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Insurability and government-funded mitigation: safer but costlier

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Abstract

Hurricanes significantly harm homeowners through physical damage and long-term financial strain due to rising insurance costs, property value loss, and repair expenses. This paper focuses on the interrelated decisions of the government mitigation funding of residential acquisitions and retrofit subsidies and of price restrictions on the insurance market in eastern North Carolina to determine the financial effects on stakeholders. The introduction of these policy interventions have impacts that propagate through the system due to risk adjustments, homeowner take-up behaviour, and insurer profit-maximising behaviour. This study uses an integrated game theoretic model to demonstrate that there are cost-effective government spending levels that reduce residential loss from hurricane damage. When insurance prices are capped at preintervention levels, the number of households and their distribution of losses, which has been altered through mitigation, leads to increased insurer insolvency. When insurance prices are allowed to adjust after mitigation, some homeowners find insurance is no longer affordable. This highlights the tradeoff between ensuring insurer stability and expanding homeowner insurance accessibility.

Keywords Insurance pricing · Household insurability · Hurricane · Buyouts and retrofits · Insurer solvency

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Introduction

Over the past 45 years, hurricanes have caused over USD 1.3 trillion in damages in the U.S. (NOAA 2023a, b). In 2020, there were a record-tying 30 named Atlantic storms (NOAA 2023a, b), including Laura and Sally, which caused over USD 25 billion in damages (NOAA 2021). In 2021, Hurricane Ida marked the 16th anniversary of Hurricane Katrina by making landfall in Louisiana as a Category 4 storm, causing USD 75 billion in damages, which included damages to all of the homes in the small barrier island town of Grand Isle, Louisiana (NOAA 2022). In 2022, Hurricane Ian caused widespread damages across Cuba, Florida, and the Carolinas, with expected losses topping USD 100 billion (NOAA 2023a, b). These large-scale damages, paired with unsustainable federal debt (Powell 2024), highlight the need for a collective effort. By pairing government interventions with private-sector decision-makers, we can incentivise behaviours such as moving out of high-risk areas, enhancing the structural resistance of houses, and insuring properties to cover expected wind and flood losses. This collaborative approach is key to achieving better outcomes, reducing losses, and improving efficiencies.

The government can nudge behavioural changes using financial or regulatory interventions. In this paper, using data from eastern North Carolina, we consider how interconnected decision-making across homeowners, insurers, and the government can reduce loss and improve insurance coverage. Specifically, we consider different government spending levels on residential mitigation (structural retrofits and property acquisition/buyouts), homeowners' propensities to accept government subsidies for mitigation, and changes in the housing inventories have on the insurance market using an integrated computational framework focussed on the case study area of eastern North Carolina. Structural retrofits are a set of wind and flood mitigation measures that improve the damage resistance of a building. These can include storm-resistant shingles, storm shutters, impact-resistant glass, home elevation, and other measures that reduce the damage a house sustains in the event of a hurricane. Home acquisitions, also called buyout programmes, offer homeowners the opportunity to sell properties in high-risk locations to the government at a fair market price. By modelling the interactions between stakeholders' decisions and the implications for housing inventory, tradeoffs between insurer solvency and insurance affordability decisions, and outcome implications for the three stakeholder groups, the resulting tradeoffs are more evident.

