost of insurance

We evaluated the effect of proportional changes in the cost of insurance by allowing λ to vary from 0 to 1.5. A value of $\lambda = 0$ corresponds to a cost of insurance that is the actuarially fair rate plus administrative cost. This rate would just balance the budget of a government-run insurance program. Increasing levels of λ represent higher profitability of private insurance. As shown in Figure 4, changes in the cost of insurance have relatively little impact on those that chose to do nothing in the base case. As the loading factor λ increases from 0 to 1.5, the number of homes that insure (with or without retrofit) decreases from 392,000 to 137,000. Of the 305,000 homes that stop insuring as the price increases, 254,000 switch to retrofit only and 50,800 switch to doing nothing. Within the ranges considered, insurance and retrofit are substitutes for some homeowners but not for others. Reducing the retrofit cost increased the number of homes doing retrofit only, and drew from the ranks of those that were neither insuring nor retrofitting without the subsidy. Reducing the premium increased both the number of homes insuring only and the number doing both insurance and retrofit but did little to change the proportion that were doing nothing to mitigate losses.

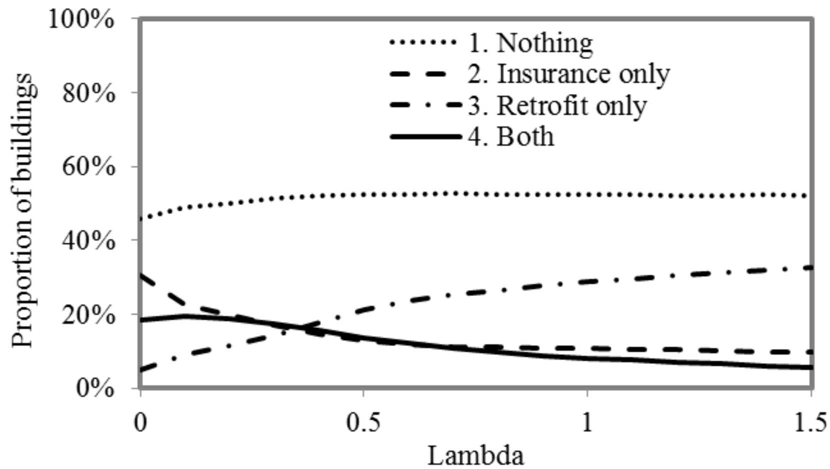

Figure 4. Proportion of buildings making each of the four main choices as a function of lambda, the insurer's profit loading factor

4.2.3. Risk attitudes

Finally, we examine the effect of risk attitude in Figure 5. Varying the risk parameter θ from -50% to $+50\%$ of the base value of $\theta = 3(10^{-5})$ reduces the percentage of homeowners who do nothing from 65% to 47%. Increasing risk aversion has a larger effect on the decision to insure than to retrofit because insurance has a larger effect on the variability in the loss distribution. The proportion of homeowners that both retrofit and insure increases with increasing risk aversion drawing switches from the other three categories.

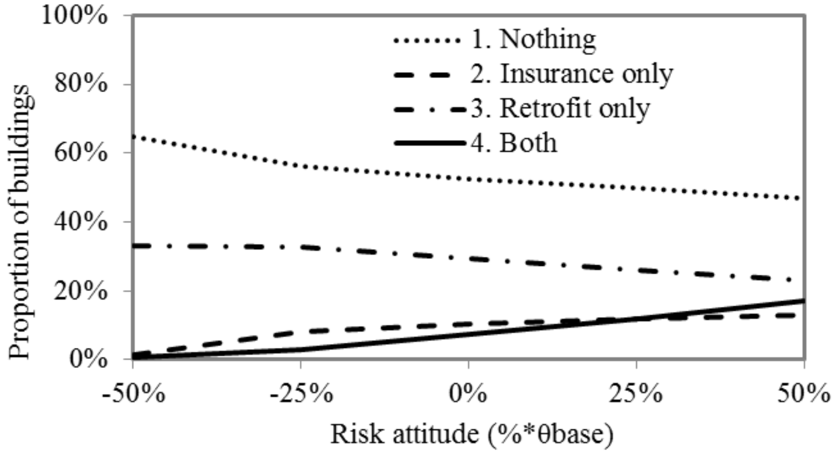

Figure 5. Proportion of buildings making each of the four main choices as a function of the coefficient of absolute risk aversion θ, (as a percentage of the base value of θ)

4.2.4. Total Expenditures on Mitigation and Recovery

The patterns in Figure 6 relate to the different effects that insurance and/or retrofit have on a homeowner's total expenditures. Figures 6a-d show the inverse cumulative distribution function of the average annual per-building total expenditures before and after insurance and retrofit actions for buildings in each of the four main decision groups, where total expenditures includes loss due to building damage, any premium or deductible paid, and any retrofit cost paid. For those that buy insurance (Figure 6b and 6d), the tails of the distributions are dramatically truncated, and those that retrofit (Figure 6c and 6d) start with a higher chance of smaller losses. Retrofitting reduces the level of loss without modifying the variability substantially (Figure 6c).

