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ORIGINAL ARTICLE

An agent-based model for evaluating reforms of the National Flood Insurance Program: A benchmarked model applied to Jamaica Bay, NYC

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Abstract

Coastal flood risk is expected to increase as a result of climate change effects, such as sea level rise, and socioeconomic growth. To support policymakers in making adaptation decisions, accurate flood risk assessments that account for the influence of complex adaptation processes on the developments of risks are essential. In this study, we integrate the dynamic adaptive behavior of homeowners within a flood risk modeling framework. Focusing on building-level adaptation and flood insurance, the agent-based model (DYNAMO) is benchmarked with empirical data for New York City, USA. The model simulates the National Flood Insurance Program (NFIP) and frequently proposed reforms to evaluate their effectiveness. The model is applied to a case study of Jamaica Bay, NY. Our results indicate that risk-based premiums can improve insurance penetration rates and the affordability of insurance compared to the baseline NFIP market structure. While a premium discount for disaster risk reduction incentivizes more homeowners to invest in dry-floodproofing measures, it does not significantly improve affordability. A low interest rate loan for financing risk-mitigation investments improves the uptake and affordability of dry-floodproofing measures. The benchmark and sensitivity analyses demonstrate how the behavioral component of our model matches empirical data and provides insights into the underlying theories and choices that autonomous agents make.

KEYWORDS
affordability, agent-based model, disaster risk reduction, dynamic adaptive behavior, flood insurance

1 | INTRODUCTION

Floods are devastating natural disasters, costing billions in damages annually. Flood risk is projected to increase as a consequence of driving forces such as socioeconomic development (Winsemius et al., 2016), population growth (Jongman et al., 2012), and climate change (IPCC, 2014). Although human adaptation responses can limit trends in flood risks, risk projections often do not consider the interplay between the flood risk environment and the dynamic adaptive behavior of the social system (Hallegatte et al., 2013; Hirabayashi et al., 2013; Jongman et al., 2014; Rojas et al., 2013). Addressing such an interplay is important for accurate risk assessments and the evaluation policies that influence adaptive behavior. Disaster risk reduction (DRR) and risk transfer instruments are examples of measures for coping with flood risk (UNISDR, 2015). However, there are many unanswered questions regarding the effectiveness of DRR over time or the way in which risk transfer policies can incentivize the implementation of DRR. For instance, insurance is a useful tool to cope with flood losses as it provides financial compensation for those impacted during a flood event. Moreover, pure risk-based premiums may incentivize policyholders to implement DRR measures, often referred to as a discount on the original premium to reflect the risk decrease from the DRR measure (Mol et al., 2018); however, few flood insurance schemes actively encourage DRR, and the amount of risk that can be reduced through such insurance incentives remains unclear (Hudson, de Ruig, et al., 2019b).

Flood insurance is one of the main means of transferring risk for households in the United States. Since 1968, the National Flood Insurance Program (NFIP) has provided federal government-guaranteed flood insurance to homeowners and businesses, holding over 5 million policies in force and covering $1.2 trillion in assets by 2015 (FEMA, 2016). This makes the NFIP the largest flood insurance market worldwide. However, the program has been criticized for incentivizing policyholders to stay in flood-prone areas, making inaccurate risk assessments, setting premiums that do not reflect risk, and having a lack of incentives to implement DRR (Dixon & Clancy, 2006; FEMA, 2019a; Michel-Kerjan & Kousky, 2009). Even after Congress canceled $16 billion to enable the NFIP to pay claims for Hurricanes Harvey, Irma, and Maria, the NFIP has been $20.5 billion in debt since 2019 (Horn & Webel, 2019; Miller et al., 2019). As a result, these problems contribute to political turmoil regarding the reauthorization and continuation of the NFIP (Kruse & Hochard, 2019).

Implementing risk-based premiums has extensively been discussed as a possible reform measure (Kousky & Kunreuther, 2014; Michel-Kerjan & Kunreuther, 2011; Michel-Kerjan et al., 2014; Miller et al., 2019), as it informs households of the true exposure of their residence to potential flood damage (Michel-Kerjan & Kunreuther, 2011). The NFIP moved toward implementing risk-based premiums in 2012, but the changes were reverted in 2014 due to concerns about the affordability of premiums (Michel-Kerjan et al., 2014). Current policies are again steering toward risk-based premiums, such as the expected implementation of the Federal Emergency Management Agency's (FEMA) Risk Rating 2.0 program in October 2021 (FEMA, 2019b), especially because the subsidized premiums are a barrier for the private sector to enter the market. However, some worry exists that affordable risk-based premiums are not feasible in high-risk areas (Kruse & Hochard, 2019; Kunreuther, 2019). Therefore, Kousky and Kunreuther (2014) have suggested coupling risk-based premiums with a discount for policyholders who take risk-reduction measures, which means that the premium remains a pure risk-based premium. Moreover, they proposed the introduction of an accessible loan structure to cover the high upfront investment of DRR measures.

Several risk assessment studies have attempted to simulate the effects of different NFIP reform measures (Kousky & Kunreuther, 2014; Michel-Kerjan et al., 2014; National Research Council, 2015). However, they have not addressed the dynamic interaction between homeowners and the changing flood risk environment. For example, studies suggest that risk perception is high after a major flood event occurs, which leads to a higher uptake of insurance and DRR measures (Brilly & Polic, 2005; Ruin et al., 2007; Siegrist & Gutscher, 2006). Such adaptation processes in turn imply reduced vulnerability and a decline in flood risk. Therefore, recent socio-hydrology studies have stressed the importance of accounting for the interactions between social and hydrological systems, but these studies often focus on macroprocesses and lack individual household decisions (Di Baldassarre et al., 2013, 2015; Viglione et al., 2014). While studies such as those by Haer et al. (2019, 2020), Tonn and Guikema (2018) or Han and Peng (2019), Tonn et al. (2019) have demonstrated that agent-based or multiagent models are able to capture the behavior of households in relation to flood risk, they are often limited by computational power and a lack of empirical data to calibrate or benchmark the behavioral elements of the models. This challenge with calibrating behavioral rules in agent-based models applies more broadly to climate change risk applications, and studies consequently have had to resort to ad hoc rules with simplified assumptions based on expert judgment (Aerts et al., 2018).

To overcome these limitations, the goal of this paper is to assess the mean impact of insurance changes on homeowners based on benchmarked empirical data. Our agent-based model (DYNAMO) on flood risk and the dynamic adaptive behavior of households is used to examine the following research aims: (1) benchmark the behavioral elements in the model to obtain an accurate set of parameters. (2) use the benchmarked model to evaluate four proposed reform changes to the NFIP: (a) a full mandatory purchase requirement in the 100-year flood zone, (b) risk-based premiums, (c) risk-based premiums with a premium discount for implementing DRR measures, and (d) a low interest rate loan for financing DRR—the latter reform measure is applied in conjunction with the other reforms, and not a separate case. The reform measures are compared to an NFIP baseline, resulting in a total of eight variations. The last aim (3) is to test the robustness of the model using a sensitivity analysis. The model is applied to Jamaica Bay, NYC.

2 | CASE STUDY: NEW YORK CITY—JAMAICA BAY

Jamaica Bay is located at the south end of the boroughs of Queens and Brooklyn. Many of the neighborhoods surrounding Jamaica Bay are low-lying and already vulnerable to flooding from high tides (Freudenberg et al., 2016). Storm surges, wetland degradation, and sea level rise are therefore major threats to the coastal communities. For example, Jamaica Bay was one of the most heavily flooded areas during Hurricane Sandy in 2012. Since then, several plans have been proposed, such as by Fischbach et al. (2018) and Jones et al. (2018), to reduce flood risk in the area. In total, $14.7 billion was assigned to city repairs and resiliency, of which only 54% has been spent because of slow federal bureaucracy and

TABLE 1 Flood exposure for three different return periods for current and future climate conditions

Flood exposure (Number of buildings)	100-year	500-year	10,000-year
2010	26,319	51,552	84,576
2055	33,843	57,000	90,958

a lack of urgency, despite the future threats of climate change (Stringer, 2019).

Seven years after Hurricane Sandy, insurance penetration rates have decreased by 18%, 8%, and 2% for Staten Island, Queens, and Brooklyn respectively, even though Staten Island and Queens were one of the hardest hit boroughs (Choi et al., 2019). Current flood insurance rate maps (FIRMs) are from 1983.[1] Updating of these maps began in 2010, and they were preliminarily released in 2013 (known as preliminary flood insurance rate maps: PFIRMs)(Miller et al., 2019). However, in 2016, the de Blasio administration won its appeal against FEMA, claiming that the maps present overestimations of risk and incorrect base flood elevations (City of New York Mayor's Office of Recovery & Resiliency, 2015). Current insurance rates for Jamaica Bay are still based on a 1983 modeling study (Dixon et al., 2013) while the new maps are being revised, with new FIRMs expected in 2022 or 2023. To highlight the severity, Table 1 shows the exposure in terms of buildings at risk of floods for different return periods. Even under current climate conditions, 26,319 buildings are in a high-risk flood zone. With the current flaws of the NFIP and the political turmoil worsening the program's effectiveness by delaying updated FIRMs in Jamaica Bay, our model is suitable for analyzing the effects and interactions regarding improving the insurance market structure and reflecting risk to homeowners.

