Mismeasuring Risk:
The Welfare Effects of Flood Risk Information*

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Abstract

I study the effect of risk-based flood insurance pricing on welfare and climate damages in the U.S. I estimate my results with flood insurance policy data and a novel survey measuring property-level flood insurance demand, risk perceptions, and objective flood risk. To identify the effects of risk-based premiums, I use variation created by outdated flood maps that caused high-risk homes to be misclassified as low-risk. My findings show that higher premiums are both a price and information signal. Owners of high-risk homes misclassified as low-risk underestimate their current and future flood risk, invest less in risk-reducing adaptation, and buy less flood insurance despite having lower premiums. Embedding these estimates in a sufficient statistics model with dynamic risk and endogenous risk beliefs and adaptation, I find that accurately classifying a new high-risk home increases welfare by $25,000 and reduces its dynamic climate damages by 50%.

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1 Introduction

Climate-exposed homeowners in the United States face skyrocketing insurance premiums (Eaglesham, 2024). On the one hand, these climate risk price signals may spur investment in adaptation to make homes more resilient against winds, fires, and floods. On the other hand, rising premiums may drive insurance coverage lower given that many homeowners already underinsure even when offered subsidized premiums (Flavelle, 2021). It is a critical but open question whether higher premiums that reflect risk will bolster or erode households' preparedness for climate change.

This paper shows that accurately pricing flood risk increases flood insurance take-up, increases investment in risk-reducing adaptation, and substantially reduces long-run climate damages. I study the effect of risk classification in the National Flood Insurance Program (NFIP), where homes are either publicly classified as low risk with low premiums or high risk with higher, risk-based premiums. I show that risk classification not only sends a price signal, but also an information signal. This information effect leads homeowners to demand *more* insurance when they are classified as high-risk despite higher premiums. In addition, risk-based premiums align incentives between insurers and developers, reducing moral hazard and the NFIP's fiscal costs through investment in risk-reducing adaptation. In total, risk-rated premiums combined with information provision yield substantial welfare benefits.

Discerning the economic effects of risk classification in insurance markets requires understanding how homeowners will respond to new information about their risk and higher premiums. I build a dynamic, sufficient statistics model where homeowners' risk perceptions endogenously respond to their risk classification. An insurer classifies homes as "high-risk" or "low-risk" to set their premiums. This classification is both a price and a signal to homeowners about their risk. The model identifies empirical sufficient statistics for estimating the welfare effects of correctly classifying high-risk homes.

The model emphasizes three novel effects of risk classification in disaster insurance markets. First, classifying a home as high-risk has an ambiguous effect on insurance take-up because, even as its owner faces higher premiums, they also receive information that changes their risk perceptions. Second, the information effect and premium incentives of high-risk classification increase investment in risk-reducing adaptation. Third, when changes in risk over time are correlated with current risk, misclassification can cause owners to also misperceive their future risk.

I estimate the information effect, price effect, and adaptation effect of high-risk classification as sufficient statistics for my welfare model in a series of empirical exercises. A first challenge is that high premiums are generally paired with high-risk information signals inside the floodplain, making it difficult to disentangle the price and information effects. I exploit variation from a NFIP policy that holds premiums fixed for homes that have been recently remapped into the floodplain to

identify the price elasticity of flood insurance demand separately from the information effect. This Newly Mapped Subsidy phases out in a staggered manner such that even policyholders who were remapped into the floodplain around the same time may face different premiums at renewal. I find a 1% increase in premiums decreases policy renewal by 0.17 percentage points.

Next, I estimate how high-risk classification changes a homeowner's risk perceptions and demand for flood insurance. While flood insurance take-up is generally higher inside than outside the floodplain, this difference cannot be entirely attributed to an information effect. Some floodplain homeowners are required to purchase flood insurance by their lenders, and, flood risk is generally higher inside than outside the floodplain. To directly identify the information effect, I survey 2,167 homeowners in high-risk coastal areas. The survey instrument measures flood insurance take-up and distinguishes voluntary buyers from those subject to lender-mandated flood insurance – a distinction that is impossible with administrative policy data. I also elicit perceptions of current and future flood risk to directly estimate the effect of floodplain status on risk beliefs. The survey links the address of each respondent to risk information from their flood map and two independent risk models. With these data, I compare the risk perceptions and voluntary flood insurance demand of homeowners inside and outside the floodplain with similar risk. Finally, I use new data released by the NFIP on its new Risk Rating 2.0 premiums that reveals areas that have been – by the agency's own estimation – incorrectly mapped outside the floodplain. I find that homeowners outside the floodplain are 17 percentage points less likely to voluntarily buy flood insurance than floodplain homeowners with similar risk, despite enjoying 60% lower premiums. The survey's risk perception measures show that mismapped non-floodplain homeowners perceive lower current and future flood risk.

Finally, I turn to estimating the adaptation effect, or how risk classification affects investment to reduce expected flood damages. Inside the floodplain, new homes face both premium incentives and minimum standards to elevate and reduce their flood risk, whereas no such incentives exist outside the floodplain. The choice of elevation at construction is particularly important given the high costs of raising an existing home, essentially making adaptation fixed over a home's life. An empirical challenge to estimating the adaptation effect is that comparing the claims of floodplain and non-floodplain homes conflates differences in underlying risk with differences in adaptation. To address this challenge, I compare the claims of homes recently remapped into the floodplain against those of homes already in the floodplain prior to remapping. Both sets of homes face similar flood risk, but only the homes that were already in the floodplain prior to remapping were elevated at construction. I control for any residual differences in underlying risk between these groups in a difference-in-difference approach using homes built before flood maps were introduced. To estimate the adaptation effect, I compare the claims of over 190,000 policies, controlling for flooding events at

the census tract level and a host of structure and policy characteristics. I find that remapped homes suffer 30% larger claims than their adapted counterparts built in the floodplain. The adaptation advantage is even larger for new construction. These adaptation gains come from floodplain homes elevating above the minimum elevation requirements, suggesting voluntary rather than mandatory adaptation investments.

In total, these empirical results suggest that the misclassification of high-risk homes leads to less investment in their adaptation, lowers perceptions of current and future risk, and decreases flood insurance take-up. I use these estimates as sufficient statistics to calculate the welfare effects of reducing misclassification. Correctly classifying a high-risk home produces four primary welfare benefits: (1) Increasing suboptimal flood insurance demand and (2) adaptation by informing homeowners about their current and future risk, (3) reducing moral hazard by creating a premium incentive to invest in adaptation, and (4) reducing the deadweight cost of public funds by eliminating subsidized premiums.

Relative to misclassification, correctly classifying a new high-risk home yields $25,000 in present value welfare gains between 2020 and 2050 and reduces the welfare costs of rising flood risk by nearly 50%. The counterfactual of remapping existing misclassified homes produces attenuated welfare gains of approximately $15,000 because old homes cannot be elevated. Nonetheless, this figure suggests that reclassifying the estimated 6 million high-risk homes outside the floodplain would produce $89 billion in present value welfare gains. The benefits of risk classification are even higher if homeowners demand too little flood insurance due to other internalities or externalities.

However, the full benefits of risk classification depend on pairing information provision with risk-based pricing. In fact, setting risk-based premiums without providing information *decreases* social welfare as higher rates exacerbate the frictions created by out-of-date flood maps. This cautionary counterfactual is especially relevant given that the NFIP's recent Risk Rating 2.0 reforms are updating premiums without correcting the information shown on flood maps (Mulder and Kousky, 2023; Ortega and Petkov, 2024).

This paper contributes to related literature on climate adaptation. Climate damages will depend on the extent to which humans adapt to increasing disaster risk by relocating or building more resilient structures (New et al., 2022). Theoretically, if agents anticipate the potential costs of climate change they will invest in adaptation (Anderson et al., 2019). Empirically, findings on the historical progress of adaptation are mixed and vary widely across outcomes (Kahn, 2005; Annan and Schlenker, 2015; Barreca et al., 2016; Burke and Emerick, 2016; Deryugina and Hsiang, 2017; Park et al., 2020; Somanathan et al., 2021; Carleton et al., 2022).

I show that accurately pricing flood insurance while informing residents about their risk is a

potent adaptive tool to reduce climate damages. Related to this finding, several studies demonstrate the value of information in reducing weather damages (Atreya et al., 2017; Molina and Rudik, 2022; Anand, 2023; Fairweather et al., 2023; Shrader et al., 2023; Burlig et al., 2024) and shifting beliefs about climate risk and related policies (Deryugina and Shurchkov, 2016; Dechezleprêtre et al., 2022; Conell-Price and Mulder, 2024). This study shows how flood risk information shifts multiple behavioral responses – from current and future risk beliefs, to insurance demand, to the elevation of flood-prone buildings – while quantifying their welfare benefits. My findings on investments in building elevation also relate to studies showing that mandatory building codes can reduce disaster losses (Wagner, 2021; Baylis and Boomhower, 2022; Ostriker and Russo, 2022; Hovekamp and Wagner, 2023). While this line of research has generally found that historically developers only adapt to meet minimum standards, I show that, for newer construction, developers elevate beyond the minimum requirements. My focus on "in-place" adaptation can be contrasted with other studies which have focused on the importance of migration and resorting (Boustan et al., 2012; Deryugina et al., 2018; Balboni, 2019; Deryugina and Molitor, 2020; Desmet et al., 2021; Ostriker and Russo, 2022; Jia et al., 2022; Bilal and Rossi-Hansberg, 2023; Cruz and Rossi-Hansberg, 2024; Desmet and Rossi-Hansberg, 2024). I show that the benefits of in-place adaptation in the context of risk rating also substantially reduce flood-related climate damages.

Closely related to this work are recent papers on information frictions in disaster insurance markets. Wagner (2021) finds that flood insurance take-up rates are lower than would be suggested by plausible risk aversion parameters with no evidence of adverse selection. Weill (2022) shows that areas remapped into the floodplain see higher flood insurance take-up. In Hu (2021), the author finds that the digitization of flood maps increased flood insurance take-up. My paper extends this growing literature along several dimensions. In Wagner (2021), both adaptation and risk misperceptions are treated as exogenous. These assumptions imply that higher premiums under risk rating would create deadweight loss given that flood insurance demand is already suboptimal and that risk is fixed. I allow adaptation and risk misperceptions to respond to new risk information, and show that when risk classification informs homeowners, risk-rated premiums can be welfare improving. Weill (2022) shows that floodplain classification significantly affects flood insurance demand, but cannot disentangle the price and information effects or estimate the impact on adaptation. Hu (2021) allows new information to affect flood insurance demand, but not beliefs about future flood risk or the adaptation of new construction. This paper ties together information and adaptation effects to estimate the welfare effects of risk rating in disaster insurance markets both under current conditions and given future flood risk projections.

Beyond the specific flood insurance setting, this paper also connects to research on financial

markets and climate change. Recent studies examine how homeowners insurance is responding to climate risk through pricing, the financial stability of insurers, and rising costs of reinsurance (Oh et al., 2022; Boomhower et al., 2023, 2024; Sastry et al., 2023; Keys and Mulder, 2024). Other research shows government aid or peer-to-peer transfers can offset disaster losses for uninsured homeowners or businesses, albeit sometimes with a regressive allocation of benefits (Deryugina, 2017; Billings et al., 2022; Cookson et al., 2023; Collier et al., 2023; Collier and Ellis, 2024; Collier et al., 2024). My findings emphasize that properly functioning disaster insurance markets can be tools for climate adaptation, echoing and extending the findings of Ehrlich and Becker (1972) and Kunreuther and Pauly (2004) on insurance pricing and moral hazard when consumers learn from insurers' premiums. Another strand of the climate finance literature studies how asset prices reflect increasing risk from hurricanes, wildfires, flooding, and sea level rise (Bernstein et al., 2019; Murfin and Spiegel, 2020; Giglio et al., 2021; Gibson and Mullins, 2020; Hino and Burke, 2021; Keys and Mulder, 2020; Lewis, 2023; Bakkensen and Barrage, 2022) with implications for lenders and governments (Goldsmith-Pinkham et al., 2019; Issler et al., 2020; Keenan and Bradt, 2020; Ouazad and Kahn, 2019; Auh et al., 2022; Liao and Kousky, 2022; Sastry, 2022; Kim et al., 2024; Bakkensen et al., 2023; Blickle and Santos, 2022; Blickle et al., 2024). This paper demonstrates that the effects of climate change will depend on price and information efficiency in disaster insurance markets. My welfare model results show that quickly identifying and pricing high-risk areas can attenuate climate damages.

Finally, my results contribute to understanding the determinants of flood insurance demand. This literature has identified puzzlingly low flood insurance take-up and offered explanations such as risk misperceptions, non-standard preferences, crowd-out from disaster aid or mortgage default, and learning frictions (Bradt et al., 2021; Gallagher, 2014; Kousky, 2017; Kousky et al., 2018a; Liao and Mulder, 2021; Mulder, 2019; Wagner, 2021; Collier et al., 2022). I identify the miclassification of high-risk properties as one contributor to low flood insurance demand. My survey provides the first evidence of the effect of floodplain designation on risk perceptions and voluntary insurance demand adjusted for lender-required insurance.

In what follows, I first model the endogenous relationships between risk classification, risk perceptions, and adaptation in a disaster insurance market. Then, I describe the institutional details, data, empirical strategies, and results of the empirical parameters needed to calculate welfare. Finally, I discuss risk classification welfare counterfactuals.

2 Theoretical Framework

This model describes homeowner choices in a disaster insurance market with dynamic risk when beliefs, adaptation, and premiums are all endogenous to information. An insurer's risk-rating technology provides public signals that simultaneously inform premiums and buyers' beliefs about their risk. Buyers choose how much to insure and how much to invest in risk-reducing adaptation based on their beliefs and premiums. Although the setting here considers flood insurance, the model could be applied to any market where buyers learn about their risk or other welfare-relevant attribute from the prices set by sellers.

2.1 Disaster Insurance with Dynamic Risk and Endogenous Adaptation and Beliefs

Consider a model that proceeds over $t = 0, ..., T$ periods with a population of homeowners indexed by i. Each homeowner is endowed with an unobserved flood risk type $F_i \in \{0, 1\}$ denoting low-risk and high-risk, respectively. In each period $t \geq 1$, homes face expected flood losses R_t^F where $R_t^0 < R_t^1$. At $t = 0$, homeowners can invest in adaptation $A_i \geq 0$ to decrease their expected flood damage to $(1 - A_i)R_t^F$. Adaptation incurs $c_i(A)$ in maintenance costs each period where $\frac{dc_i}{dA} \geq 0$, $\frac{d^2c_i}{dA^2} \geq 0$, and $c_i(0) = 0$. For $t > 0$, adaptation is fixed. Before flooding is realized each period, homeowners choose whether to buy insurance $I_{it} \in \{0, 1\}$ that fully covers all flood damage for premium P_{it} from a public insurer. After flooding is realized, owners pay their adaptation maintenance, insurance premiums, and any uninsured flood damage and consume their remaining per-period income Y.

Premiums are set according to a public signal $f_i \in \{0, 1\}$ at $t = 0$ that is correlated with each home's true risk type F_i. We will assume that the risk model always correctly classifies low-risk homes, but misclassifies high-risk homes as low-risk with probability ρ.[1] If the signal shows a home as high-risk, the insurer measures a property's adaptation and sets its premiums equal to its expected costs, $P_{it}^1 = (1 - A_i) * R_t^1$. For low-risk homes, the insurer does not measure adaptation and sets a uniform, flat premium $P_{it}^0 = \overline{P}_t$.[2]

The insurer must be budget neutral at the end of each period and levies taxes or remits surpluses, equal to τ_t per household, to meet ex-post discrepancies between premiums and claims. The following budget constraint holds in expectation:

[1] To focus on the empirical application of identifying and pricing homes with high flood risk, we ignore the case where the model misclassifies low-risk homes as high-risk. This framework can be extended without loss general of generality to incorporate such cases.

[2] Transaction costs are one reason an insurer would measure adaptation for high-risk but not low-risk homes. The $600 average cost of elevation certificates led the National Flood Insurance Program not to use elevation to set premiums outside the floodplain (Price, 2019).

$$\overline{\tau_t} = E\left[\int_h I_{it} * (P_{it} - (1 - A_i) * R_{it})\right] \tag{1}$$

Owners do not observe their true risk type F_i, but they do observe the public signal f_i at $t = 0$ before choosing adaptation. If $f_i = 0$, the owner perceives their risk type as $R_{it}^{B0} = (1-\alpha)R_t^0 + \alpha R_t^1$, where α is the probability that the owner's home was misclassified. If $f_i = 1$, the owner knows they are high-risk with certainty and forms risk type beliefs $R_{it}^{B1} = R_t^1$.

We express households' indirect utility in each period as a function of insurance take-up, adaptation, and risk:

$$u_{it}^f = Y_i - c_h(A_i) - I_{it} * P_{it}^f - (1 - I_{it}) * w_i^f * (1 - A_i) * R_{it}^{Bf}, \tag{2}$$

where $w_i^f \geq 1$ is the markup that household i is willing to pay over their expected loss. The household insures if $P_{it} < w_i^f * (1 - A_i) * R_{it}^{Bf}$. Each household's markup may reflect differences in preferences, liquidity, or wealth. We allow w to vary by whether the household receives a low-risk or high-risk signal. Equation 2 assumes that insurance demand scales linearly with adaptation, treating insurance and adaptation as perfect substitutes.

Note that when a homeowner is classified as high-risk, they will only forgo insurance when they are risk-neutral, that is $w_i = 1$. Without loss of generality, we could also introduce loading fees into the cost of insurance, in which case homeowners would self-insure whenever w_i is less than the loading fee markup. In practice, the NFIP's loading fees paid to insurance agents and loss adjusters are substantial at approximately 35% of premiums (GAO 2019). Homeowners may also be willing to pay less than their expected loss if they are liquidity constrained, given that the NFIP requires insureds to pay their entire annual premiums in one payment (Ericson and Sydnor, 2018). Another reason homeowners might choose to self-insure even when correctly classified is if behavioral biases reduce their insurance demand (Wagner, 2021). We discuss this point further in Section 6.2.

Next, we turn to owners' adaptation decisions, which follow the first-order condition:

$$\frac{dc(A_i)}{dA} = E\left[\sum_{t=1}^{T}(1 - I_{it}) * w_i^f * R_{it}^{BF} - I_{it}\frac{dP_{it}}{dA}\right] \tag{3}$$

Owners adapt until maintenance costs equal the expected future sum of benefits from reduced uninsured risk or lower premiums. Note that owners of homes classified as low-risk by the insurer have no premium incentive to adapt because $\frac{dP^0}{dA} = 0$.

Next, I specify the evolution of dynamic risk and beliefs. I assume that low-risk homes' flood damages remain constant while high-risk homes' damages increase by a constant factor γ^1. That is:

Assumption 1 *The dynamic flood damages of low-risk and high-risk homes are, respectively:*

$$R_t^0 = R_0^0$$

$$R_t^1 = (1 + t * \gamma)R_0^1$$

The respective expected flood damages of buyers classified as low-risk and high-risk are:

$$R_t^{B0} = (1 - \alpha)R_0^0 + \alpha(1 + t\gamma^1)R_0^1 = (1 + t\gamma^0)$$

$$R_t^{B1} = (1 + t\gamma^1)R_0^1$$

The γ^0 term is the expected increase in low-risk classified homeowners' risk given the probability α that they are misclassified. The insurer adjusts premiums according to risk classification such that for high-risk properties $P_t^1 = (1 + t\gamma^1)P_0^1$ and for low-risk properties $\overline{P}_t = (1 + t\gamma^0\overline{P}_0)$. Because premiums increase at the same rate as expected risk, households will make the same insurance take-up decision I^1 or I^0 for all t depending on their risk classification.