Literature

In the U.S., the government supports homeowners attempting to reduce their risk of hurricane, wind, and flood damage through buyout programmes, which remove at risk houses from the housing stock. Researchers have focussed on home location and homeowners' economic and demographic factors that impact buyout decisions. Fraser et al. (2006) discuss the importance of government-supported mitigation, evaluate essential factors such as homeowner acceptance, and provide several suggestions to build strong mitigation policies. Kick et al. (2011) explore the factors affecting the relocation decisions of repetitive flood loss victims, using data from Federal Emergency Management Agency (FEMA) officials' interviews and flood victim survey, highlighting the importance of rational choices related to finances, risk perceptions, community attachment, and interactions with local officials. Bukvic et al. (2015) examine the influence of socioeconomic characteristics on household willingness to relocate from high-risk coastal urban areas. Robinson et al. (2018) use logistic regression analysis of survey data to identify factors influencing property owners' decisions to accept acquisition offers, finding that location in a floodplain, shorter future tenure, more past hurricanes, less control, and being White are associated with higher acceptance rates. Siders (2019) argues that social justice requires a solidarity-based insurance regime to guarantee flood insurance access for vulnerable UK households, warning that further marketisation will undermine fairness and social justice. Mach et al. (2019) analyse over 40,000 US flood buyouts, revealing that regions with high population and income administer more retreats, and properties bought out are often in socially vulnerable areas. The government can also support homeowners to reduce the risk of damage through structural adjustments to their homes by subsidising retrofits. Botzen et al. (2013) consider a case of flood risk in the Netherlands, finding that 52% of homeowners are willing to invest EUR 10,000 to elevate new houses to eliminate flood risk, and homeowners are willing to pay between EUR 35 and EUR 45 per month as a "safety premium". Jasour et al. (2018) develops mixed logit models to find homeowners' retrofit decisions, and the results indicate that offering grants increases the likelihood of homeowners retrofitting; particularly, homeowners are more likely to retrofit when they are closer to the coast, younger, have a newer home, and have recent hurricane experience. Furthermore, interventions to protect households and homes necessarily have distributional impacts. O'Neill and O'Neill (2012) distinguish between the individualist, risk-sensitive insurance model in which individuals' payments are proportional to their risk level and the solidaristic model in which the risk burden is shared with lower-risk households. Penning and Pardoe (2012) attribute the benefits of residential flood alleviation schemes to homeowners whose flood risk was reduced and to insurers whose book of business has lower risk but whose premiums remain constant.

This study is an extension of a series of previous studies, and the framework is built upon those studies. Frimpong et al. (2019) focuses on acquisition aspects, examining the impact of price on homeowners' willingness to accept flood acquisition offers, building a pooled probit model and using bootstrap methodology to determine the effects of home price offers on homeowners' decisions, finding that higher prices offered increase acceptance likelihood. Chiew et al. (2020) concentrates on retrofit programme design, which examines the influence of different grant programmes for homeowners' decisions to retrofit, finding that offering a grant triples the likelihood of retrofitting. Contrary to previous research, households experiencing multiple hurricanes are less likely to retrofit. Gao et al. (2016), on the other hand, discusses insurance pricing, which models the primary natural catastrophe insurance market using a Cournot-Nash game and a regional loss estimation model. Gao et al. finds that market concentration logically influences insurers' decisions, with a more competitive market reducing insurers' profitability but being more attractive to homeowners. Researchers (Wang et al. 2020; Guo et al. 2022; Liu et al. 2024) have proposed a computational framework among stakeholders by considering acquisition, retrofit, and insurance together, including four stochastic optimisation models, which supports government decisions on mitigation spending, insurance regulation, allocation between retrofit grants and property acquisition. A case study in eastern North Carolina suggests potential win–win solutions.

Data

Our data include nearly 300,000 single-family wood-framed houses within 2 miles of the North Carolina coast (see Fig. 1). The low-lying region of coastal North Carolina and its barrier islands has a history of damaging hurricane and tropical storm events. From 2000 to the present, over 400 hurricanes and tropical cyclones have impacted this region, making North Carolina the third most at risk state in the US. During this period, Hurricane Florence and Hurricane Matthew were the most

