

# Underwater

The Effect of Federal Policies on Households' Exposure to Climate Change Risk\*

Ahyan Panjwani †

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September 16, 2022

## Abstract

Two government policies implicitly encourage homeownership in areas increasingly threatened by climate change. First, government-sponsored enterprises, Fannie Mae and Freddie Mac, do not charge mortgage borrowers for location-specific climate risk. Second, the government spends billions of dollars helping rebuild homes and infrastructure after major disasters. In this paper, I introduce climate risk into a canonical lifecycle model of consumption and housing choice to estimate how removing both distortions would affect the number of homeowners living in areas exposed to climate risk, specifically flood risk. I use Hurricane Sandy's landfall in New Jersey as a natural experiment to quantify the two distortions and discipline the model. My model predicts that jointly removing both distortions would have reduced the number of homes affected by Hurricane Sandy by 20%. I further show that a vast majority of the reduction in the number of homeowners exposed to climate risk could have been achieved by two measures, taxing at-risk homeowners and charging them a flood risk premium as part of the mortgage. This latter policy regime would have reduced residential losses from the storm by 30%, i.e., \$2.3 billion, despite continuance of post-disaster public assistance.

**Keywords:** Climate change, real estate, mortgages

**JEL Classification:** G21, R21, R32, Q54

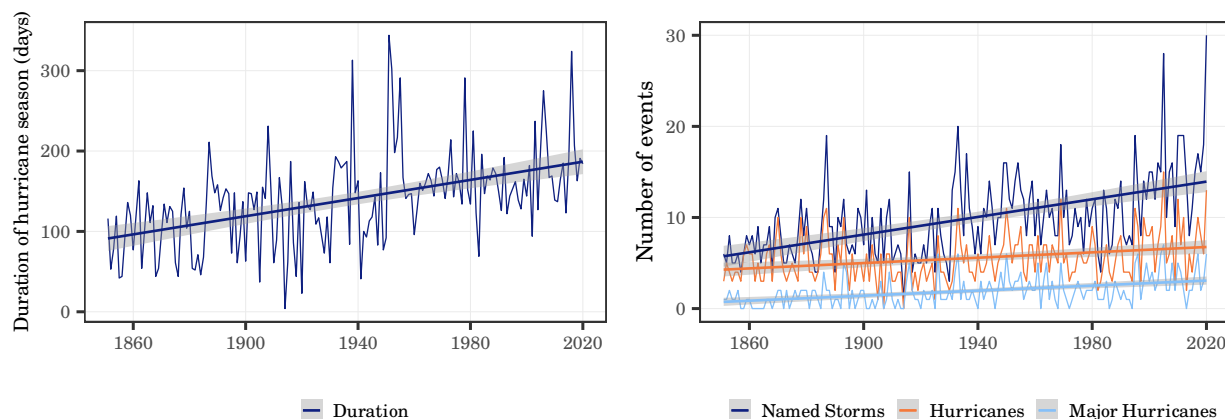
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\*I am grateful to John Geanakoplos, Atif Mian, and Eduardo Davila for their valuable advice and feedback. I also want to thank George-Marios Angeletos, Chris Clayton, Stefano Giglio, Will Goetzmann, Paul Goldsmith-Pinkham, Zhen Huo, Ben Keys, Guiseppe Moscarini, Michael Peters, Aazam Virani, Oliko Vardishvili, Nancy Wallace, Scott Castleton, John Finlay, Faizaan Kisat, Vitor Possebom, Chase Ross, Jaehee Song, Kaushik Vasudevan and seminar participants at Yale, UC Berkeley—Haas, McGill—Desautels, Southern Methodist University, Fudan University, Federal Reserve Board, Richmond Fed, Bank of Canada, Bank of England, Reed College, Swarthmore College, Fulcrum Asset Management, the Mortgage Market Research Conference at the Philadelphia Fed, and the Society of Economic Measurements annual meetings for fruitful comments and suggestions. The analysis and conclusions set forth are those of the author and do not indicate concurrence by other members of the Board of Governors of the Federal Reserve System, the Office of Financial Research, or their staffs.

†Board of Governors of the Federal Reserve System. E-mail: [ahyan.panjwani@frb.gov](mailto:ahyan.panjwani@frb.gov).

