Why is Flood Insurance Take-Up Low? Insights from a Dynamic Model

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Abstract

Fewer than half of US homeowners in high-risk flood zones purchase flood insurance despite subsidized premiums. This paper develops a dynamic model of household decision-making under flood risk that incorporates key institutional features: the National Flood Insurance Program (NFIP), disaster grants, and liquidity-providing policies that enable households to smooth the impact of flood damages on consumption (disaster loans, penalty-free retirement fund withdrawals, and mortgage relief). We find that a modest 10% underestimation of flood risk is sufficient to replicate the observed insurance protection gap. Under rational expectations about flood risk, the median willingness to pay for flood insurance exceeds the actuarially fair premium by only 5%, which is insufficient to cover NFIP administrative costs. Our results suggest that the availability of post-disaster liquidity support, rather than wealth transfers or risk misperception, primarily explain the low willingness to pay for flood insurance.

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1 Introduction

Flooding imposes $32 billion in average annual losses on the United States, making it the nation's costliest natural hazard. Climate change and continued development in flood-prone areas will exacerbate these risks, with losses projected to reach $41 billion by 2050 under the moderate RCP4.5 scenario (Wing et al., 2022). While adaptation measures such as flood defenses and home elevation can reduce exposure, they cannot eliminate flood risk entirely. Flood insurance therefore plays a crucial role in protecting households from financial hardship and accelerating the recovery of affected communities (Kousky, 2019; You and Kousky, 2024).

Fewer than half of US homeowners in high-risk flood zones purchase flood insurance, and only about 2% nationwide (Bradt et al., 2021). This low take-up rate is puzzling given that the National Flood Insurance Program (NFIP) is effectively subsidized by the federal government. Premiums fall short of covering even the expected costs of flood claims, let alone the administrative expenses necessary to operate the program. Consequently, the NFIP currently owes $22.5 billion to the US Treasury, with an additional $16 billion in debt forgiven in 2018. While the NFIP's current transition to more risk-based pricing will improve its financial sustainability, the associated premium increases for existing policyholders appear to have widened the insurance protection gap further (Collier et al., 2023).

To understand which NFIP reforms could succeed, we must identify the underlying reasons for low take-up. Do homeowners forgo flood insurance because they underestimate flood risk, or because government wealth transfers and liquidity provision to uninsured households reduce the need for insurance? Disaster relief policies focused on liquidity provision include low-interest disaster loans, mortgage relief, penalty-free withdrawals from retirement accounts and borrowing against such accounts. If households underestimate flood risk, better risk communication and education could increase take-up even as prices rise. If households rationally choose not to insure due to disaster relief, better communication would have limited impact, and price increases would further reduce take-up. In this case, the government could increase coverage by providing more targeted disaster relief, though credible commitment to such policies may prove difficult.

We develop a dynamic model of household decision-making under flood risk to answer these questions. The core of the model is a standard consumption-savings problem of an infinitely-lived household that faces income uncertainty. Households decide whether to buy or rent housing, and homeowners can borrow against housing equity subject to loan-to-value constraints. Housing wealth is exposed to flood risk, but homeowners can purchase insurance against this risk. Disaster grants are modeled as lump-sum transfers that cover a fraction of uninsured flood damages, while disaster relief policies that provide liquidity are implicitly

captured by the liquidity of financial assets and the borrowing constraints.

The model is calibrated to US survey data on household income and wealth, as well as administrative data on NFIP claims and policies. We focus on high-risk flood zones, where annual flood probabilities are at least 1%. In our baseline calibration with a relative risk aversion of 2, only a modest underestimation of flood risk of approximately 9% is necessary to explain the observed insurance take-up rate of 48% in high-risk flood zones.

We explore the reasons behind the low median willingness to pay (WTP) for flood insurance through counterfactual scenarios. Removing disaster grants increases the median WTP only slightly, from 5% below the actuarially fair premium to 1% above it. Correcting flood risk perceptions increases the median WTP by approximately 9 percentage points. Even when we eliminate disaster grants and correct risk perceptions, the median WTP reaches only 10% above the actuarially fair price, far below the 25-30% loading necessary to cover administrative costs and achieve financial sustainability. While we cannot turn off liquidity provision programs in the model, our simulations show that uninsured households spread the impact of flood damages through dis-saving and borrowing well across many years. This suggests that liquidity provision through disaster loans, mortgage relief, and penalty-free retirement fund withdrawals is the main reason for the low WTP.

Next, we analyze the heterogeneity in WTP across households. The WTP is strongly negatively correlated with the ratio of savings to property value: homeowners who have heavily borrowed against their housing equity are willing to pay significantly more for flood insurance than those who own their homes outright. This pattern reflects that highly leveraged homeowners are closer to their borrowing constraints and have higher exposure to flood risk relative to their total wealth. We also find that renters would have substantially higher WTPs for flood insurance than current homeowners if they were forced to become homeowners. This pattern indicates that the selection of wealth-poor households into the rental market is an additional reason for low WTPs among homeowners.

Finally, we simulate insurance take-up under counterfactual pricing schemes. While removing disaster grants or correcting risk perceptions would substantially increase take-up under subsidized or actuarially fair pricing, none of the scenarios we consider would lead to high take-up under premiums that include administrative costs. Even if both distortions were eliminated, take-up would reach only 6% at such financially sustainable premiums.

This paper relates to four strands of literature. First, it contributes to the theoretical literature on the WTP for flood insurance, which has so far relied only on static models (Wagner, 2022; Collier et al., 2022). We argue that a dynamic model allowing households to finance repairs through borrowing and dis-saving is essential for understanding the WTP for flood insurance.

Second, the paper relates to the empirical literature on flood risk, flood insurance, and disaster relief. Important findings in this literature are low insurance take-up even in high-risk areas (Bradt et al., 2021) and decreased take-up following premium increases (Hennighausen et al., 2023; Collier et al., 2023). Moreover, Wagner (2022) finds no or limited adverse selection based on private information about flood risk, and Kousky et al. (2018) quantifies the limited effect of disaster grants on insurance take-up. Collier et al. (2024) examines the effects of disaster loans and finds that the liquidity provided substantially reduces financial distress after floods.

Third, the paper contributes to the theoretical literature using dynamic models of household decision-making under flood risk. Bakkensen and Barrage (2022) study how belief heterogeneity affects house prices in high-risk areas, while Fried (2022) focuses on private adaptation. This paper is the first to apply a dynamic model specifically to study flood insurance decisions.

Fourth, the paper also relates to the macroeconomic literature on consumption and savings dynamics and the role of liquidity constraints. Kaplan and Violante (2014) and Boar et al. (2021) show that many US households effectively live hand-to-mouth despite substantial wealth because they cannot easily access housing and pension assets. We argue that floods and other natural disasters are an exception since US institutions make both housing and pension wealth more liquid through disaster loans and penalty-free retirement fund withdrawals.