Fig. 1 Study region: North Carolina coast

destructive hurricanes to hit North Carolina, resulting in economic losses of 16.7 billion and 1.5 billion (NOAA 2024), respectively. The most recent event, Hurricane Helene, resulted in nearly 100 fatalities in the state. The region is demographically diverse, with a wide range of home values, making it an excellent case study for our analysis. We simulate 100 alternative 20-year futures for this area using 97 probabilistic hurricane events (Apivatanagul et al. 2011) that match the mean of and variance in annual losses compared to the probability-weighted 97 events. We divide a year into 20 time intervals, ensuring at most one hurricane can occur in each interval. Based on the distribution of 97 probabilistic hurricane events, we randomly generate the occurrence of hurricanes within these predefined intervals over a span of 20 years to create a single scenario. These scenarios allow for multiple hurricanes to strike in the same year. The estimated dollar values of residential losses are influenced by the weather, house structure and location, resistance levels, and home values. The hurricane-related wind and flood loss estimates are based in part on an early version of the Florida Public Hurricane Loss Model as described in Gurley et al. (2005) and Pinelli et al. (2004, 2008) (for wind loss), and on van de Lindt and Taggart (2009) (for flood loss). The houses are geographically distributed, with assigned attributes of 8 different structure types, 192 different resistance levels (Peng 2013), and home values (Zillow 2019) which ranged from USD 34,700 to USD 488,400 in 2019. The characteristics of the houses are approximated based on actual homes in North Carolina.

In our computational model, the decisions of each group, policymakers, homeowners, and insurers, are separately motivated. The government considers different levels of funding for interventions and prioritises them with the highest loss reduction per dollar spent considering a 30-year potential loss horizon for households. Survey-based discrete choice models represent homeowner decisions to mitigate and/or purchase insurance. The survey details and methodology can be found in Frimpong et al. (2019). Our initial estimated take-up rate of insurance in this high-risk zone is 54.1%, which is comparable to Bradt et al.'s (2021) estimate that 48.3% of households in the 100-year floodplains purchased insurance in 2019. As mitigation measures (property acquisition and retrofit subsidies) are adopted, the expected loss is reduced; profit-maximising insurers respond by altering premium prices on risk-adjusted wind and flood coverage in response to mitigation which, in turn, influences homeowner insurance take-up rates. This study tracks how the adoption of mitigation measures propagates through the system to affect the insurability of houses and how the insurers' cash positions and solvency are affected over the 20 years of government interventions. We also experiment with tradeoffs between insurers and homeowners by considering price restrictions that limit the ability of insurance pricing to adjust.

We find that the expected value of loss avoided is greater than the cost of the government-supported retrofits and acquisitions. For homeowners with buyouts, they are no longer in the high-risk pool; for those who remain, insurance is more affordable when prices are held constant. However, holding premium pricing constant undermines insurers' ability to adjust to the changing housing stock and associated risks. When we factor in premium price adjustments, there is a tradeoff between insurers' solvency and insurance affordability.

Computational framework

Guo et al. (2022) and Liu et al. (2024) developed a computational framework consisting of interacting models representing the objectives of homeowners, insurance carriers, and the intervening policymakers. Our modelling framework extends their analyses by including different levels of government spending on mitigation with a focus on the financial impact on stakeholders of the resulting risk reduction and housing inventory changes.

Figure 2 shows a sequential schematic representation of the relationships among the three main stakeholders and the modelling sequence in two stages within each simulation year. The first stage entails an interaction between the government and homeowners. The government offers buyouts and retrofit subsidies to homeowners. With buyouts, houses are removed from the inventory and no structures can be rebuilt; thus, future expected losses are zero. With retrofits, the house damage resistance to wind and flood is improved. Homeowners decide whether or not to accept buyout offers or retrofit subsidies. In stage two, the reduction in expected losses and change in the housing inventory alter homeowners' and insurers' strategic interactions.