## 1 Introduction

Costly climate events are happening more frequently. The left panel in Figure 1 shows that the Atlantic hurricane season lasts longer, while the right panel shows that named storms and hurricanes occur more often in a season. Yet, two government policies encourage homeownership in areas exposed to climate change. First, government-sponsored enterprises, Fannie Mae and Freddie Mac, do not charge mortgage borrowers for climate change-related default risk despite large variation in regional climate risk across space.<sup>1</sup> Second, the government spends billions of dollars helping rebuild homes and infrastructure after a major climate event. How would removing these distortions affect homeowners' exposure to climate risk, specifically flood risk?<sup>2</sup> In this paper, I estimate how many fewer homeowners would live in flood-prone areas if the policymaker i) stops providing aid after a large hurricane and ii) charges a flood risk premium as part of the mortgage. However, the policymaker will likely help flooded households ex-post due to political incentives. I show that the government can achieve a majority of this reduction in the number of households exposed to climate risk by two measures: taxing at-risk homeowners and charging them a flood risk premium as part of the mortgage, despite continuing post-disaster public assistance.



**Figure 1: Longer Hurricane Seasons and More Frequent Climate Events.** The left panel shows the increasing number of days between the first and the last storm in the Atlantic based on the National Hurricane Center's HURDAT2 Best Track data archive from 1851 to 2020, based on Kossin (2008, 2021). The right panel shows the increasing number of named storms, hurricanes, and major hurricanes in a given season based on Colorado State University's Tropical Meteorology Project database.

I develop a lifecycle model of consumption, housing and mortgage choice, and climate risk to quantify the effects of possible policy regimes. Households are heterogeneous in their initial endowment of wealth and their credit score (FICO). They can choose either to rent or own a

<sup>1</sup>Fannie Mae and Freddie Mac guarantee the payment of principal and interest to the investor. They charge the borrower a fee for this guarantee to cover for default risk. This fee does not account for climate risk, in particular flood risk, which varies significantly across space.

<sup>2</sup>This paper focuses on flood risk as a manifestation of climate risk. The methods developed here are equally applicable to studying wildfire risk.

home. They can buy a home in a safe region immune to disasters or in an at-risk area. While the latter is vulnerable to natural disasters, it also offers an ‘amenity value’ from living by the shoreline. Importantly, in the model, at-risk homeowners can default on their mortgages. In this case, their FICO score is reset to the lowest possible, and they have to rent for at least one period. Households face a menu of mortgage contracts. They can choose the contract that is optimal for them, given their FICO score. Those with lower FICO scores face higher mortgage rates. So defaulting today raises the cost of homeownership in the future. The combination of heterogeneity in wealth and credit score allows me to determine the effect of policy changes on various groups, particularly creditworthy households with limited wealth.

My first main finding empirically quantifies the magnitude of the two distortions, which I use to discipline the model. I estimate these distortions in the context of Hurricane Sandy. First, how large is the mispricing of mortgage rates due to climate change-related default risk? I combine mortgage origination data from Corelogic and flood insurance policy data from the National Flood Insurance Program (NFIP) to compute mortgage rates adjusted for flood risk. My measure of the flood risk premium is the difference between the two mortgage rates: one that accounts for flood risk and the actual rate. I find that the mean flood risk premium in New Jersey is 26 basis points, and since the homeowner does not pay for this specific credit risk, they receive an implicit subsidy every period during the life of the mortgage.

Additionally, how large was government assistance after Sandy? I use the hurricane’s landfall in New Jersey in October 2012 as a natural experiment to determine the effect of government assistance on flooded homeowners’ decision to pay their mortgage dues. Using difference-in-differences, I find that government aid reduced the probability of flooded homeowners failing to stay current on their mortgages by 15%. By targeting this moment from the natural experiment in the lifecycle model, I infer that government assistance per household was \$48,000 on average.

My second main finding is that removing both distortions together would have led to 73,000, or about 20%, fewer homeowners being exposed to Hurricane Sandy in New Jersey. The model predicts that these would be low and moderate wealth, albeit creditworthy, households who would choose to live in a safer region. Intuitively, in the absence of government assistance ex-post, a homeowner is likely to find both their house and mortgage underwater.<sup>3</sup> Unable to pay for repairs, poor homeowners would default. As a result, they would lose their high FICO score, making future homeownership more costly. Moreover, now that mortgage rates account for flood risk, owning a home in the at-risk area is more expensive. The two channels

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<sup>3</sup>A mortgage where the outstanding balance is more than the value of the house is said to be underwater.

combined nudge poor but creditworthy households towards the safe region. This result serves as a benchmark for comparing an alternate policy regime.