Although assumption 1 does not incorporate climate uncertainty, it does capture the important fact that the expected losses of homes with high flood risk today are expected to grow much faster than those of homes with low risk today. In section 6.1, I describe the calibration of γ^1 and provide evidence that assumption 1 is plausible in the context of flood risk.

2.2 Welfare Effects of Risk Information

Next, I describe how risk classification affects social welfare. A household's classified risk type, $f \in \{0, 1\}$, determines its choices of insurance and adaptation, I_i^f and A_i^f, and premium schedule P_{it}^f. Each household's net impact on social welfare is the sum of its private utility, $u_{it}^F(I_i^f, A_i^f, P_{it}^f)$, and net fiscal impact, $\tau_{it}^F(I_i^f, A_i^f, P_{it}^f)$, where $F \in \{0, 1\}$ is the home's actual risk type. Social welfare also includes a cost of public funds $\lambda > 0$.

Consider the difference in social welfare over T periods at discount rate β if high-risk household i is misclassified as low-risk ($f = 0$) versus correctly classified as high-risk ($f = 1$):

$$\begin{aligned}\frac{dTW}{df_i} =& \sum_{t=1}^{T} \beta^{t-1}\big(u_{it}^1(I_i^1, A_i^1, P_{it}^1) - u_{it}^1(I_i^0, A_i^0, P_{it}^0) + (1+\lambda)(\tau_{it}^1(I_i^1, A_i^1, P_{it}^1) - \tau_{it}^1(I_i^0, A_i^0, P_{it}^0))\big) \\ =& \sum_{t=1}^{T} \beta^{t-1}\big((u_{it}^1(I_i^1, A_i^1, P_{it}^1) - u_{it}^1(I_i^1, A_i^0, P_{it}^0)) + (u_{it}^1(I_i^1, A_i^0, P_{it}^0) - u_{it}^1(I_i^0, A_i^0, P_{it}^0)) \\ &+ (1+\lambda)(\tau_{it}^1(I_i^1, A_i^1, P_{it}^1) - \tau_{it}^1(I_i^0, A_i^0, P_{it}^0))\big)\end{aligned}$$

Normalizing $A^0 = 0$, the expression for the change in total welfare simplifies to:

$$\begin{aligned}\frac{dTW_{it}}{df_i} =& \overbrace{\lambda I_i^0(R_t^1 - \overline{P}_t))}^{\text{Public Funds}} + \underbrace{(I_i^1 - I_i^0) * (w_i^1 - 1) * R_t^1}_{\text{Take-Up}} \\ &+ \overbrace{\int_0^{A^1} (1 - I_i^1)}^{\text{Adaptation}} \underbrace{(1 + \gamma^1 - \gamma^0)(R^1 - w_i^0 * R^{B0})}_{\text{Dynamic Risk Misperception}} + \overbrace{I_i^1 * R_t^1}^{\text{Moral Hazard}} - c'(A_i)\, dA\end{aligned} \tag{4}$$

To simplify Equation 4 further and make it estimable from empirical sufficient statistics, we make the following conservative additional assumptions:

1. $I_i^1 \geq I_i^0 \; \forall i$ OR $I_i^1 \leq I_i^0 \; \forall i$: That is, all buyers are either weakly buy more flood insurance when classified as high-risk or weakly buy less flood insurance when classified as high-risk. In reality, the net demand effects of high-risk classification are almost certainly heterogeneous, causing some buyers to drop their policies in response to higher premiums, and others to buy given the signal that they face more flood risk than they thought. This assumption takes the most conservative possible stance on the welfare effects of the take-up term given this likely treatment heterogeneity. For example, consider the case where high-risk classification causes some otherwise buyers to not buy and an equal number of the otherwise uninsured to insure. Under this assumption, we would measure no net effect of high-risk classification on take-up and thus conclude no welfare effect from the $I_i^1 - I_i^0$ term. In reality, such a reform would have welfare benefits for all the consumers who switched.

2. $c'(A)$ is linear between A^0 and A^1, allowing a trapezoidal approximation of the $\int_0^{A^1}$ term following Kleven (2021).

3. $w_i^1 R^1$ forms an isoelastic insurance demand curve.

4. $w_i^0 * R^{B0} = \overline{P}$ if $I_i^0 = 0$ and $I_i^1 = 0$: Homeowners who only insure when classified as high-risk are indifferent to buying insurance when classified as low-risk. This is the highest possible flood insurance willingness-to-pay of uninsured homeowners and thus the most conservative assumption of the welfare impacts of the dynamic risk misperception term.

The model also assumes that risk classification does not change where homeowners live and does not allow household to move. Allowing for sorting would increase the welfare effects of risk information. If risk information changes households' willingness-to-pay for different homes, subsequent resorting would create additional welfare benefits (Bakkensen and Ma, 2020; Ostriker and Russo, 2022). See Appendix Section C for more details on this point.

Finally, we assume no adverse selection for correctly classified high-risk households. I argue this assumption is plausible for flood insurance. As discussed in section 3, the last decade has seen rapid advances in flood risk modeling technology. The granular data on elevation and historical flooding used in advanced flood models surpass the information available to most homeowners. Supporting this assumption, an extensive literature has documented homeowners' difficulties gauging flood risk due to biased and costly learning about rare events and cognitive biases (Meyer and Kunreuther, 2017), while Wagner (2021) finds no evidence of adverse selection in flood insurance.

2.3 Empirical Parameters for Welfare Estimation

Under the assumptions described above, we can express the expected change in welfare from changing a random high-risk household i from being misclassified as low-risk to being correctly classified as high-risk:

$$E[\frac{dTW_{it}}{df_i}] = \overbrace{\lambda I^0(R_t^1 - \overline{P}_t))}^{\text{Public Funds}} + \underbrace{\int_{I^0}^{I^1}(W(I) - R_t^1)dI}_{\text{Take-Up}} + \frac{1}{2}\big(\underbrace{A^1(1-I^1)t * (1+\gamma^1-\gamma^0)(R_0^1 - \overline{P}_0)}_{\text{Self-Protection}} + \overbrace{A^1 * I^1 * R_t^1}^{\text{Moral Hazard}}\big), \tag{5}$$

where $I^0 = E[I_i^0|F_i = 1]$, $I^1 = E[I_i^1|F_i = 1]$, and $A^1 = E[A_i^1|F_i = 1]$.

Equation (5) divides the welfare effects of improved risk-rating into four terms that reflect the deadweight losses caused by misclassification:

1. Public Funds: Raising revenue to cover the excess losses of misclassified homes creates dead-

weight loss according to parameter $\lambda > 0$. Under correct classification, expected losses equal premiums.

2. Take-Up: Note that it is ambiguous whether $I^1 > I^0$ or $I^0 > I^1$. Owners of misclassified high-risk homes may underestimate their risk and not buy enough flood insurance, or they may overinsure because of their low premiums.

3. Self-Protection: Misclassified uninsured households underestimate their risk, and thus underinvest in adaptation as a form of self-protection. Note that the underestimation of risk has two terms: The static misperception in period $t = 0$ ($R_0^1 - \overline{P}_0$) and dynamic misperception of the growth in risk over time ($1 + \gamma^1 - \gamma^0$).

4. Moral Hazard: Insured misclassified high-risk homeowners have no premium incentive to invest in adaptation. Correct classification sets premiums according to risk, resolving the moral hazard problem and increasing adaptation in investment.

I will estimate my model in the setting of the National Flood Insurance Program (NFIP). The model's risk types correspond to FEMA's mapping of properties inside ("high-risk") or outside ("low-risk") the floodplain. Several of the parameters above can be calibrated from data summary statistics (the average premiums of high-risk and low-risk homes, P^1 and $\overline{P}$) or risk models (the expected rate of risk increase γ^1). Following the sufficient statistics literature, parameters for the behavioral responses of agents to policy changes can be empirically estimated with reduced form methods (Chetty, 2009; Einav et al., 2010; Kleven, 2021).

To calculate equation (5), I need to identify three causal effects. First, the price elasticity of insurance demand ("price effect") to calibrate $W(I)$. Second, the "information effect" to determine the net change in flood insurance take-up ($I^1 - I^0$) as well as the differences in future risk perceptions ($\gamma^1 - \gamma^0$) caused by misclassification. And, finally, the "adaptation effect" of risk classification on adaptation investment A^1 (recalling that A^0 is normalized to zero).

The next sections describe the institutional details of the NFIP as well as the data and empirical strategies used to estimate each of these parameters.

3 The National Flood Insurance Program

The National Flood Insurance Program (NFIP) is a publicly run flood insurer. The program is the primary provider of flood insurance in the United States, writing over 95% of flood insurance policies (Kousky et al., 2018b). Historically, the program's insurance underwriting was based on flood maps produced by the Federal Emergency Management Agency (FEMA). FEMA flood maps

use elevation data and hydrological models to delineate the land area that has at least a 1% chance of flooding each year, and the corresponding flood depth with a 1% chance of being exceeded ("100-year flood depth"). Inside this "100-year floodplain", a property's premiums are based on its first floor's elevation relative to the 100-year flood depth. Outside the floodplain, premiums are independent of elevation or any other measure of flood risk and almost always lower than premiums inside the floodplain. The floodplain guides building standards as well as premiums. The NFIP requires all floodplain homes built since the community's first flood map to have a first floor elevation that equals or exceeds the 100-year flood depth. Lenders who are federally regulated or selling a loan to a federally backed agency must require their borrowers inside the floodplain to carry flood insurance. Numerous federal reports have discussed the enforcement of the mandatory purchase requirement (see e.g. GAO 2021).

Flood maps are publicly available online, and many states have floodplain disclosure laws for real estate transactions (Federal Emergency Management Agency , FEMA; Natural Resources Defense Council , NRDC). Flood maps have often been criticized for being infrequently updated and relying on out-of-date models or elevation information that result in the misclassification of properties inside and outside the floodplain (Wilson and Kousky, 2019). Another frequently raised issue is that most properties outside the floodplain face the same premiums despite having very different risks (Bradt et al., 2021).

As FEMA updated its flood maps, moving some homeowners into the floodplain, the NFIP started the Newly Mapped Subsidy program in 2015. Under the Newly Mapped Subsidy, a homeowner whose property was remapped into the floodplain may still purchase flood insurance within two years of remapping at lower, non-floodplain premiums. Beginning in the second calendar year after the new flood map, renewing remapped policies are subject to approximately 15% annual premium increases. Even in the oldest remapped areas, premiums under the Newly Mapped program remain below their corresponding floodplain rates as of 2019.

The NFIP implemented "Risk Rating 2.0" (RR2) reforms beginning in October 2021 (Federal Emergency Management Agency , FEMA). Under RR2, flood insurance premiums are based on property-level loss estimates from historical claim data that are independent of flood zone. However, there is no publicly available information about potential premiums, making flood maps still the main source of flood risk information for the public and the legal basis for most building standards (Mulder and Kousky, 2023).

4 Data

To estimate the sufficient statistics for welfare analysis, I combine several data sources to compare the flood insurance demand and adaptation of properties classified as low- and high-risk. First, I use administrative data on National Flood Insurance Program (NFIP) policies and claims in zip codes where homes outside the floodplain have been remapped into the floodplain. Second, I design and field a survey of the flood insurance demand and risk perceptions of homeowners in flood-exposed coastal areas. Survey responses are merged to two property-level risk models, flood map information, and data on geographic variation in premiums under the NFIP's Risk Rating 2.0 reforms. The section below describes how these data are used to construct the analysis samples and variables.

4.1 National Flood Insurance Program Policy and Remapping Data

I use data on National Flood Insurance Program (NFIP) policies and claims from the OpenFEMA Redacted Policies and Redacted Claims databases (OpenFEMA 2021). These data show the universe of policies and claims from 2009-2020 with information on the amount of coverage, the dates the policy was originally written and most recently renewed, location at the census tract level, and the property year built. The claims data record the date of loss and amount paid for each claim. Following the methodology described in Mulder and Kousky (2023), I am able to link policies over time to track whether or not they renew, and match policies to claims.

The primary empirical variation for estimating the price effect and adaptation effect come from areas that were newly mapped into the floodplain by the NFIP from 2015-2019. As described in Section 3, the Newly Mapped Subsidy program started by the NFIP in 2015 allows homes newly mapped into the floodplain to purchase flood insurance at their original non-floodplain rates. Beginning two years after remapping, newly mapped homes' premiums increase by 15% per year. The policy data have indicators for policies written under the Newly Mapped Subsidy program. Using these indicators and the schedule for Newly Mapped premium increases, I identify zip codes where properties were newly mapped into the floodplain and the year that the remapping occurred.

The top panel of Figure 1 maps the counties with zip codes with newly mapped policies and the year they were remapped. The estimation sample contains 359 counties with approximately 900,000 active flood insurance policies as of 2020. The bottom panel of Figure 1 plots the distribution of remapping years across newly mapped policies active in 2020. In these zip codes, average annual premiums are $530 and $1,330 outside and inside the floodplain, respectively, prior to remapping.

4.2 Flood Insurance Survey

Working with the Wharton Risk Center, I designed and fielded a survey of high-risk coastal homeowners to estimate the information effect. The purpose of the survey was to elicit two critical but otherwise "invisible factors" not available from administrative flood insurance policy data (Stantcheva, 2023). The first is a measure of voluntary flood insurance demand distinct from policyholders forced to insure by their lender. The second is subjective beliefs about current and future flood risk.

The survey was conducted through Online Qualtrics Panels from March-May 2021. Participants were screened for single-family homeowners living in one of 1,908 coastal zip codes where at least 30% of properties are at some risk of flooding according to the First Street Foundation Flood Model (FSF-FM), approximately the 95th percentile of the national risk distribution.[3] The full text of the survey questions used are in Appendix section G.1.

2,167 participants completed the survey. Of these, the estimation sample was limited to the 1,080 respondents age 25 or older willing to volunteer their home address and who provided a purchase year for their homes within two years of CoreLogic deed records if available. Of these, the sample was further restricted to 885 participants who passed an attention check, and finally to 703 participants whose homes were within one mile of the floodplain boundary. Figure 2 maps the number of respondents by county in the survey estimation sample.

The survey elicited whether each participant had flood insurance. A common misperception among homeowners is that flood insurance is included in their standard homeowners insurance policy, but this is almost uniformly untrue. Among participants who reported having flood insurance, the survey asked if the policy was included in their homeowner's insurance policy and whether they paid a separate premium for their flood insurance. Respondents who indicated that their flood insurance was part of their homeowner's policy and that they did not pay a separate flood insurance premium were not counted as flood insurance purchasers.[4]

A challenge assessing flood insurance demand is the mandatory purchase requirement legally required for most mortgages inside the floodplain. All respondents reporting flood insurance and a mortgage were asked if their lender required the policy. Respondents indicating that they face a mortgage purchase requirement were asked how likely they would be to buy flood insurance if their lender didn't require it on a 1-5 Likert scale. Only such respondents who indicated they would be "Extremely likely" – or a five out of five – to buy flood insurance anyways are counted as voluntary flood insurance purchasers. 70% of SFHA homeowners with a mortgage reported that their lender

[3]The detailed methodology behind the FSF-FM is described in First Street Foundation (2020).

[4]30% of respondents who reported having flood insurance thought it was a standard part of their homeowner's policy. This misperception was more common outside the floodplain (38%) than inside the floodplain (12.5%).

required them to buy flood insurance, versus only 9% of borrowers outside the floodplain.[5] Of these borrowers with mandatory flood insurance, 53% report that they would be "extremely likely" to purchase their flood insurance even without their lender's requirement.

The survey asks participants about their flood risk perceptions, including both subjective (e.g. worry) and quantitative (e.g. probability of and expected damages from flooding) assessments. The survey also elicited risk perceptions with an incentivized hypothetical insurance purchase scenario. Participants were asked how much they would be willing to pay for an annual flood insurance policy on their homes. The risk participants faced was based on actual historical flood claims in another zip code with similar risk according to the FSF-FM. Participants were entered into a raffle for a $100 Amazon gift card mailed to their address, minus flood insurance premiums or flood losses. Appendix section G.1.2 describes the incentivized elicitation as seen by the survey respondents, while G.2 describes its implementation details.

The survey also includes questions on self-reported risk, time, and patience preferences (Appendix section G.1.6). Given the length of the survey and the cognitive demands of the incentivized flood insurance demand elicitation, we elicit self-reported preference measures following Falk et al. (2022) that are designed to predict incentivized elicitations out-of-sample.

4.3 Risk Models, Flood Maps, and Risk Rating 2.0 Premiums

Each survey respondent was linked to their property-specific FSF-FM and KatRisk flood risk models using their self-reported address. Both models estimate average annual flood losses and expected flood depths across different return periods (e.g. the "500-year" or "100-year" flood). The primary risk model measure is the average 500-year flood depth between the two models. Averaging the results of the two models attenuates the idiosyncracies of relying on any one flood risk estimation methodology. Reassuringly, even though the two models were built independently, their 500-year flood depths have a correlation coefficient of 0.79 in the estimation sample. The survey also asked each participant if their current home had been damaged by a flood while they lived there. Respondents' locations were linked to the most recent flood maps, most critically recording whether they are located inside the floodplain

The FSF-FM includes a climate projection of the changes in expected flood depths through 2050. I use the change in average annualized losses between 2020 and 2050 as a measure of the expected 30-year change in flood risk. Respondents were also asked whether they expected their own flood risk to increase, decrease, or stay the same over the next thirty years.

[5] An additional 7% of SFHA borrowers and 6% of non-SFHA borrowers report being required to buy flood insurance by their lender but that their policy is a standard part of their homeowners insurance. We classify these respondents as mistakenly believing that the homeowners insurance required with most mortgages includes flood coverage.

Finally, I merge each property by zipcode to data released by the NFIP showing average full-risk premiums under its new Risk Rating 2.0 (RR2) reforms. As described in Section 3, the NFIP transitioned from setting its premiums based on flood maps to using a new RR2 algorithm starting in October 2021 (Mulder and Kousky, 2023). The RR2 pricing algorithm sets premiums according to losses estimated from the most recent available geospatial data and flood models trained to predict losses from the NFIP's database of over 1.7 million claims (Federal Emergency Management Agency, 2023). Higher risk-rated premiums are being phased in at a maximum annual increase of 18% for renewing policies. In response to requests for more information about how RR2 will ultimately impact flood insurance costs, FEMA released data showing what average RR2 premiums will be by zipcode for active policies as of September 2022 once the old map-based subsidies are fully phased out. These premiums reflect FEMA's own best estimates of where its flood maps have underpriced risk.

Table A1 reports summary statistics from the survey estimation sample. Given that respondents were recruited from an online sample, there are plausible concerns that the sample may not be representative of the population of coastal homeowners or that the responses may be low quality. In addition to the incentives and screening for accurate address reporting and attention to the survey as described above, the survey data show reassuring signs of accuracy and quality. On observable characteristics, the survey respondents resemble the population of homeowners in the surveyed region along income, age, and education, although white homeowners are over-represented. The property-level risk measures in the FSF-FM and KatRisk models align with respondents' self-reported risk beliefs. We would not expect these relationships to hold if respondents were reporting spurious information based on fabricated addresses. These measures of survey quality are discussed further in Appendix Section D.