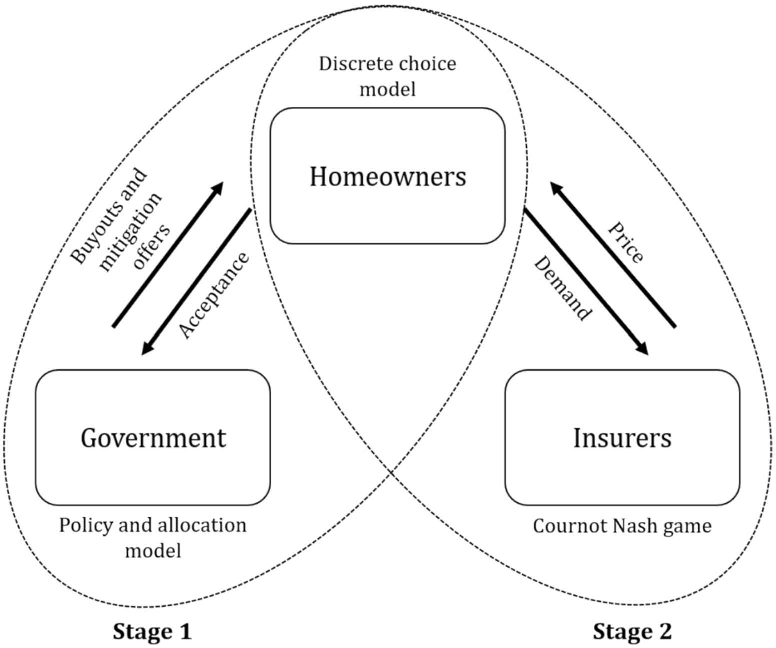

Fig. 2 Schematic representation of computational framework annual stages

Government and homeowner interactions

In Stage 1, the government offers buyouts and retrofit grants (Guo et al. 2022). In Eq. (1), an acquisition offer of C_n^{buy} dollars is made to homeowner n. If the house is undamaged, the offer price is V_n dollars, which is the house value of homeowner n. If the house was damaged by a hurricane in the previous year, the offer is discounted by $shock^{buy}$.

$$C_n^{buy} = \begin{cases} V_n \; if \; not \; damaged \; by \; a \; hurricane \; last \; year \\ shock^{buy} \times V_n \; if \; n \; experiences \; hurricane \; damage \; last \; year \end{cases} \tag{1}$$

In Eq. (2), the size of the retrofit subsidy awarded to homeowner n, $C^{mit}_{n,m,c,c\prime}$ dollars, either covers the price of the mitigation, $p^{mit}_{m,c,c\prime}$, or is set to a maximum subsidy amount, $\bar{J}$, whichever is smaller. The price ($p^{mit}_{m,c,c\prime}$) denotes the cost of retrofitting homeowner n's house of type m from initial resistance level c to an enhanced resistance level $c\prime$.

$$C^{mit}_{n,m,c,c\prime} = min\{p^{mit}_{m,c,c\prime}, \bar{J}\} \tag{2}$$

Following Wang et al. (2020), we consider nine types of retrofits and all physically possible combinations of them. Six of the retrofits are wind-related: (1) replacing roof cover, (2) installing water barriers within the attic, (3) intensifying gable ends, (4) strengthening roof-to-wall connections, (5) installing impact-resistant glass, or (6) installing shutters. Three of the retrofit options are flood-related: (7) elevating appliances and electrical outlets, (8) elevating the entire house, and (9) improving siding and insulation. The government allocates its limited annual budget across retrofit subsidies and buyout offers, prioritising based on cost-effectiveness ratios calculated as the expected loss avoided relative to the mitigation expense (Guo et al. 2022).

Our models of homeowners' behaviours are based on survey data collected from residents of eastern North Carolina. Buyout behaviours are well modelled using a cumulative standard normal distribution of errors, thus the acceptance of buyout offers is based on a pooled probit model which includes covariates for distance to the coastline, the length of time the homeowner has been in the house, the homeowner's income, prior experience with hurricanes, and a prior-year hurricane damage indicator (Frimpong et al. 2019). Homeowners' decisions to retrofit are modelled using a mixed logit because the errors are well modelled using the logistic distribution; we include controls for homeowner employment status, distance to the coastline, hurricane experience, retrofit price, and the maximum grant amount (Chiew et al. 2020). It is important to note that the grant amount and percentage of cost covered can influence homeowners' decisions on whether to retrofit. We assume the subsidy fully covers the retrofit cost or reaches a predefined maximum limit.