My third main finding is that i) a tax—equal to the median flood insurance premium—on homeowners in the at-risk area and ii) pricing flood risk into mortgage rates, while also helping flooded homeowners ex-post, would have reduced the number of homeowners exposed to Hurricane Sandy by 58,000, or 17%.<sup>4</sup> Consequently, residential losses due to the superstorm would have been lower by \$2.34 billion, or 30%. Relative to the benchmark, poorer households with lower FICO scores choose to live in the safe region. Since the cost of living in the at-risk area has risen in two ways: a new tax and higher mortgage rates, poorer households are priced out of the high-amenity, high-risk housing market. Compared to the benchmark result, this policy regime still reduces the number of households exposed to climate risk by 80% without requiring the policymaker to make a less than credible commitment *not* to help flooded homeowners after the fact.

**Relation to Literature** My paper contributes to two literatures. First, there is a growing literature on household behavior in the face of climate risk. Ouazad and Kahn (2019) find that following a large flood, mortgage lenders are more likely to pass mortgages in vulnerable areas to the GSEs. On the flip side, Issler et al. (2019) find that mortgage foreclosures decrease when wildfires are larger. Moreover, Kousky (2018) shows that take-up rates for flood insurance, even in high risk flood zones, is very low while Wagner (2020) and Netusil et al. (2021) document a remarkably low willingness-to-pay for flood insurance. Landry, Turner, and Petrolia (2021) show that expectations of disaster assistance may nudge homeowners in disaster-prone areas to forego flood insurance. I add to this literature by quantifying the long-term effect of removing existing distortions due to federal policies on households' housing decisions. In particular, I take challenges to ensuring universal flood insurance coverage as given and determine the effect on household behavior of restricting assistance after a disaster and of differentially charging mortgagors in a high-risk area for increased credit risk. My empirical estimates of the distortions contribute to the ongoing discussion on reducing and removing subsidies for flood insurance.

Second, my paper is linked to the literature on housing choice and mortgage design. Kaplan, Mitman, and Violante (2020) create a lifecycle model of consumption, housing, and mortgage choice with aggregate risk to investigate household behavior in the context of the 2008 housing crisis. Guren, Krishnamurthy, and McQuade (2020) use a similar model to study the effect of mortgage design on macro-volatility and default. Hurst et al. (2016) augment this model

<sup>4</sup>The median annual flood insurance premium in New Jersey between 2010 and 2015 was \$564.

by introducing spatial variation to show that a national mortgage rate policy affects welfare by redistributing resources across space. To my knowledge, my paper is the first to introduce climate risk into the lifecycle model and to show how, given incentives set by the policymaker, households facing climate risk sort across space.

Relatedly, I introduce endogenous leverage as in Geanakoplos (1997, 2010), and Fostel and Geanakoplos (2014, 2015). I do so by designing a menu of mortgage contracts from which the household chooses the optimal contract. This menu is called the credit surface. Geanakoplos and Rappoport (2019) and Geanakoplos and Pedersen (2014) show how changing beliefs and collateral value can affect the supply of mortgage credit. My model shows how households change their housing decisions as the supply of credit evolves. Since leverage is endogenous, a household can borrow against the entire value of the house. The household that does so, however, ends up paying a higher mortgage rate and understands that it may be underwater physically and financially in the event of a flood. Thus, I can characterize the effects of policy experiments for a wide range of households in terms of wealth and creditworthiness. Modeling these salient features of the US housing and mortgage market is critical to quantifying the effect of future federal policies on communities exposed to climate risk, e.g., FEMA’s newly announced methodology for determining flood risk premiums.<sup>5</sup>

The rest of the paper is structured as follows. In Section 2, I describe the lifecycle model of consumption and housing choice in the face of climate risk. I outline the empirical exercises to quantify the two distortions in Section 3. Section 4 describes the calibration exercise. In Section 5, I report the model fit and results from the policy experiments. Section 6 concludes.