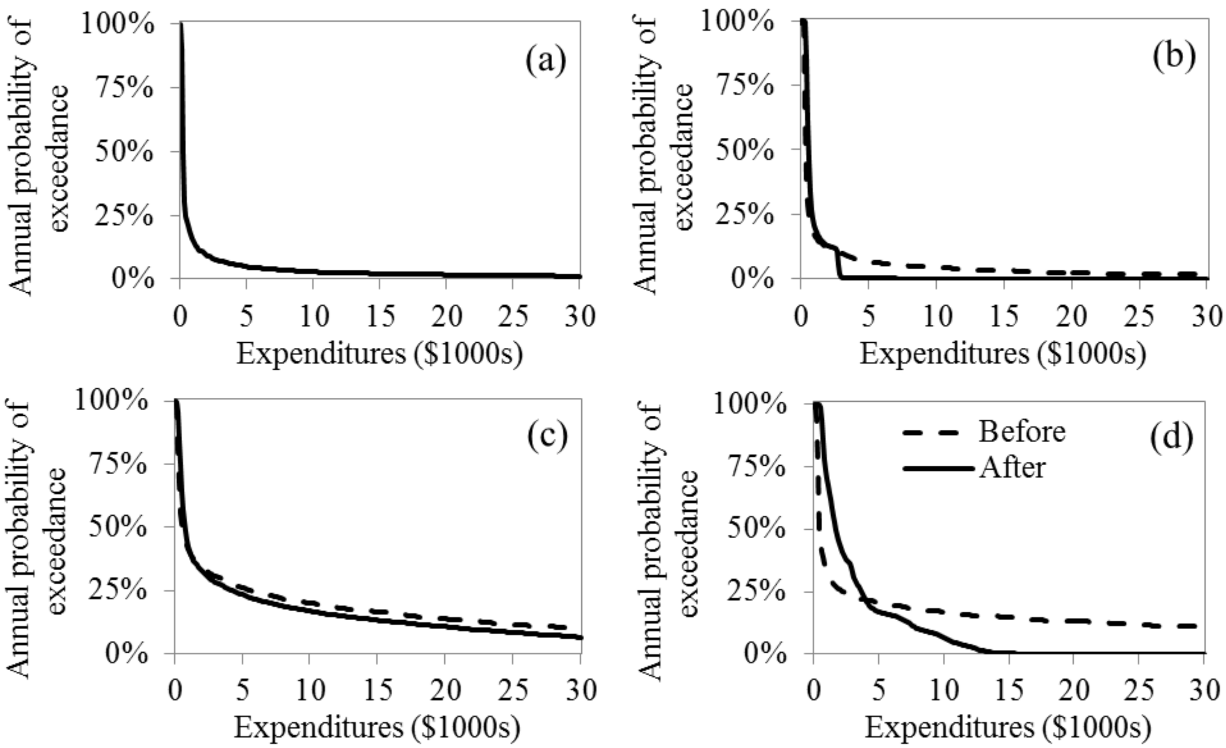

Figure 6. Inverse CDFs of total annual expenditures per home before and after actions for each of the four main groups of homeowners, those that (a) do nothing, (b), insure only, (c) retrofit only, and (d) both insure and retrofit.

4.3. Aggregate effects

Finally, we examine the aggregate risk for the regional residential building stock in our case study and consider cost effectiveness of a retrofit subsidy. Figure 7a shows the inverse cumulative distribution function of annual loss for the region, and breaks down the total to indicate the loss that the insurer, insured homes, and uninsured homes each incur, given the base case analysis (no retrofit subsidy). Uninsured homeowners still have the greatest risk, because 82% of homeowners remain uninsured in the base case, with 52% choosing not to retrofit either. We use the 90th percentile of that loss distribution to examine the aggregate effect of a retrofit subsidy. Looking at the proportion of the retrofit cost covered by the homeowner, as it decreases from 100% to 0% (Figure 7b), the total regional loss after retrofit decreases from $8.2 to $6.3 billion. We also calculate the total expense of regional loss plus the amount spent on the subsidy, and find that for the case study region that sum is minimized when an 80% subsidy is offered (homeowners pay 20% of retrofit cost).