3 | METHODS

Figure 1 illustrates our methodological framework. The input data, and climate change and socioeconomic scenarios are shown in the top-left box. The first analysis entails a benchmark of the model to derive a reliable set of parameters, indicated in the left-most box. The model, consisting of a flood risk model and behavioral modules, subsequently simulates four NFIP market structures: NFIP baseline, NFIP full mandatory, NFIP risk-based, NFIP risk-based with premium discounts. In addition, the impact of an accessible loan structure is applied to those four market structures. Lastly, a sensitivity analysis is conducted to test the robustness of the model. The model runs and sensitivity analysis are both visualized by indicators of flood risk, insurance, and disaster risk reduction by homeowners.

[1] Only minor changes were made in 2007 to the riverine part of the FIRM, though not relevant for this study (Dixon et al., 2013).

This section is structured as follows: first, the flood risk model, the input datasets, and the scenario settings of the models' runs are described in Section 3.1. We build upon DYNAMO - **DYN**amic climate impact **A**daptation **Mo**del by Haer et al. (2019), which is an agent-based model on adaptive human behavior within a flood risk modeling framework; however, it does not include an advanced insurance market. Therefore, we expand the agent-based model to include the NFIP scenarios and account for affordability. Section 3.2 briefly describes the essential modeling features and focuses on the changes made to DYNAMO compared with the one by Haer et al. (2019). Lastly, the benchmark and sensitivity analyses are described in Section 3.3.

3.1 | Flood risk model, data, and scenarios

The flood risk component of the model is a commonly applied hazard-exposure-vulnerability model (de Moel et al., 2013; Kron, 2005). The flood hazard is represented by water depth data from hydrodynamic model simulations for a set of nine storms that span a wide range of intensity from 5- to 10,000-year return periods. The relationship between probability and water level was previously determined using a joint probability method-based hazard assessment that was an ensemble simulation of a diverse set of thousands of possible storms, including both tropical and extratropical cyclone events (Orton et al., 2016). Here, nine representative storms were selected that matched the water levels inside the bay for the 5-, 10-, 30-, 50-, 100-, 300-, 500-, 1000-, and 10,000-year flood events. Lastly, two-dimensional flood simulations for these storms were run on a 30-m resolution nested grid for Jamaica Bay (Fischbach et al., 2018; Orton et al., 2020), and water levels were differenced with the model's land elevations to compute water depth. In the agent-based model runs, risk calculations over time are based on an interpolation of the present day inundation data and future projections. In addition, a flood can stochastically occur each year during each model run, based on the probability of occurrence of each storm.

The National Land Cover Database (NLCD) 2016 (USGS and The Multi-Resolution Land Characteristics (MRLC) Consortium n.d.) was used for exposure. Depth-damage curves and maximum damage values represent the vulnerability of the model and were taken from FEMA's HAZUS Multihazard model (FEMA, 2013a). Depth-damage curves describe the relationship between inundation depth and percentage damage to a land-use class. These curves can subsequently be altered to represent a household that has implemented dry-floodproofing measures to its property. Dry-floodproofing is preventing water from entering the property, which will lead to a decrease in damages up to 85% for the first meter of inundation (Aerts et al., 2013; de Ruig et al., 2019). However, inundation > 1 m will cause overtopping and will result in full damages. It should be noted that FEMA recommends the implementation of dry-floodproofing measures, but does not provide a discount

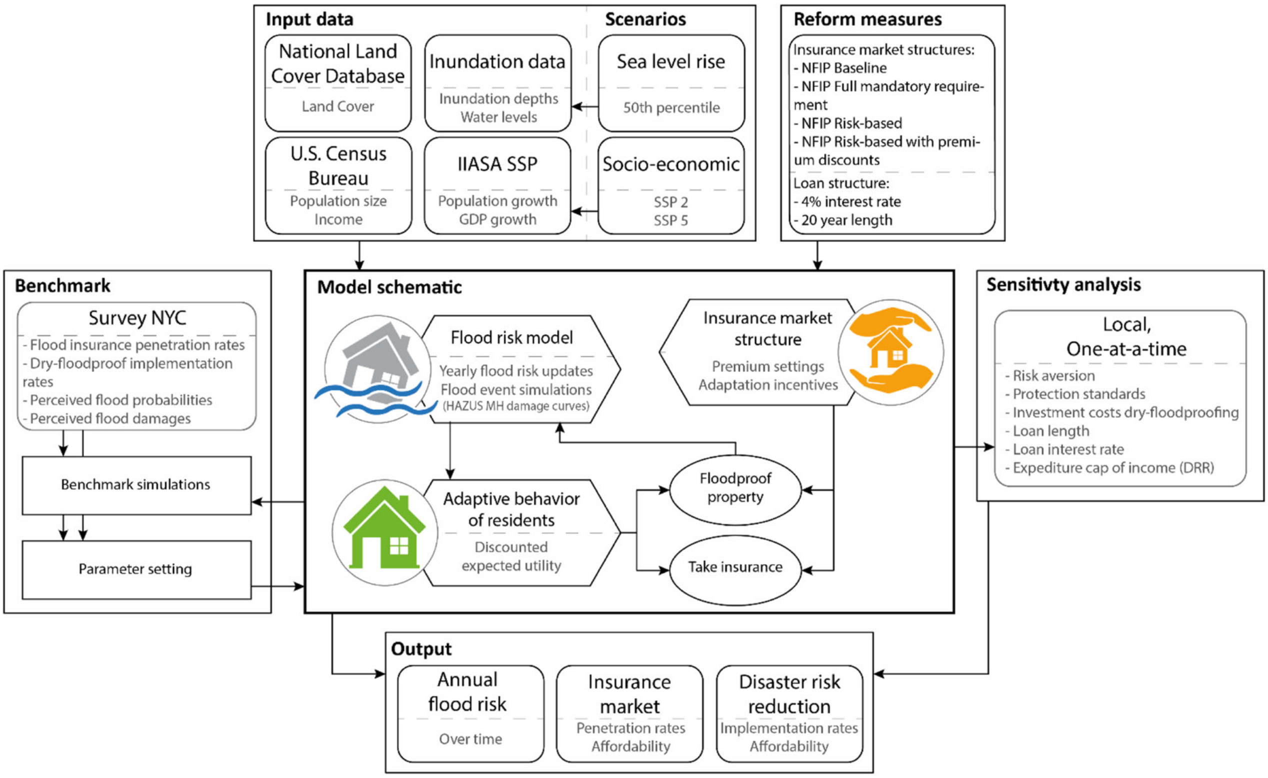

FIGURE 1 Methodological framework

on insurance premiums for taking these measures. By calculating the damages per return period, the expected annual damage (EAD) or flood risk (in \$/year) can be computed as the integral of the exceedance probability curve.

The initial setup of the population was based on United States Census data (U.S. Census Bureau, 2010b). Shared socioeconomic pathway (SSP) (Crespo Cuaresma, 2017; Dellink et al., 2017; Jiang & O'Neill, 2017; KC & Lutz, 2017; Leimbach et al., 2017; Riahi et al., 2017) scenarios were used to represent population growth and economic growth, which have proven to be major drivers in flood risk (Winsemius et al., 2016). We applied the SSP2 and SSP5 scenarios, as they are most commonly applied in similar studies. SSP2 is a middle-of-the-road scenario (Fricko et al., 2017), and SSP5 is an energy- and resource-intensive scenario (Kriegler et al., 2017); the former is used throughout the paper, and the results of the SSP5 scenario can be found in the Supporting Information S4. The GDP growth from the SSPs was used to increase value of properties and income over time.

3.2 | Agent-based flood risk model and market reforms

Flood risk models are commonly modeled as a function of the hazard, the exposure of assets, and the vulnerability of assets (e.g., to flood events). However, these often assume vulnerability to be static over time, although no adaptation measures are taken in response to changing risk from climate change. In contrast, the agent-based flood risk model, as developed by Haer et al. (2019), integrates the dynamic adaptive behavior of homeowners and governments within a flood risk framework. Homeowners can decide to (a) take flood risk insurance and (b) invest in DRR measures, such as dry-floodproofing. Furthermore, they make decisions following a subjective, (discounted) expected utility theory, which is the standard economic theory of decision making under risk. Governments can make decisions on macro-scale adaptation, such as elevating dike heights, following a cost-benefit analysis. For this study, we adapted DYNAMO by Haer et al. (2019) and primarily focus on homeowners and their adaptive behavior in relation to that of insurance markets, as we are particularly interested in the interaction between the two. While governmental interaction is included, it only statically maintains the protection standard over time. The sensitivity analysis includes the effects of different protection standards. The following subsections explain specific parts of the model that were adjusted to the needs of the research aims set in this paper. For a detailed description of original version of DYNAMO, refer to the Supporting Information of Haer et al. (2019).