5 Estimating Sufficient Statistics for Welfare

In this section, I describe the methods and results for estimating the three sufficient statistics to calculate welfare with equation (5): The price effect, information effect, and adaptation effect.

5.1 Remapping, Take-Up, and Premiums

A challenge estimating the price elasticity of flood insurance demand is that different premiums can also imply different risk classifications, conflating the information and price effects. The NFIP's Newly Mapped Subsidy program, described in section 4.1, delays flood insurance premium increases for homes newly remapped into the floodplain for two calendar years, after which their rates increase

by approximately 15% annually, independent of risk.

I study how remapping affects flood insurance take-up and premiums for newly mapped properties using the sample of remapped counties described in section 4.1, with results shown in Appendix E. I find that the number of active newly mapped policies increases sharply in the two years after remapping before beginning to fall as the newly mapped premium subsidy fades.[6]

These results suggest a positive information effect with the initial increase in policies and a price effect from their subsequent relative decline with rising premiums. However, some newly mapped homeowners may have bought flood insurance to satisfy the federal mandatory purchase requirement with their mortgage, confounding the information effect. Other dynamics, such as decreasing salience of the new maps or poor enforcement of the mandatory purchase requirement, could also confound estimation of the price effect.

I return to the issue of identifying the information effect in section 5.2. Next, I describe how to separately identify the price effect from the remapped policy data.

5.1.1 Price Effect Estimation Strategy

Separating the price elasticity of flood insurance demand requires comparing newly mapped policyholders making renewal decisions but facing different premiums. The phase-out of the Newly Mapped Subsidy is based on the number of *calendar years* when the home was first remapped into the floodplain, rather than the number of months. Providing ideal empirical variation, this means that two homeowners remapped into the floodplain around the same time may face different premiums at renewal.

To illustrate, consider a "homeowner A" mapped into the floodplain in October 2015 who buys flood insurance under the Newly Mapped Subsidy in January 2016. When they decide whether to renew in January 2017, their premium will be 15% higher because the flood map will be two (calendar) years old. By contrast, consider a "homeowner B" mapped into the floodplain in January 2016 who buys flood insurance in April 2016. When they decide whether to renew in April 2017, their premium will be unchanged because their flood map will only be one (calendar) year old. Thus, at their first renewal homeowner A has a 15% higher premium than homeowner B even though they were both remapped into the floodplain around the same time.

I identify the price elasticity from the relative renewal probabilities of homeowner A versus homeowner B. The estimating equation is:

[6] In a broader and more empirically rigorous analysis of the effect of remapping on flood insurance take-up, Weill (2022) reaches similar conclusions as the results in Appendix Section E. Weill (2022) also reports findings suggestive evidence of the information effect and the importance of the mandatory purchase requirement, two key mechanisms that are more precisely identified here.

$$Renew_{iqt} = \alpha_{qt} + \beta X_{iqt} + \sigma \Delta P_{iqt} + \epsilon_{iqt} \tag{6}$$

where $Renew_{iqt}$ is an indicator variable for whether policy i originally written in year q under the Newly Mapped Policy renews in year t. The equation includes originally written year by renewal year interacted fixed effects and additional controls. Standard errors are clustered by county.

ΔP_{iqt} is the percent increase in premiums according to the Newly Mapped Subsidy schedule. ΔP_{iqt} will vary across policies written within the same year based on whether the map was updated earlier in the same year versus the end of the previous calendar year. σ is the price elasticity of flood insurance demand, or the change in the probability of renewal from a 1% increase in premiums. The key identifying assumption is that the policies with different underlying map years but written in the same year would have had the same propensity to renew, absent their different premium changes.

5.1.2 Price Effect Results

Table 1 shows the results from estimating Equation (6). The baseline specification, with only first policy year by renewal year interacted fixed effects, suggests that a one percent premium increase decreases the probability of renewal by 0.15 percentage points. Subsequent columns add increasing controls: State fixed effects, controls for the past two years of claims in the renewing policy's county, and fixed effects for the month of year written. Across all of these specifications, the renewal elasticity remains around 0.17.

The results in Table 1 suggest that flood insurance demand is inelastic, a finding similar to other estimates which have found elasticities of 0.25 and 0.29 (Bradt et al., 2021; Wagner, 2021). Part of the reason for the generally low elasticity of flood insurance demand found here and elsewhere in the literature may be because some policyholders cannot drop their coverage due to the mandatory purchase requirement associated with their mortgage. In section 5.2.3, I adjust the estimated price elasticity for the share of mandatory purchasers from the survey data described in section 4.2.

5.2 Information Effect

This section uses evidence from the flood insurance demand survey to identify the information effect. Higher flood insurance take-up observed inside the floodplain may be driven by both differences in risk perceptions and the mandatory purchase requirement for floodplain mortgages. Thus, although we identified the price elasticity of flood insurance demand using premium variation from the newly mapped subsidy, aggregate take-up rates from the policy data cannot separately identify the information effect.

An innovation of my survey is that it measures flood insurance demand independent of lender purchase requirements and includes rich measures of objective flood risk and demographics. To estimate the information effect, I will use the survey data to compare the voluntary flood insurance purchase by floodplain homeowners against homeowners with similar risk who have been misclassified outside the floodplain. The difference in take-up inside and outside the floodplain will be a combination of both the positive information effect and the negative effect of higher premiums inside the floodplain. I will use the price elasticity estimated in the previous section to back out the information effect from the net take-up results. The survey also measures how floodplain classification affects beliefs about current and future risk.

5.2.1 Voluntary Flood Insurance Demand Methodology

The treatment effect of interest is how being inside the floodplain changes voluntary flood insurance demand relative to being outside the floodplain, conditional on flood risk. The estimating equation is:

$$VoluntaryInsured_{iz} = \alpha_0 + \beta_0 X_i + \beta_1 RISK_i + \beta_2 Floodplain_i + \epsilon_{iz} \tag{7}$$

where $VoluntaryInsured_i$ is an indicator variable for respondent i voluntarily buying flood insurance (i.e. not due to a mandatory purchase requirement) as measured by the survey. X_i is self-reported controls for log income, education, risk preferences, liquidity, sex, age, time in home, political party affiliation, and mortgage status. $RISK_i$ is a set of flood risk controls: flood zone type[7], an indicator for whether the respondent reports their home being previously flooded, and the average 500-year flood depths from the two risk models minus the estimated first floor height in the FSF-FM model. The total floodplain voluntary take-up effect identified by β_2 in Equation 7 is the sum of the negative price effect from higher premiums and any information effect of risk salience from floodplain designation. This total demand effect is the relevant welfare parameter for the sufficient statistics welfare model as it gives the difference between I^0 and I^1 in Equation 5.

The identification assumption in Equation 7 is that, conditional on the risk controls, differences in voluntary take-up between floodplain and non-floodplain homes are driven by differences in their premiums and flood risk perceptions rather than their actual flood exposure. Figure A1 plots the models' average 500-year flood depth minus estimated first floor elevations among survey respondents outside the floodplain (blue) and inside the floodplain (grey). We do see that homes inside the

[7]Categories are "non-floodplain" (omitted category), 500-year X zones (non-floodplain homes with higher risk but without any change to premiums or regulations). SFHA homes can be mapped into lower-risk floodplains (A, AH, AO zones) that have lower premiums that do not vary as much with elevation.

floodplain have higher risk on average than those outside it, albeit with substantial overlap between the two groups.

Although the risk controls in Equation 7 adjust for these differences, endogeneity concerns remain if there are differences in risk between floodplain and non-floodplain homes that are also observed by the homeowners but not by the risk models. To address this concern, I use the NFIP's own estimates of where the floodplain is incorrect according to its new Risk Rating 2.0 (RR2) premiums. As described in Section 4, RR2 is a new model developed by FEMA that uses catastrophe risk models and rich geospatial data trained on historical flood insurance claims to set flood insurance premiums.

Rather than assuming that the third-party risk models are "right" and the flood maps are "wrong," RR2 premiums provide an ideal ex-post measure of where the floodplain has systematically excluded high-risk properties. The RR2 model is based on the NFIP's own data, capturing the same features that go into determining the floodplain boundaries. But, like the FSF-FM, it also captures differences in risk caused by rainfall-driven flooding and smaller bodies of water, does not imply a sharp change in risk at the floodplain boundary, and reflects variation in risk outside the floodplain. In short, RR2 reflects the NFIP's own internal estimate of where high-risk properties are outside the floodplain.

My measure of risk according to RR2 is the average full RR2 premiums by zipcode, reflecting the average premium that will be paid by existing policies once all of their remaining subsidies phase out. Figure 3 shows the zipcode-level binscatter of log RR2 premiums against the share of properties inside the floodplain in 2020 according to the First Street Foundation. There is a strong, linear, and positive relationship between floodplain share and RR2 premiums. However, this average relationship masks substantial heterogeneity in RR2 premiums between zipcodes with similar floodplain shares.

I construct a zipcode-level index of mismapping as the residuals from the following specification:

$$Ln(RR2_z) = \alpha_0 + \beta_1 FloodplainShare_z + \beta_2 FloodplainShare_z^2 + \mu_z,$$

where the dependent variable is the log full RR2 zipcode premium and the independent variables are a quadratic of the share of properties in the zipcode inside the floodplain as of 2020. The regression is weighted by the number of properties with non-zero flood risk (i.e. FloodFactor greater than 1) according to the FSF-FM. $\widetilde{\mu_z}$ gives the "mismapping index" of zipcode z, where $\widetilde{\mu_z} > 0$ indicates higher RR2 premiums relative to other zipcodes with a similar share of properties inside the floodplain.

I use $\widetilde{\mu_z}$ as an instrument in the following first stage:

$$Floodplain_{iz} = \alpha_0 + \gamma_0 X_i + \gamma_1 RISK_i + \gamma_2 Ln(RR2_z) + \gamma_3 \widetilde{\mu_z} + \epsilon^1_{iz}, \tag{8}$$

leading to the second stage:[8]

$$VoluntaryInsured_i = \alpha_0 + \beta_0 X_i + \beta_1 RISK_i + \beta_3 Ln(RR2_z) + \beta_3 \widehat{Floodplain}_{iz} + \epsilon^2_{iz}. \tag{9}$$

The exclusion restriction requires that $\widetilde{\mu_z}$ is uncorrelated with unobserved determinants of flood insurance demand. Supporting this assumption, the NFIP designed RR2 around predicting losses, not maximizing revenue or flood insurance take-up. Meanwhile, RR2 premiums were not available to homeowners at the time of the survey.[9] In Figure A2, we see no statistically significant relationships between $\widetilde{\mu_z}$ and survey measures of income or prior flood experience.

All standard errors are clustered by zipcode, with 500 bootstrap samples in the instrumental variable specifications.

5.2.2 Voluntary Flood Insurance Demand Results

Table 2 shows the results from estimating equation (7). In column (1), we use having flood insurance, whether required by their lender or not, as the outcome variable and condition on demographic but not risk controls. Homeowners inside the floodplain are 35 percentage points more likely than their non-floodplain counterparts to have flood insurance. In column (2), we instead use our voluntary demand measure as the outcome variable instead and find that the take-up gap shrinks to only 20 percentage points. The difference between the floodplain coefficients in columns (1) and (2) show that without a measure of voluntary flood insurance demand, comparing take-up rates inside and outside the floodplain will overstate differences in demand.

The results in column (2) show that higher take-up inside the floodplain is not entirely driven by the lender flood insurance requirement. To test whether it can be explained by differences in risk, column (3) adds the model flood depth, zone type, and past flood controls. Even adjusting for these differences in risk, floodplain homeowners are 17 percentage points more likely to demand flood insurance. These results are surprising given that floodplain respondents reported paying $1,100 per year higher flood insurance premiums than their non-floodplain counterparts (Table A1).

Column (4) applies the mismap index to instrument for floodplain status. The first stage has a

[8] In Equations 8 and 9, the $RISK_i$ terms omit the floodzone-type variables because that would create multiple endogenous variables with only one instrument. Results are similar when I include the floodzone types as exogenous regressors.

[9] As of writing, the NFIP still does not have a publicly available calculator where homeowners can calculate their RR2 premium.

strong F-state of 160. The IV specification shows that floodplain designation induced by systematic mismapping in a respondent's zipcode causes them to be 21 percentage points more likely to demand flood insurance, similar to the OLS results in columns (2) and (3).

Table A2 shows the results of a number of robustness checks. Relative to the baseline results, the floodplain coefficients are little changed when adding a quadratic model flood depth term, dropping SFHA properties with less than 1% annual chance of flooding, or using the "Obviously Related Instrumental Variable" (ORIV) technique to address risk model measurement error by using the FSF-FM and KatRisk model depths as instruments for each other in a stacked regression (Gillen et al., 2019). Furthermore, there is no statistically significant difference in the floodplain coefficient estimates for properties with versus without a mortgage, suggesting that the results are not driven by imputing voluntary demand for mandatory buyers.

5.2.3 Information Effect: Current and Future Risk Beliefs

The results above show that, despite their much higher premiums, floodplain households are more likely to voluntarily buy flood insurance than non-floodplain homeowners with similar risk. We can use the flood insurance price elasticity estimate in Table 1 to infer the size of the information effect by netting out the effects of the higher premiums inside the floodplain from the take-up effects estimated in Table 2.

Using column (3) of Table 2 as our take-up effect estimate, voluntary flood insurance take-up for non-floodplain homeowners in the survey data would be approximately 43% instead of 26% if they were mapped inside the floodplain. This 17 percentage point increase includes both a positive information effect and a negative price effect. To isolate the information effect, I calculate how much higher the floodplain take-up rate would be if premiums remained fixed. Using the estimated price elasticity adjusted for the mandatory purchase requirement of 0.37 (Appendix Section F). Under an isoelastic demand curve, this implies that voluntary floodplain take-up would be approximately 58% if premiums remained at the non-floodplain average of $530 instead of increasing to the floodplain average of $1,330. Thus, the information effect, holding premiums fixed, would increase flood insurance demand by over 30 percentage points.

For direct evidence of the information effect, Table 3 reports the results of estimating Equation 7 with the dependent variables as each of the six flood risk perception and insurance demand proxies elicited in the survey. Conditional on modeled risk, past flood experiences, and demographic covariates, participants inside the floodplain have statistically and economically significantly higher perceptions of their chance of flooding in the next ten years, self-reported and incentivized flood insurance willingness-to-pay, and are more worried about a flood. Floodplain status is associated with

a positive albeit statistically insignificant increase in expected flood damages and a lower likelihood of reporting that a flood is too unlikely to be worried about at the 10% level of significance. These results indicate that floodplain status increases the perceived likelihood of flooding across a range of measures.

Next, we estimate how floodplain classification shifts homeowner's beliefs about their future risk. Given the correlation between current risk and projected future risk according to the FSF-FM, floodplain classification may also affect future risk perceptions. To estimate how risk classification affects future risk perceptions, I re-estimate Equation (7) with a binary indicator for whether the respondent believes their flood risk will be higher in 30 years. I include controls for political affiliation, flood zone types, and an indicator that equals 1 if the FSF-FM predicts that the property's average annual loss will be higher in 30 years.

Table 4 shows that floodplain respondents were 12.5 percentage points more likely to believe their flood risk would be higher in 30 years, a 29.4% relative increase from the non-floodplain baseline rate of 42.5%. In column (2), I interact political affiliation with the floodplain indicator to test for treatment effect heterogeneity. I find no economically or statistically significant variation in the floodplain effect across political groups, although Republican and politically disengaged homeowners are less likely to believe their risk is increasing than Democratic homeowners, whether inside the floodplain or not.

5.3 Adaptation Effect

This section estimates the adaptation effect, or the difference in expected losses inside and outside the floodplain for homes facing the same flood. The NFIP promotes investment in adaptive home elevation through two channels. First, floodplain homes must be built to at least the flood map 100-year flood depth. Second, elevated floodplain homes pay substantially lower premiums. As illustrated in Figure A3, a floodplain home just meeting the minimum 100-year flood depth elevation pays three times premium of a home elevated three feet higher. There are no such elevation requirements or premium incentives outside the floodplain.

5.3.1 Adaptation Effect: Methodology

Estimating the adaptation effect faces two challenges. First, there is no data on the elevation of homes outside the floodplain. To address this obstacle, one could estimate the adaptation effect using the difference in claims between floodplain and non-floodplain homes. However, this would conflate differences in adaptation with differences in underlying risk. My approach compares the claims of policies already inside the floodplain ("floodplain-built") against homes in the same census

tract newly mapped into the floodplain ("remapped") between 2010-2019. Despite facing similar risk according to the most up-to-date flood maps, remapped homes were constructed without the floodplain incentives to elevate. Furthermore, when homes are remapped into the floodplain, it will be difficult for them to adjust their elevation because elevating an existing home can cost well over $100,000 (Dawson Foundation Repair 2021).[10]

Although remapped homes still do not have elevation data, comparing their claims against those of floodplain-built homes will be less biased by differences in underlying risk. Nonetheless, these homes may still be in different parts of the floodplain with different risk, even within the same census tract. To adjust for any residual confounding variation in underlying risk, I use a difference-in-difference approach with "pre-map" homes built before the floodplain boundaries were drawn. Most communities received their first flood map in the 1970s or 1980s as they joined the NFIP. Floodplain homes built before a community's first map received subsidies and rates that were independent of their elevation. Given that these homes had no incentives to elevate at construction, the difference between the claims of pre-map homes inside and outside the remapped part of the floodplain will reflect differences in risk between those areas.

It is instructive to consider the visualization of this identification strategy in Figure 4. In period 1, two pre-map homes A and B are built near the water (in blue) before any flood maps are drawn. In period 2, a flood map line is drawn (dashed blue line) placing home A inside the floodplain and home B outside it. In period 3, two post-map homes are built: home C inside the floodplain and home D outside the floodplain. In period 4, the floodplain boundary is redrawn so that homes B and D are now also inside the floodplain. We observe claims data whenever a flood occurs sometime after period 4 in this example. In this simple framework, the adaptation effect would equal:

$$(C - D) - (A - B)$$

where A is the claims of home A, B the claims of home B, and so on.

Wagner (2021) and Ostriker and Russo (2022) use a related approach to identify the adaptation effects of introducing minimum elevation standards. Using the terminology above, those authors identify an adaptation effect as $(C - A)$ for a post-map home C and pre-map home A built just after and just before a flood map was introduced. This discontinuity-in-time approach identifies local adaptation treatment effects for homes built as flood maps were introduced in the 1970s and 1980s, whereas my empirical strategy can identify adaptation treatment effects for newer construction

[10]Flood adaptation includes other investments such as flood vents, sump pumps, or raising utilities. Although these are not incentivized through NFIP premiums, insofar as newly mapped households respond along these margins too, my estimates will understate the adaptation effect. However, Ge et al. (2022) finds that existing homes do not respond to higher flood insurance premiums with significant investments in adaptation.

too. To see this point, consider that the difference-in-difference expression can be rearranged as $(C-A)-(D-B)$. The $(D-B)$ term adjusts for time trends in adaptation (i.e. with year built fixed effects) that may otherwise bias adaptation estimates when homes C and A were built in different years.