2 Flood insurance and disaster relief in the United States

This section provides an overview over the institutional setup in the United States, covering the National Flood Insurance Program (NFIP) as well as the disaster grant, disaster loan, retirement fund withdrawal, and mortgage relief programs available to uninsured households.

2.1 The National Flood Insurance Program

The National Flood Insurance Program is the primary source of flood insurance in the United States and operates through a public-private partnership: the Federal Emergency Management Agency (FEMA) sets rates and bears risk, while private insurers handle policy sales and claims processing. The program provides coverage limits of $250,000 for residential buildings and $100,000 for contents. Private flood insurance constitutes a small market segment, primarily providing excess coverage above NFIP limits.

FEMA produces Flood Insurance Rate Maps based on elevation data and hydrologic modeling that define Special Flood Hazard Areas (SFHAs) with a 1% annual chance of flooding. Mortgage borrowers in SFHAs with federally-backed loans must purchase flood insurance, though this requirement is not consistently enforced, leading to significant non-compliance (Government Accountability Office, 2021). Prior to 2022, Flood Insurance Rate Maps also formed the foundation of NFIP risk assessment and pricing.

The NFIP is effectively subsidized by the federal government. Premiums fall short of covering the expected costs of flood claims, let alone the administrative expenses necessary to operate the program. Currently, the NFIP owes $22.5 billion to the US Treasury, not including $16 billion in debt forgiven in 2018. This shortfall is driven by explicit subsidies from grandfathering provisions, as well as implicit subsidies from inaccurate flood maps and the NFIP's coarse pricing structure. Despite these subsidies, flood insurance take-up remains low, with only 48% of homeowners in SFHAs and 2% outside SFHAs purchasing flood insurance (Bradt et al., 2021).

The Biggert-Waters Act of 2012 mandated phasing out grandfathered rates, but the Homeowner Flood Insurance Affordability Act of 2014 slowed this transition due to affordability concerns. The Risk Rating 2.0 initiative, implemented in 2022, replaced the zone-based pricing system with individualized risk assessment. However, the transition will take more than a decade to complete due to an 18% cap on annual premium increases for existing policyholders (Congressional Research Service, 2022). Ongoing policy debates focus on increasing insurance coverage and balancing the NFIP's financial sustainability with affordability. Appendix A compares the US flood insurance system with those in Germany, France, the United Kingdom, and the Netherlands.

2.2 Disaster relief for uninsured households

FEMA's Individuals and Households Program provides grants for essential needs, such as temporary housing or basic home repairs. The maximum grant for housing assistance in 2025 is $43,600 (adjusted annually for inflation). However, most grants remain modest, with an average grant of $4,200 to homeowners in the period 2016-2018, reflecting the program's focus on making damaged homes habitable rather than restoring their full value (Government Accountability Office, 2020). While insured damages are ineligible for grant assistance, insured households can still receive grants for temporary housing.

The Small Business Administration (SBA) offers low-interest disaster loans to uninsured or underinsured homeowners. The maximum loan amounts were $200,000 for primary residences and $40,000 for personal property replacement until mid-2023, when these limits were substantially increased to $500,000 and $100,000, respectively. While homeowners are asked to provide collateral for loans exceeding $25,000, the SBA explicitly states that loan applications will not be declined solely due to insufficient collateral. However, rejections remain possible based on credit history or inadequate repayment capacity. With maturities up to 30 years, below-market interest rates, and no payments or interest accrual during the first 12 months, SBA loans offer attractive terms for uninsured households who need to rebuild (Congressional Research Service, 2025).

The SECURE 2.0 Act of 2022 made permanent the ability for disaster victims to access retirement funds penalty-free. Individuals whose primary residence is in a federally declared disaster area and who have suffered economic losses can withdraw up to $22,000 from IRAs or employer-sponsored retirement plans (such as 401(k) or 403(b) plans) without paying the standard 10% early withdrawal penalty. These qualified disaster recovery distributions remain subject to income taxes, though taxpayers can spread the tax burden equally over three years. Importantly, individuals may repay the distributed amount within three years and recover taxes paid by filing amended returns. For employer-sponsored plans that opt into the provisions, participants may also access increased loan limits of up to $100,000 with suspended repayments.

Homeowners affected by disasters may also receive relief through mortgage forbearance and loan modification programs, especially those with federally-backed mortgages. For borrowers in FEMA-declared disaster areas, servicers typically offer an initial forbearance period of 90 days to 12 months, during which mortgage payments are suspended or reduced without late fees or negative credit reporting. At the end of forbearance, several options exist for returning the loan to good standing: payment deferral moves missed payments to the end of the loan without interest, repayment plans spread missed payments over time, or loan

modifications permanently adjust loan terms to lower monthly payments.

The four disaster relief policies described above differ in their economic effects. FEMA grants constitute both wealth transfers and liquidity provision, as they provide funds that need not be repaid. In contrast, SBA loans, mortgage forbearance, retirement fund withdrawals and loans primarily provide liquidity and include no or modest wealth transfers through below-market interest rates and suspended payments.

3 A quantitative model of household decision-making under flood risk

This section develops a dynamic stochastic model of household decision-making under flood risk. We focus on model features that are relevant for understanding the willingness to pay for flood insurance and abstract from details of the housing and mortgage markets that are not essential for our analysis. In section 3.1, we describe the household's problem both verbally and in terms of Bellman equations. In section 3.2, we discuss the key assumptions made to keep the model parsimonious, and explain why these simplifications are reasonable to study flood insurance decisions.

3.1 The household's problem

Households are infinitely lived and choose consumption and housing in each period to maximize expected lifetime utility. The timing within each period is as follows. First, households observe their state, which is characterized by three variables: the income state η following a discrete Markov chain, available financial resources m at the start of the period, and variable b which keeps track of borrowing capacity due to the long-term nature of mortgages. Second, they decide whether to be an uninsured homeowner, an insured homeowner, or a renter, and, conditional on this tenure choice, they choose consumption c, financial assets a (where $a > 0$ represents savings and $a < 0$ represents borrowing), and house size h. Finally, flood realizations occur and decrease the housing wealth of uninsured homeowners. Available financial resources for the next period m' are the sum of income, financial assets plus interest, and remaining housing wealth after depreciation and flood damage.