3.2.1 | Homeowners' decisions regarding flood insurance

The dynamic behavior of homeowners is represented per 30-m resolution grid cell, with in total 324,900 unique representative agents. Each year homeowners make a decision about purchasing or canceling flood insurance. The analysis ran the following four market reforms twice (once with personal loans and once with a reformed accessible loan, Figure 1):

a. The NFIP baseline. This market structure simulates the current NFIP practices as closely as possible. Part of the NFIP is a mandatory purchase requirement for federally funded mortgages in a 100-year flood zone (Zhao et al., 2015). Dixon and Clancy (Dixon & Clancy, 2006) have estimated that, on average, only 55% of the properties are bound to the mandatory requirement, and 78% of those households comply (Dixon & Clancy, 2006; Zhao et al., 2015). Based on this mandatory share and compliance rate, households in the 100-year flood zone are randomly selected as mandatorily required policyholders in the setup.
b. The NFIP with a full 100-year flood zone mandatory requirement. This second market structure enforces a full mandatory requirement in the 100-year flood zone (regardless of mortgage type), but without risk-based premiums.
c. The NFIP with risk-based premiums. This third market structure applies risk-based premiums to all flood zones, without a mandatory requirement.
d. The NFIP with risk-based premiums and a premium discount. Similar to market structure C, but in addition a premium discount on the original risk-based premium is offered to policyholders who floodproof their homes, to incentivize disaster risk-reducing behavior.

For homeowners without a mandatory requirement, the choice to take insurance follows a subjective expected utility (Haer et al., 2019; Hudson et al., 2019a; Von Neumann & Morgenstern, 1947) (EU) model, which accounts for bounded rationality in understanding risk, as indicated in Equation 1. For each time step and for each grid cell, the EU was calculated and compared for two strategies:

> **Strategy 1**: take insurance, accepting the deductible; or
>
> **Strategy 2**: do not take or cancel insurance.

The strategy that yields the highest EU will be chosen. If Strategy 1 is followed, then affordability of the annual premium is first calculated. If the premium is deemed unaffordable, then insurance is not adopted (see Section 3.2.4). The subjective EU equation is as follows:

$$EU_s = \int_{p_i}^{p_I} \beta p_i U \left(W_t - \gamma D_{i,t} \times \delta_s - C_{\text{premium},t} - d_{\text{premium},t} \right) dp. \tag{1}$$

Equation 1 calculates EU_s for each strategy s. Each flood event i has a probability p_i of occurring. The total set of events I are the return periods of each flood event and the probability of no flood event: a return period of 5 years. The EU_s is subsequently calculated as the approximation of the integral over I. Individuals are assumed to be boundedly rational in understanding the flood risk they face, which is represented by the risk perception factor β, which is uniform between agents but is based on survey data as described in Section 3.3.

Utility is calculated as a function of wealth W, uncovered damage D, premium C, and a premium discount d (if applicable for the scenario). Damage D per event i for year t is calculated using the hazard-exposure-vulnerability model; however, it can be misperceived per individual by factor γ, described in more detail in Section 3.3. For Strategy 1, homeowners must pay a deductible of 10% of the incurred damages ($\delta = 0.1$), while Strategy 2 has full damages (as no damage is covered, so that $\delta_2 = 1$, $C = 0$, and $d = 0$). The NFIP offers policyholders a choice in flat rate deductibles ($500; $1,000; $2,000; $3,000; $4,000; and $5,000 (Michel-Kerjan & Kousky, 2009) and a choice of coverage. Collier and Ragin (2019) have highlighted the difficulty of accurately explaining these decisions in behavioral models; for example, they have demonstrated that approximately 12% of new policyholders over-insure, selecting a coverage exceeding the expected replacement value of their property. Furthermore, adding the additional choice of selecting the coverage amount and a deductible would have significantly increased the computational cost of the model. Therefore, we followed Haer et al. (2019) and Hudson et al. (2019a), who applied a 10% deductible and full coverage.

A general utility function is assumed, as shown in Equation 2, as a function following constant relative risk aversion (Bombardini & Trebbi, 2012; Harrison et al., 2007; Wakker, 2008):

$$U(x) = \frac{x^{(1-\sigma)}}{1-\sigma}. \tag{2}$$

The following different variations of risk aversion σ were analyzed: risk seeking (−1), risk neutral (0), and risk averse (1, 2, and 4). Note that when $\sigma = 1$, the Equation 2 is $U(x) = \ln(x)$ instead.

While homeowners are aware of increasing risk over time, it is assumed that they are not fully informed due to their bounded rationality, which implies that they have limited cognitive capabilities in processing risk (i.e., imperfect information). Therefore, at the start of each 2010−2080 simulation each agent is assigned a different risk increase value picked from a random-uniform distribution of the objective risk increase and no increase at all.

3.2.2 | Premium setting

For this study, we applied the 100-year flood zone as defined by our own probabilistic flood data, which is slightly larger than the NFIP 100-year flood zone based on the 1983 FIRMs, as shown in Figure 2. We require a wide range of probability storms from 5-year (20% annual chance) to

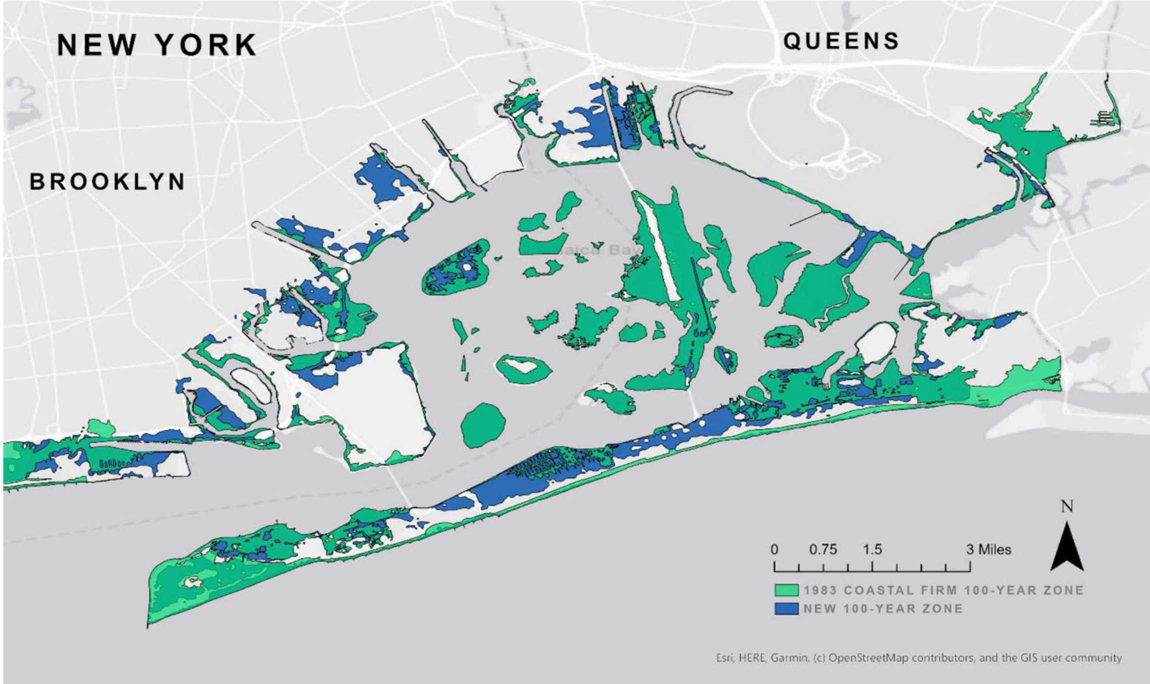

FIGURE 2 Jamaica Bay, NYC with green indicating the 1983 FIRM 100-year flood zone, and blue the newly defined 100-year flood zone by our inundation model. Buildings outside the 100-year flood zone that have a chance of coastal flooding are also included in the analysis

10,000-year (0.001% annual chance) for our integration across all probability events, and this data is not available from FEMA's studies. Moreover, given the large differences between the 1983 FIRM and the 2013 PFIRMs (that were successfully appealed as inaccurate), it is ambiguous which FEMA flood data should be used.

However, this has significant implications for the premium setting of the current NFIP market structure, as about 16,000 properties are located in the 1983 FIRM 100-year flood zone, whereas the newly defined 100-year flood zone includes about 26,000 properties. Dixon et al. (2017) show that properties that would be included in the PFIRM 100-year flood zone would see large increases in premiums, to about the same price as current high-risk premiums. However, the NFIP applies a discount to properties built before the flood risk was mapped in that area (referred to as pre-FIRM properties)(FEMA, 2013b; Kousky & Kunreuther, 2014). In addition, grandfathering is a practice where homeowners are allowed to keep their old premiums when an update to FIRMs reclassifies them into a higher risk zone (Kousky & Kunreuther, 2014). If grandfathering and pre-FIRM discounts are allowed, increases of premiums might be less severe (Dixon et al., 2017). Notwithstanding the potential change in mean premiums, the benchmark of this study will be conducted with a survey based on 1983 FIRM rates. Altogether, we assume no grandfathering, pre-FIRM or other building-specific effects on the premium, as this would overcomplicate the behavioral module of the model, but use a county-wide mean premium of $1,275 per household in high-risk zones, and $820 per household for low risk zones for the current NFIP market structure (Czajkowski et al., 2017). To correct for future changes in risk, the current NFIP premiums are adjusted with percentual risk changes over time.