To construct my estimation sample, I identify census tracts with both newly mapped and floodplain-built policies that experienced large floods, or "loss events." I measure loss events by the total flood insurance claims on a single day in a single county. I subset the data to the 598 largest county loss events between 2010 and 2020, yielding a sample of 1,279 census tracts that account for about 85% of total claims over the period.[11] The estimation sample consists of the 192,987 policies with 44,088 claims. To address the excess mass of zeroes and skewed distribution of claims (see Figure A4), I use a hurdle model. The first stage of the model estimates the probability of having a claim in a linear probability model, and the second stage estimates the size of the log claim conditional on having a claim.[12]

The first stage of the hurdle model is given by:

$$I[Claim > 0]_{iqL} = \alpha^1_{qL} + \beta^1_0 X_i + \beta^1_1 Post_i + \beta^1_2 Remapped_i + \beta^1_3 Post_i X FloodplainBuilt_i + \epsilon_{iqL} \quad (10)$$

and the second stage by:

$$ln(Claim)_{iqL} = \alpha^2_{qL} + \beta^2_0 X_i + \beta^2_1 Post_i + \beta^2_2 Remapped_i + \beta^1_3 Post_i X FloodplainBuilt_i + \mu_{iqL} \quad (11)$$

In the equations above, i indexes policies, q census tracts, and L loss events. Standard errors are clustered by loss event. α_{qL} are the census tract by loss event interacted fixed effects, and X_i is a vector of fixed effects for the year the home was built, deductible, and the amount of coverage purchased in \$10,000 increments. $Post_i = 1$ for homes built after a census tract's first flood map, while $Remapped_i = 1$ for homes identified as "Newly Mapped" preferred risk policies in the data.

The β_1 coefficients control for differences in risk between pre-map and post-map homes built outside the flodoplain and remapped in later, while β_2 controls for differences in risk between the parts of each census tract already inside the floodplain versus those that were remapped inside later. The adaptation effect – the difference in claims driven by being built inside the floodplain – is identified by the β_3 coefficient on the interaction between the post-map and floodplain-built

[11] Results are similar when I expand the set of loss events to cover 95% of total claims.
[12] Results are similar when I estimate the first stage with a fixed effects logit model.

indicators.

5.3.2 Adaptation Effect: Results

Table 5 shows the results of the floodplain adaptation effect from estimating equations (10) and (11), where the first and third columns estimate the probability of having a claim and the second and fourth columns estimate the size of the log claim conditional on having one.

The specification in the first two columns shows the estimated adaptation effect as indicated by the coefficients on the post-map and floodplain-built interaction term. In the first column, there is little difference in the probability of having a claim between floodplain-built homes and those that were remapped into the floodplain after construction. The coefficient on the interaction term in the second column shows that floodplain-built homes have 27% lower losses conditional on having a claim than their remapped counterparts.

The results in the first two columns show the pooled adaptation effect across cohorts built at different times. For our welfare counterfactual, we are interested in the treatment effect specifically for relatively new construction. The second specification in the third and fourth columns explores the dynamics of the adaptation effect with a triple interaction of the Post and floodplain-built indicators with the time when the house was built (1975-1984,1985-1994,1995-2004, and 2005-2020). As in the first column, the third column shows little impact of being floodplain-built on the probability of having a claim. The fourth column shows a large decrease in expected claims for post-map homes remapped into the floodplain, a trend that is increasing for newer construction. Floodplain-built homes constructed between 1975 and 1984 have 20% lower expected claims than their remapped counterparts, whereas those built between 2005 and 2020 have 37% lower claims.

FEMA's rate manuals show that the premium gap between floodplain homes with higher and lower elevations increased after 2005 — the same vintage of construction where we see the largest adaptation effects. Although the estimates in Table 5 do not separate the information and premium incentives component of the adaptation effect, the coincidence between the trend of increasing elevation premium discounts and increasing elevation relative to remapped homes that were built without these incentives suggests that prices motivated adaptation investment.

One explanation for the difference in adaptation between floodplain-built and newly mapped homes is the minimum elevation standards, as shown to result in lower claims for homes built in the 1970s and 1980s across several studies (Hovekamp and Wagner, 2023; Ostriker and Russo, 2022; Wagner, 2021). If we observe many homes in the data only elevating to the minimum NFIP requirements, then this would suggest that the adaptation effect is mostly driven by the mandatory requirement. Conversely, if homes adapt beyond the minimum standards, it suggests that the adaptation effect is

driven by the flood map information and premium incentives and welfare improving.

Examining the distribution of floodplain elevations, 90% of floodplain-built properties in the estimation sample are elevated more than a half-foot above the 100-year flood minimum elevation. This suggests that for a large majority of homes the minimum elevation standard is not binding. To provide further evidence on the role of mandatory versus voluntary adaptation, I infer the first floor elevations of newly mapped policies by re-estimating equations (10) and (11) with indicator variables for the elevations of floodplain-built homes above the 100-year minimum elevation as dependent variables. Figure A5 shows the results of this estimation, where the top panel shows the results for the probability of having a claim, and the bottom panel shows the results for log claims conditional on a positive claim. The figures plot the coefficients of each half-foot elevation indicator with newly mapped properties as the omitted category (labelled as "remapped" in the figure).

In both models, newly mapped properties' average claims were similar to those of floodplain-built properties one to two feet above the 100-year flood elevation. This provides further evidence that the minimum elevation requirement was not binding in newly mapped areas. This evidence suggests that we can attribute most of the adaptation effect to risk-rated premiums and information rather than the minimum elevation requirement.

One concern about the adaptation results is that they may be biased by asymmetric information. I only observe the claims of insured properties, so differential adverse selection between remapped and floodplain-built properties could bias adaptation estimates. As remapped premiums are uniformly low under the Newly Mapped Subsidy, we would expect any adverse selection to cause lower-risk floodplain-built homes to go uninsured, understating the adaptation effect. To directly test for adverse selection, I conduct a positive correlation test as described in Chiappori and Salanié (2000). The positive correlation test assesses whether expected losses and insurance coverage are independent conditional on the information used by the insurer to set premiums. The test proceeds by estimating two models: the first with coverage choice as the dependent variable and the second having a claim. Both specifications include controls for the covariates used by the insurer to determine premiums. Under the null hypothesis of no asymmetric information, the residuals of these two models will be uncorrelated. Although I cannot compare the losses of homes with and without insurance, I can compare the claims of homes that do and do not choose to supplement their standard flood insurance policy with voluntary contents coverage. The dependent variable in the first model is choosing non-zero contents coverage; in the second it is having a claim on their primary structure coverage. Whereas the null hypothesis in a traditional positive correlation test can be rejected due to moral hazard as well as adverse selection, a benefit of my specification is that contents coverage is unlikely to induce moral hazard on structural damage claims, making it a plausibly pure test of

adverse selection. The controls are property elevation by flood zone type indicators and the number of stories in the insured home.

In the data, 75% of floodplain-built homes in the sample opt-in to contents coverage. The share of homes with structure claims is actually slightly *lower* for homes with contents coverage, at 19%, compared to 19.4% of homes without contents coverage. The formal positive correlation test bears out the absence of adverse selection in this raw data.[13] These findings are consistent with Wagner (2021) who also finds no adverse selection in flood insurance.

6 Welfare

This section embeds the sufficient statistics estimated in section 5 to equation 5 to calculate the welfare effects of identifying and pricing high flood risk homes. First, I describe the calibration of each welfare parameter. Then, I describe the welfare effects of risk classification, and extend the results to different pricing and information provision counterfactuals.

6.1 Fitting Empirical Estimates to Model Parameters

Below, I describe the empirical counterparts for the welfare parameters in equation (5). Table 6 summarizes the welfare parameters and their sources.

Premiums and Flood Insurance Take-Up Rates Outside (I^0) and Inside (I^1) the Floodplain:

In the survey data, the flood insurance take-up rate for non-floodplain homeowners is 25.7% (I^0). I^1 is the counterfactual take-up rate if all of the non-floodplain homes in our data were mapped inside the floodplain instead, which we estimated using the survey data in Section 5.2. We add the floodplain coefficient in column (3) of Table 2 to I^0 to get our baseline estimate of the counterfactual voluntary take-up rate, $I^1 = 42.7\%$.

The results in Table 2 show that even more homeowners would involuntarily purchase flood insurance under the mandatory purchase requirement. We ignore the mandatory purchase effect in the welfare counterfactuals, effectively treating the take-up effect of these extra buyers as welfare neutral. The welfare effects of the mandatory purchase requirement would depend on whether correctly risk rated homeowners make fully rational insurance decisions, a point we return to in later welfare counterfactuals.

[13] The chi-squared test statistic p-value is 0.867.

We use the policy data of zipcodes where homes were remapped into the floodplain between 2015 and 2019 (Section 4.1) to calibrate average premiums. We calibrate P^0 as the average non-floodplain premium in the year before remapping ($530) and P^1 as the average floodplain premium in the year before remapping ($1,330). We assume that P^1 reflects the expected loss of floodplain properties in these areas when they adapt at levels A^1.

Price Elasticity of Flood Insurance Demand

The premium coefficient in column (4) of Table 1, estimated from variation in the Newly Mapped Subsidy as described in Section 5.1.2, implies a flood insurance price elasticity of 0.177. However, as documented in our survey data, a substantial number of flood insurance policyholders are required by their lenders to hold flood insurance and thus would not have been able to drop their coverage even as the cost rose above their willingness-to-pay. As a result, the estimated premium elasticity in Table 1 is attenuated relative to the true price elasticity of flood insurance demand. I use the share of mandatory flood insurance buyers in my survey data to calculate a mandate-adjusted price elasticity, as described in section F, of 0.37.

I calibrate the isoelastic flood insurance demand curve $W(I)$ to have a constant price elasticity of 0.37 and so that $W(I^1) = W(0.427) = P^1 = 1330$.

Adaptation Effect

The difference-in-difference results in Table 5 imply that remapped homes suffer 36.8% higher flood damages than their counterparts that were built in the floodplain. This implies that D_0^0 (the expected losses of homes outside the floodplain at $t = 1$) is equal to $P^1 * 1.368 = 1330 * 1.368 \approx 1820$. The relevant counterfactual expected loss for the welfare gains of correctly classifying new homes is the difference in expected losses for the most recent vintage of homes, where we see an even larger 55% gap. I parameterize the counterfactual adaptation effect on homes being built today as $A^1 = 0.354 (\approx 1 - \frac{1}{e^{0.437}})$. This implies that the expected loss of new homes built inside the floodplain at $t = 0$ is $A^1 * 1820 \approx 1175$. This also implies that P^1 for new homes is 1175.

Dynamic Risk and Perceptions

My framework estimates welfare in a dynamic setting where flood risk is expected to increase over time and where homeowners are choosing their adaptation based on their future risk expectations that are endogenous to risk classification. We calibrate future flood damages from the First Street Foundation Flood Model (FSF-FM) described in Section 4.2. I use the FSF-FM's projections for the approximately 1 million homes in Florida with at least a 1% annual chance of flooding, comparing

their annual flood losses (AAL) in 2020 and 2050. Over this period, the high-risk AALs increase 79%. Assuming linearly increasing risk, this is an annual growth rate of 2.6% of the 2020 AAL ($\gamma^1 = .026$). Figure A6 plots 2020 and 2050 AALs for high-risk and low-risk properties. In contrast to the sharp increase in expected losses for already high-risk properties, low-risk homes see a muted increase from \$5 in 2020 to \$90.[14] The relatively flat AAL trajectory of low-risk homes justifies assumption 1, which holds that low-risk homes' expected losses will remain constant over time.

The results on the effects of risk classification on future flood risk beliefs in Table 4 show that only 42.5% of high-risk homeowners outside the floodplain believe their flood risk relative to 55% of floodplain homeowners with similar future risk. We use this estimate to calibrate γ^0, the perceived risk growth rate for misclassified high-risk homeowners, as $\frac{42.5}{55} * 0.026 = \gamma^0 = 0.02$.

6.2 Welfare Counterfactual Results

New and Existing Homes

First, I calculate the welfare effects of correctly classifying a home built in 2020 as high-risk versus misclassifying it as low-risk, as given by Equation 5. We consider the present value welfare gains over 30 years (2020-2049).

Using the calibrated parameters from Table 6, we can write the present value welfare benefit of correctly classifying a new home as high-risk in period t:

$$\begin{aligned} E[\frac{dTW_{it}}{df_i}] =& 0.99^t(1+0.026) * t(\overbrace{0.3 * 0.254(1820-530)}^{\text{Public Funds}} + \underbrace{\frac{1820}{1175}\int_{0.254}^{0.427}(W(I)-1330)dI}_{\text{Take-Up}} \\ &+ \frac{1}{2}(\underbrace{0.354(1-0.427)t * (1+0.026-0.02)(1820-530)}_{\text{Self-Protection}} + \overbrace{0.354 * 0.427 * 1820}^{\text{Moral Hazard}})) \end{aligned} \tag{12}$$

Figure 5 shows the undiscounted annual welfare gains of risk classification over 30 years for each term in Equation 12. The figure underscores the importance of accounting for dynamic risk in disaster insurance counterfactuals. While the welfare benefits of risk classification are approximately \$685 in 2020, that figure nearly doubles by 2050. Assuming that flood risk remains constant would underestimate the welfare benefits of risk classification by 26%.

Table 7 shows the present value 30-year welfare gains of high-risk classification relative to mis-

[14] For low-risk homes built on ground with at least a 0.2% annual chance of flooding, AALs increase from \$10 in 2020 to \$125 in 2050.

classification across different counterfactuals in each column and for each of the four welfare terms in each row. Row 1 shows that the welfare gain from correctly classifying a new high-risk home is $24,840, or over 5% of the median home value in 2020. The decomposition of this welfare gain into its components emphasizes the importance of endogenous beliefs and adaptation. If one assumed that flood insurance demand and adaptation investment are fixed, thus ignoring the take-up, self-protection, and moral hazard terms, then the welfare benefits of risk classification would be 85% lower.

In column (2) of Table 7, we consider the welfare gains from reclassifying existing misclassified homes as high-risk. Under this counterfactual, $A^1 = 0$ given the high cost of elevating existing homes as discussed in Section 5.3. The present value welfare gain of reclassifying an existing misclassified home is $14,800. Contrasting the new and existing home counterfactuals shows the importance of getting risk classification correct at construction before adaptation is fixed. The First Street Foundation estimates that approximately 6 million high-risk homes are currently misclassified outside the floodplain, implying from our results that remapping these homes inside the floodplain would increase present value social welfare by approximately $89 billion over the next 30 years.

Although the aggregate welfare gains of risk classification are large, they may have distributional consequences. An owner of a misclassified high-risk home that is reclassified as high-risk would face $23,000 higher present value premiums over the next thirty years. However, reclassification also creates benefits for misclassified homeowners because it gives them information to make better insurance decisions. The value of this information, represented by the take-up welfare term, creates a $11,200 present value benefit, offsetting but not eliminating the cost of higher premiums. In addition, if the perceived higher future risk of a reclassified home capitalizes into its price, the homeowner will be even further worse off. However, these homeowners' losses are transfers to future buyers and taxpayers, and, as the welfare calculations show, social welfare is higher with better risk information.

Risk Classification as Climate Adaptation

We estimate how risk classification affects the cost of rising flood risk. We define climate costs as the reduction in annual welfare in 2050 relative to 2020 due to the change in flood risk.

First, consider the climate costs of a correctly classified new high-risk home. Climate costs to an insured household are the change in premiums, which equal the change in expected losses. Uninsured households, by the first order condition, are risk neutral and thus also suffer the change in expected losses. Higher risk has no deadweight loss of public funds because premiums equal expected claims. Thus, climate costs for a correctly classified high risk household are:

$$C^1 = \overbrace{A^1 * 30 * \gamma^1 * R^1}^{\text{Physical Damages}} \quad . \tag{13}$$

That is, climate costs equal the increase in expected losses in 2050 relative to 2020.

Next, we turn to climate costs for a misclassified high-risk household:

$$C^0 = 30 * \gamma^1 * \big(\overbrace{R^1}^{\text{Physical Damages}} + \underbrace{R^1 \int_{I^0}^{I^1} W(I) - 1 \, dI}_{\text{Uninsured Risk}} + \overbrace{\lambda(1 + \gamma^1 - \gamma^0)(R^1 - \overline{P})}^{\text{Public Funds}} \big). \tag{14}$$

Equation 14 shows that misclassification introduces two additional climate cost terms: uninsured risk, reflecting risk-averse households who suboptimally forgo insurance, and the public funds, which is driven by the deadweight loss of raising additional funds as risk and premiums continue to diverge.

Table 8 expresses the flood climate costs in 2050 relative to 2020 for correctly classified and misclassified high-risk homeowners. As shown in the first column of the table, annual climate flood costs for correctly classified high-risk homes are $890, equal to the increase in expected annual losses.

The second column of Table 8 shows climate costs for owners of misclassified high-risk homes. Due to their lower adaptation, 2050 annual physical climate costs are $480 higher for misclassified than correctly classified high-risk homes. In addition to higher physical losses, some uninsured misclassified households are not risk neutral, creating an "uninsured risk" climate cost of $240. Second, the subsidized premiums of insured high-risk homeowners creates a fiscal climate cost of $80.

In total, the climate costs of misclassified high-risk households in 2050 are $1,690, nearly double the climate costs of their correctly classified counterparts. Achieving a similar reduction in climate costs as risk classification would require reducing the expected growth rate of flood risk from 2.6% to 1.4% of 2020 AALs per year. The decomposition of climate costs in Table 8 emphasizes that the climate costs of flood risk are greater than the increase in expected losses in the presence of information frictions and fiscal externalities.

Unbundling Price and Risk Signals

High-risk classification combines pricing a home's premiums at its expected loss and releasing a public signal of its risk. In the counterfactuals below, we consider the welfare effects of pricing high-risk properties without the information signal ("risk-rating only"), or releasing information without risk based premiums ("information only"). These counterfactuals may be relevant under the NFIP's Risk Rating 2.0 reforms, which risk rate premiums but do not release granular information on

the underlying risk (Mulder and Kousky, 2023). Conversely, were Risk Rating 2.0 rolled back or augmented with premium subsidies, the continuing proliferation of flood risk data may nonetheless lead to better informed homeowners but with continuing subsidies (Fairweather et al., 2023).

The empirical welfare parameters were estimated from the bundled classification counterfactual. Thus, these counterfactuals require two additional assumptions:

- High-risk homeowners have the same price elasticity regardless of risk classification (i.e. risk information shifts but does not rotate the flood insurance demand curve).
- With risk-rating only, insured homeowners will adapt at A^1 and uninsured homeowners will adapt at A^0. With information only, uninsured homeowners will adapt at A^1 and insured homeowners will adapt at A^0.

With these additional assumption, we first consider the risk-rating only counterfactual. One difference between the risk-rating only and full risk classification is that take-up is lower ($I = 0.16$) rather than higher without any information effect to offset the price effect. As a result, risk based pricing exacerbates rather than ameliorates information frictions from misclassification, paralleling findings in Wagner (2021).