## 2 A Life Cycle Model of Housing and Mortgage Choice

### 2.1 Overview

In this section, I describe a quantitative model that captures the principal features of the US housing and mortgage market. The layout of the model economy, and sorting of households across space (in equilibrium), is shown in Figure 2. In the model, households are heterogeneous in initial wealth and credit score (FICO). As a result, they choose between becoming a homeowner or a renter. If they decide to become a homeowner, they can buy a house in a safe region that is immune to flooding or in an at-risk area susceptible to floods. The latter entails a higher amenity value. Renters are also immune to disaster shocks as a deep-pocketed institutional landlord bears the responsibility for repairs.<sup>6</sup> Disaster risk is the sole source of

<sup>5</sup>In April 2021, FEMA announced a new methodology—Risk Rating 2.0—for computing “actuarially sound” flood insurance premiums as part of the National Flood Insurance Program. These new premiums will be phased in starting October 2021 (FEMA, 2021).

<sup>6</sup>In this sense, rental housing is nested within the safe housing sector.

uncertainty in the model as income is age-deterministic.

A mortgage contract is a pair of mortgage rate and loan-to-value ratio (equivalently, leverage). If a household chooses to buy a house, a lender offers a menu of mortgage contracts conditional on the household's FICO score. The household selects the optimal mortgage contract from the menu. In this sense, leverage is endogenous in the model. Following Geanakoplos (1997, 2010), I refer to this menu of mortgage contracts as the *credit surface*.

Designing mortgage contracts this way allows me to fully capture the effect of government policies and natural disasters on households by their wealth and creditworthiness. In the absence of exogenous collateral constraints, households in principle can purchase a house without any downpayment. This possibility is particularly appealing for asset-limited households. How does a policy regime affect such a household's exposure to climate risk? The credit surface enables my model to answer such questions.

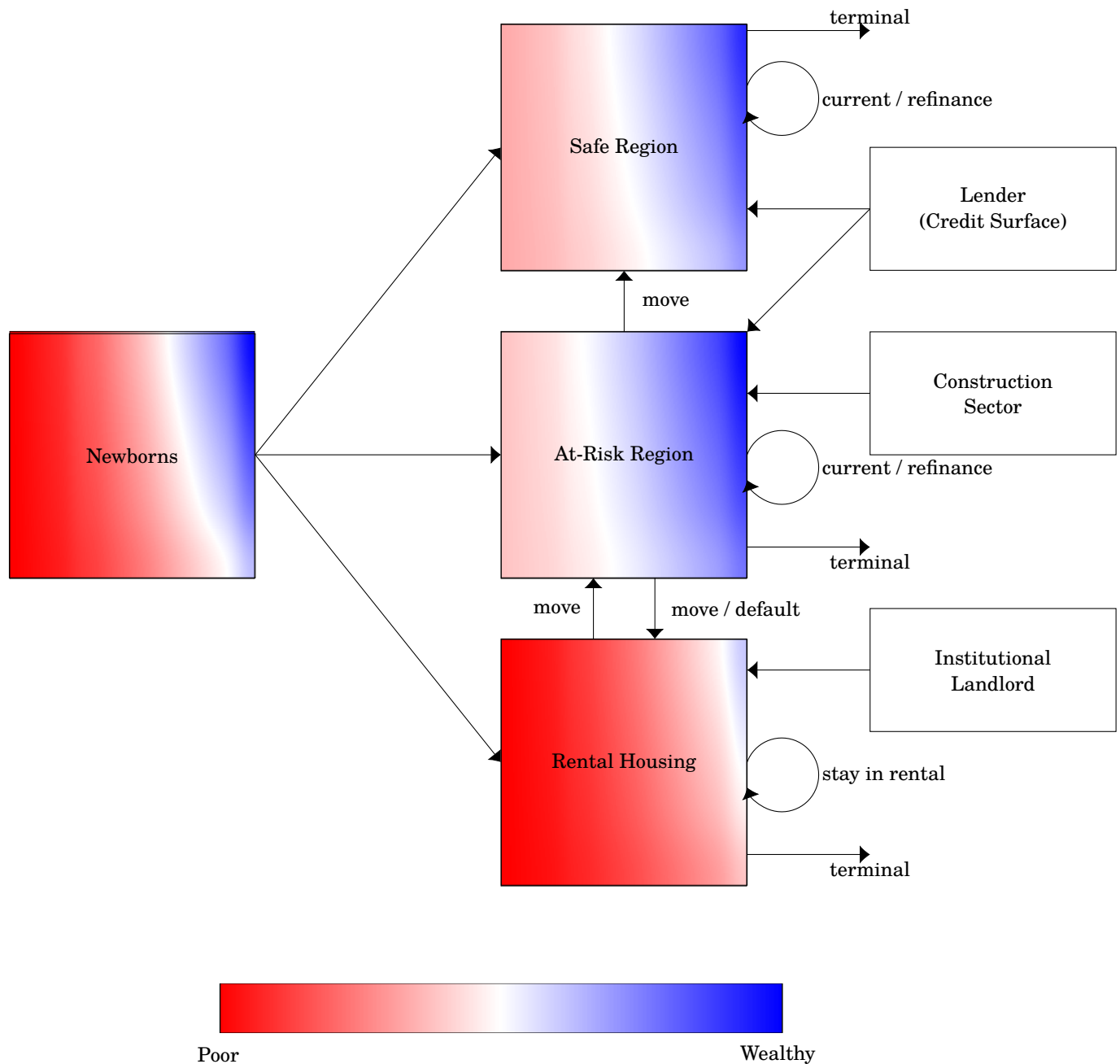
The economy also features a construction sector that optimally provides housing for the at-risk region.<sup>7</sup> Thus, given i) housing prices, ii) the credit surface, iii) government policies, and iv) initial distributions over endowment and FICO scores, households optimally choose consumption, housing type, and mortgage contract. The price of at-risk housing is determined in equilibrium so that the at-risk housing market clears. This way, I can determine how households sort across space and housing types depending on their wealth and FICO scores in response to government policies. Figure 2 shows how agents sort in equilibrium. Agents who are asset-poor and less creditworthy are in deep red, while agents rich in both dimensions are deep blue. Poor agents largely rent while middle and high-wealth households become homeowners in the safe and risky regions.