For the risk-based market structures, the annual premium $C_{\text{premium},t}$ was calculated as an actuarially fair premium for each 30 m resolution cell by the flood risk module, as described in Section 3.1. The premiums are converted to household-level using population data, with the addition of a loading factor and minus the deductible. The loading factor was the same for all market structures and was based on the current NFIP loading factors and additional costs that are estimated at 37% (FEMA, 2013b). Only for the fourth scenario, a premium discount $d_{premium,t}$ was offered when homeowners implemented dry-floodproofing, equivalent to the reduction of risk due to the implementation of floodproofing measures (i.e., the premium remains a pure risk-based premium).

Figure 3 compares the distribution of risk-based premiums for all households in the 100-year flood zone with the mean NFIP baseline high-risk premium (as the dotted line). Michel-Kerjan et al. (2014) have demonstrated that NFIP premiums can be more than 15 times the actuarial premium for some areas, while for other areas, premiums can be three times lower than the actuarial premium. As seen in Figure 3, risk-based premiums have significant spatial variation within the 100-year flood zone. As a result, a share of households might experience a decrease in premiums, while others will experience an increase. Because of some extreme outliers, mean risk-based premiums for the 100-year flood zone is estimated at $3373.

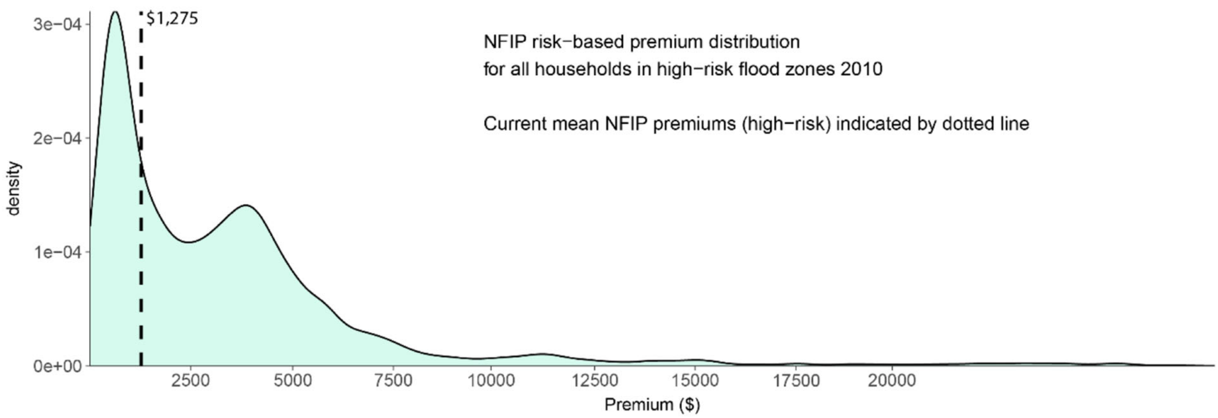

FIGURE 3 NFIP risk-based premium distribution for all homeowners in the 100-year flood zone. The dotted line indicates the current mean NFIP premium for high-risk flood zones

3.2.3 | Homeowners' decisions regarding adaptation

In terms of adaptation, homeowners can decide to implement dry-floodproofing measures. These measures are often found to be the most economically efficient option compared with wet-floodproofing or elevation of existing buildings (Aerts & Botzen, 2011; de Ruig et al., 2019). Dry-floodproofing measures are assumed to reduce damages by 85%, unless inundation exceeds 1 m, in which case full damages are assumed (Aerts & Botzen, 2011). Per annual time step, Equation 3 calculates the subjective discounted expected utility (Haer et al., 2019; Von Neumann & Morgenstern, 1947) (DEU) per homeowner for two strategies:

Strategy 1: implement dry-floodproofing measures; or

Strategy 2: do nothing.

The homeowners will follow the strategy that yields the highest DEU. For Strategy 1, the affordability of investing in dry-floodproofing measures is first determined. If the investment appears to be unaffordable, then no action is taken for that year. The unaffordability is further described in Section 3.2.4. The DEU equation is as follows:

$$
\begin{aligned}
DEU_s &= \int_{p_i}^{p_I} \beta p_i U\left(NPV_s\right) dp \\
&= \int_{p_i}^{p_I} \beta p_i U\left(\sum_{t=1}^{T} \frac{W_t - \gamma D_{i,t,s}}{(1+r)^t} - \sum_{t=0}^{L} \frac{C_{\text{annual},s}}{(1+r)^t}\right) dp \\
&= \int_{p_i}^{p_I} \beta p_i U\left(\sum_{t=1}^{T} \frac{W_t - \gamma D_{i,t,s}}{(1+r)^t} - \sum_{t=0}^{L} \frac{\frac{n*C_{0,s}}{1-(1+n)^L}}{(1+r)^t}\right) dp \qquad (3)
\end{aligned}
$$

The DEU model is calculated for strategy s. The variables D, β, γ, W, p, and i and the general utility function $U(x)$ are similar to those in Equation 1. The NPV_s is the sum of the wealth W_t minus the (reduced) damages $D_{i,t,s}$ over the lifespan of dry-floodproofing T, discounted to the present value using discount rate r. The lifespan of dry-floodproofing is assumed to be 75 years, following Aerts et al. (2011). The discount rate is the pure time preference for residents and is assumed to be 3%, following Tol (2011). Lastly, the investment cost for dry-floodproofing $C_{0,s}$ (assumed to be \$100 per m^2, following Aerts, 2018) is funded through a loan structure with an interest rate n and a length of L. Therefore, residents are valuing their annual loan payment $C_{annual,s}$ against the benefits. For Strategy 2 without action, the NPV_s contains full perceived damages and no investment costs.

3.2.4 | (Un-)affordability: Providing accessible loans

The affordability of insurance and DRR investments is important to consider because market structures or incentives for risk reduction do not work if one is simply not able to afford it. While the affordability of insurance is well discussed in the literature (Hudson, 2018; Kousky & Kunreuther, 2014; National Research Council, 2015; Zhao et al., 2015), the affordability of homeowner-level DRR, such as floodproofing of buildings, has not been extensively studied (Hudson, 2020). Following Kousky and Kunreuther (2014) and Hudson (2018), we applied an expenditure cap definition for unaffordability. For insurance, it is assumed that households can afford flood insurance if their annual premium is within the 2.5% expenditure cap of their annual income. Income is distributed per county (i.e., Queens, Nassau, and Kings county) through a log-normal distribution based on mean and median income from the United States Census Bureau (U.S. Census Bureau, 2010a).

TABLE 2 The observed perception factors of damages and probabilities of a flood event

		Subjective over objective damage factor	Subjective over objective storm probabilities factor
FEMA 100-year flood zone	Mean	1.2456	7.9773
	N	310	234
	Std. Deviation	3.35611	38.80917
FEMA 500-year flood zone	Mean	1.0855	12.1462
	N	167	129
	Std. Deviation	2.60621	37.62726

The investment for dry-floodproofing is a long term-investment, and its affordability is more difficult to assess using an annual income. For example, households save, on average, 6.9% of their disposable annual income (OECD, 2019), but these savings might not be intended for adaptation investments. Therefore, we assume that homeowners can take personal loans and that the annual loan payment is used to evaluate affordability. We applied different variations of personal loan interest rates and lengths in the benchmark assessment to accurately represent the implementation rates of dry-floodproofing. A reform measure was also evaluated, as suggested by Kousky and Kunreuther (2014), with federally funded loans for floodproofing measures, with a 4% interest rate for 20 years.

3.3 | Benchmark using post-Sandy survey data and sensitivity analysis

Many have argued that calibrating or benchmarking a multiagent or agent-based model that simulates human behavior is important; however, this is difficult due to a lack of data (Crooks et al., 2008; Moss, 2008; Smajgl & Barreteau, 2017). In our case, such data are available, and we benchmarked a set of six model parameters using a survey conducted by Botzen et al., and Michel-Kerjan (2015). These parameters are risk aversion, governmental protection standards, investment costs of dry-floodproofing, both the length and the interest rate of personal loans, and the expenditure cap of dry-floodproofing.