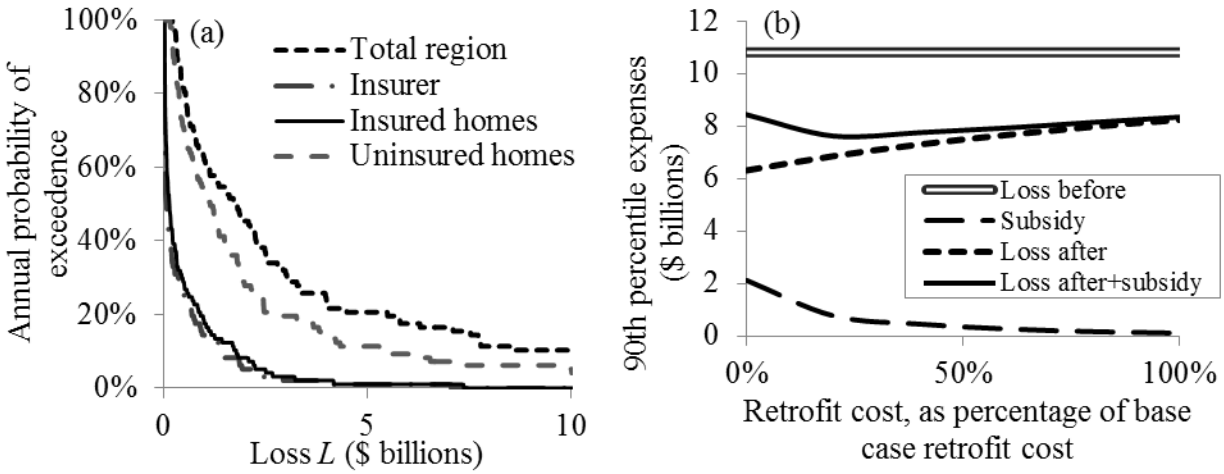

Figure 7. (a) Annual probability of exceedance of loss to total region, insured homes, uninsured homes, and insurer, and (b) 90th percentile of total regional loss before and after retrofit, and with the cost of subsidies, as a function of retrofit cost

5. Conclusions

In this paper, we examine the optimal voluntary insurance and retrofit decisions of homeowners with a menu of retrofit options, insurance premiums that reflect the effects of risk reduction and empirical representation of hurricane damage potential. The analysis is novel in linking the analysis of homeowner decisions at a regional scale to a detailed, state-of-the-art hurricane loss model and realistic representation of possible retrofits. With this representation of the risk, we show that structures are heterogeneous in terms of their loss distributions, and the characteristics of the first and second moments of the structure- and location-specific distribution.

The results also provide some insight into the factors that influence homeowner decisions. We see that the initial loss distribution (as represented by the coefficient of variation and mean loss) is influential in determining whether homeowners choose to do nothing, insure only, retrofit only, or both insure and retrofit. This is because insurance and retrofit have different effects on the loss distribution, with the former reducing the variability by removing the tail of the distribution, and the latter having a larger effect on the mean of the distribution. As expected, the costs to insure and retrofit are important. For our case study, subsidizing retrofit was more effective in moving homeowners that were neither retrofitting nor insuring to some form of risk reduction. A subsidy to reduce retrofit cost could potentially be used to great effect. In fact, the government benefits associated with a reduction in uninsured loss resulting from a subsidy may more than offset the cost of the subsidy.

This numerical analysis also contributes to the on-going discussion in the literature about whether market insurance and retrofit (self-insurance) are substitutes or complements. In this case study, they can be substitutes, but are not always. It depends on the homeowner's loss distribution, available retrofits, and risk attitude. Finally, homeowners' risk attitudes can also influence the best choice, but affects the appeal of insurance more than retrofit.

This model can be used by the insurance industry to identify optimal pricing, and by state insurance regulatory bodies and policymakers that are considering different policy options to increase voluntary mitigation by homeowners. Our analysis indicates that targeted subsidies on retrofit aimed at the highest risk properties is most effective for the population and risk characterized in our scenarios. A logical extension of this model could include changes in the homeowner objective function to explore the effect of well documented behavioral biases on choices to insure or retrofit. Future work could also couple this model of homeowner demand for insurance and retrofit with profit-maximizing insurers that can utilize reinsurance within their own risk management strategies. This coupled analysis will enhance our understanding of the interaction between the reinsurance and home insurance market.

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Disclaimer

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