## 2.2 Household Environment

**Demographics** Time is discrete. One period in the model corresponds to one year of life. The economy is populated by a continuum of households on the unit interval,  $h \in [0, 1]$ . These households live from age  $j = 1$  to  $j = J$ , entering the economy at age 25 and living until age 75. At age 65, agents retire from their working life and receive social security benefits.

**Housing and preferences** Formally, there are three housing sectors in the economy, i) a safe region, ii) an at-risk region, and iii) a rental market. Homes are of one fixed size, and homeownership gives utility to the agent, in line with Guren, Krishnamurthy, and McQuade

<sup>7</sup>The construction sector also provides housing for the safe region, albeit inelastically.



**Figure 2: Layout of the Economy and Spatial Sorting of Households in Equilibrium.** This diagram shows the layout of the economy in the quantitative model. Each period, a cohort of newborns enters the economy and chooses whether to live in the safe, at-risk, or rental sector. Homeowners in the at-risk region can stay current, refinance, or move to either the safe area or become a renter. They can also default and become a renter. Homeowners in the safe region stay current or refinance their mortgage. Renters can continue to rent or become a homeowner in the at-risk area. Agents in their terminal period of life liquidate any asset holdings they have and leave a bequest. A representative lender offers a menu of mortgage contracts from which homeowners can select the optimal contract based on their wealth, income, and FICO score. In equilibrium, poorer agents (red) primarily rent while more affluent agents (blue) buy a home.

(2020). A homeowner in the safe region receives the flow payoff

$$u^{safe}(c) = \frac{c^{1-\gamma}}{1-\gamma} + \alpha_{safe} \cdot 1,$$

where  $\alpha_{safe}$  is the utility from homeownership in the safe region and  $1/\gamma$  is the intertemporal elasticity of substitution.

Living in the at-risk region brings more utility due to an added amenity value. Hence,

$$\alpha_{at-risk} > \alpha_{safe} > 0.$$

However, homeowners in the at-risk region are vulnerable to natural disasters like flooding. Flooded homeowners experience a loss in utility due to living in a devastated house. This loss in welfare is parameterized by  $\theta$ . Thus, homeowners in the at-risk region receive a flow payoff

$$u^{at-risk}(c, \theta) = \frac{c^{1-\gamma}}{1-\gamma} + \alpha_{at-risk} \cdot (1-\theta) \cdot 1.$$

Households not able to afford homeownership have to rent. Renters benefit purely from consumption of nondurable goods, i.e.

$$u^{rental}(c) = \frac{c^{1-\gamma}}{1-\gamma}.$$

A renter is immune to disaster shocks as a deep-pocketed institutional landlord bears the brunt of the devastation either by investing in adaptation structures to mitigate the impact of a storm or paying for repairs after a catastrophe. Thus, rental housing is effectively nested in the safe region. Since my focus is on the effect of federal policies on *homeowners'* exposure to climate change, I abstract away from the intricacies of risk faced by tenants and landlords.