The survey by Botzen et al. (2015) was conducted 6 months after Hurricane Sandy, and it focused on the flood risk perception, flood experiences, and flood preparedness of property owners in flood-prone areas in NYC. For our study, we subset the survey for Brooklyn and Queens, which are most relevant for Jamaica Bay. Literature suggests that residents are likely to overestimate their risk after a flood event (Brilly & Polic, 2005; Ruin et al., 2007; Siegrist & Gutscher, 2006), while they underestimate their risk after a period of no flood events (Fox & Hadar, 2006; Hertwig et al., 2004). This form of bounded rationality of residents is modeled as a variable perception of storm probabilities and damages per individual. Table 2 shows the perceived probability factor β and perceived damage factor γ for the 100-year and 500-year flood zones. For example, a household in a 100-year flood zone with a perceived probability factor of 7.9773, will perceive a 500-year flood as a 63-year flood instead (Equation 4a, b).

$$\text{Objective flood probability} \times \text{perceived factor} = \text{Subjective flood probability.} \tag{4a}$$

$$\text{Objective flood damage} \times \text{perceived factor} = \text{Subjective flood damage.} \tag{4b}$$

In DYNAMO, immediately after a storm event (i.e., the grid cell experiences some level of inundation), β and γ increase to the observed overestimation from the NYC survey (1.2456 for flood damage and 12.1462 for storm probabilities), and will adjust the objective probabilities and damages per flood event (p_i and D_i in Equations 1 and 3) to their subjective equivalent. In years with no storm events (i.e., the grid cell experiences no inundation), β and γ will subsequently decay to the inverse of the observed values in approximately six years after the storm event, in line with empirical evidence (Bin & Landry, 2013; Kunreuther, 1996; Kunreuther et al., 1985). Equations 5a and b mathematically portray the perceived probability and damage factor function respectively. If a flood occurs, then $\alpha_t = 1$, and if no flood occurs, then $\alpha_t = \alpha_{t\text{-}1}/1.6$.

$$\beta = 12.0639 \times \alpha_t^{3.71657} + 0.08233, \tag{5a}$$

$$\gamma = 0.442774 \times \alpha_t^{1.1671} + 0.802826. \tag{5b}$$

The benchmark aims to match the observed penetration rates of insurance and the implementation rate of dry-floodproofing measures (Table 4) with modeling outcomes when risk perceptions (β and γ) are at post-Sandy levels, as listed in Table 2. Starting values for the benchmark of β and γ are based on Table 2 and differ per flood zone, while for regular model runs β and γ have an average starting value of $\alpha_t = 0.1$). In addition, the benchmark is used to gain a better

TABLE 3 Observed dry-floodproofing and insurance penetration rates based on a household survey in Jamaica Bay

Number of dry-floodproof measures[a]	Count	Frequency (%)	Insurance	Count	Frequency (%)
0	210	29.96	**Yes**	**462**	**65.91**
1	257	36.66	No	232	33.1
2	155	22.11	Don't know	7	1
3	**79**	**11.27**			
Total	701	100	Total	701	100

[a]For dry-floodproofing, three questions on individual measures were asked, and when combined, they counted as a fully floodproofed property.

TABLE 4 The parameter setting of the model as an outcome of the benchmark

Parameter	Benchmarked setting
Risk aversion	4
Protection standard	30 years
Investment costs of dry-floodproofing	100 $/m^2$
Expenditure cap of dry-floodproofing investment	2.5%
Loan interest rate	15%
Loan duration	5 years
Test run outcome: Dry-floodproofing implementation rate	12.8%
Test run outcome: Insurance penetration rate	68.2%

understanding of the underlying theories and processes and how they respond to different sets of parameters. The benchmark was run for the NFIP baseline scenario; it ran 1215 different combinations of all six parameter variations for 50 repetitions.

Dry-floodproofing is often seen as a package of individual measures (e.g., shields in front of doors, water-resistant coating on walls, and a backflow valve). The survey asked respondents whether they implemented individual measures of dry-floodproofing, and Table 3 lists how many of those measures respondents implemented. FEMA (2014) recommends implementing all three measures for optimal protection, and 11.27% was thus used in the benchmark evaluation. When benchmark outcomes were equifinal, literature was used to support the final selection of the parameter set.

A local, one-at-a-time sensitivity analysis was conducted with the same set of parameters as those used for the benchmark. The sensitivity analysis only used the SSP2 middle-of-the-road scenario and risk-based scenarios, and it purely focused on the variation of parameter values. This allowed for a better understanding of the robustness of the model and how individual parameters influence modeling results.

4 | RESULTS

4.1 | Benchmarked parameter setting

Table 4 presents the outcome of the benchmarked parameter set, and Section SI1 of the supplementary information provides a sample of the most relevant outcomes out of the 1215 unique runs. In addition, Table 4 lists the implementation rate of dry-floodproofing and the penetration rate of insurance for a single model run with a forced 500-year flood, similar to the estimated 400- to 500-year return period of Sandy (Lin et al., 2012, 2016). Both values are slightly higher than the observed values in Table 3; however, they are within acceptable margins.

To further explore the benchmark results, we made density plots for each parameter over the penetration rate of dry-floodproofing and insurance policies, as illustrated in Figure 4, wherein the dotted line denotes the observed penetration rates from Table 3. For each of the density plots in Figure 4, all the observations are shown, with different groupings per variable. Figure 4 indicates that a large variety of unique parameter combinations could match the benchmark outcome with the observed penetration rate of dry-floodproofing. However, the observed insurance penetration rate is in the tail end of most density plots, meaning that only a limited combination of parameters will result in the observed insurance penetration rate. Risk aversion in particular only has matching outcomes with a value of 4.

Moreover, the results from Figure 4 can be used to gain a better understand of the underlying interactions and theories due to changes in parameter settings, such as tipping points. Two tipping points are highlighted. First, Figure 4B illustrates that dry-floodproofing penetration rates increase with rising risk aversion (the highest peak of −1 is found at an implementation rate of 18%, while the highest peak of 2 is found at 40%), except for a risk aversion value of 4 (which reveals a more flattened out pattern). With rising risk aversion, homeowners start to increasingly value protection against low-probability events. This initially causes a higher uptake of dry-floodproofing. However, dry-floodproofing is not effective for extreme events with high inundation depths that cause overtopping. A tipping point consequently occurs where homeowners' risk aversion is so high that they begin to value extreme events even more. Simply put, increasing the coefficient for risk aversion does not necessarily increase the penetration rate of dry-floodproofing, as a resident with high-risk aversion can find dry-floodproofing to be ineffective in reducing flood risk. We did not observe this behavior for flood insurance demand in Figure 4A, as insurance provides benefits for all storm probabilities.

The second tipping point is observed in Figure 4C. The three highest peaks in Figure 4C are associated with insurance penetration rates of approximately 47%, 52%, and 47% for a protection standard of 10, 30, and 50 years respectively. As Equation 2 indicates, the EU for insurance policy uptake is a balance between how much perceived damage is covered