When acquired, houses are removed from the housing inventory and have no future expected losses. Retrofits improve structural resistance; the modified properties remain in the housing stock and have lower, but still positive, expected losses. Table 1 depicts the result of the interactions between the government offers and

Table 1 Average loss reductions over 30-year horizons from 20 years of mitigation spending, based on the 100 scenarios

Government budget	Buyout USD billion (% of budget)	Retrofits USD billion (% of budget)	Expected loss reduction 30-yr. horizon USD billion (per USD spent)
\$1B	0.89 (89.0%)	0.11 (11.0%)	1.23 (1.23)
\$2B	1.80 (90.0%)	0.20 (10.0%)	2.19 (1.10)
\$3B	2.64 (88.0%)	0.36 (12.0%)	3.07 (1.02)

If a homeowner does acquisition or retrofit at year y, the expected loss reduction of a 30-year horizon is calculated through year $y+1$ to year $y+30$

household decisions. Applying the government's cost-effectiveness prioritisation, most of the spending is allocated to acquisitions. Acquisitions remove the house from stock; thus, future expected losses are zero, whereas retrofits reduce expected future losses. When the government spends USD 1 billion total over 20 years (USD 50 million per year), 89% of the spending goes to buyouts, and 11% funds retrofit grants (Table 1). In total, the acquisitions and retrofits reduce expected losses by USD 1.23 billion over a 30-year period. When the budget is increased to USD 3 billion, the loss reduction is USD 3.07 billion, indicating a positive return on investment.[1]

Homeowner and insurer interactions

In North Carolina and other hurricane-impacted states, insurers offer separate policies for different types of damages; specifically, wind and flood policies are separate instruments. In the second stage, insurers offer risk-adjusted wind and flood insurance, and homeowners make discrete choices about purchasing insurance. To model the insurance market, we assume four homogeneous, profit-maximising firms operating in a Cournot-Nash equilibrium market as described in Gao et al. (2016). Revenue is calculated as insurer i's demand (d_i) for coverage times the market-determined price (p^{ins}). Their total cost, $Cost(d_i)$, associated with meeting demand d_i, includes administrative costs and claims payouts. They can hedge their risks by purchasing reinsurance which includes the costs of reinsurance premiums and reinsurance payouts if claims are made.

[1] The choice of a discount rate to account for the long-term benefits of hazard mitigation is a complex problem. For example, Newell and Pizer (2004) discuss the theory and intuition behind the choice of discount rates for climate policy analysis, noting the role of uncertainty to further challenge our ability to select an appropriate discount rate. Further current trends in the robust US housing market add to the uncertainty of evaluating future fair market value of mitigation. Consequently, we have chosen to distribute government investments equally over a 20-year period and do not attempt to discount future benefits.

The homeowners' decisions to purchase insurance at the prices offered (p^{ins}) are estimated using survey data from residents in the case study area and two mixed logit models (one for wind and one for flood) with controls for homeowner's age, income, previous hurricane experience, number of years since the last hurricane, distance to the coastline, and a floodplain indicator (Wang et al. 2017). We also include an affordability constraint (Eq. 3) such that the cost of insurance must be less than an analyst-specified fixed proportion (K) of the value of homeowner n's house, V_n. We use a value of 5% for K.

$$p^{ins} \sum_h P^h (L_n^h - B_n^h) < K \times V_n \tag{3}$$

On the left side, p^{ins} is the premium price per dollar of expected loss; P^h is the annual probability of hurricane h occurring; L_n^h is the estimated loss for homeowner n in hurricane h; and $B_n^h = \{L_n^h, \bar{B}\}$ is the deductible for homeowner n in hurricane h, where $\overline{B}$ is the maximum deductible.

Computational simulations

To understand how government investments in mitigation impact households and insurers, we experimented with four different government budget levels for mitigation (buyouts and retrofit grants)—USD 0, USD 1 billion, USD 2 billion, and USD 3 billion, all evenly distributed over 20 years. Table 2 depicts the market impacts of the different levels of USD 0 and USD 3 billion of government spending. Note that the insurance data in Table 2 reflect completed insurance purchases, rather than eligibility. When there is no mitigation, the average profit-maximising, risk-adjusted insurance price is USD 2.49 per dollar of expected loss across the 100 scenarios. As government intervention increases to USD 3 billion over 20 years, the optimal price increases to USD 3.40 and the quantity (in terms of dollars of coverage) of insurance demanded decreases. In the 20th year of intervention, total revenue is down by USD 1 million, but their costs drop by 27.4% to USD 82.93 million. This gap translates into higher profits of USD 122.26 million in the 20th year with mitigation compared to USD 91.75 million without government intervention.