The third column of Table 7 describes the welfare effects of adjusting premiums but not information for a new high-risk home. We see that the aggregate effects of risk-rating only is to *decrease* present value welfare by $35,750. This is driven primarily by the negative take-up effect term, and only partially offset by positive public funds and moral hazard welfare benefits.[15] There is no self-protection adaptation benefit because uninsured households are unaffected by the premium change and receive no new information that would cause them to invest in adaptation. In short, pricing risk without providing correct information can backfire by exacerbating the information frictions created by inaccurate flood maps.

Next, we consider the information only counterfactual. Providing information while keeping premiums subsidized increases voluntary take-up ($I = 0.674$). As shown in the fourth column of Table 7, the information only counterfactual improves present value welfare by $8,400. This value is only $\frac{1}{3}$ of the potential welfare benefits from bundling information and pricing reforms. This aligns with findings in Handel et al. (2019) that debiasing and risk based pricing are complementary policies in insurance markets. Although homeowners realize the full take-up and self-protection welfare benefits with information only, insured homeowners have no premium incentive to invest in adaptation, elim-

[15]The negative take-up welfare effect in Table 7 should be interpreted with caution given that it extrapolates the isoelastic flood insurance demand curve well below take-up levels observed in the data. The broader point that the take-up effect will be negative under a pricing only counterfactual and may outweigh the other welfare gains stands regardless of the exact magnitude.

inating any moral hazard benefits.[16] Furthermore, the increased take-up by subsidized homeowners leads to higher cost of public funds.

Internalities

The welfare model assumes that correctly classified high-risk homeowners make fully informed and rational decisions. However, recent research has shown evidence that homeowners may systematically underestimate their flood risk for a variety of behavioral factors (Wagner, 2021; Ostriker and Russo, 2022; Weill, 2022). When we add a general "internality" that reduces flood insurance demand, this increases the welfare benefits of risk classification.[17] Column five of Table 7 shows the welfare benefits of risk classification for a new home if high-risk homeowners' flood insurance demand is on average $1,000 below their privately optimal willingness-to-pay. The $36,070 welfare improvement with internalities is greater than the $24,840 benefit of classification without internalities. The higher gains are driven by higher take-up and self-protection benefits.[18] Thus, the assumption that correctly classified high-risk homeowners make unbiased insurance decisions leads to a conservative estimation of the welfare effects of risk classification. Another upshot is that, in the presence of internalities, accounting for the mandatory purchase requirement would further improve welfare. Accurate risk classification better targets the mandatory purchase requirement to biased buyers, aligning with findings in Weill (2022) and Ostriker and Russo (2022).

7 Conclusion

This paper finds that bundling risk-based pricing with public information signals for high-risk households in the National Flood Insurance Program (NFIP) creates large welfare gains by increasing flood insurance take-up and investment in adaptation to reduce risk. Risk classification can facilitate adaptation to climate change by providing valuable information to households about their current and future risk. This information can change insurance demand and adaptation by households exposed to increasing risk. In total, homeowners inside the floodplain are 17 percentage points more likely to buy flood insurance despite facing higher premiums, and elevated new floodplain homes have 35% lower expected losses. Correctly classifying a new high-risk home cuts its climate damages from increasing flood risk in half.

[16] As with mandatory buyers, we treat excess purchase of flood insurance due to low premiums as welfare neutral.

[17] Similar calculations hold for externalities, such as if leveraged homeowners strategically forgo flood insurance or homeowners substitute formal insurance for disaster aid (Kousky et al., 2018a; Liao and Mulder, 2021). Furthermore, we could also consider separate internalities that reduce adaptation investment (Hovekamp and Wagner, 2023).

[18] Following Kleven (2021), the internality take-up benefit is given by $(I^1 - I^0) * 1000$ while the self-protection benefit is $A^1 * (1 - I^1) * 1,000$.

Thus, this analysis suggests a silver lining to rising premiums in disaster-exposed areas. However, it also cautions that risk-based premiums are most effective at spurring climate adaptation when paired with information provision. Furthermore, such reforms can create large losses for the owners of existing homes that cannot be easily readapted. Open questions remain about the potential and limits of information provision in private versus public disaster insurance markets, and on the forces that shape the long-run adaptation of existing climate-exposed homes.

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Tables

	Probability of Renewal			
Premium Increase (%)	-0.148***	-0.172***	-0.172***	-0.177***
	(0.046)	(0.038)	(0.038)	(0.040)
Observations	78,174	78,174	78,174	78,174
R-squared	0.013	0.024	0.024	0.025
State FEs	N	Y	Y	Y
Past Claims Control	N	N	Y	Y
Month Written FEs	N	N	N	Y

*** p<0.01, ** p<0.05, * p<0.1

Table 1: Results from estimating the renewal probability of flood insurance policies newly mapped into the floodplain. The independent variable is an indicator variable for whether a policy renews. The dependent variable is the percent increase in the policy's premiums from the previous year under the Newly Mapped Subsidy schedule. All models include first policy year by renewal year interacted fixed effects. Additional controls, described in the bottom section of the table, are progressively added across columns from left to right. Standard errors are clustered by county.

	Insured		Voluntarily Insured	
	(1)	(2)	(3)	(4)
Floodplain	0.350***	0.201***	0.170***	0.214**
	(0.044)	(0.043)	(0.052)	(0.101)
Risk Model Flood Depth			0.017***	0.018***
			(0.005)	(0.006)
Past Flood			0.124*	0.117*
			(0.068)	(0.069)
Constant	-0.903***	-0.682**	-0.698**	-0.298
	(0.335)	(0.337)	(0.338)	(0.434)
Observations	703	703	703	703
R-squared	0.144	0.110	0.145	0.138
First-Stage F				159.517
Demographics	Y	Y	Y	Y
Flood Risk	N	N	Y	Y
Mismap Instrument	N	N	N	Y

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by zipcode and bootstrapped in column (4)

Table 2: Results from estimating flood insurance demand from the survey of coastal homeowners. In the column (1), the outcome is having flood insurance whether voluntarily or because of a lender requirement, and in columns (2)-(4) the outcome is voluntarily demanding flood insurance. Column (3) adds the average model 500-year flood depth relative to the home's first floor elevation in feet and flood zone type controls. Column (4) instruments for floodplain designation with the zipcode mismapping index. All models include controls for respondent income, liquidity, education, risk preferences, age, mortgage status, and time in home.

VARIABLES	(1) Flood Chance	(2) Damages	(3) WTP	(4) Incent. WTP	(5) Unworried	(6) Worry
Floodplain	6.486**	0.318	0.638***	0.721***	-0.084*	0.316**
	(2.846)	(0.230)	(0.137)	(0.171)	(0.050)	(0.153)
Risk Model	0.605**	0.040*	0.045***	0.020	-0.016***	0.025*
	(0.260)	(0.024)	(0.015)	(0.021)	(0.005)	(0.015)
Past Flood	21.010***	0.498**	0.604***	0.869***	-0.231***	1.277***
	(4.128)	(0.229)	(0.164)	(0.164)	(0.054)	(0.200)
Constant	52.258***	4.629***	4.246***	5.760***	1.027***	0.451
	(18.304)	(1.738)	(1.251)	(1.214)	(0.345)	(0.982)
Observations	703	703	703	703	703	703
R-squared	0.156	0.051	0.126	0.126	0.081	0.155
Demographics	Y	Y	Y	Y	Y	Y
Flood Risk	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Results from estimating the effect of floodplain status on flood risk perceptions. Outcomes from left to right are (1) % chance of being flooded in the next 10 years; (2) Log expected damages if home floods; (3) arcsinh transformed self-reported willingness-to-pay for flood insurance; (4) arcsinh transformed willingness-to-pay for flood insurance from incentivized elicitation; (5) If flooding is "too unlikely to be worried about" (below the threshold of concern); (6) Self-reported worry about flooding from 1 (not at all worried) to 5 (extremely worried). More details about flood risk perception elicitations are provided in Appendix Section G.1. Standard errors are clustered by zipcode.

VARIABLES	(1) Believes Risk Will Increase	(2)
Floodplain	0.125**	0.148*
	(0.053)	(0.083)
Modeled Risk Increasing	0.168***	0.167***
	(0.041)	(0.041)
Not very political	-0.112	-0.114
	(0.072)	(0.077)
Independent	-0.016	-0.006
	(0.048)	(0.056)
Republican	-0.162***	-0.160***
	(0.045)	(0.051)
Floodplain X Not very political		0.017
		(0.199)
Floodplain X Independent		-0.045
		(0.115)
Floodplain X Republican		-0.023
		(0.104)
Constant	0.584	0.515
	(0.369)	(0.383)
Observations	703	703
R-squared	0.109	0.111

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Results from estimating future flood risk beliefs from the survey of coastal homeowners. The dependent variable is a binary indicator for whether the respondent believes their flood risk will be higher in 30 years. "Modeled Risk Increasing" is an indicator variable that equals one if the FSF-FM predicts the respondent will have higher flood risk in 30 years. The model includes controls for respondent demographic and current flood risk. Standard errors are clustered by zipcode.

	(1)		(2)	
	Pr(Claim)	Log Claim (Claim > 0)	Pr(Claim)	Log Claim (Claim > 0)
Post X FP-Built	-0.003	-0.313***		
	(0.008)	(0.050)		
FP-Built ('75-'84)			-0.007	-0.219***
			(0.009)	(0.054)
FP-Built ('85-'94)			-0.010	-0.262***
			(0.009)	(0.051)
FP-Built ('95-'04)			0.003	-0.367***
			(0.009)	(0.062)
FP-Built ('05-'20)			-0.000	-0.468***
			(0.013)	(0.106)
Post	-0.014*	0.074*	-0.011	0.029
	(0.008)	(0.042)	(0.008)	(0.044)
Remapped	-0.006	-0.142***	-0.006	-0.142***
	(0.008)	(0.034)	(0.008)	(0.033)
Constant	0.242***	10.770***	0.240***	10.803***
	(0.005)	(0.032)	(0.005)	(0.036)
Observations	192,987	44,088	192,987	44,088
R-squared	0.461	0.418	0.461	0.418

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Results of the hurdle model estimating flood insurance claims. The first and third columns estimate the probability of claim, the second and fourth columns estimate the magnitude of the log claim conditional on having one. All models include census tract by loss event interacted fixed effects and controls for property year built, deductible, and amount of coverage purchased. Standard errors are clustered by loss event.

Parameter Name	Model Notation	Estimate	Source
Non-floodplain Take-Up Rate	I^0	0.36	Survey Data
Floodplain Take-Up Rate	I^1	0.58	Survey Estimates
Adaptation Effect (New Construction)	$1 - A^1$	0.65	Remapped Claims Estimates
Floodplain Premium	P^1	\$1,330	Floodplain Policy Data
Non-floodplain Premium	P^0	\$530	Non-floodplain Policy Data
Flood Risk Growth Rate	$1 + \gamma^1$	1.026	FSF-FM
Misperceived Flood Risk Growth Rate	$1 + \gamma^0$	1.02	Survey Risk Change Beliefs
Cost of Public Funds	λ	0.3	Poterba (1996)
Discount Rate	β	0.99	Giglio et al. (2021)

Table 6: Empirical parameters for welfare estimation

Scenario	New Home	Old Home	Pricing Only	Info Only	Internality
Take-Up	11,200	11,200	-41,170	11,200	15,630
Self-Protection	5,170	0	0	2,980	12,020
Moral Hazard	4,860	0	1,820	0	4,860
Public Funds	3,600	3,600	3,600	-5,790	3,600
Total	24,840	14,800	-35,750	8,400	36,110

Table 7: Welfare gains from classifying versus misclassifying a high-risk home. Each column specifies a different scenario and the rows show the decomposition of welfare gains. Numbers in each cells are present discounted value welfare effects between 2020 and 2050.

	Classified as High-Risk	Misclassified as Low-Risk
Climate Damages		
Physical Damages	890	1,370
Uninsured Risk	0	240
Public Funds	0	80
Total	890	1,690

Table 8: Annual flood climate damages in 2050 for high-risk homes that are correctly classified (first column) and misclassified as low-risk (second column). Flood climate damages are defined as the change in the annual welfare costs of flood risk between 2020 and 2050.

Figures

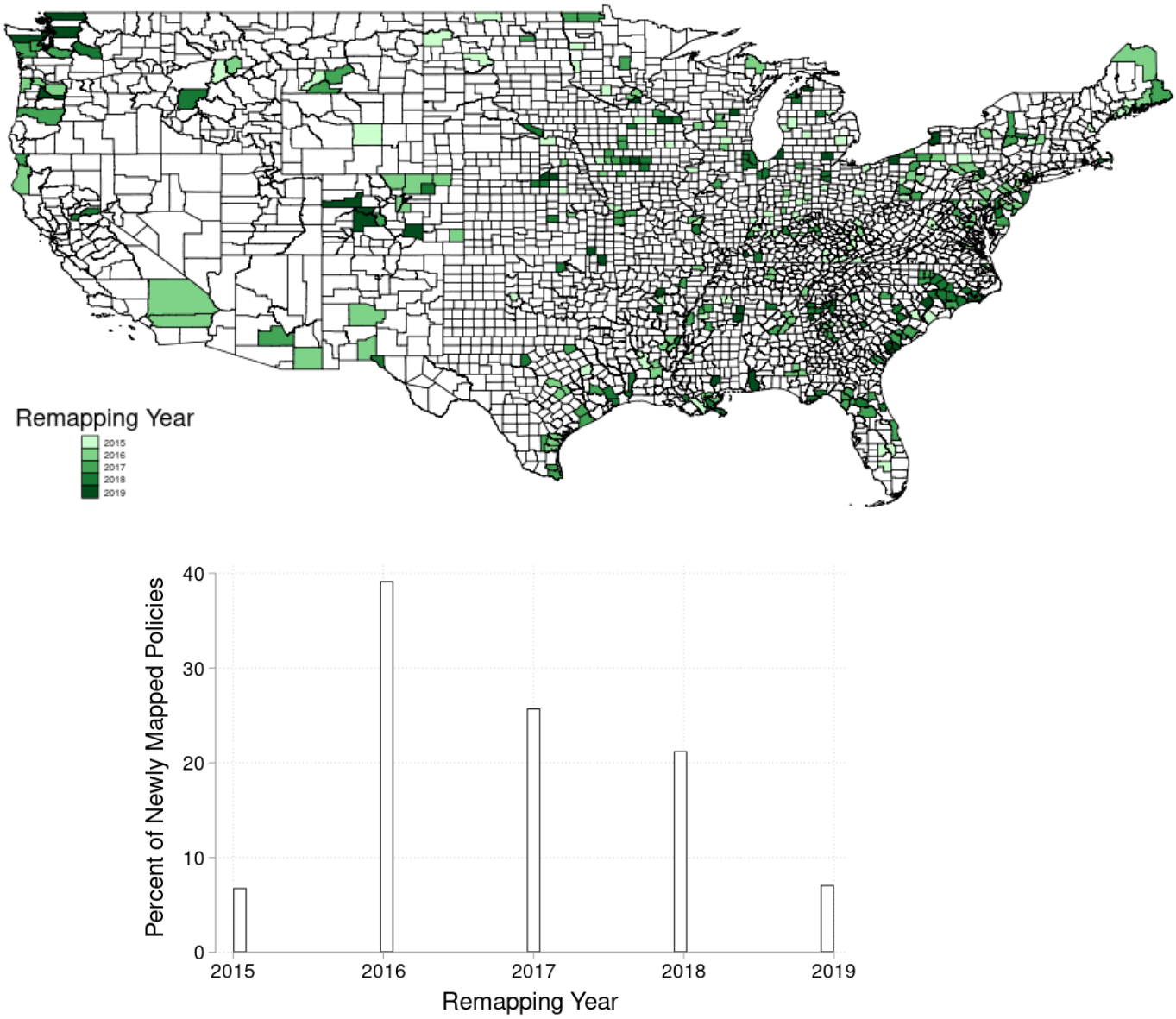


Figure 1: The top panel maps counties with zip codes where homes were remapped into the floodplain between 2015-2019. Shading indicates year of remapping. Clear counties did not have floodplain newly mapped policies. The bottom panel shows the distribution of remapping years across the sample of 2020 remapped policies. Source: OpenFEMA policy data

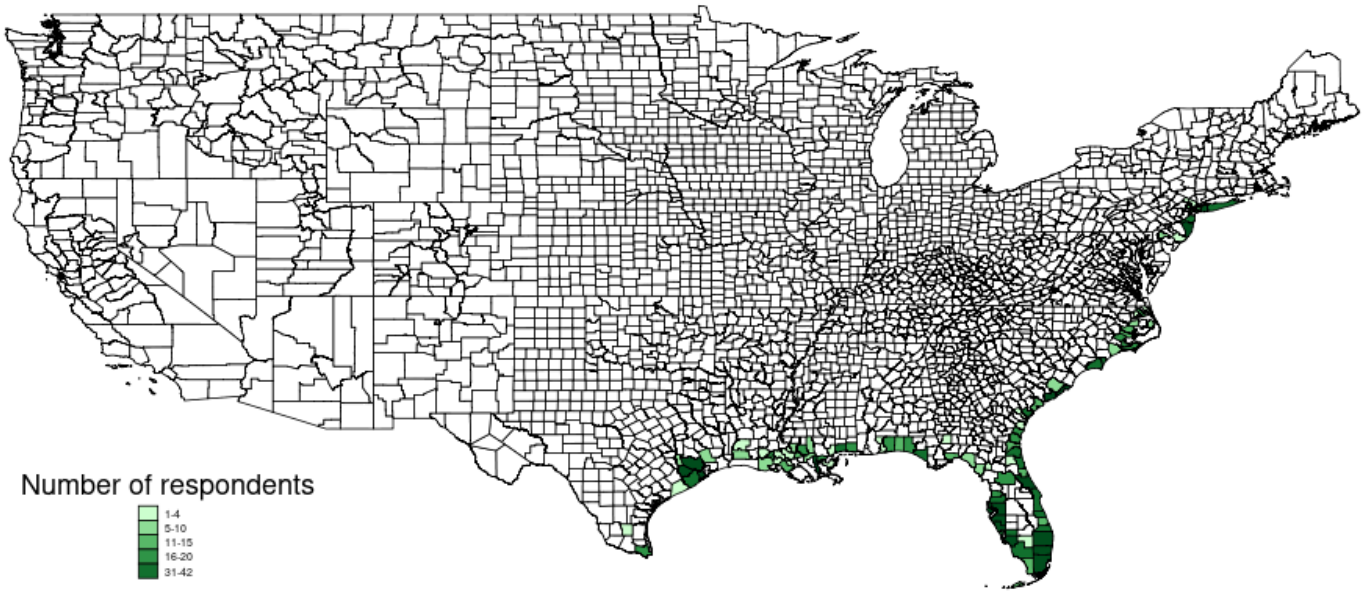


Figure 2: Number of respondents by county in estimation sample of the flood insurance survey.