In the terminal period, agents have a bequest motive. Regardless of homeownership status, their flow payoff is

$$u^{terminal}(c_J, b) = \frac{c_J^{1-\gamma}}{1-\gamma} + \psi \frac{(b + \xi)^{1-\gamma}}{1-\gamma},$$

where  $b$  is the bequest made by the terminal old.  $\psi$  measures the strength of the bequest motive while  $\xi$  is a measure of how much the bequest is a luxury good. This specification follows De Nardi (2004).

**Endowment structure** During every period of life, households receive labor income endowment,  $y_j$ . This endowment is determined solely by age, sans idiosyncratic uncertainty,



and so an entire cohort of age  $j$  gets the same amount,  $y_j$ .

Households are heterogeneous in their initial endowment of wealth upon entering the economy at  $j = 1$ . This initial endowment is drawn from an exogenous distribution. Thus, agents within the same cohort have different starting points for wealth (and FICO) which leads to variation in housing and wealth outcomes over the course of their lifetime.

**Liquid savings** Every period, households choose how much to save in liquid one-period bonds,  $a$ , that yield a risk-free return of  $r\%$ . This interest rate is set exogenously.

**Housing choices** Agents in each segment of the economy have multiple options. Each agent has to decide on their course of action in each period until the terminal period of life.

A new entrant can choose to become a homeowner in either the safe or at-risk regions or become a renter. This choice depends on the household's initial endowment of wealth and FICO score since homeownership requires making a downpayment which may not be feasible for an agent with limited assets or a low FICO score.

A homeowner in the at-risk region can remain current on an existing mortgage or refinance their existing mortgage. Alternatively, they can move to a safe area or become a renter. Lastly, they can default on their mortgage. In case of default, the household has to rent for at least one period, and its FICO score is reset to 500, the lowest possible score.

A homeowner in the safe region can remain current on their mortgage or refinance it throughout their lives. These homeowners cannot move to any other housing segment and, as such, provide an outside option for at-risk homeowners.

Lastly, renters can choose to stay in rental housing or become a homeowner in the at-risk region.

**Disaster risk** Every period, households living in the at-risk region draw a disaster shock,  $\theta \in \{0, \bar{\theta}\}$ . The shock is binary: either a household is flood ( $\theta = \bar{\theta} > 0$ ), or not ( $\theta = 0$ ). Conceptually, a disaster like Hurricane Sandy destroys  $\theta$  percent of a house so affected homeowners get utility from only the remaining  $(1 - \theta)$  fraction of their home.

I model disaster risk as a Markov chain

$$\theta_{j+1} \sim \mathbb{P}(\theta_{j+1}|\theta_j),$$

with a transition matrix  $\Pi$ . Such a specification allows for persistence of disaster risk: although unlikely, a home can become flooded year after year or only witness a one-off disaster event.

**Mortgage** A household can finance the purchase of a home using a mortgage contract. A mortgage contract consists of a pair of mortgage rate and origination loan-to-value ratio:  $(m, oltv)$ . All mortgages are i) 30-year fixed rate contracts, ii) subject to a closing cost, iii) pre-payable (either in case of a refinancing or sale), and iv) defaultable, in the case of the at-risk region.

Conditional on the household's FICO score, the lender offers a menu of mortgage contracts to a homeowner from which the latter selects the optimal contract, see Figure 3. I denote the menus by  $\mathcal{C}$ . In particular,  $m = \mathcal{C}_{fico}(oltv)$  denotes the mortgage rate charged for a loan with origination loan-to-value ratio of  $oltv$  and borrower FICO score of  $fico$ . Following Geanakoplos (1997, 2010), I call the mapping  $\mathcal{C}$  a credit surface.

Having selected a mortgage contract  $(m, oltv)$  conditional on their FICO score, the homeowner makes a periodic mortgage payment,  $x$ , where

$$x \equiv \frac{m \times oltv}{1 - (1 + m)^{-N}} p_{region}, \quad (1)$$

where  $p_{region} \in \{p_{safe}, p_{at-risk}\}$  depending on whether the homeowner resides in the safe or at-risk region, respectively.  $N$  is the term of the mortgage. Since all mortgages are 30 year fixed-rate only,  $N = 30$ .