The final two columns of Table 2 show the impacts on households in aggregate. The number of households with insurance decreased by 9270 in the 20th year of the intervention relative to the status without intervention. Having such a high number of households no longer insured may, on the surface, seem like an undesirable outcome; however, nearly 88% of the mitigation funding removed houses from the inventory through buyouts. These aggregate measures do not capture the changes in the housing inventory. As houses are removed, the inventory is smaller, and total losses are further reduced due to retrofits. Thus, we constructed figures to depict how the inventory changes with mitigation and insurance price adjustments. Figure 3 describes the number of houses that transition from uninsurable, meaning that the price of insurance exceeds households' affordability constraints under three case scenarios. We report the number of houses rather than the percentage of houses because both the number of insurable houses and

Table 2 Homeowner insurance coverage under different mitigation budgets and insurance market conditions at year 20 following homeowner decision-making; averaged over 100 scenarios

	Market outcomes		Insurance industry profitability			Households	
Government budget	Price (USD) per dollar loss	Quantity of coverage demanded USD million	Total revenue USD million	Total costs USD million	Total industry profit USD million	Number of households insured	Average annual premium (USD) per household
USD 0	2.49	82.70	206.02	114.27	91.75	152,878	1,348
USD 3 billion	3.40	60.27	205.19	82.93	122.26	143,608	1,429

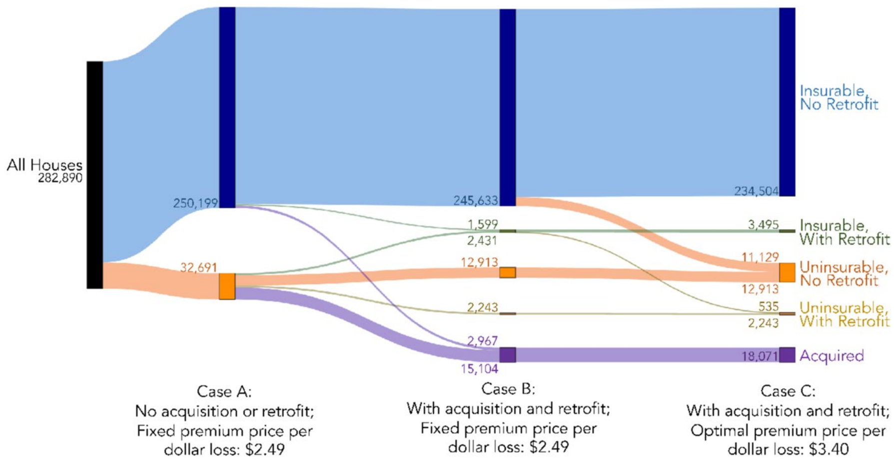

Fig. 3 Change in the distribution of households across insurance eligibility statuses when there is no government spending (Case **A**), the government spends USD 3 billion on mitigation over 20 years (Case **B**), and insurance prices adjust (Case **C**)

the number of houses in the stock are changing simultaneously. It should be noted that 'insurable' indicates whether households are eligible to purchase insurance, based on the 5% of home value constraint. For comparison purposes, the Institutes Insurance Research Council (2024) reports the national average homeowner insurance spending to income ratio was 2% in 2021. Our affordability constraint does not consider households' final decision to actually purchase insurance or not (as in Table 2). Figure 4 tracks the same stages of mitigation, insurability, and insurance price adjustment, but from the perspective of dollars of loss avoided