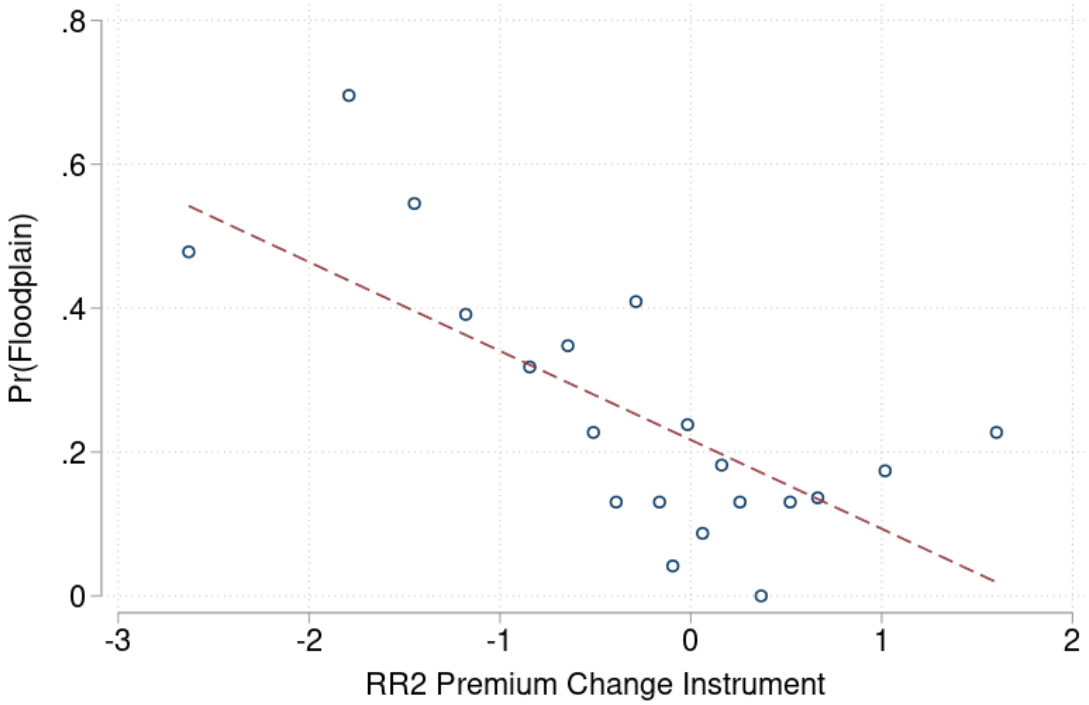


Figure 3: Share of homes inside the floodplain (y-axis) by 20 bins of the Risk Rating 2.0 (RR2) premium change instrument (x-axis)

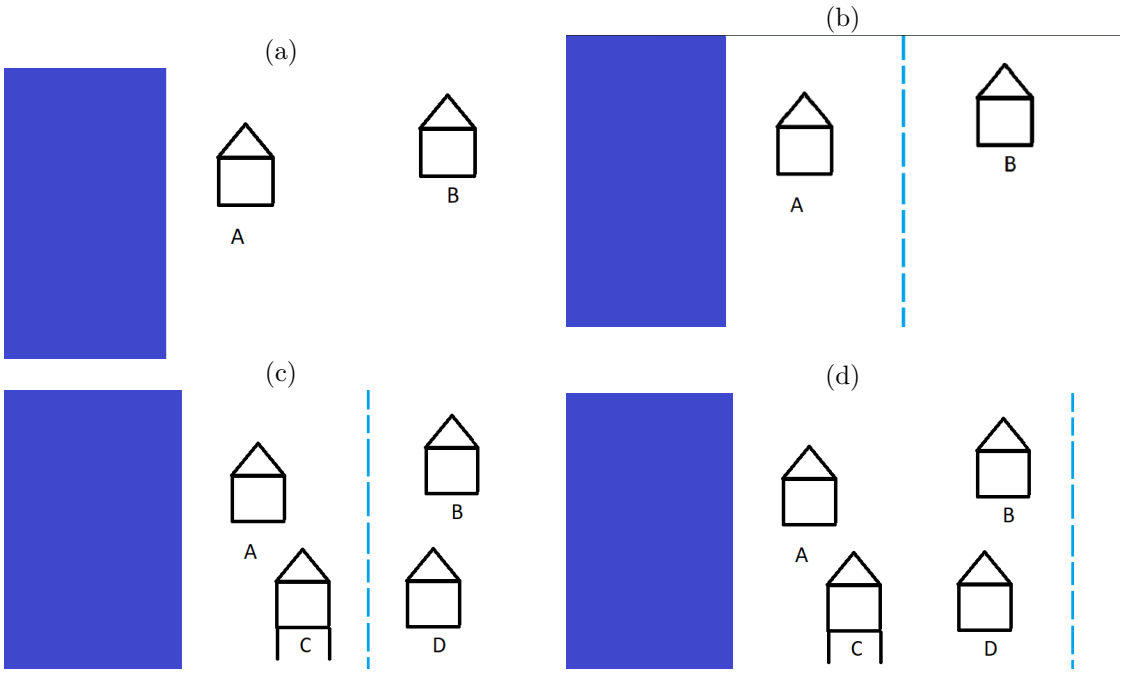


Figure 4: Series of panels illustrating the sequence of events that lead to the treatment and control units used in the difference-in-difference specification to identify the adaptation effect. In period 1 (panel a) two homes A and B are built near the water before any floodplain boundary exists. In period 2 (panel b) a floodplain boundary is drawn placing home A inside and home B outside the floodplain. In period 3 (panel c) home C is built inside and home D built outside the floodplain. In period 4 (panel d) the floodplain boundary is moved so that homes B and D are also inside the floodplain. Loss data are generated sometime after period 4 when a flood occurs (not shown). Then, the adaptation effect is estimated as the differences in claims of: $(C - D) - (A - B)$.

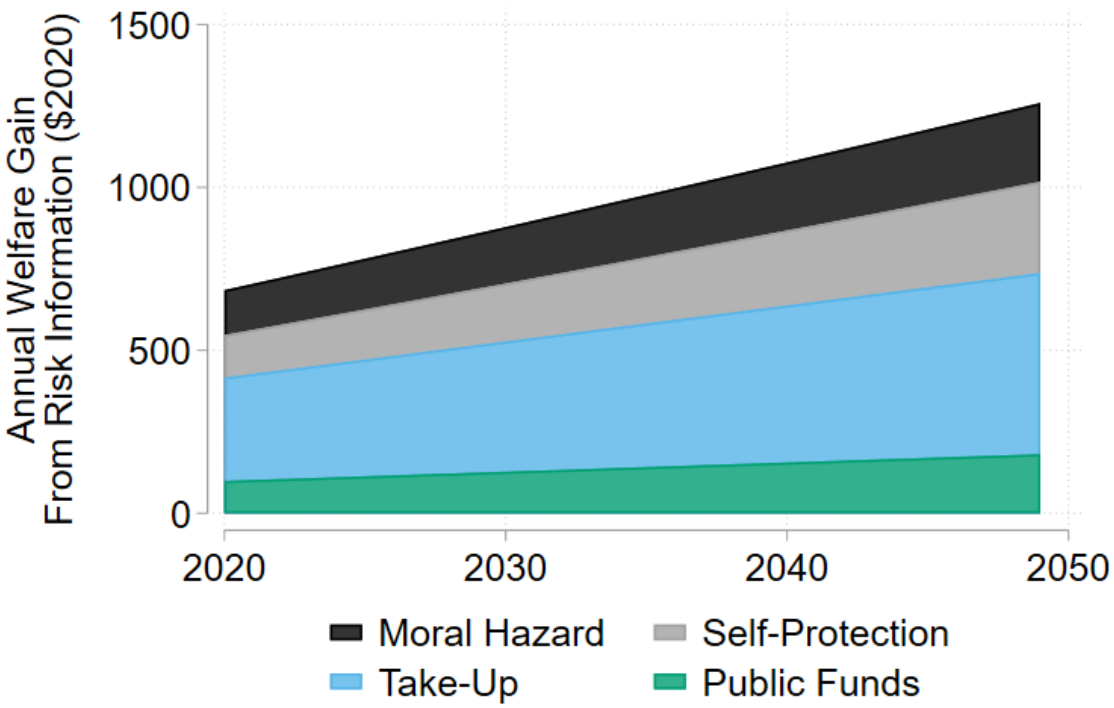


Figure 5: Stacked area plot describing the undiscounted annual welfare gains from 2020-2049 from correctly mapping high-risk homes inside rather than outside the floodplain. The total welfare gains are separated into distinct terms as described in Equation 5.

A Appendix Tables

Variable Means	Outside Floodplain	Inside Floodplain
Income	90672	99433
Has College Degree	.66	.57
Age	56	57
Risk Preferences	4.71	4.58
10-Year Risk of Flooding	17.5	27.75
Believe Flood Risk Higher in 30 Years	0.43	0.57
Has Flood Insurance	.30	.66
Insurance Required by Lender	.06	.39
Report Wanting Flood Insurance	.29	.55
Reported Flood Insurance Premium	665	1762
Observations	543	159

Table A1: Summary statistics for estimation sample from survey of flood insurance demand and risk perceptions. Risk Preferences are self-reported willingness to take risks from one to 10, where one is the most risk averse.

	Voluntarily Insured			
	(1)	(2)	(3)	(4)
Floodplain	0.170***	0.156***	0.136***	0.145**
	(0.045)	(0.052)	(0.045)	(0.072)
Floodplain X Mortgage				0.042
				(0.082)
Risk Model Flood Depth	0.019***	0.018***	0.016***	0.017***
	(0.006)	(0.005)	(0.006)	(0.005)
Flood Depth Squared	-0.001			
	(0.001)			
Past Flood = 1	0.127**	0.158**	0.132**	0.126*
	(0.060)	(0.067)	(0.061)	(0.065)
Mortgage				-0.088**
				(0.041)
Constant	-0.692**	-0.684**		-0.693**
	(0.335)	(0.330)		(0.338)
Observations	703	680	703	703
R-squared	0.146	0.151	0.414	0.145
Demographics	Y	Y	Y	Y
Flood Risk	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Robustness checks for estimating the information effect. Column (1) adds a quadratic model flood depth term; Column (2) drops all SFHA properties with a less than 1% annual chance of flooding; Column (3) instruments for the modeled flood depth using the stacked Obviously Related Instrumental Variables design; Column (4) adds a floodplain-by-mortgage interaction term.

B Appendix Figures

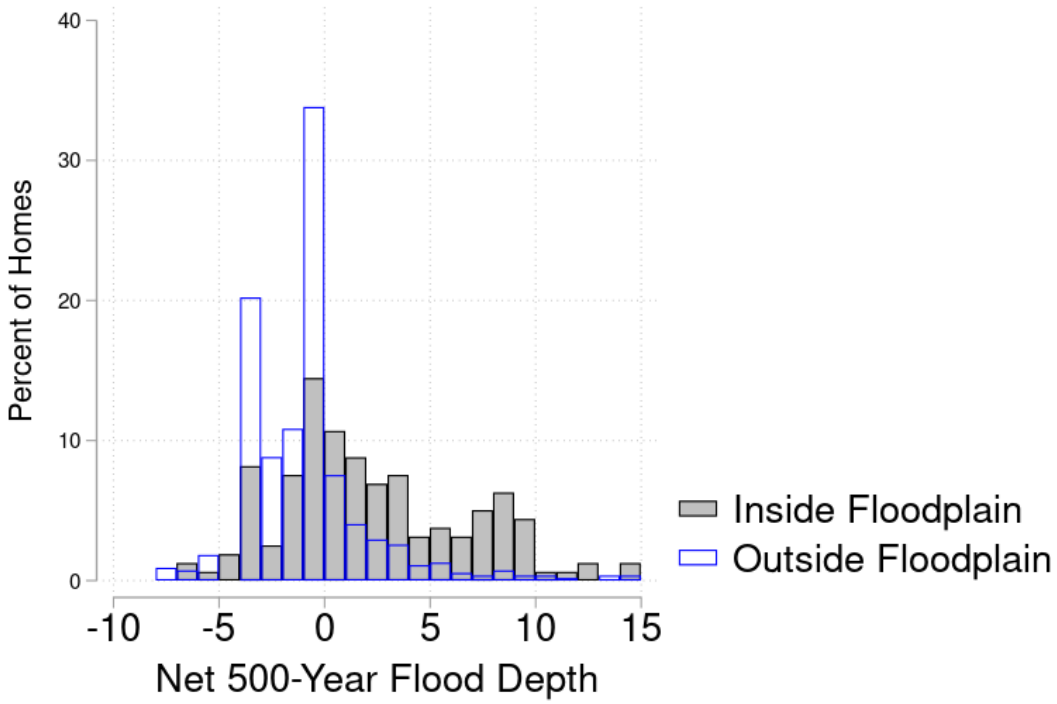


Figure A1: Distribution of 500-year flood depths from the First Street Foundation and Kat Risk flood models minus estimated first floor heights in the flood insurance survey estimation sample inside (grey) and outside (blue) the floodplain.

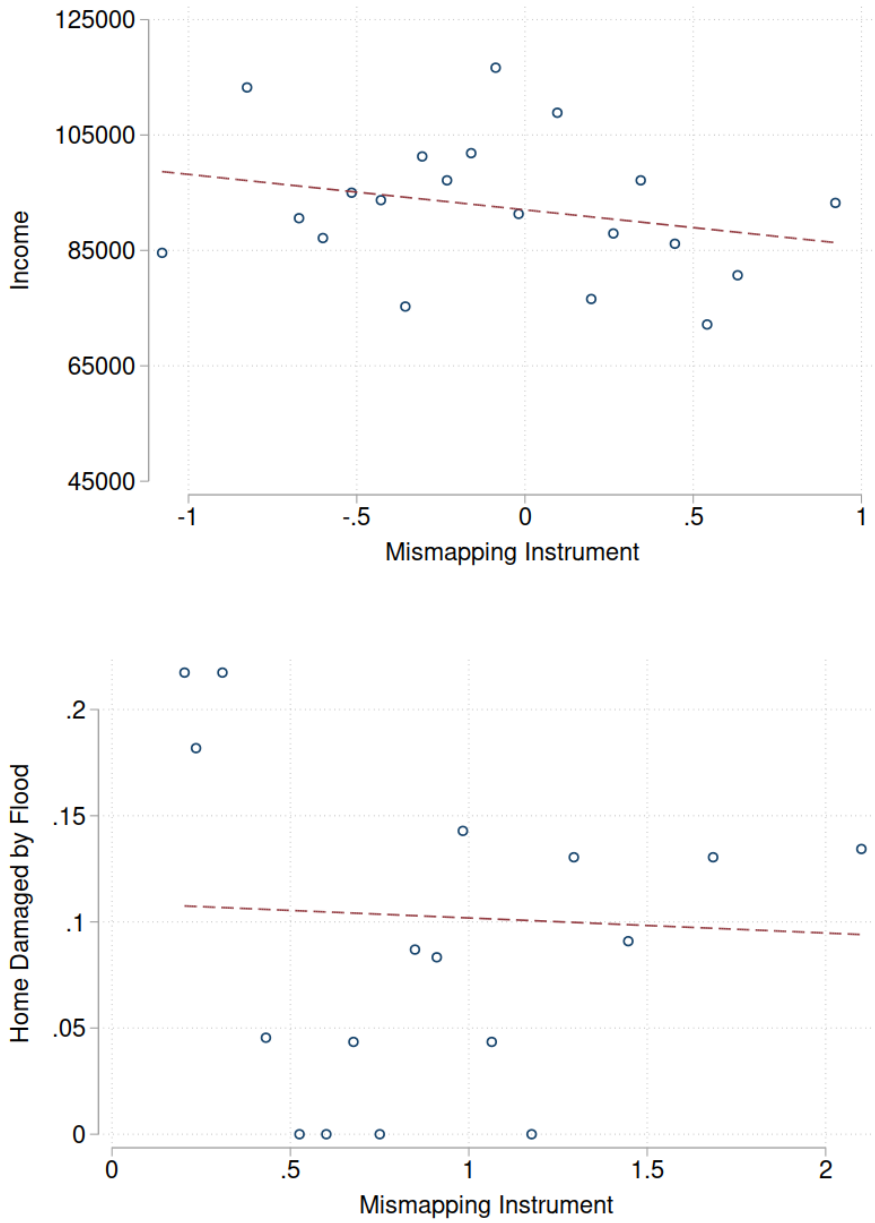


Figure A2: Plots on the y-axis the average log income survey measure (top panel) and share of homeowners who report being damaged by a flood in their current home (bottom panel) against 20 bins of the Risk Rating 2.0 (RR2) premium change instrument on the x-axis.

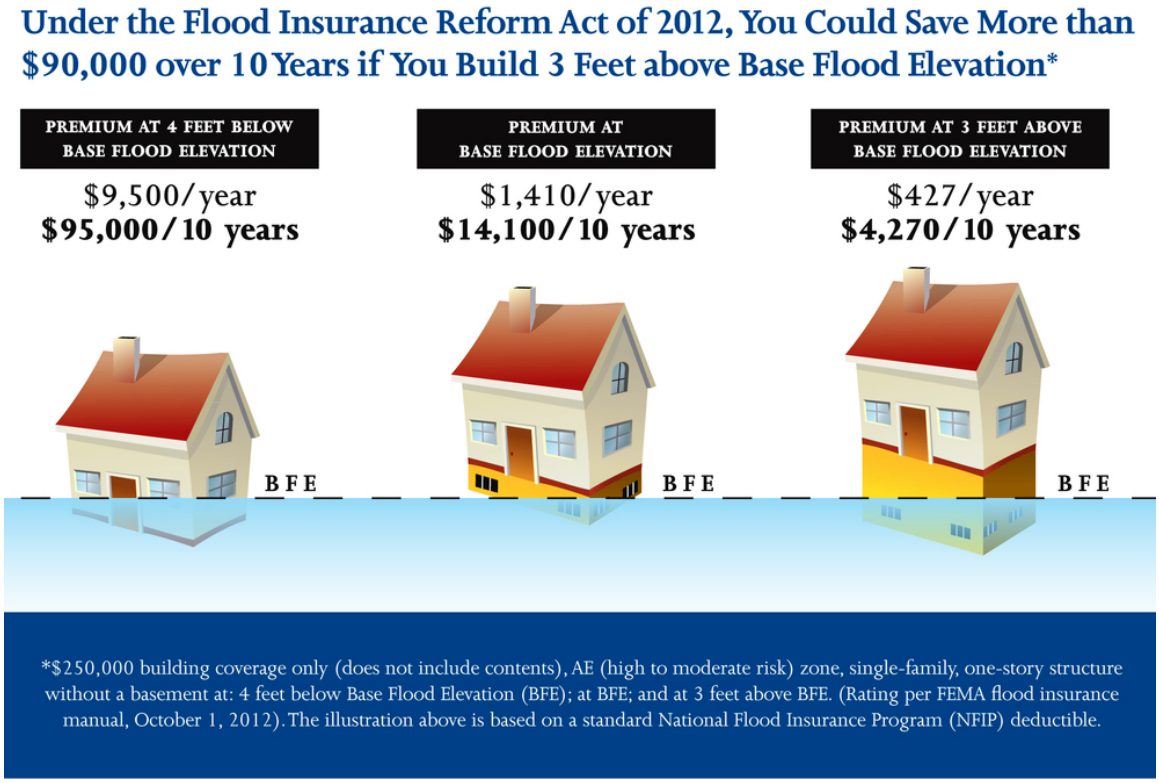


Figure A3: Sample National Flood Insurance Program policy premiums for a single-family floodplain (AE) home elevated four feet below (left), at (middle) and 3 feet above (right) the 100-year flood depth (base flood elevation) as of October 1, 2012. Source: Northeast Engineers & Consultants, Inc. (2024)