All mortgages can be prepaid. Every period, homeowners have the option of refinancing their mortgage, in which case they can repay their outstanding balance and start a new mortgage. As a result, homeowners can extract their home equity in any period. This option is particularly relevant for flooded homeowners as the windfall from cash-out refinancing can help pay for repairs. Homeowners wishing to move can also prepay.

Homeowners in the at-risk region can default on their mortgage. If a homeowner defaults, they live in their existing home for one period before being foreclosed upon by the lender. Defaulters have to move to rental housing for at least one period. Additionally, their FICO score is reset to 500, the lowest possible score, and remains that for the rest of their life. Consequently, a defaulter will face higher mortgage rates in the future (a steeper credit surface), making homeownership costlier in the future.

Currently, mortgage rates in the US do not account for location-specific flood risk; I empirically show this is the case in Appendix A. In the baseline specification of the model, households considering purchasing or refinancing in the safe and at-risk regions face the same credit surface. However, one of the policy changes I examine is that flood risk is priced into mortgage rates. Thus, in the counterfactual specification, mortgage rates for the at-risk region are higher than mortgage rates in the safe area by  $\varphi_m$ , which I empirically estimate.

**Government** A flooded homeowner in the at-risk region receives a transfer,  $\tau$ , from the government to help rebuild and repair. Only homeowners who choose to remain in their existing (flooded) homes, either by staying current on their mortgage or refinancing, receive this transfer. Households that move or default do not receive this transfer. I calibrate  $\tau$  such that the change in the probability of flooded homeowners staying current on their mortgage in the aftermath of Hurricane Sandy in the model matches its empirical counterpart.

In a counterfactual experiment, I ask how many households would choose not to live in the risky area if the government introduced a tax on homeowners in the at-risk area? I answer this question by introducing such a tax,  $\lambda$ . In particular, at-risk homeowners wishing to remain in the at-risk region, either by staying current or refinancing, pay this tax. I set this tax equal to the median flood insurance premium in New Jersey between 2010 and 2015.

### 2.3 Household Problems

I now formally describe the recursive problems for a homeowner residing in the at-risk region. For brevity, I describe the recursive problems for the newborn agents, homeowners in the safe region, and renters in Appendix B.

**Terminal at-risk homeowner** If a homeowner in the at-risk region is in the terminal period of life, their primary goal is to determine the size of their bequest. Note that the household draws a disaster shock and incurs a cost of  $\theta p_{at-risk}$  in damages when selling the house, where  $p_{at-risk}$  is the housing price in the at-risk region. It solves the problem

$$V^{at-risk}(J, a, oltv, fico, n, \theta) = \max_b u(c, b),$$

$$s.t. \quad c + b = (1 + r)a + y_J + (1 - ltv)p_{at-risk} - \theta p_{at-risk},$$

where  $a$  is the risk-less asset the household entered the period with,  $oltv$  is the loan-to-value ratio at origination,  $fico$  is the FICO score,  $n$  is the number of periods since the mortgage

originated, and  $\theta$  is the disaster shock.  $b$  is the bequest, and  $y_J$  is the income (social security benefit) received at age  $J$ .  $ltv$  is the contemporaneous loan-to-value ratio.<sup>8</sup>  $(1 - ltv)p_{at-risk}$  is the equity stake of the homeowner before the disaster hits while  $(1 - ltv)p_{at-risk} - \theta p_{at-risk}$  is their equity stake net of the shock.

**Interim at-risk homeowner: remaining current** A homeowner in the at-risk region considering staying current on their mortgage solves the following problem

$$V_{current}^{at-risk}(j, a, oltv, fico, n, \theta) = \max_{a'} u^{at-risk}(c, \theta) + \beta EV^{at-risk}(j + 1, a', oltv, fico, n + 1, \theta'),$$

$$s.t. \quad c + a' + x + \text{maintenance cost} + \theta p_{at-risk} = (1 + r)a + y_j + \tau \cdot \mathbf{1}(\theta = \bar{\theta}),$$

where  $a'$  is the amount of risk-less asset the homeowner wishes to carry into the next period.  $x$  is their periodic mortgage payment, described in equation (1). Maintenance cost is akin to HOA fees and other expenses a homeowner must pay every period and fully offsets any routine depreciation of the house.  $\theta p_{at-risk}$  is the value of the home destroyed by the disaster shock and the amount the homeowner has to pay for repairs. The household cannot live in the same house without paying for the repairs. If a house is flooded, i.e.,  $\theta = \bar{\theta}$ , then the homeowner receives a transfer  $\tau$  from the government to rebuild and repair their home.