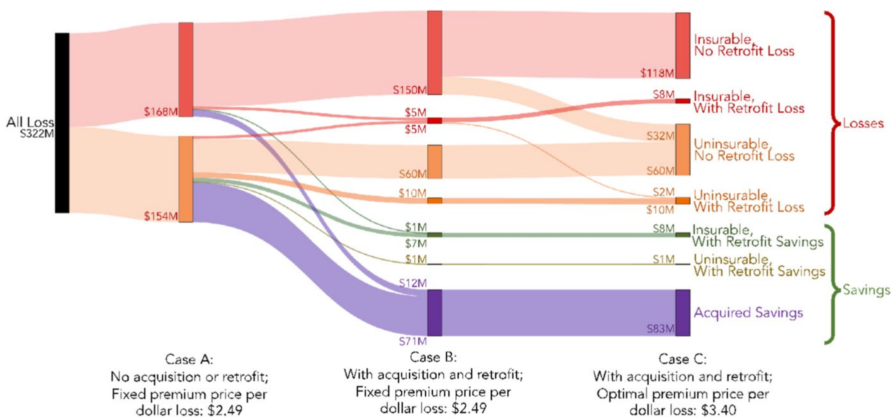

Fig. 4 Change in the distribution of expected losses across insurance eligibility statuses when there is no government spending (Case **A**), the government spends USD 3 billion on mitigation over 20 years (Case **B**), and insurance prices adjust (Case **C**)

rather than house counts under three case scenarios. The values in these two figures are the average values over the 100 scenarios in the 20th year.

When the government spent USD 3 billion on mitigation, expected losses for the housing inventory fell and insurance coverage increased. The left side of Fig. 3 depicts the outcome in the 20th year when there was no mitigation (Case A): 32,691 homeowners or 11.5% were unable to purchase insurance. These uninsurable homes represented 47.8% or USD 154 million of the expected loss in year 20 (Case A in Fig. 4). The difference between the percentage of uninsurable houses and the percentage of uninsurable losses highlights that these are high-loss homes. When the government spent USD 3 billion on mitigation, 18,071 houses, or 6.4% of the inventory, were removed through acquisitions and 6,273 houses were retrofitted (Fig. 3, Cases B and C), reducing expected losses by USD 83 million due to buyouts and USD 9 million due to retrofits (Fig. 4, Cases B and C).

For 2431 households, the retrofits reduced loss sufficiently that they were able to afford insurance (Fig. 3, Case B). After mitigation, the percentage of houses that were insurable was 94.3% compared to 88.4% without mitigation; the number of insurable households was down, 249,663 compared to 250,199. These differences were due to the 18,071 reduction in inventory resulting from acquisitions. In terms of expected losses (Fig. 4), USD 3 billion of government spending reduced expected losses from USD 322 million to USD 230 million with only 30.4% being uninsurable.

Insurance is key to financial recovery from hurricane damages. Without government mitigation spending, the insurers' optimal price is USD 2.49 and the insurance industry's median cash position in the 20th year is USD 3.62 billion (Fig. 5, Case A). As the government spends USD 3 billion on mitigation, the inventory changes due to acquisitions and retrofits. When the price per dollar of expected losses is held constant (Case B), the insurers' median cash position in the 20th year drops to USD 3.59 billion, with 5 of the 100 scenarios resulting in negative cash positions, 3 of which are significant loss outliers. In the most extreme scenario, the region is impacted by 7 hurricanes, including one that causes approximately USD 14 billion in losses, and the firms' cash position drops to -USD 3.5 billion. In the other extreme scenarios, there are multiple hurricanes with at least one of them being a high-loss event. When we enable insurance price flexibility, insurers' profit-maximising price per dollar of expected loss coverage increases from USD 2.49 without mitigation to USD 3.40 with mitigation (Case C). For context, the profit-maximising prices range from USD 2.96–3.69 across the 100 scenarios. The higher prices enable the insurers to have a stronger median cash position, USD 3.83 billion, and less negative cash positions under extreme scenarios (Fig. 5, Case C). Acquisition reduces the number of high-risk houses and retrofits reduce the probability of damage to the remaining housing stock. Together, these mitigation measures change the elasticity of insurance demand for the region resulting in a higher equilibrium price of coverage per dollar of expected loss.