The value function can be expressed as the maximum of three value functions that capture the problem of uninsured homeowners, insured homeowners, and renters:

$$V(\eta, b, m) = \max\{V_{\text{unins}}(\eta, b, m), V_{\text{ins}}(\eta, b, m), V_{\text{rent}}(\eta, m)\} \tag{1}$$

For uninsured homeowners, the value function and constraints are

$$V_{\text{unins}}(\eta, b, m) = \max_{c,a,h} u(c,h) + \beta \mathbb{E}[V(\eta', b', m')|\eta] \tag{2}$$

$$\text{s.t.} \quad m = c + p_o h + a \tag{3}$$

$$a \geq -\max\{\lambda p_o h, b\} \tag{4}$$

$$h \in \{h_1, h_2, \ldots, h_H\} \tag{5}$$

$$m' = y' + (1+r)a + (1-\delta)(1-(1-\xi)z)p_o h \tag{6}$$

$$y' = \bar{y}\exp(\eta' + \zeta') \quad \text{where } \eta' \sim F_{\eta'|\eta},\ \zeta' \sim F_\zeta \tag{7}$$

$$b' = \max\{-a, 0\} \cdot 1_{z>0} + \max\{b - \Delta b(b), 0\} \cdot 1_{z=0} \tag{8}$$

$$z \sim F_z \text{ with prob. } \psi_{\text{perc}},\ z = 0 \text{ with prob. } 1 - \psi_{\text{perc}} \tag{9}$$

where p_o is the house price per unit, r is the risk-free interest rate, and β is the discount factor. Income y follows a standard stochastic process with median $\bar{y}$, persistent state η, and transitory shock ζ. The house size is chosen from a finite set of possible sizes. Homeowners can borrow against the house value, subject to a maximum loan-to-value ratio λ.

Uninsured homeowners face flood risk which has two components: the probability that a flood occurs, and the severity of damage when it does occur. Each period, a flood occurs with actual probability ψ_{act}, though households may perceive a different probability ψ_{perc}. Conditional on a flood occurring, the damage rate $z \in \{z_1, \ldots, z_Z\}$ is drawn from the discrete distribution F_z. This damage is applied on top of the standard depreciation rate δ and therefore reduces the house value from $(1-\delta)p_o h$ to $(1-\delta)(1-z)p_o h$. Households receive disaster aid $(1-\delta)\xi z p_o h$, which covers a fraction ξ of the flood damage.

To capture the long-term nature of mortgage debt, we introduce the variable b, which allows households to maintain pre-existing mortgage debt even when house values fall. Loan-to-value constraints bind only at origination and refinancing, and lenders cannot demand immediate repayment of existing mortgages if a house was damaged. When a flood occurs, we therefore set b equal to outstanding debt $\max\{-a, 0\}$, and the borrowing constraint becomes $a \geq -\max\{\lambda p_o h, b\}$. This allows debt to remain above the loan-to-value limit $\lambda p_o h$ that would apply to a new mortgage. In periods without floods, b decreases through regular payments $\Delta b(b) = \max\{\omega b, \Delta b_{\min}\}$, where ωb captures that larger mortgages have higher payments and $\Delta b_{\min}$ ensures full repayment within finite time.

The liquidity-provision policies described in Section 2.2 are incorporated implicitly through three modeling choices. First, we treat financial assets a as liquid, reflecting that uninsured homeowners can access retirement funds penalty-free or borrow against their retirement accounts after a flood. Second, the way the loan-to-value constraint is interpreted after a

flood captures the key properties of disaster loans. In normal periods, this constraint means that mortgage debt used to finance the house purchase cannot exceed a fraction λ of house value. After a flood, however, it means that the sum of existing mortgage debt and any new borrowing to finance repairs cannot exceed a fraction λ of the repaired house value, thus capturing the availability of disaster loans even when the damaged house provides insufficient collateral. Third, when mortgage debt remains below the value of the repaired house, we impose no repayment schedule, thereby capturing the flexibility provided by mortgage forbearance and loan modification programs. Only when existing debt exceeds the value of the repaired house do we explicitly model a one-year forbearance period followed by regular mortgage payments $\Delta b(b)$ to gradually reduce the debt level.

For insured homeowners, the value function and constraints are

$$V_{\text{ins}}(\eta, b, m) = \max_{c,a,h} u(c,h) + \beta \mathbb{E}[V(\eta', b', m')|\eta] \tag{10}$$

$$\text{s.t.} \quad m = c + p_o h + \pi p_o h + a \tag{11}$$

$$\pi = (1+\ell)\pi_{\text{fair}} \tag{12}$$

$$\pi_{\text{fair}} = \mathbb{E}[z] \cdot \frac{1-\delta}{1+r} \tag{13}$$

$$a \geq -\max\{\lambda p_o h, b\} \tag{14}$$

$$h \in \{h_1, h_2, \ldots, h_H\} \tag{15}$$

$$m' = y' + (1+r)a + (1-\delta)p_o h \tag{16}$$

$$y' = \bar{y}\exp(\eta' + \zeta') \quad \text{where } \eta' \sim F_{\eta'|\eta},\ \zeta' \sim F_\zeta \tag{17}$$

$$b' = \max\{b - \Delta b(b), 0\} \tag{18}$$

where π is the insurance premium rate as a fraction of house value, π_{fair} is the actuarially fair premium rate, and ℓ is the insurance loading (i.e., deviation from the actuarially fair premium). Insured homeowners pay the premium $\pi p_o h$ to receive complete protection against flood losses, so the house value evolves deterministically as $(1-\delta)p_o h$. Like uninsured homeowners, insured homeowners can borrow against the house value, subject to a maximum loan-to-value ratio λ. If an insured homeowners has positive borrowing capacity b from a previous period with uninsured damages, this capacity continues to decrease through regular mortgage payments $\Delta b(b)$ in each period until it reaches zero.

For renters, the value function and constraints are

$$V_{\text{rent}}(\eta, m) = \max_{c,a,h} u(c,h) + \beta \mathbb{E}[V(\eta', b' = 0, m')|\eta] \tag{19}$$

$$\text{s.t.} \quad m = c + p_r h + a \tag{20}$$

$$a \geq 0 \tag{21}$$

$$h \in \{h_1, h_2, \ldots, h_H\} \tag{22}$$

$$m' = y' + (1+r)a \tag{23}$$

$$y' = \bar{y} \exp(\eta' + \zeta') \quad \text{where } \eta' \sim F_{\eta'|\eta},\ \zeta' \sim F_\zeta \tag{24}$$

where p_r is the rental price per unit of housing. Renters face no flood risk and cannot borrow.

The utility function takes the Cobb-Douglas form nested within a constant relative risk aversion (CRRA) utility function:

$$u(c,h) = \frac{(c^\alpha h^{1-\alpha})^{1-\gamma}}{1-\gamma} \tag{25}$$

where α governs the relative importance of consumption versus housing services and γ is the coefficient of relative risk aversion.

3.2 Discussion

This section discusses key simplifications made to keep the model tractable while capturing the essential features of household decision-making under flood risk. One important simplification is that liquidity-provision policies are only included implicitly since explicitly modeling each disaster relief policy described in Section 2.2 would substantially increase the state space. Instead, we model savings, borrowing constraints, and mortgage repayment to approximately capture the liquidity provision of these programs after floods. One side effect is that financial assets are fully liquid in normal periods, not just after floods. However, since our focus is on flood insurance decisions rather than consumption-savings decisions in normal times, we consider this a reasonable compromise.