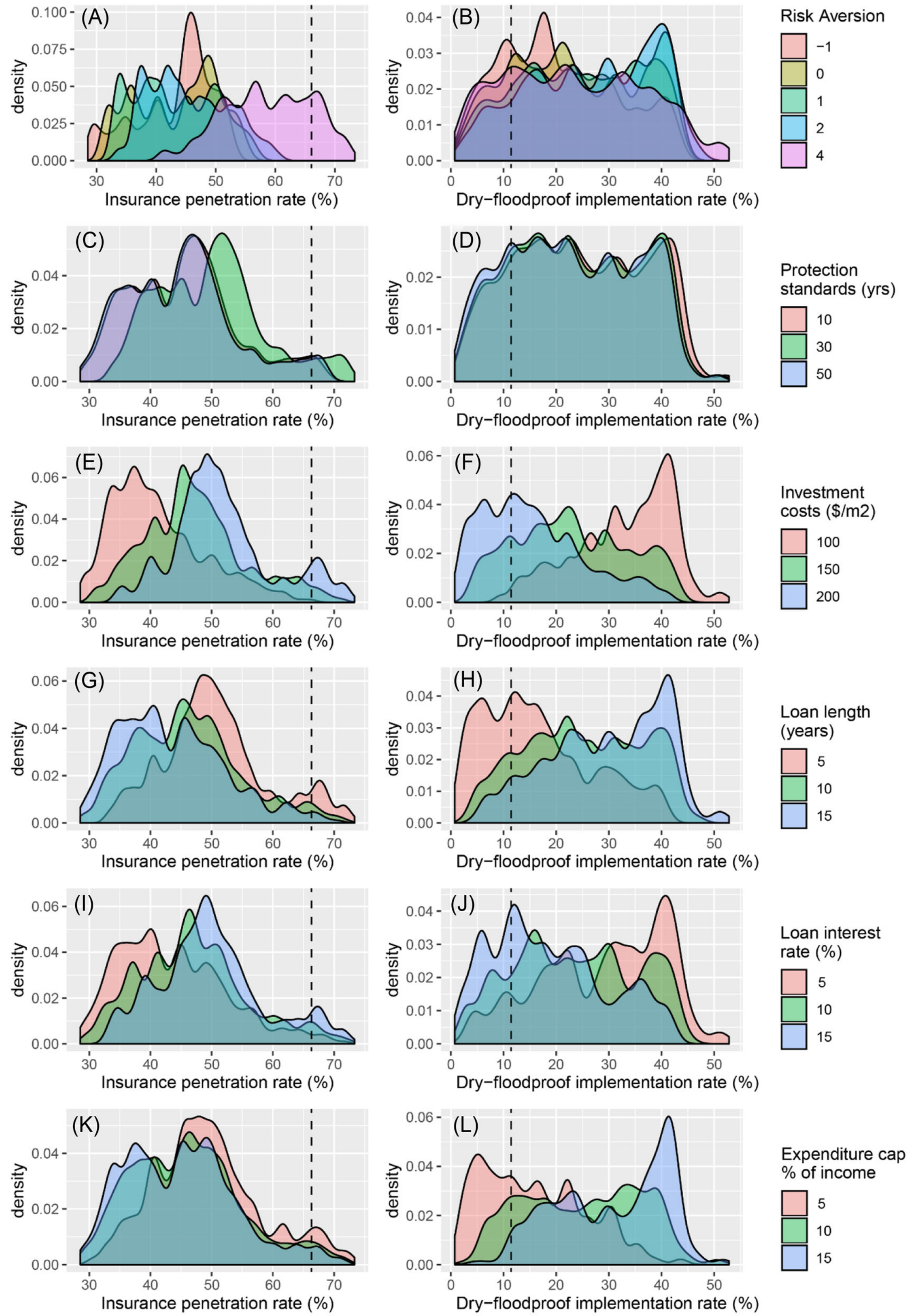

FIGURE 4 Density plots for the different parameters over the penetration rate of insurance and the implementation rate of dry-floodproofing. The dotted, vertical lines indicate the observed values, also found in Table 2

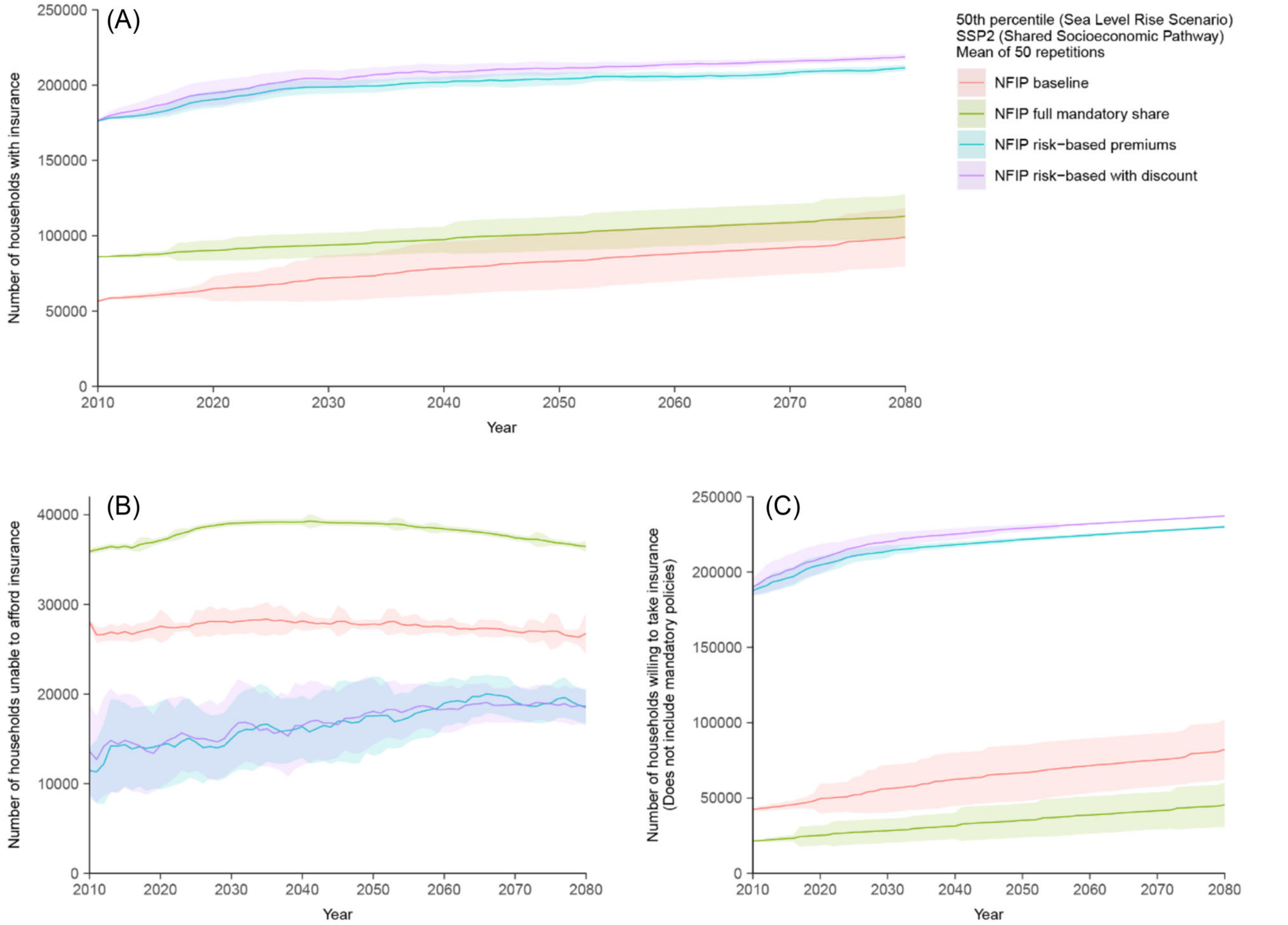

FIGURE 5 The mean of 50 model repetitions for the four different insurance market structures. (A) The number of households with a policy in force (including mandatory policyholders), (B) the number of households that are not able to afford insurance, and (C) the number of households that are willing to take insurance (excluding mandatory policyholders)

due to the deductibles and how high premiums are. Higher protection standards prevent more flood events, thus reducing risk and resulting in a lower premium; however, this also translates to a less effective insurance policy (i.e., the prevented floods no longer require insurance). We observed an increase in penetration rate if the assumed protection standard increases from 10 to 30 years—the lower premium outweighs the lower coverage. Moreover, a tipping occurs when the protection increases from 30 to 50 years—the lower coverage outweighs the lower premium.

4.2 | Application on Jamaica Bay

4.2.1 | Insurance indicators

Figure 5 illustrates the mean outcomes of 50 modeling runs for the four different scenarios using the benchmarked parameter settings (see Supporting Information S2 for convergence tests that confirm stability of results). Figure 5A portrays the number of households with a policy in force over time (including the mandatory share), while Figure 5B depicts the number of households with an unaffordable premium, and Figure 5C presents the number of households willing to obtain insurance based on their EU (excluding the mandatory share).

The number of policies within the baseline NFIP market structure increases over time, from approximately 60,000 policies in 2010 to 75,000 policies in 2080, which implies penetration rates of about 19% and 25%, respectively. Although the penetration rate might seem low compared to the observed values in Table 2, note that the observed values from Table 2 are directly after Hurricane Sandy (estimated as a 400- to 500-year storm (Lin et al., 2012, 2016) and thus under high-risk perception conditions. In the model, storms occur stochastically, based on their return period, and they influence risk perceptions accordingly. Our model demonstrates that for Jamaica Bay for the NFIP baseline market structure, roughly 60,000 policies are in force, 27,000 of which are due to the mandatory requirement. The mandatory share is expected to be slightly larger than current NFIP practice, as our 100-year flood zone is based on our inundation data instead of FEMA's FIRM.

For the NFIP mandatory market structure, penetration rates are higher, with 85,000 total policies in force in 2010, increasing to around to 115,000 policies in 2080 (34% and

35%, respectively). However, the mandatory share increases to around 65,000 policies, which also translates to the highest unaffordability out of all scenarios. Note that the mandatory requirement is not only enforced in the 100-year flood zone but for all properties and without a compliance rate.

The NFIP risk-based (with or without premium discount) market structures performed best out of all scenarios, with penetration rates of around 65% in 2010 to about 74% in 2080, corresponding to roughly 180,000 policies in force in 2010 and increasing to 215,000 in 2080. The market structure with a discount yielded slightly higher uptake and penetration rates, as seen in Figure 5A. Unaffordability was also lowest, with about 11,000 households in 2010 and increasing to 18,000 households in 2080. Part of the increase in penetration rates and affordability is that a large share of high-risk zone households have a lower premium for the risk-based market structure, than the mean observed NFIP premium. For 2010, the mean premiums in the high-risk zone are $818 for risk-based premiums (based on agents with insurance) and $1,275 for the current NFIP baseline market-structure. However, the distribution of premiums (as shown in Supporting Information S3), shows that there is a tail-end with a share of households with significantly more costly premiums than the NFIP baseline average. The share of households with very large changes in premiums, as shown in Figure 3, did not purchase insurance.

While unaffordability was relatively low, it increased over time by approximately 7000 households. To analyze unaffordability, only households with mandatory forced policies and those that were willing to buy insurance were considered. Offering a premium discount when risk-reduction measures are in place does not seem to improve affordability, as seen in Figure 5B. If the annual insurance premium is unaffordable for a household, then it most likely does not have the funds to invest in dry-floodproofing measures, not even through a personal loan, and thus cannot apply for the premium discount.