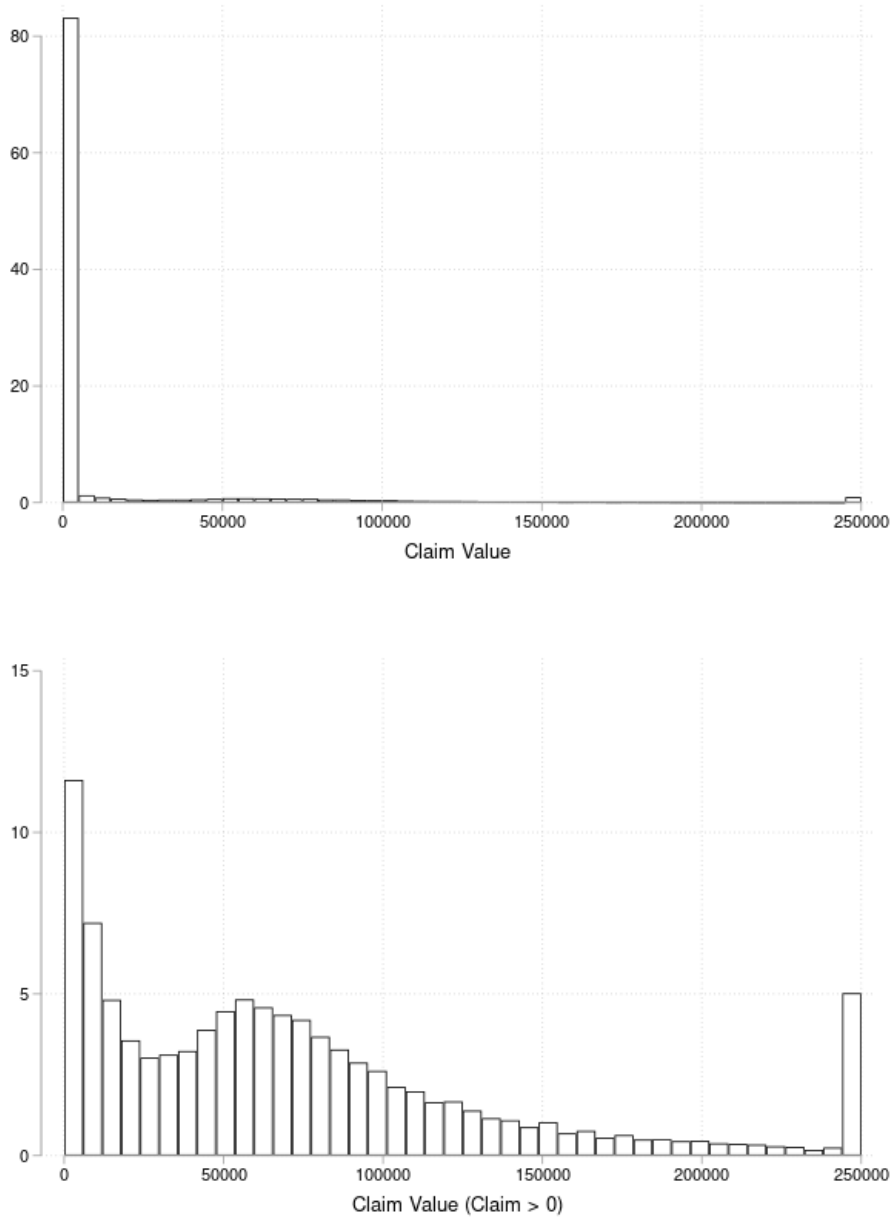


Figure A4: Histograms of the distribution of flood insurance claims across the loss events estimation sample. The top panel shows the claims distribution for all claims, while the bottom panel shows the distribution for claims greater than 0. Source: OpenFEMA claims data

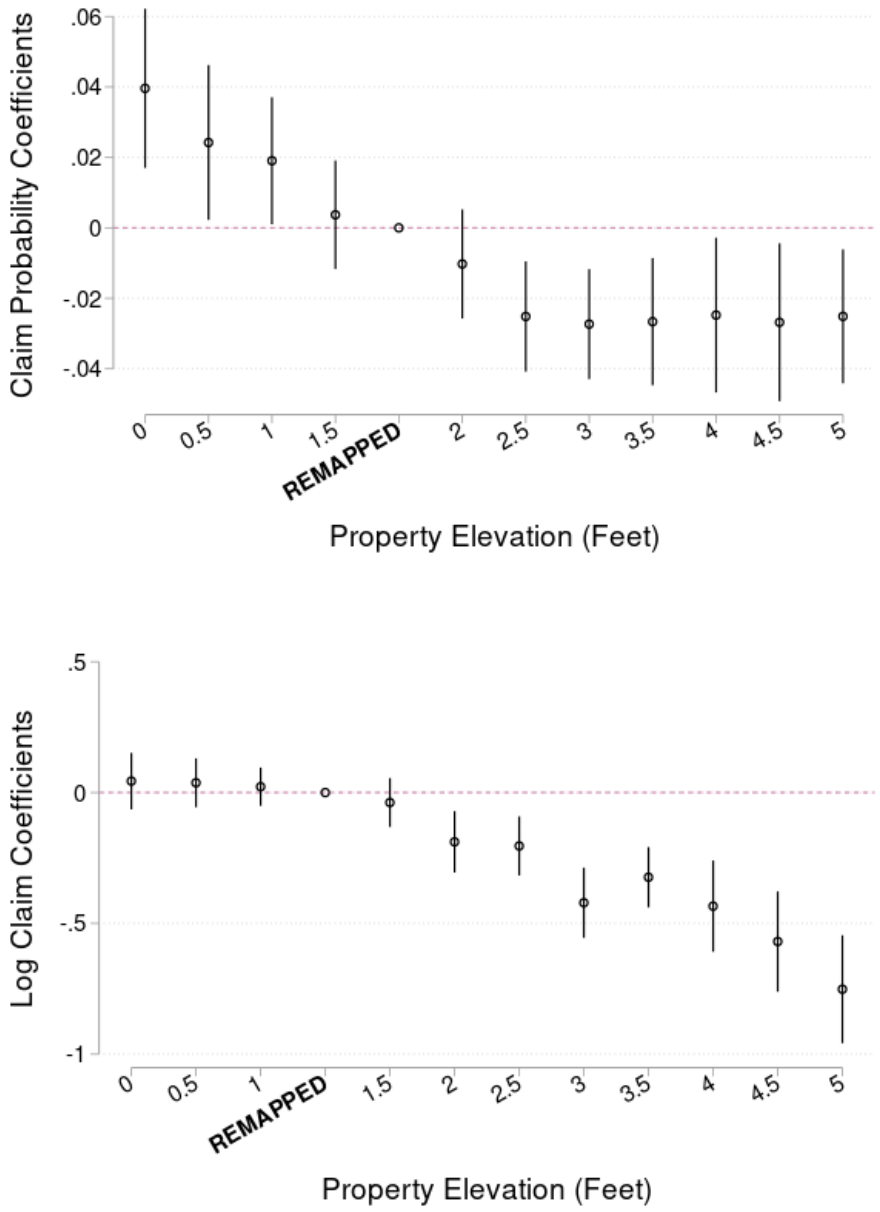


Figure A5: Results from hurdle model predicting flood insurance claims. The top panel shows results for having a claim as the dependent variable, and the bottom panel shows results for log claims conditional on having a claim as the dependent variable. The figures plot the coefficients of each half-foot elevation indicator with newly mapped properties as the omitted category. Both models include census tract by loss event interacted fixed effects and controls for property year built, deductible, and amount of coverage purchased. Standard errors are clustered by loss event.

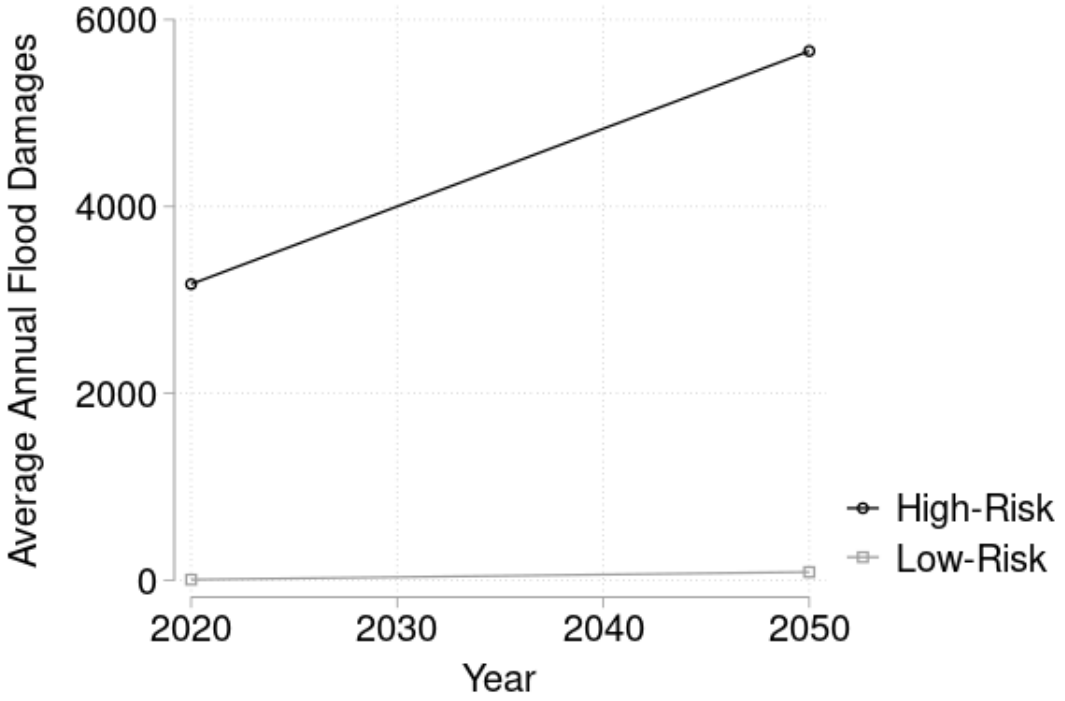


Figure A6: Average annual flood damages for high-risk and low-risk properties in 2020 and 2050 according to the First Street Foundation Flood Model (FSF-FM). High-risk properties are single family homes built on ground with at least a 1% annual chance of flooding.

C Sorting Effects

One of the welfare model's assumptions for tractability is that risk information does not affect the location choices of residents. This section describes the likely direction of the bias in my welfare estimates caused by shutting down resorting given relevant estimates in the literature.

First, we consider the case where the decision of whether to live in a high risk location is endogenous to its risk classification. In principle, changes in the number of high risk homes could be included as another empirically estimable term in Equation 4. However, this would require the calculation of many cross-price elasticities of demand if there are other externalities in the housing market, such as displaced floodplain housing creating agglomeration externalities, fiscal externalities, or increasing housing supply in other mismapped areas. Using a structural housing supply and demand model, Ostriker and Russo (2022) estimate that the number of homes inside floodplain-designated areas is 15% lower due to floodplain regulations and premium costs.

Second, consider the case where the high risk home is still built but high risk classification causes some other household k rather than i to live there with different risk preferences such that $E[w_i^1] \neq E[w_k^1 | f = 1]$. Assuming that residents i and k are optimizing over their new location decisions and that those decisions do not interact with any other externalities or internalities, then by the envelope theorem w_k^1 is not welfare relevant. Thus, Equation 5 remains correct and w_i^1 is a sufficient statistics for welfare. The challenge for this analysis is in empirically identifying the distribution of w_i^1. Because our empirical strategy compares homes with similar risk inside and outside the floodplain, then under resorting the information effect would actually identify w_k^1 instead of w_i^1.

To gauge this bias, consider how w_k^1 – the risk preferences of the "new" resident – likely to differ from w_i^1 – the counterfactual preferences of the resident who only lives in a high risk home if it is misclassified as low risk? Bakkensen and Ma (2020) find that Miami residents with lower risk aversion sort into floodplain areas, suggesting $w_k^1 < w_i^1$. Relatedly, Bakkensen and Barrage (2022) show that high-risk areas tend to attract residents with more biased risk beliefs while Bernstein et al. (2022) find that Republicans are more likely to live in properties exposed to sea level rise. These findings imply a bias that would be interpreted in our results as $w_k^1 < w_i^1$, and would relate to the scenario where floodplain residents are still have risk misperceptions even with correct risk classification.

Both these behavioral and preference-based mechanisms would bias downwards my main information effect finding: That floodplain classification increases flood risk perceptions and flood insurance demand. Thus, ignoring resorting likely biases my welfare estimates downwards.

Finally, one may be interested in how much of the welfare effects of risk classification we miss

by ignoring resorting. Ostriker and Russo (2022) find that an optimal corrective tax on flood risk would increase welfare by $2,700 per newly built house. By contrast, the information, adaptation, and public finance effects I document result in a $25,000 present value welfare gain per new home. Bakkensen and Ma (2020) find that resorting creates a $103 per year welfare gain, or a 30-year discounted value of $2,691, for Miami residents, whereas I find a present value social welfare gain of $15,000 for mapping existing high-risk homes into the floodplain. Thus, the information and adaptation effects studied here are of first-order welfare importance relative to the resorting effects studied in the literature.

D Survey Quality

This section describes measures of survey quality and representativeness in more detail.

To gauge whether respondents are representative of the surveyed population, I compare their self-reported socioeconomic characteristics against those of the surveyed regions in the 2017-2021 American Community Survey 5-year estimates for homeowners in all of the high risk coastal zip code tabulation areas identified from the First Street Foundation Flood Model (FSF-FM). This comparison is shown below in Table A3.

Surveyed respondents are broadly similar to the population in terms of income, education, age, and mortgage rates. However, the share of non-white respondents – black and latino homeowners in particular – is less than half the population share. The share of properties at risk in the population according to the FSF-FM is similar to the share among survey respondents. Flood insurance take-up is slightly higher as self-reported by survey respondents compared to the population. Besides sampling error, another potential reason is that some survey respondents may be reporting private flood insurance policies. Figure A7 shows the average 10-year probability of a flood in the FSF-FM by 20 quintiles of the self-reported 10-year probability among survey respondents. Respondents with higher self-perceived flood risk have higher objective risk according to the FSF-FM, on average. The two measures have a correlation coefficient of 0.18.

Another important part of the survey is inferring the voluntary flood insurance demand of respondents who are subject to the mandatory purchase requirement by their lender. We code such subjects as voluntary buyers if they report being "extremely likely" to buy flood insurance even if it weren't required by their lender. To test whether this is a reasonable classification, we run the following specification:

$$WTP_i = \alpha_0 + \beta_0 X_i + \beta_1 RISK_i + \beta_2 Likely_i * I[Mandate_i = 1] + \beta_3 Uninsured_i * I[Mandate_i = 0] + \epsilon_i, \tag{A1}$$

where WTP_i is the log incentivized flood insurance willingness-to-pay of respondent i, and X_i and $RISK_i$ are the demographic and risk controls as described in Equation 7.

$Likely_i \in \{ExtremelyUnlikely, SomewhatUnlikely, NeitherLikelynorUnlikely, SomewhatLikely, ExtremelyLikely\}$ is a categorical variable reported by participants subject to the mandatory flood insurance purchase requirement ($Mandate_i = 1$) indicating how likely they would be to buy flood insurance even if their lender didn't require it. $Uninsured_i$ is an indicator variable that equals 1 if a participant not subject to the mandatory purchase requirement ($Mandate_i = 0$) has no flood insurance.

The results of Equation A1 are reported in Table A4. We see that mandatory buyers who report being "extremely likely" to still buy flood insurance absent their lender's requirement report an approximately 50% higher willingness-to-pay for flood insurance than voluntary buyers not subject to the mandate. Thus, the classification scheme for categorizing voluntary buyers among mandatory policyholders is likely conservative.

Characteristics	Surveyed Respondents	Population
Median Income	\$70K-\$80K	\$75K-\$100K
Post-Secondary Education	.63	.69
Median Age	58	55-64
Share with Mortgage	.59	.55
Share Latino	.06	.19
Share Black	.05	.11
Share with Flood Insurance	.37	.29
Share Properties at Risk	0.59	0.62

Table A3: Comparison of socioeconomic, flood insurance, and flood risk characteristics between the surveyed estimation sample and the target population of high risk coastal zip codes. Population income, education, age, mortgage share, latino share, and black share estimates come from 2017-2021 five-year American Community Survey homeowner estimates. Population share with flood insurance is estimated as total active flood insurance policies in the NFIP policy database at year-end 2020 divided by the total number of properties according to the 2020 CoreLogic tax assessor data. Share of properties at risk is taken from First Street Foundation Flood Model as properties with a FloodFactor greater than one.

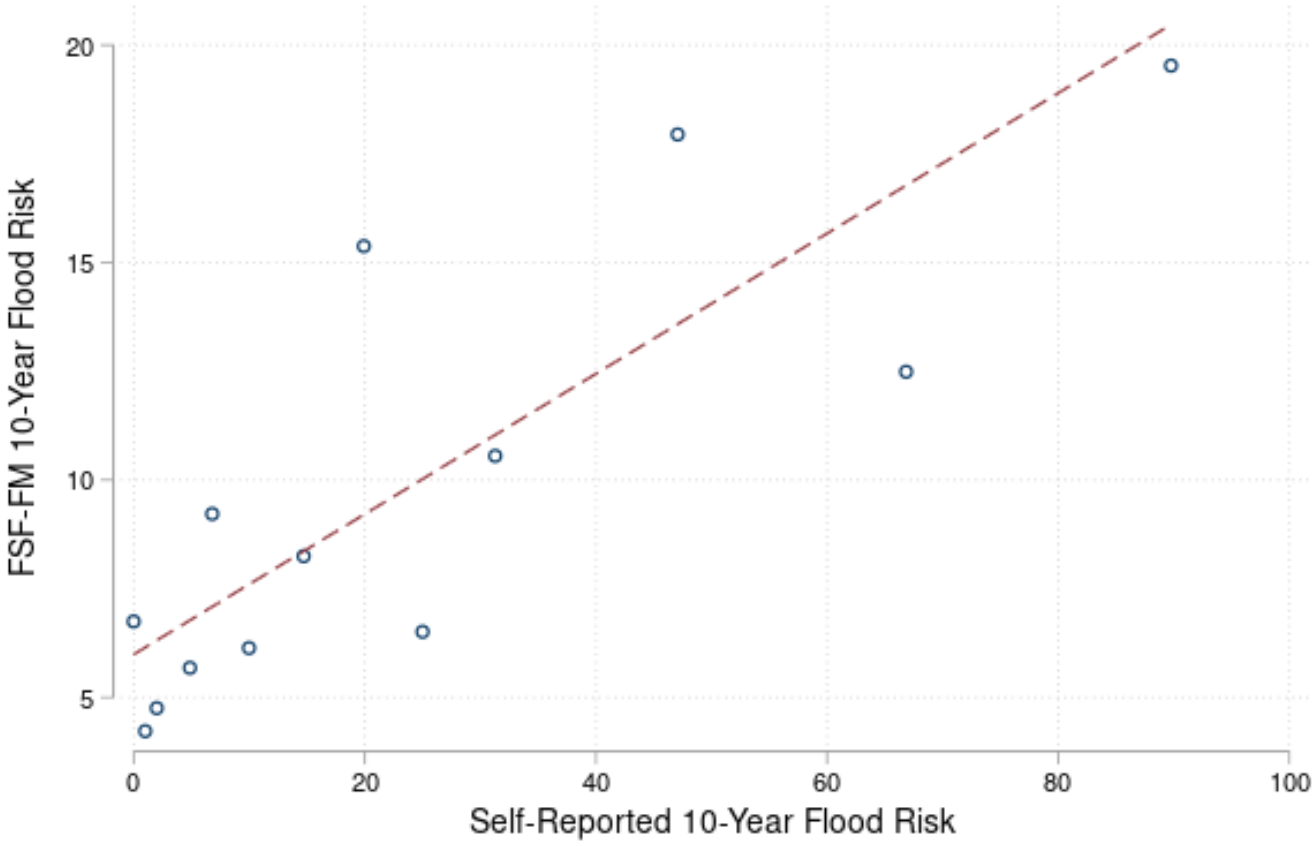


Figure A7: Modeled Versus Perceived Risk. Y-axis indicates average 10-year flood probability in the First Street Foundation Flood Model by 20 quintiles of self-reported 10-year flood probability among survey respondents.