The model assumes that households are infinitely lived, which allows us to abstract from details required to model retirement. While this simplification could overstate how well agents can smooth the impact of flood damages on consumption compared to a finite horizon model, we argue that it is nevertheless an acceptable approximation, even for older households. In the United States, retired homeowners typically have sufficient liquid savings to finance flood repairs out-of-pocket, particularly given the unlimited and penalty-free access

to retirement funds after age 59 1/2. Moreover, the net worth of retirees declines slowly, reflecting bequest motives and savings for elderly care (De Nardi et al., 2016). The infinite horizon assumption thus implicitly captures how older households can smooth flood impacts through reduced bequests or lower spending on elderly care.

We model mortgage borrowing in a simplified way by combining regular mortgages, home equity loans, and disaster loans into a single state variable. In normal periods, mortgages are one-period loans with a maximum loan-to-value ratio, allowing us to abstract from amortization schedules and the terms for refinancing or home equity loans. The long-term nature of mortgages becomes important after floods and is therefore explicitly included through the state variable b. Additional borrowing up to the loan-to-value ratio remains possible after a flood, which captures the availability of disaster loans and mortgage relief rather than traditional refinancing. We do not model loan modifications or defaults, which would substantially complicate the model. In practice, defaults following flood losses are rare (Kousky et al., 2020), as disaster loans and mortgage relief typically allow homeowners to avoid foreclosure.

The model treats flood insurance as a binary choice, where households either purchase full coverage or none at all. This reflects common practice in the United States, where many homeowners insure their entire house and select low deductibles of \$500 or \$1,000 (Collier et al., 2022). For expensive houses with replacement costs exceeding the maximum coverage limit of \$250,000, homeowners can often purchase additional private insurance to cover the excess value. We focus on flood insurance for the primary residence and abstract from contents insurance, which represents a small share of total coverage and damages for most homeowners. The model assumes that NFIP participation is voluntary, which approximates the current situation where a partial insurance mandate exists but is not consistently enforced.

We ignore real estate transaction costs and investment in flood-proofing measures. While transaction costs would make downsizing costly for households that lose significant net worth, these households can partially adjust their housing consumption through delayed repairs or reduced maintenance. Regarding flood-proofing, while adaptation measures such as elevating the house can reduce flood risk exposure, they do not eliminate flood risk entirely, and flood insurance remains relevant even for houses with such measures in place.

4 Parameterization of the model

This section describes the parameterization of the model to match high-risk flood zones (SFHAs) in the United States. Our strategy is to set parameters based on external sources, such as survey data and literature, whenever possible. The remaining parameters are calibrated to match relevant empirical targets. Since one of the internally calibrated parameters is the perceived flood probability, an important result of our analysis, we postpone the discussion of the moment matching to Section 5.1. Table 1 shows all model parameters, including the ones that are calibrated internally. We set the time period in the model to one year, normalize one unit of the consumption good to \$100,000 in 2022 dollars, and normalize the price of housing to 1 so that one unit of housing corresponds to \$100,000 as well.

The risk aversion parameter is set to $\gamma = 2$, as in Collier et al. (2022) and most quantitative macroeconomic models. We also consider $\gamma = 1$ and $\gamma = 4$ as robustness checks in Section 5.1. The two remaining preference parameters, the discount factor β and the utility weight on non-housing consumption α, are calibrated to match empirical moments.

Log income follows a standard persistent-transitory process

$$\log y_t = \log \bar{y} + \eta_t + \zeta_t \tag{26}$$

$$\eta_t = \rho \eta_{t-1} + \epsilon_t \tag{27}$$

where $\bar{y}$ is the median net household income, η_t captures the persistent stochastic component with innovations $\epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2)$, and $\zeta_t \sim \mathcal{N}(0, \sigma_\zeta^2)$ is a transitory income shock. The median household income $\bar{y}$ is set to 0.65, based on a gross median household income of \$70300 in the 2022 wave of the Survey of Consumer Finances (SCF) (Aladangady et al., 2023), and an effective tax rate of 8% for the middle quintile of the income distribution (Congressional Budget Office, 2023). The estimation of ρ, σ_ϵ^2 and σ_ζ^2 is based on the empirical moments from Kaplan and Violante (2022). See Appendix B for more details. The AR(1) process for the persistent component is discretized using the Rouwenhorst method to obtain a Markov chain with 4 discrete states. The transitory shock ζ_t is discretized into two values $\zeta_1 = -\sigma_\zeta$ and $\zeta_2 = +\sigma_\zeta$.

We set the maximum loan-to-value ratio to $\lambda = 80\%$, which implies a down payment of 20% for homeowners, following Sommer and Sullivan (2018). The depreciation rate of housing capital equals $\delta = 2.5\%$ per year, based on Harding et al. (2007). We assume a real interest rate r of 2%. This is in line with the average real yield on 10-year Treasury Inflation-Protected Securities (TIPS) in times without quantitative easing.

The price of housing is normalized to 1, so that one unit of housing corresponds to

Table 1: Baseline parameterization

Parameter	Symbol	Value	Source
Preferences			
Risk aversion	γ	2	Literature
Discount factor	β	0.938	Moment matching
Utility weight on consumption	α	0.856	Moment matching
Income Process			
Median household income	$\bar{y}$	0.65	SCF (Aladangady et al., 2023)
Autocorrelation	ρ	0.925	PSID (Kaplan and Violante, 2022)
Persistent shock variance	σ_ϵ^2	0.0676	PSID (Kaplan and Violante, 2022)
Transitory shock variance	σ_ζ^2	0.0359	PSID (Kaplan and Violante, 2022)
Housing and Financial Markets			
Real interest rate	r	2%	10-year TIPS
Maximum LTV ratio	λ	80%	Sommer and Sullivan (2018)
Depreciation rate	δ	2.5%	Harding et al. (2007)
House price	p_o	1.0	Normalization
Rental price	p_r	0.0457	Moment matching
Minimum house size	$h_{\min}$	0.5	AHS
Maximum house size	$h_{\max}$	10.0	AHS
Land share	s	40%	Davis et al. (2021)
Mortgage repayment rate	ω	1/30	30-year mortgage
Minimum mortgage payment	$\Delta b_{\min}$	0.1	
Flood Risk			
Actual flood probability	ψ_{act}	1%	SFHA definition
Perceived flood probability	ψ_{perc}	0.91%	Moment matching
Damage rates for structure	$\{\tilde{z}_i\}_{i\in\{1,Z\}}$	Figure 1	NFIP data
Damage probabilities	$\{\nu_i\}_{i\in\{1,Z\}}$	Figure 1	NFIP data
Flood Insurance and Disaster Aid			
Insurance premium load	l	-5%	NFIP data
Disaster aid coverage	ξ	5%	Congressional Research Service (2024)

Notes: AHS = American Housing Survey; PSID = Panel Study of Income Dynamics; SCF = Survey of Consumer Finances; NFIP = National Flood Insurance Program. One unit of the consumption good is normalized to \$100,000 in 2022 dollars.