4.2.2 | Dry-floodproofing indicators

Figure 6A illustrates the number of households that implemented dry-floodproofing, and Figure 6B indicates the number of households that were unable to afford dry-floodproofing, assuming households have access to a personal loan structure. Note that flood-proofing costs between market structures does not change, and thus unaffordability is almost identical in Figure 6B. The NFIP baseline, the NFIP full mandatory, and the NFIP risk-based without a premium discount revealed no significant differences in terms of implementation rates. Approximately 15,000 households initially invested in dry-floodproofing measures for all market structures, increasing to about 20,000 in 2080. This number translates to an implementation rate of roughly 5% and 8% in 2010 and 2080, respectively. The increase of households who invested in dry-floodproofing over time, as depicted in Figure 6, is primarily caused by the increase in flood risk over time. Similar to the observed insurance market penetration, the observed dry-floodproof implementation rates in Table 2 are higher than those found in the modeling runs. Note again that the values in Table 2 should be interpreted as high-risk perceptions, causing homeowners to overestimate the probability and damages of floods.

Providing a premium discount to incentivize the adoption of dry-floodproofing resulted in a distinct increase in implementation rates compared to the other three market structures (Figure 6A). With about 15,000 policies in force in 2010 to roughly 23,000 policies in force in 2080 (implementation rate of 5.5% to 9.2%, respectively), the premium discount demonstrates the effectiveness of incentivizing DRR through an insurance market structure. The increase is the result of households that are likely to have insurance with or without a discount, but because of the discount are incentivized to invest in flood-proofing measures as well. Hence, unaffordability is unchanged between market structures.

The implementation rate as seen in Figure 6A stagnates over time. The willingness of homeowners to invest in dry-floodproofing is hence decreasing over time, despite sea level rise exacerbating risk. Dry-floodproofing is not effective during events that cause overtopping of the floodproofing height. Therefore, with increasing risk, some homeowners are no longer willing to invest in dry-floodproofing measures. This also explains the patterns found in Figure 6B—affordability is decreasing over time to close to zero. Unaffordability was only measured for households that were willing to implement dry-floodproofing. If no households were willing to invest in dry-floodproofing measures, then there would also be no households that cannot afford dry-floodproofing. The lifespan of dry-floodproofing is assumed to be 75 years. Homeowners who were initially investing in dry-floodproof measures might have changed their minds later in time and would not have reinvested in measures after their lifespan had been depleted. However, as the lifespan covers the total modeling run, this is not visible in the results. Exactly this emergence of patterns is the unique benefit of agent-based models.

4.2.3 | Alternative loan structure

For the regular scenarios, we used a personal loan structure for funding dry-floodproofing measures. However, personal loans (modeled here as a 15% interest rate over 5 years) can be expensive by themselves; therefore, we also analyzed the effects of providing a governmentally funded loan with a 4% interest rate and a length of 20 years, based on proposals by Kousky and Kunreuther (2014). Figure 7 presents both the number of households that implemented dry-floodproofing and those that were unable to afford dry-floodproofing in graphs a and b; graphs c and d depict the penetration rate and unaffordability of insurance. As expected, investments in dry-floodproofing increase significantly, starting at approximately 25,000 households in 2010 and increasing to about 40,000 households in 2080 (equivalent to implementation rates of 10% to 15%, respectively). Including a premium discount has a positive effect on the implementation rate of

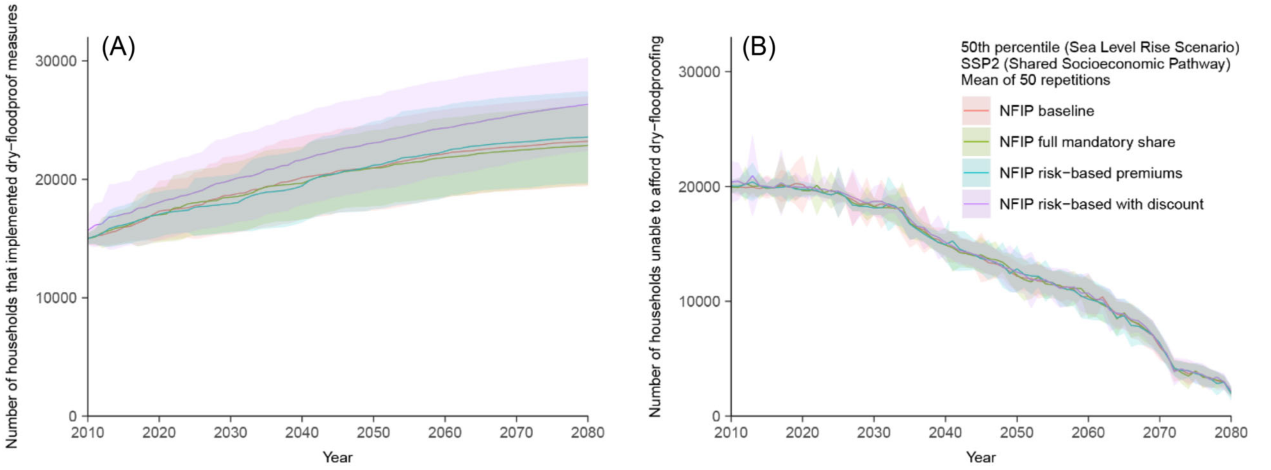

FIGURE 6 The mean of 50 modeling repetitions depicting (A) the number of households that implemented dry-floodproofing measures and (B) the number of households unable to afford dry-floodproofing for all four insurance market structures

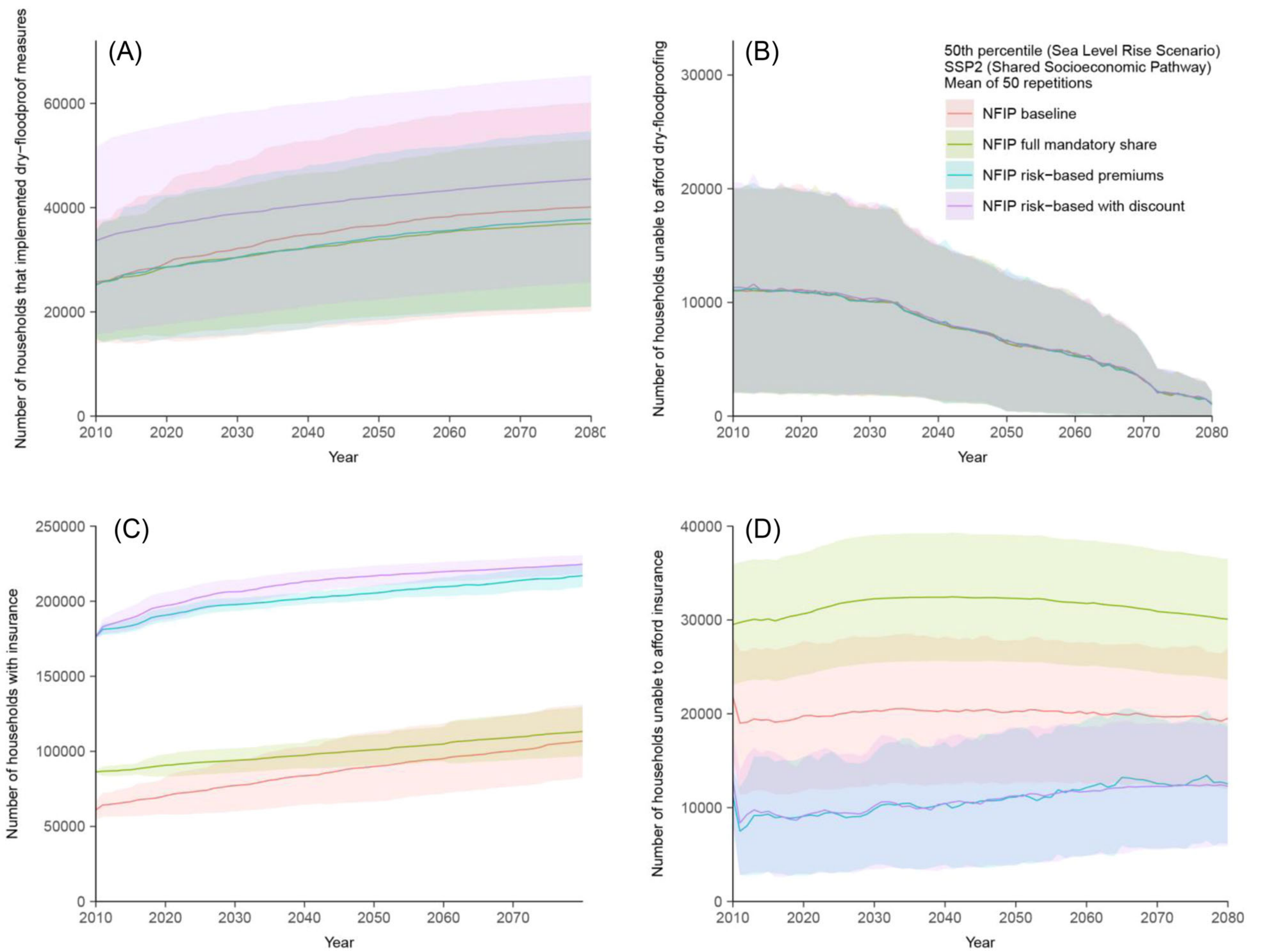

FIGURE 7 The mean of 50 modeling repetitions for the reformed loan structure, with an interest rate of 4% and a length of 20 years, for all four NFIP market structures. (A) The number of households that implemented dry-floodproofing measures, (B) the number of households unable to afford dry-floodproofing, (C) the number of households with a policy in force (including mandatory policyholders), and (D) the number of households that are not able to afford insurance (excluding mandatory policyholders)

dry-floodproofing, starting at roughly 33,000 households in 2010 and increasing to 46,000 households in 2080 (or 13% and 17%, respectively). In addition, the reformed loans decrease unaffordability for all scenarios compared with Figure 7B, with approximately 11,000 households being unable to afford dry-floodproofing in 2010, which is a decrease of 45%.