	Outcome: Incentivized WTP
"Extremely Likely"	0.434**
	(0.205)
"Somewhat Likely"	-0.386
	(0.320)
"Neither Likely nor Unlikely"	-0.458
	(0.323)
"Somewhat Unlikely"	-0.183
	(0.386)
"Extremely Unlikely"	-0.818**
	(0.328)
No Flood Insurance	-0.901***
	(0.149)
Constant	7.022***
	(1.593)
Observations	674
R-squared	0.167
Demographics	Y
Flood Risk	Y

County clustered standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Regresses incentivized willingness to pay for flood insurance elicited as described in Appendix Section G.2 over indicators for respondent's self-reported flood insurance demand. The "Extremely likely" to "Extremely unlikely" categories are how likely respondents who were forced to buy flood insurance by their lender report they would be to buy flood insurance even absent the requirement. No flood insurance equals 1 for respondents who did not have flood insurance. The omitted category is respondents who voluntarily bought flood insurance without being required to by a lender. Includes controls for respondent demographics and flood risk.

E Remapping, Take-Up, and Premiums

My estimating equation is given by:

$$Policies_{inmt} = \alpha_{imt} + \alpha_{inm} + \sum_{t=m}^{t=2020} \lambda^{t-m} I[NewlyMapped_n = 1] + \epsilon_{inmt} \tag{A2}$$

where $Policies_{inmt}$ is the inverse hyperbolic sine transformed count of active policies in county i that were remapped into the floodplain ($n = 1$), "newly mapped", or remained outside the floodplain ($n = 0$), "non-floodplain", during remapping that occurred in year m as of year t. To estimate changes in premiums, I replace policies with log average premiums as the dependent variable. α_{imt} is county by remapping year by year interacted fixed effects, and α_{inm} is county by newly mapped status by remapping year interacted fixed effects. λ^{t-m} traces out the dynamic effects of remapping on the number of newly mapped policies from the year of remapping ($m = t$) through 2020.[19] The key identifying assumption is that, in the absence of remapping, the premiums and policy counts of these two sets of non-floodplain policies would have remained on parallel trends.

Figure A8 plots the estimated remapping coefficients from Equation ($A2$) for policy counts (top panel) and premiums (bottom panel) of homes remapped into the floodplain relative to homes that remained outside the floodplain. By the first year after remapping, the relative number of policies in areas remapped into the floodplain approximately doubled. By contrast, premiums one year after remapping are less than 5% higher for homes moved inside the floodplain, an increase that reflects an extra 25$ policy fee levied on policies under the Newly Mapped Subsidy program.

In the second year after remapping, newly mapped premiums begin to increase more sharply as the statutory 15% annual price increase at policy renewal take effect. Five years after remapping, premiums are 45% higher on the policies of homes moved into the floodplain. As premiums increase, the relative increase in the number of policies on homes moved into the floodplain stalls and declines. By the fifth year after remapping, there is only a 55% relative increase in newly mapped policies.

[19] Note that equation $A2$ does not estimate the $\widehat{\lambda}$ coefficients from differences in the timing of flood map changes. Rather, the α_{imt} fixed effects restrict the empirical comparisons to variation between newly mapped and non-floodplain homes within the same county in the same year. This approach avoids the dynamic biases in staggered difference-in-difference settings (Baker et al., 2021; Goodman-Bacon, 2021).

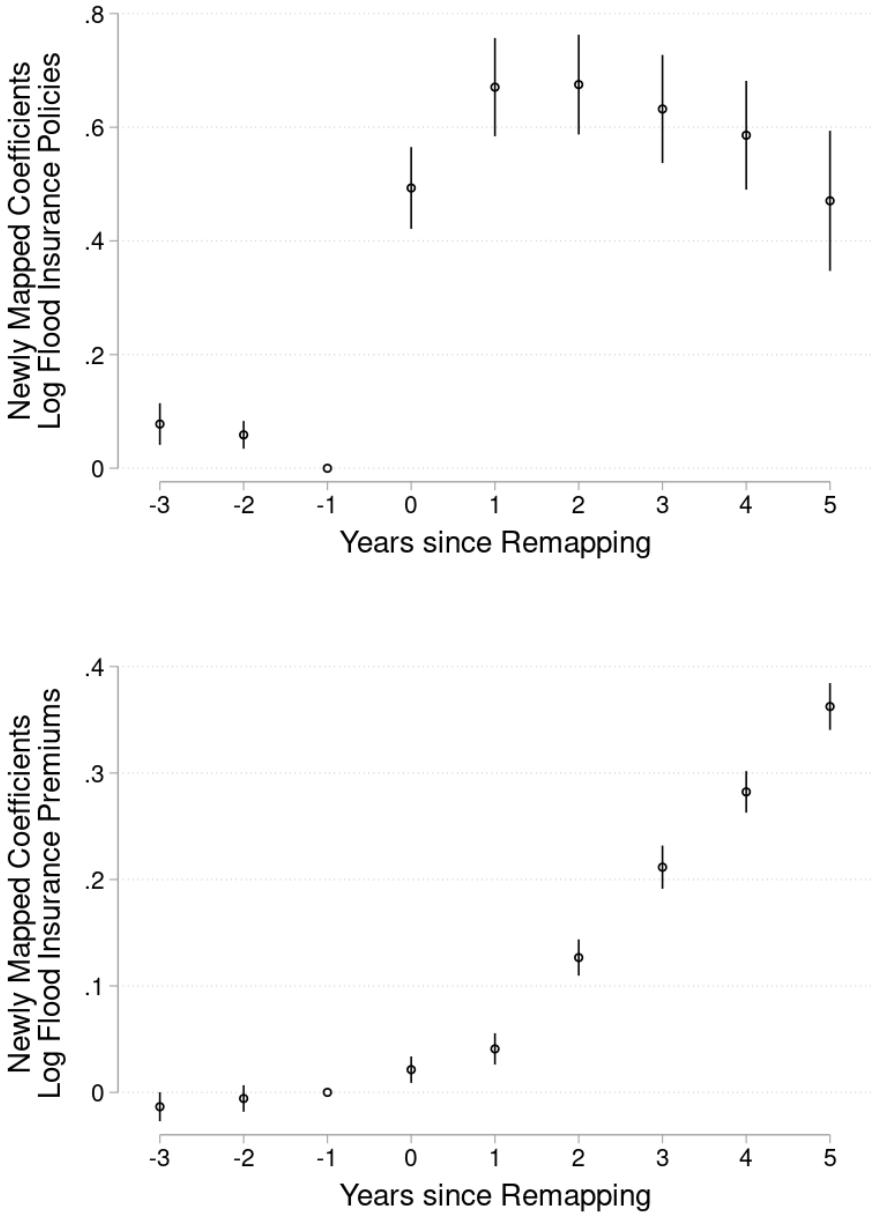


Figure A8: Coefficients estimating the effect of remapping on the inverse hyperbolic sine transformed number of policies (top panel) and log average premiums (bottom panel) by years since remapping for homes moved inside the floodplain relative to homes that remained outside the floodplain. Lines indicate 95% confidence intervals with standard errors clustered by county.

F Adjusted Price Elasticity of Voluntary Flood Insurance Demand

In this section, I adjust the price elasticity of flood insurance demand estimate from Table 1 for the share of floodplain flood insurance buyers subject to the mandatory purchase requirement according to the survey data. This adjusted elasticity represents the estimated percent of voluntary flood insurance purchasers who drop their policies in response to a 1% premium increase.

In the survey data, 36% of high-risk buyers outside the floodplain have flood insurance. Applying the newly mapped take-up estimates from Figure A8, this implies that their take-up rate would increase to 72% absent any premium increases one year after being remapped into the floodplain. Given that 39% of homeowners inside the floodplain reported being subject to a mandatory purchase requirement, this implies that $\frac{72-39}{72} = 46\%$ of purchasers are not subject to this mandate.

I assume that the estimated price elasticity in the newly mapped results comes entirely from purchasers not subject to the mandatory purchase requirement not renewing their policies. This implies that the 0.17% of all purchasers not renewing their policies in response to a 1% premium increase represents an elasticity of $\frac{0.17}{0.46} = 0.37$ among voluntary purchasers.

G Survey

G.1 Survey Questions

The following are the questions used in this study from the Homeowner's Risk Perceptions and Insurance Demand survey:

G.1.1 Home and Flood Insurance

1. Do you have a mortgage on this home?
    - Yes
    - No
2. What year did you purchase this home? [free response]
3. Is your home insured against flood damage caused by water entering your home?
    - Yes
    - No

- Don't know

4. [If yes to Q3] Is your home's flood insurance part of your homeowner's policy or a separate insurance policy?

    - Separate policy
    - Included in homeowner's policy
    - Don't know

5. [If Q4 is NOT "separate policy"] Do you pay a separate premium for your flood insurance, or just one overall homeowner's insurance premium?

    - I pay a separate flood insurance premium
    - I only pay one homeowner's insurance premium
    - Don't know

6. About how much do you pay each year for flood insurance?

    - [Free response]
    - Don't know

7. [If the respondent reports having a mortgage and flood insurance] Does your mortgage lender require you to buy flood insurance?

    - Yes
    - No
    - Don't know

8. [If lender requires flood insurance] Suppose that your mortgage did not require you to buy flood insurance. How likely would you be to purchase flood insurance anyway?

    - Extremely unlikely
    - Somewhat unlikely
    - Neither likely nor unlikely
    - Somewhat likely
    - Extremely likely

9. Has a home you've lived in ever been damaged by flooding from a storm while you lived there (and if so, when)?

- Yes, The most recent year this happened was: [free response]
- No

G.1.2 Hypothetical Scenario Task

Next, you will participate in a hypothetical scenario where you make decisions about buying flood insurance as if you were making this decision for your real home.

Bonus Payment Details for Insurance Choice Task

You begin with E$250,000 (E$s = "experimental dollars").

Your payout will equal your leftover E$s at the end of the task.

1 in every 100 participants will be randomly selected to receive a bonus Amazon gift card. If you are select, your gift card will be worth $20 plus $1 for every E$3,125 you win. This means that if you win all E$250,000 and are selected, you will be sent an Amazon gift card worth $100.

[Next Screen]

To randomly decide who gets the bonus, every participant is being given a random number from 100-199. Your number is: [participant number]. You will win a bonus only if the last two digits of your number matches the winning number (between 00-99) of the evening Florida Pick 2 lottery on [pick 2 date, depending on survey wave].

We will remind you of this information and your number at the end of the study.

[Next Screen] Flood Insurance Decision-Making Task

You have E$250,000 in savings and a home that could be damaged by a flood over the next year. If your home floods, you will have to pay for the repairs with your savings unless you buy flood insurance. Your payout will be your leftover savings after paying for either flood damage or flood insurance.

[Next Screen]

Flood Risk: Your flood risk is very similar to the flood risk of your real house. Your flood damage will be based on the real flood claims of a one-year flood insurance policy covering a randomly selected home sometime in the last ten years. This randomly selected home will be in a location with flood risk similar to your real house's flood risk.

[Next Screen]

Cost of Flooding: If the randomly selected home did not flood, then you will have no flood damage. If the randomly selected home did flood, your repair costs will equal the actual flood insurance claim up to E$250,000.

Flood Insurance: You can buy a flood insurance policy that completely pays for any flood damage. The flood insurance price will be set by drawing a random number. You will buy flood insurance if the price is at or below what you're willing to pay.

[Next Screen]

Buying Flood Insurance: Next, we will help you narrow down how much you are willing to pay for flood insurance by asking whether or not you would buy it at different prices.

[On the next screen, participants saw the following text:]

Task Summary

-Chance of flood: Based on your real house's annual flood risk.

-Cost of flood: Equal to actual flood insurance claim of a home with risk like yours

-Flood insurance: Pays for all your flood damage

-Payout: Leftover savings after paying for either flood damage or flood insurance

Would you buy flood insurance for E$1,000?

- Yes
- No

[On the next page, participants would see the same task summary and question, but with E$1,000 replaced with E$2,000 for participants who chose "Yes" or E$500 for participants who chose "No." After making their second choice, participants would make a third choice where the prompted value is either E$250 (No/No), E$750 (No/Yes), E$1500 (Yes/No), or E$4000 (Yes/Yes). After making their third answer, participants go to a final screen where they are presented with their highest and lowest stated willingness-to-pay and asked to specify the most they would pay for flood insurance. For example, a participant who answered yes, yes, then no would see:]

Task Summary

-Chance of flood: Based on your real house's annual flood risk.

-Cost of flood: Equal to actual flood insurance claim of a home with risk like yours

-Flood insurance: Pays for all your flood damage

-Payout: Leftover savings after paying for either flood damage or flood insurance

You said you would buy flood insurance if it cost E$2,000 but would not buy if it cost E$4,000.

What is the most you would pay for flood insurance? [Free response]

G.1.3 Flood Risk Perceptions

We will determine your winnings from the Flood Insurance Decision Task at the end of the survey. First, we are going to ask you some questions about your real home.

1. How worried are you about a flood from a storm damaging your home?
    - Not at all
    - A little worried
    - Somewhat worried
    - Moderately worried
    - Very worried
    - Extremely worried
2. Over the next ten years, how likely do you think it is that your home will be damaged by flooding from a storm? Please give your answer from 0% (will never happen) to 100% (certain to happen). [Free response]
3. If your home were damaged by flooding this year, what do you predicted it would cost to repair and/or replace the damage to your home?
   Please enter your estimate of the damage (in dollars), regardless of whether or how you would pay for them. [Free response]
4. Some people may think that a flood is too unlikely to be concerned about. Is this true for you?
5. What is the most you would be willing to pay for a one-year flood insurance policy on your home? [Free response] [This question is prefaced with "Suppose flood insurance was not included in your homeowner's policy" for respondents who report that their flood insurance is included in their homeowner's policy and with "Suppose that your lender did not require you to buy flood insurance." for responsents who report that their lender required them to buy flood insurance.]

G.1.4 Attention Check

This is an attention check. Simply select 4 on all the items below.
[Participants see a matrix of five topics (Work colleagues, Parents, Siblings, Family friends, and acquaintances) where they rate each topic from 1 (not at all important) to 5 (extremely important).]

G.1.5 Future Risk

1. Over the next 30 years, do you think the risk of your home flooding will increase, decrease, or stay the same?
    - Increase
    - Decrease
    - Stay the same
2. How would you describe your political affiliation?
    - Democrat
    - Republican
    - Independent
    - I'm not very political

G.1.6 Risk & Time Preferences

1. In general, how willing are you to take risks? Answer on a scale of 0 (I dislike taking risks) to 10 (I like tasking risks). [Below the question, participants see a slider scale from 0 to 10 that they adjust.]
2. How much do you agree or disagree with the following statement: "I am often too impatient for my own good"
   (E.g. "too impatient" might mean putting off a task even when you know it would be better to do it right away).
    - Strongly Disagree
    - Somewhat Disagree
    - Neither Agree nor Disagree
    - Somewhat Agree
    - Strongly Agree

G.1.7 Demographics

1. What year were you born? [Free response]
2. What is your gender?
    - Male
    - Female
    - Other
3. What is your highest level of school you have completed?
    - Less than high school degree
    - High school graduate (high school diploma or equivalent)
    - Some college but no degree
    - College degree (e.g. BA or Associate's)
    - Graduate degree (e.g. JD, MD, Master's)
4. What race(s) or ethnic group(s) do you consider yourself? Please select all that apply.
    - White
    - Black or African American
    - American Indian or Alaska Native
    - Asian
    - Native Hawaiian or Pacific Islander
    - Hispanic or Latino
    - Other [Free response]
5. Which of the following best describes your current employment status?
    - Employed full-time
    - Employed part-time
    - Temporarily unemployed (looking for work)
    - Self-employed or freelance
    - Not in the labor force (e.g. student, retired, etc.)

6. Which of the following best describes the total income for your household in 2020? Please include all sources of income for all household members including wages and benefits. [Participants choose from a series of $10,000 brackets ranging from less than $10,000 to more than $200,000]

7. If you were to lose your main source of income (e.g. paycheck, retirement, government benefits), could you cover your expenses for 3 months?

    - Yes
    - No

G.2 Incentivized Insurance Demand Elicitation

This section describes in detail how the hypothetical scenario to task eliciting an incentivized measure of flood insurance demand was administered and constructed. The text of the hypothetical scenario task as seen by the respondents is shown in section G.1.2.

The goal of the hypothetical scenario task was to elicit willingness-to-pay for flood insurance where the risk of flooding was correlated with their home's actual risk and the respondents' choices would affect a real monetary payout.

As incentive, each participant had a 1-in-100 chance to receive an Amazon gift card worth up to $100 mailed to their self-reported address. The exact value would depend on their choices during the hypothetical scenario task - in particular how many "experimental dollars" (E$) they have leftover after paying for flood insurance or paying for flood damages.

Respondents were told that their flood damage would be based on, "...the real flood claims of a one-year flood insurance policy covering a randomly selected home sometime in the last ten years. This randomly selected home will be in a location with flood risk similar to your real house's flood risk."[20] To execute this, we matched each zip code in the survey sample to the other zip code with the closest average "FloodFactor" score in the First Street Foundation Flood Model. Next, we measured the number of active flood insurance policies and the number of claims in the matching zip code between 2010 and 2020. The number of claims divided by the number of policies was the respondent's probability of having a flood. Conditional on having a flood, their damages were equal to the structure claim of one of the matching zip code's randomly chosen claims.

We measure maximum willingness-to-pay (WTP) for flood insurance in the hypothetical scenario by guiding respondents through a Becker-DeGroot-Marschak (BDM) method. Before learning

[20] We chose to draw from a similar location rather than the respondent's same zip code so that their choices would be based on their risk rather than recent flood realizations.

whether they flooded, participants are told that a flood insurance policy will cover all flood damages, and then asked if they would pay E$1,000 for such a policy. If they respond yes, they are asked if they would pay E$2,000, or for no if they would pay E$500. After two more such questions, respondents are presented with their highest and lowest stated WTP so far (e.g. "you said you would pay E$500 but would not pay E$1,000") before being asked to enter the most they would be willing to pay. At the end of the experiment, we draw a random premium uniformly distributed between E$0 and E$20,000.[21] Respondents buy flood insurance at the randomly drawn premium if their stated maximum WTP is at or above it, and do not buy otherwise.

[21] This distribution was not communicated to respondents.