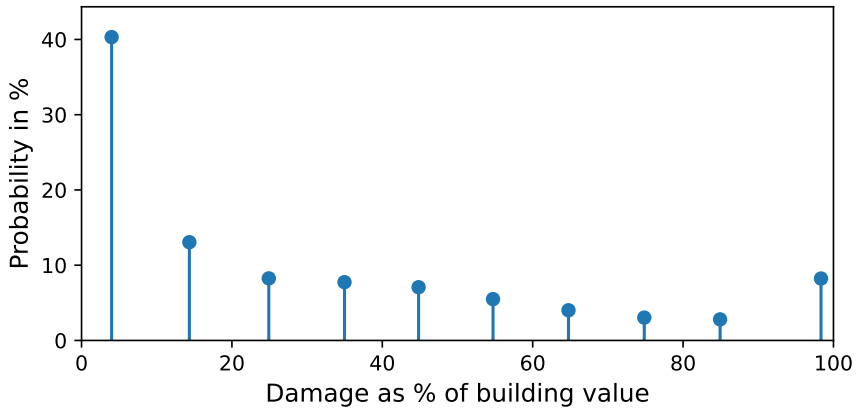


Figure 1: Discretized distribution of flood damage rates for physical structures $\tilde{z}$ based on NFIP claims data. To obtain the damage rates relative to property values z used in the model, we multiply the damage rate for physical structures by $1 - s = 0.6$ to account for the land share s.

\$100,000 in 2022 dollars. The rental price of $p_r = 0.0457$ represents the annual rent as a percentage of the property value, which is calibrated jointly with preference parameters to match the empirical moments in Table 2. This implies a price-to-rent ratio of approximately 22, which is consistent with current US housing market conditions. We choose a house size grid with $H = 10$ discrete sizes, ranging from $h_{\min} = 0.5$ to $h_{\max} = 10$ and with smaller house sizes being more densely spaced than larger ones. This range is based on the AHS data, which shows that 88% of owner-occupied houses have a value between \$50,000 and \$1,000,000. We verify ex-post that no households want to rent or own houses outside this range in the fully calibrated model.

We calibrate the decline in the borrowing capacity b as follows: The value of b decreases at rate $\omega = 1/30$ annually, corresponding to a 30-year amortization schedule. Moreover, there is a minimum annual payment of \$10,000 to ensure amortization within a finite period.

We set the flood probability in our baseline calibration to $\psi_{\text{act}} = 1\%$, in line with the NFIP's definition of SFHAs. For the parameterization of the flood damage distribution, we proceed in three steps: First, we compute the continuous distribution of flood damage rates for the physical structure $\tilde{z}$ from NFIP claims data filed by homeowners in SFHAs. Second, we discretize the continuous distribution into 10 equally spaced damage rate bins by computing the average damage rate and the probability mass within each bin. The resulting discrete damage levels $\tilde{z}_i$ and associated probabilities ν_i are shown in Figure 1. The fine discretization is crucial to capture the right tail of the distribution accurately, which has a significant impact on households' willingness to pay for insurance. Third, we transform the damage rates for the physical structure $\tilde{z}$ into overall damage rates for the property z in the

model by taking the share of land s in the total property value into account: $z_i = (1-s)\tilde{z}_i$. Following Davis et al. (2021), we set $s = 0.4$, so that property damage is 60% of structure damage.

The insurance premium load is set to $l = -5\%$, indicating that premiums are 5% below actuarially fair rates. This is based on our analysis of NFIP claims and policies among homeowners in SFHAs. The implied annual insurance premium is $\pi = 0.162\%$ of the property value for full coverage against flood damage. To set the disaster grant parameter ξ, we rely on information from Congressional Research Service (2024). The average FEMA disaster assistance grant is $\$4,200$ for homeowners and $\$1,700$ for renters. Since FEMA housing assistance is designed to cover costs for both temporary housing and simple repairs, we interpret the $\$2,500$ difference as a proxy for the average amount allocated toward housing repairs after a flood. This represents approximately 5% of the average NFIP claim, which is why we set $\xi = 5\%$.

5 Results

First, we compute the degree of flood risk underestimation necessary to match the observed insurance take-up rate. Next, we focus on understanding the median WTP and the heterogeneity in WTP across households. Finally, we analyze counterfactual insurance take-up rates under different pricing schemes and assumptions about flood risk perceptions and disaster grants.

5.1 Underestimation of flood risk

The perceived flood probability ψ_{perc} is calibrated jointly with the discount factor β, the weight of non-housing consumption in the utility function α, and the rental price p_r to match the moments listed in Table 2. Median wealth is particularly informative about the discount factor, while the median house size of homeowners helps calibrate the relative weights of housing services and non-housing consumption in the utility function. The homeownership rate of 66% matters most for the calibration of the rental price, while the insurance take-up rate is most sensitive to the perceived flood probability.

Table 2: Moments used for calibration

Moment	**Empirical Value**	**Source**	**Simulated Value**
Median wealth	1.93	SCF	1.93
Median house value of homeowners	3.23	SCF	3.22
Homeownership rate	66%	SCF	66%
Insurance take-up rate	48%	Bradt et al. (2021)	48%

SCF = Survey of Consumer Finances. The empirical values are taken from (Aladangady et al., 2023). Wealth and house values are expressed in units of $100,000 (2022 dollars).

In the baseline calibration, we set risk aversion to $\gamma = 2$, as in Collier et al. (2022). The calibrated perceived flood probability is $\psi_{\text{perc}} = 0.91\%$, which implies a relatively small underestimation of flood risk of approximately 9% compared to the actual flood probability of $\psi_{\text{act}} = 1\%$. The calibrated values for the discount factor, non-housing consumption weight, and rental price (expressed as a fraction of house value) are reported in Table 3 and all lie within the range of values commonly seen in the macro-housing literature. With the calibrated parameters, we match the empirical moments almost perfectly, with deviations in Table 2 of less than 1%.

We also report results for lower and higher values of risk aversion as robustness checks in Table 3. With lower risk aversion of $\gamma = 1$, an even smaller underestimation of flood risk of about 4% is sufficient to match the observed insurance take-up rate. This is because

Table 3: Calibrated parameters for different risk aversion levels

Parameter	**Symbol**	**Value** ($\gamma = 1$)	**Value** ($\gamma = 2$)	**Value** ($\gamma = 4$)
Discount factor	β	0.965	0.938	0.852
Utility weight on consumption	α	0.857	0.856	0.840
Rental price	p_r	0.0458	0.0457	0.0457
Perceived flood probability	ψ_{perc}	0.964%	0.914%	0.749%

$\gamma = 2$ corresponds to the baseline calibration. The rental price is expressed as a fraction of the house value.

more risk-tolerant households are willing to pay less for flood insurance with correct risk perceptions, and thus a smaller degree of underestimation is sufficient to reduce WTPs to levels implied by the observed insurance take-up. Conversely, with a higher risk aversion of $\gamma = 4$, the WTP for flood insurance with correct flood risk perceptions is higher, requiring a moderately large underestimation of flood risk of about 25% to match the insurance take-up rate of 48%. The rental price and utility weight barely change with different risk aversion levels, while the discount factor decreases with higher risk aversion to keep median wealth constant.