In terms of insurance, the NFIP baseline market structure yielded a slightly larger growth compared to Figure 5A, but overall, no significant differences were found. In terms of affordability, all market structures improved slightly due to the new loan structure. Even though the insurance market structures without a premium discount do not offer a premium discount, their affordability still improves. Risk is lowered as more households invested in dry-floodproofing due to the more affordable loans. The lower expected damage causes households that were willing to buy insurance but were unable to afford it, to no longer want insurance.

4.3 | Sensitivity analysis

The figures displaying the results of the sensitivity analysis can be found in Supporting Information S5. They present the mean of 50 repetitions of the model with variations in one variable to test the robustness of the model.

Insurance outcomes demonstrated robustness for all variables except risk aversion. The benchmark picked a specific set of variables that resulted in the observed penetration rates of insurance and the implementation rate of dry-floodproofing for high-risk perception. As we applied a one-at-a-time, local sensitivity analysis, it is not surprising that lower values of risk aversion result in the lowest penetration rates of insurance.

For dry-floodproofing, the results vary more than the insurance outcomes but are relatively robust with no major outliers. As we based our values on the benchmark and literature, we are confident in the selection of variables; however, the sensitivity analysis results do suggest that these variables have an impact on the decision of investing in dry-floodproofing. For example, it is unsurprising that when investment costs decrease, the implementation rates of dry-floodproofing increase, and vice versa.

5 | DISCUSSION AND CONCLUSION

Hurricane Sandy induced nearly $70 billion in damages in 2012, and recent flood events in the Midwest have caused an estimated $2.9 billion in damages. These events illustrate flood risk as we are experiencing it today, and it is expected to worsen over time, driven by climate change and socioeconomic development. Flood insurance can be an essential tool in transferring risk and incentivizing individuals to implement risk-reduction measures. However, the NFIP is criticized for incentivizing policyholders to stay in flood-prone areas and having inaccurate premiums, and the program is over $30 billion in debt. Many suggestions have been made to reform the NFIP (Kunreuther, 2018; Michel-Kerjan & Kunreuther, 2011), although predicting their effects is difficult due to the lack of systematic evaluations of these reforms using flood risk assessment models that account for dynamic human adaptation behavior. We applied an agent-based model coupled with a flood risk model to evaluate several reform changes: a full mandatory purchase requirement in 100-year flood zones, risk-based premiums with and without a premium discount, and an accessible loan structure to help finance DRR measures.

While most studies have employed ad hoc rules with parameter values based on assumptions and expert judgement, we applied a benchmark with survey data to ground our behavioral rules in economic theories. The benchmark demonstrated the wide variety of model outcomes that can be obtained by different sets of parameters. While most of the variables are in line with literature, the risk aversion parameter that best matched observed flood adaptation behavior has a relatively high coefficient value of 4. Many similar modeling studies have applied a risk aversion coefficient of 1, representing slight risk aversion (Haer et al., 2019; Hudson et al., 2019a), which is often based on evidence found in Bombardini and Trebbi (2012), Falk et al. (2018), or Vieider et al. (2015). However, risk aversion estimates vary highly across different studies and contexts. For example, some studies have found a difference in risk aversion between genders (Falk et al., 2018; Vieider et al., 2015), whereas others have not (Niederle, 2014). In addition, Eckel et al. (2009) found risk-seeking choices from Hurricane Katrina evacuees, suggesting a varying value of risk aversion over time. For agent-based models, collecting more empirical data designed for modeling applications is essential to allow for more extensive calibration and validation of the models, preferably over an extended period of time. Further refinements in behavioral rules of the model are possible in case more empirical information becomes available through future research. For example, the increase of perceived probabilities and damages by homeowners following a flood event is based on Hurricane Sandy, but applied in our model to each of the flood return periods, while in reality a lower intensity storm might trigger a different response. This aspect of the behavioral rule could be calibrated in more detail if information on the updating of flood risk perceptions following floods with various intensities becomes available. Moreover, future research could assess how start-values of risk aversion, perceived flood probability and perceived flood damage based on distributions instead of start-values affect the initial agent's purchasing behavior.

We found that for Jamaica Bay, risk-based premiums would overall increase penetration rates and decrease unaffordability compared to the NFIP baseline market structure, although a share of policyholders might still experience significant increases in their rates and higher unaffordability. This is surprising because the Biggert-Waters Flood Insurance Reform Act of 2012 was designed to move toward risk-based premiums and was almost entirely reverted in

2014 due to unaffordability issues (Dixon & Clancy, 2006; Kousky & Kunreuther, 2014; Miller et al., 2019). In terms of unaffordability, NYC is relatively wealthy, and thus unaffordability might not be as much of a problem compared to other regions; however, a US-scale study would be necessary to confirm this. Furthermore, a major problem of the NFIP is the inaccuracy of current inundation mapping, based on historic losses and national averages (FEMA, 2013b; Kousky et al., 2016). The increased accuracy of the 30 m resolution flood risk model shows that within the 100-year flood zone there is still a large variability of risk. This variability results in a large share of households benefiting from risk-based premiums (Michel-Kerjan et al., 2014). Still, a subset of households will experience a significant increase in premiums. These households are unlikely to purchase insurance, either due to affordability issues or not perceiving the risk as high enough, or in other words they believe the insurance policy not to be a worthwhile investment. The current NFIP high-risk coastal zone for NYC is based on FIRMs from 1983 (City of New York Mayor's Office of Recovery & Resiliency, 2015; Miller et al., 2019); this zone is smaller than the 100-year flood zone of our high-resolution inundation data, capturing only extremely high-risk properties. Our larger 100-year flood zone is more nuanced and includes properties that are still vulnerable for a 100-year flood event but have a relatively lower risk than those within the NFIP high-risk zone. This can cause the current NFIP premiums to be overestimations of premiums for high-risk areas. With the release of FEMA's risk rating 2.0 program and the introduction of FEMA's new methodology on assessing local flood risk (FEMA, 2019b), a more extensive comparison can be made with local scale inundation models, and how they related to the 1983 FIRMs and 2013 PFIRMs. In addition, we recommend that application of the model to different areas to assess the impact of risk-based premiums.

The current NFIP has a little under 20% of all policies receiving discounts for being pre-FIRM properties or properties that follow grandfathering benefits (Kousky et al., 2016). These properties sustain more damages and have higher claims, although they pay less, and the NFIP is not compensated for these lower premiums. Changing to a risk-based premium setting will have a financial impact on these specific households. To relieve financial but also political stress, compensation for managed retreat or a voucher incentivizing risk reduction can be offered to policyholders for whom premiums are unaffordable due to a transition, although that is not explored in this paper. Our model captured the discounts by applying mean observed NFIP premiums for the NFIP baseline premium setting and therefore should not have caused the differences found in penetration rates or unaffordability. Despite some of these stylistic changes to the NFIP baseline market structure, our model demonstrates the interactions between insurance and risk-reduction indicators for different market structures and reform changes. For example, most of the unaffordability caused in both NFIP scenarios is due to the mandatory requirement, forcing homeowners to obtain insurance despite not being able to afford it. Though it should be noted that households that cannot afford insurance are probably not equipped to deal with uninsured flood damage either. Even for the NFIP baseline market scenario, the initial unaffordability is caused by 65% of the mandatory policies. As NYC is relatively wealthy, future research should explore and compare the results with different areas.

Following our findings, premium discounts, and a loan structure to incentivize the implementation of risk reduction are recommended reform changes, in addition to the aforementioned risk-based premiums. Offering a premium discount that reflects the reduction in risk can significantly increase the uptake of risk-reduction measures. In addition, we find that a premium discount does not reduce the unaffordability of insurance or risk-reduction measures. If a household is unable to afford an annual insurance premium, then they are unlikely to be able to afford a personal loan to fund dry-floodproofing measures to receive the discount. Instead, the proposed loan structure is demonstrated to significantly improve the penetration rates and affordability of DRR. While we evaluated the current state of the NFIP and some of the most discussed reform changes, there are still many other proposed reform changes, such as the entry of private insurers, that should be addressed in future research.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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