The higher premium price offsets some of the insurability gains from the mitigation expenditures. These changes are depicted as Case C in Figs. 3 and 4. While the distribution of mitigation spending across acquisitions and retrofits does not change, the higher insurance prices shift 11,664 houses, or 4.4% of the housing inventory,

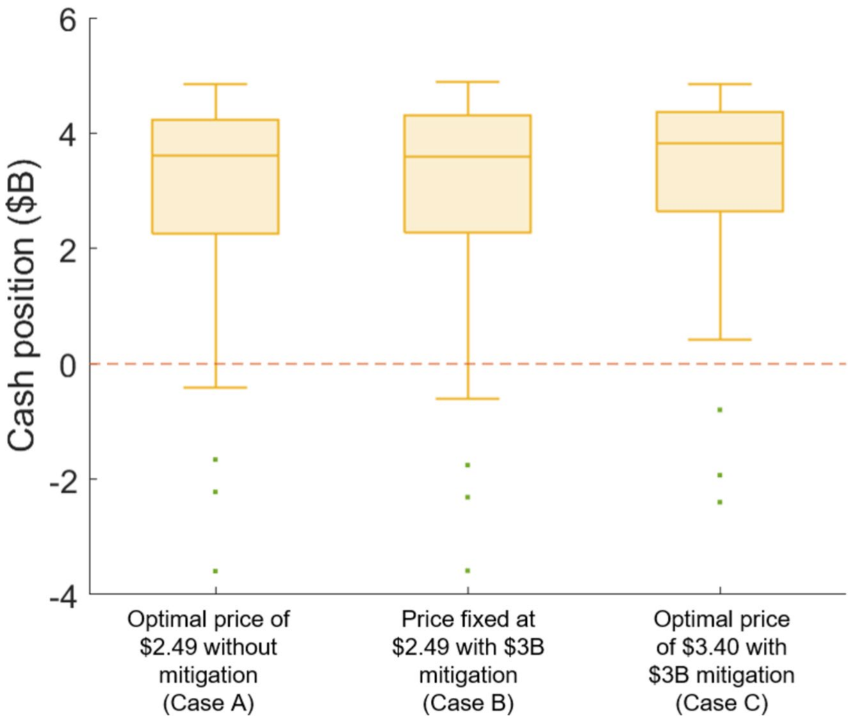

Fig. 5 Insurance solvency across the 100 scenarios with prices per dollar of expected loss fixed at USD 2.49 compared to prices set at profit-maximising level of USD 3.40 with mitigation

out of the affordable insurance category (Fig. 3, Case C). This change includes 535 uninsurable mitigated houses, or USD 2 million in expected loss, that otherwise would have shifted from uninsurable to insurable and 11,129 houses, or USD 32 million in expected losses, that had been insurable and were priced out of the insurance market. Enabling price adjustment in the insurance market results in USD 34 million, or 14.8%, of expected losses becoming uncovered (Fig. 4, Case C). Mitigation spending reduces losses, reduces the number of houses at risk, and changes the insurance landscape. Market adjustments offset adverse impacts to insurers, which may enable them to remain solvent, and thus continue to serve as a risk management tool for homeowners.

Summary and policy implications

This study examines the distribution of impacts across stakeholders that can result from a government policy intervention designed to reduce hurricane losses. This integrated analysis indicates that the resulting outcome for individual stakeholders is not simple. As the intervention(s) play out over the time horizon, insurer solvency, insurance affordability, and if not constrained, insurance prices will change. The contribution of this study is to track what happens to the housing stock, expected losses, and insurability over the two mitigation interventions: retrofits and acquisitions. Without price changes, the buyout and retrofit interventions dramatically reduce losses and increase the insurability of houses. Without allowing insurers to adjust to the changes in the housing inventory, their cash position and solvency are at risk. All three classes of stakeholders, government, households, and insurers must be considered. Once insurance prices adjust, the tradeoff between insurer solvency and household insurability becomes more evident. For some households, the higher cost of insurance makes it unaffordable. However, the takeaway is still positive. With buyouts, there are fewer houses at risk; of those that remain, retrofits reduce the expected losses. Even with higher prices, mitigation spending results in a greater percentage of households insured and more of the expected losses covered. This study highlights the distribution of benefits of government intervention across households and insurance providers. A caveat on this result is that government spending on mitigation amounts to a cross subsidisation to people who live in risky areas. However, the design of these policies is to encourage people to reduce risk. Future work will expand our analysis to consider regional economy-wide implications of this and additional government policy interventions.

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