5.2 Understanding the low median WTP

The median willingness to pay for flood insurance in the calibrated model is 5% below the actuarially fair price. This follows mechanically from calibrating the perceived flood probability to match the observed insurance take-up rate of 48% given the insurance load of -5%. To understand what drives this low median WTP, we examine the contribution of risk misperceptions and disaster grants through counterfactual simulations.

Table 4 reports the median WTP under three counterfactual scenarios. Removing disaster grants ($\xi = 0\%$) increases the median WTP only slightly, from 5% below the actuarially fair premium to 1% above it. While disaster grants distort incentives to purchase flood insurance, their effect on the WTP is small due to their limited generosity.

Table 4: Median WTP under different counterfactual scenarios

	ξ	ψ_{perc}	Median WTP
Baseline calibration	5%	0.91%	5% below fair premium
No disaster grants	0%	0.91%	1% above fair premium
Correct perceptions	5%	1%	4% above fair premium
Both combined	0%	1%	10% above fair premium

Correcting flood risk perceptions by setting $\psi_{\text{perc}} = 1\%$ increases the median WTP by approximately 9 percentage points to 4% above the actuarially fair price. This shows that the

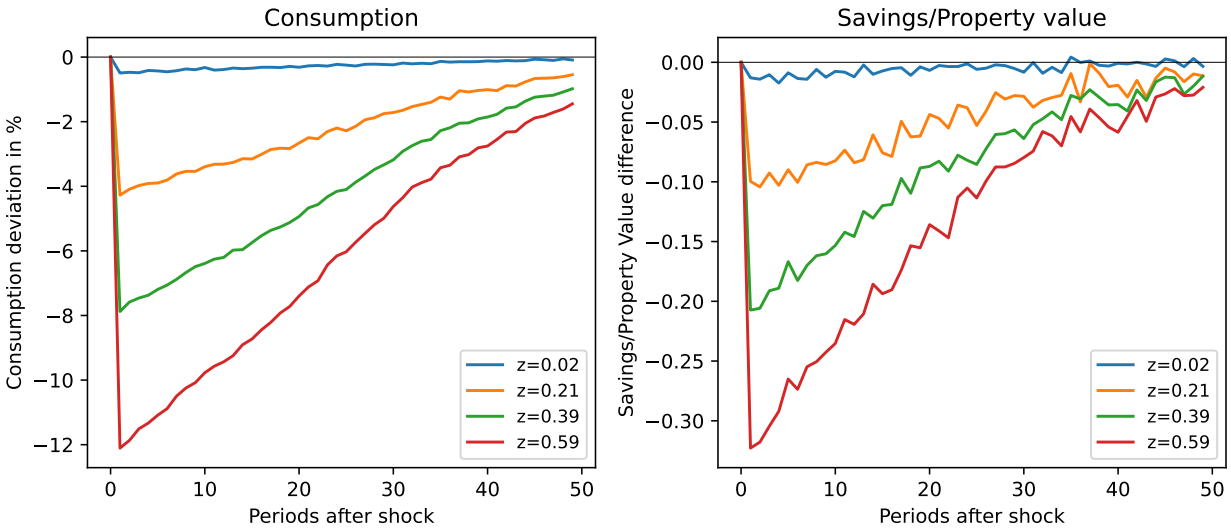


Figure 2: Average effect of flood damage on non-housing consumption and savings over time for uninsured homeowners

WTP is approximately linear in the perceived flood probability when the perceived annual probability remains sufficiently low.

When we combine both counterfactuals, the median WTP reaches 10% above the actuarially fair price. However, this remains far below the loading necessary for financial sustainability. Commercial property insurers typically require loadings above 25% to cover administrative costs, and the NFIP spends approximately 30% of premium income on agent commissions and operating expenses. Therefore, risk misperception and disaster grants do not appear to be the main reasons why the big majority of homeowners are not willing premiums that would ensure the financial sustainability of the NFIP.

This finding contrasts with the previous literature, which has often attributed low flood insurance take-up primarily to risk misperceptions. For example, after ruling out adverse selection based on private information, Wagner (2022) identifies risk misperception as the main explanation for low willingness to pay. The limited role of disaster grants in our results aligns with prior research: Kousky et al. (2018) similarly finds that disaster grants have only a modest effect on insurance take-up.

If risk misperceptions and disaster grants are not the main drivers of the low WTP, what else could explain it? We argue that disaster relief policies focused on liquidity provision play a crucial role. Since the effects of these policies are implicitly included in the model but not explicitly modeled, we cannot directly quantify their effect by removing them from the model. Instead, we analyze how uninsured households respond to floods in the baseline calibration to understand how they limit the impact of flood damages on contemporaneous

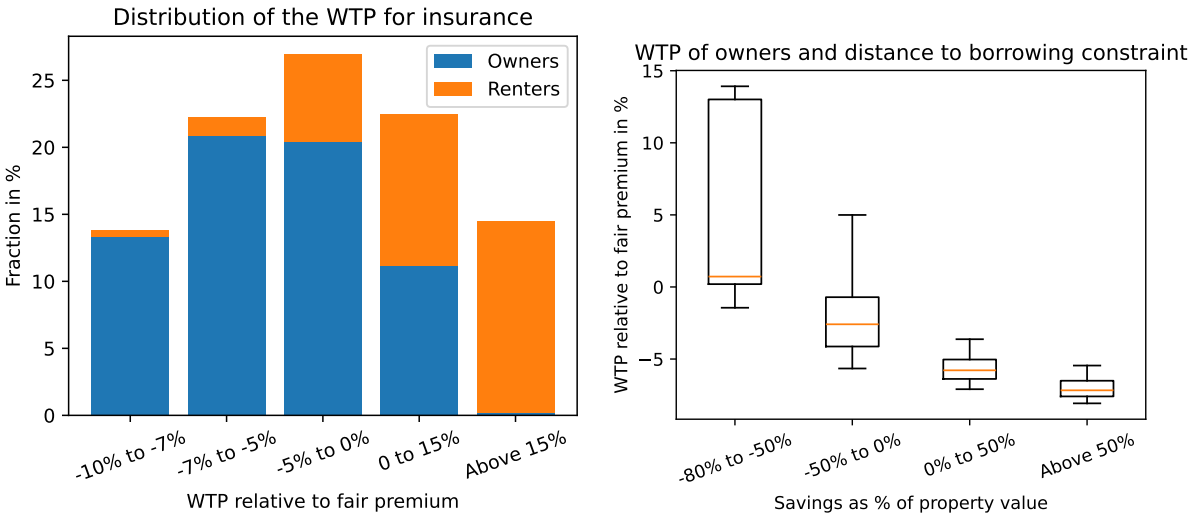


Figure 3: Left: Distribution of willingness to pay for flood insurance among homeowners and renters. Right: Willingness to pay for flood insurance among homeowners by ratio of savings to property value.

consumption.

The left panel of Figure 2 shows the average effect of flood damage on non-housing consumption over time for homeowners who remain uninsured in the baseline calibration. The model predicts that floods with low damage rates, which are most common, lead to only a small reduction in non-housing consumption during the flood year. Even severe floods that destroy more than 20% of property value reduce non-housing consumption by just 4% to 12%, depending on severity.[1]

Uninsured households limit the impact of floods on non-housing consumption by drawing down savings or borrowing. The right panel of Figure 2 illustrates the impact on savings normalized by property value. Severe floods reduce savings or increase borrowing by 10% to 30% of property value. As the reduction of consumption is modest but persistent, lower expenditures enable households to gradually rebuild their savings over time.

5.3 Household heterogeneity in the WTP

After analyzing the low median WTP, we now turn to the heterogeneity in the WTP across households. The left panel of Figure 3 shows the distribution of the WTP for flood insurance among homeowners in the baseline calibration. The distribution of the WTP among homeowners is relatively concentrated around the median of 5% below the actuarially fair price,

[1]Note that we define flood damage rates as damage relative to property value. Due to the assumed land value of 40%, the maximum flood damage rate is $z = 60\%$.

with most households having a WTP between 10% below and 15% above the fair price.

The left panel of Figure 3 also shows the WTP that renters would have if they were forced to become homeowners in the current period. The WTP among renters tends to be substantially higher than among owners, with a median of 10% above the actuarially fair price and a much wider distribution. About 35% of renters have a WTP more than 50% above the actuarially fair price. Note that the WTP among renters is hypothetical and should be interpreted with caution, as renters have lower wealth than they would have if they knew they would become homeowners in the next period. Nevertheless, this points to selection of households into the rental market as an additional factor behind the low WTP among homeowners: households with little wealth who are in a worse position to smooth damages over time and therefore have a higher WTP are more likely to rent.

The WTP of homeowners is strongly negatively correlated with the ratio of savings to property value. The right panel of Figure 3 shows that homeowners who borrow 50% or more against their housing equity have a median WTP of about 1% above the actuarially fair price, with WTPs 10% above the fair price also being common. In contrast, homeowners who own their homes outright (i.e., they have net savings greater than or equal to zero) have a median WTP of about 7% below the actuarially fair price, with no households willing to pay the fair price.

Homeowners who have heavily borrowed against their housing equity are willing to pay more for flood insurance for two reasons. First, they are closer to their borrowing constraint and therefore either might not be able to fully finance the reconstruction of their home after a flood, or their ability to absorb income shocks in the future through borrowing is limited. Second, their exposure to flood risk relative to their total wealth (including the present value of future income) is higher than for homeowners who own their homes outright and have savings.

When discussing the heterogeneity in the WTP, it is important to keep in mind that the calibrated model abstracts from sources of heterogeneity beyond differences in income, wealth, and housing. For instance, all households share the same flood risk perceptions and expectations about disaster grants. This implies that the variation in the WTP reported here is a lower bound on the true heterogeneity in the population.

5.4 Counterfactual insurance take-up

Using the calibrated model, we can also analyze counterfactual insurance take-up rates under different pricing schemes and assumptions about flood risk perceptions and disaster grants. The rows in Table 5 refer to the four scenarios analyzed in Table 4, while the columns refer

Table 5: Counterfactual take-up rates under different policy scenarios

	Current subsidy $\ell = -5\%$	Actuarially fair $\ell = 0\%$	Incl. admin. costs $\ell = 25\%$
Baseline calibration	48%	17%	0%
No disaster grants	100%	56%	0%
Correct perceptions	100%	100%	0%
Both combined	100%	100%	6%

to different pricing schemes for flood insurance. In addition to the baseline pricing with an insurance load of -5%, we also consider actuarially fair pricing (0% load) and pricing that includes administration costs (25% load).[2]

Removing disaster grants and correcting flood risk perceptions both lead to substantial increases in insurance take-up under the current subsidized pricing and actuarially fair pricing. Under the baseline calibration, insurance take-up among homeowners would decrease from 48% to 17% with actuarially fair pricing. Without disaster grants, we would see complete coverage with the current subsidized pricing and a take-up above 50% with fair pricing. With correct perceptions of flood risk, the model predicts complete coverage with fair pricing.

However, none of the scenarios considered here would lead to high insurance take-up under a financially sustainable pricing scheme that includes administration costs. Even if both the distortions from disaster grants and flood risk misperceptions were removed, take-up would only be 6% with such pricing. If just one of the two distortions were removed, the model even predicts zero insurance take-up. This finding highlights that factors other than risk misperceptions and disaster grants are behind the NFIP's problems in achieving high insurance take-up at financially sustainable pricing.

Insurance take-up in the model is very sensitive to premiums, disaster grant generosity, and flood risk perceptions, as the sources of heterogeneity included in the model create a relatively concentrated distribution of WTPs. Adding further sources of heterogeneity, such as differences in flood risk perceptions, would make insurance demand more inelastic. With sufficiently large variation in beliefs, insurance take-up might not even reach 100% even in the most favourable scenario of subsidized pricing with no disaster grants and correct flood risk perceptions. On the other hand, the presence of households with overly pessimistic flood risk perceptions could lead to some insurance take-up even with very expensive insurance

[2]Changes in insurance premiums would not only affect insurance take-up, but also house prices. To study these effects, the current household decision model would need to be embedded in an equilibrium framework with endogenous house prices. However, the effect of insurance premiums on house prices is not the focus of this paper. We verify that take-up rates do not vary much with house prices in an unreported sensitivity analysis.

premiums. However, the finding that the median WTP is far below premium levels necessary for financial sustainability would remain valid with belief heterogeneity. Therefore, addressing flood risk misperceptions and disaster grants alone is unlikely to solve the NFIP's insurance take-up problem while achieving financial sustainability.

6 Conclusion

This paper develops a dynamic model of household decision-making under flood risk to understand why fewer than half of US homeowners in high-risk flood zones purchase flood insurance despite substantial subsidies. We find that the observed take-up rate is consistent with a modest underestimation of flood risk of approximately 9% in our baseline calibration, suggesting that factors beyond risk misperception play a more important role than previously thought. Our analysis identifies disaster relief policies focused on liquidity provision as the primary driver of low willingness to pay. Disaster loans, mortgage relief programs, and penalty-free retirement fund withdrawals allow affected households to smooth consumption after floods through dis-saving, borrowing, and delaying debt repayment, which reduces the value of flood insurance. In contrast, disaster relief policies that constitute a wealth transfer such as FEMA disaster assistance explain only a small portion of the low willingness to pay due to their limited generosity. Counterfactual simulations show that eliminating both disaster grants and risk misperceptions would yield only 6% insurance take-up under financially sustainable pricing that includes administration costs.

These findings have important policy implications. Improved risk communication is unlikely to substantially increase take-up, as only modest underestimation is needed to explain observed behavior. Ending liquidity provision policies could theoretically increase insurance demand but would impose substantial hardship on uninsured households and therefore does not seem politically feasible. Given these constraints, mandatory insurance coverage may be the only possible path to achieving broad coverage at risk-based premiums.

Future research could extend this analysis by incorporating heterogeneity in perceived flood risk to generate more realistic demand elasticities, or by conducting a normative analysis of the optimal mix of disaster grants, liquidity provision, and insurance subsidies in the presence of risk misperceptions.

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A Flood Insurance in Germany, France, the UK, and the Netherlands

International approaches to flood insurance vary significantly in their institutional arrangements and premium structures, ranging from voluntary market-based solutions to mandatory government-backed systems. Table 6 compares the flood insurance system in the United States with those in Germany, France, the United Kingdom, and the Netherlands. We focus on whether flood insurance is mandatory, the premium structure, and any planned future reforms.

Table 6: International Comparison of Flood Insurance Systems

Country	Insurance Mandate	Premium Structure	Future Reforms
United States	For federally-backed mortgages in high-risk areas	Partially risk-based	Shift towards fully risk-based pricing
Germany	No	Risk-based	Flood insurance mandate?
France	Yes	Not risk-based	(No reforms planned)
United Kingdom	No legal mandate, but typically required by mortgage lenders	Partially risk-based	Shift towards fully risk-based pricing
Netherlands	(No market for flood insurance)		Establish flood insurance market

Germany represents a market-oriented model for flood insurance provision. Private insurers offer flood coverage as optional supplements to standard homeowners policies, with premiums set according to actuarial risk assessments. Despite facing significant riverine flood exposure along major rivers like the Rhine and Elbe, Germany maintains no insurance mandate and does not provide government backing for private insurers. This voluntary system achieves nationwide penetration rates of approximately 50%. The devastating floods of 2013 and 2021, which caused billions in uninsured damages, have intensified political debates about introducing mandatory coverage (Fuest and Thum, 2021).

France exemplifies the opposite extreme, operating a mandatory system that prioritizes accessibility and solidarity over actuarial pricing. The Catastrophes Naturelles regime, administered by the Caisse Centrale de Réassurance, requires all property insurance contracts to include natural disaster coverage at flat rates. This uniform structure creates substantial cross-subsidies from low-risk to high-risk areas. The state provides unlimited reinsurance backing through CCR, ensuring the stability of the system even after major catastrophic

events. Universal coverage is achieved through this mandatory framework, with virtually 100% of French households protected against flood losses (Caisse Centrale de Réassurance, 2025).

Like the United States, the United Kingdom employs a hybrid approach without a comprehensive insurance mandate and a premium structure that is not fully risk-based. The Flood Re scheme, established in 2016, provides reinsurance for high-risk flood properties, effectively capping premiums for vulnerable households. This transitional arrangement aims to maintain affordable coverage while gradually shifting toward risk-based pricing. The system achieves remarkable coverage rates of 99% in high-risk areas, because mortgage lenders require homeowners insurance that typically includes flood coverage (Browning, 2025).

The Netherlands follows a fundamentally different strategy due to its unique geography. Since maritime flooding from storm surges could potentially inundate large portions of the nation, the Dutch system emphasizes comprehensive flood protection through massive infrastructure investments. When flooding does occur despite these protections, the government provides compensation through the Disaster Damage Compensation Act. This state guarantee and the high correlation of flood risks in the Netherlands have prevented the development of a private flood insurance market. Following the 2021 floods along the Maas river, however, the Dutch government is exploring how to facilitate a market for insurable flood risks (De Nederlandse Bank, 2022).

B Details on the calibration of the quantitative model

B.1 Income process

We model individual income as

$$\log y_t = \eta_t + \zeta_t \tag{28}$$

where η_t follows an AR(1) process

$$\eta_t = \rho \eta_{t-1} + \epsilon_t \tag{29}$$

with

$$\epsilon_t \sim \text{iid } \mathcal{N}(0, \sigma_\epsilon^2) \quad \text{(persistent shock innovation)} \tag{30}$$

$$\zeta_t \sim \text{iid } \mathcal{N}(0, \sigma_\zeta^2) \quad \text{(transitory shock)} \tag{31}$$

$$\text{Cov}(\epsilon_t, \zeta_s) = 0 \quad \forall t, s \tag{32}$$

The theoretical moments are

$$\text{Var}(\log y_t) = \frac{\sigma_\epsilon^2}{1-\rho^2} + \sigma_\zeta^2 \tag{33}$$

$$\text{Cov}(\log y_t, \log y_{t-1}) = \rho \cdot \frac{\sigma_\epsilon^2}{1-\rho^2} \tag{34}$$

$$\text{Cov}(\log y_t, \log y_{t-2}) = \rho^2 \cdot \frac{\sigma_\epsilon^2}{1-\rho^2} \tag{35}$$

Kaplan and Violante (2022) provide the following statistics for log annual income:

$$\text{Var}(\log y_t) = 0.504 \tag{36}$$

$$\text{Var}(\log y_t - \log y_{t-1}) = 0.142 \tag{37}$$

$$\text{Var}(\log y_t - \log y_{t-2}) = 0.207 \tag{38}$$

Since only variance statistics are available, we recover the required autocovariances as follows:

$$\text{Cov}(\log y_t, \log y_{t-1}) = \frac{2\text{Var}(\log y_t) - \text{Var}(\log y_t - \log y_{t-1})}{2} = 0.433 \tag{39}$$

$$\text{Cov}(\log y_t, \log y_{t-2}) = \frac{2\text{Var}(\log y_t) - \text{Var}(\log y_t - \log y_{t-2})}{2} = 0.401 \tag{40}$$

Using method of moments, we can estimate the parameters of the income process as follows

$$\hat{\rho} = \frac{\text{Cov}(\log y_t, \log y_{t-2})}{\text{Cov}(\log y_t, \log y_{t-1})} = 0.925 \tag{41}$$

$$\hat{\sigma}_\zeta^2 = \text{Var}(\log y_t) - \frac{1}{\hat{\rho}} \cdot \text{Cov}(\log y_t, \log y_{t-1}) = 0.0359 \tag{42}$$

$$\hat{\sigma}_\epsilon^2 = \text{Var}(\log y_t) - \hat{\rho} \cdot \text{Cov}(\log y_t, \log y_{t-1}) - \hat{\sigma}_\zeta^2 = 0.0676 \tag{43}$$