**Interim at-risk homeowner: refinancing** A homeowner considering refinancing solves the following problem

$$V_{refinance}^{at-risk}(j, a, oltv, fico, n, \theta) = \max_{a', oltv' \in \mathcal{C}_{fico}} u^{at-risk}(c, \theta) + \beta EV^{at-risk}(j + 1, a', oltv, fico, n = 2, \theta'),$$

$$s.t. \quad c + a' + x(oltv') + \text{maintenance} + \text{closing costs} + \theta p_{at-risk} = (1 + r)a + y_j$$

$$+ (oltv' - ltv - \theta)p_{at-risk}$$

$$+ \tau \cdot \mathbf{1}(\theta = \bar{\theta}).$$

In addition to deciding how much risk-less asset  $a'$  to carry over, they also have to decide on a new mortgage contract given the credit surface and their FICO score, i.e. select  $oltv' \in \mathcal{C}_{fico}$ . In addition to the usual maintenance amount, the homeowner also has to pay a closing cost associated with the new mortgage.  $\theta p_{at-risk}$  is the cost of repairs due to flooding.  $(oltv' - ltv - \theta)p_{at-risk}$  is the equity the homeowner cashes out via refinancing.<sup>9</sup> Note that the mortgage payment  $x$  is now a function of the new origination loan-to-value ratio. While the agent can extract more equity by selecting a higher origination loan-to-value ratio, it will also face a higher mortgage payment as a result. Since the homeowner is staying in the same

<sup>8</sup>To compute the contemporaneous loan-to-value ratio, I keep track of the number of periods already elapsed on the mortgage contract,  $n$ , and the origination loan-to-value ratio,  $oltv$ .

<sup>9</sup>Since the credit surface is stationary, refinancing is purely to extract equity out of housing and not to get a better rate.

home and merely refinancing, they receive the transfer  $\tau$  from the government to help pay for repairs in case of flooding.

A counterfactual policy that I consider is levying a tax,  $\lambda$  on homeowners who live in the at-risk region either by staying current on their mortgage or refinancing. In this case, the budget constraint for staying current will be

$$c + a' + x + \text{maintenance cost} + \theta p_{at-risk} = (1 + r)a + y_j + \tau \cdot \mathbf{1}(\theta = \bar{\theta}) - \lambda,$$

and the budget constraint for refinancing will be

$$c + a' + x + \text{maintenance} + \text{closing costs} + \theta p_{at-risk} = (1 + r)a + y_j + (oltv' - ltv - \theta)p_{at-risk} + \tau \cdot \mathbf{1}(\theta = \bar{\theta}) - \lambda.$$

Note that in the baseline specification  $\lambda = 0$ . In the counterfactual experiment, I will set  $\lambda$  equal to the median flood insurance premium in New Jersey between 2010 and 2015.

**Interim at-risk homeowner: moving** Alternatively, a homeowner may choose to move either to a rental or buy a home in the safe region. Moving to the safe region entails solving the following problem

$$V_{move-safe}^{at-risk}(j, a, oltv, fico, n, \theta) = \max_{a', oltv' \in \mathcal{C}_{fico}} u^{safe}(c) + \beta V^{safe}(j + 1, a', oltv, fico, n = 2),$$

$$s.t. \quad c + a' + x' + \text{maintenance} + \text{closing cost} + \text{moving cost} + (1 - oltv')p_{safe} = (1 + r)a + y_j + (1 - ltv - \theta)p_{at-risk},$$

where  $(1 - oltv')p_{safe}$  is the downpayment for the new home while  $(1 - ltv - \theta)p_{at-risk}$  is the equity stake net of flood damage in the existing home. The homeowner sells their home "as is," i.e., without paying for the repairs. Relative to refinancing, the homeowner has to pay an additional moving cost. However, there is no uncertainty regarding the continuation value since the agent will not face any shocks living in the safe region. In the continuation value,  $n = 2$  since the homeowner makes the first mortgage payment on the new home alongside the downpayment.

On the other hand, the agent can choose to become a renter in which case they solve the

following problem

$$V_{move-rent}^{at-risk}(j, a, oltv, fico, n, \theta) = \max_{a'} u^{rental}(c) + \beta V^{rental}(j+1, a', fico),$$

$$s.t. \quad c + a' + p_{rental} + \text{maintenance} + \text{moving cost} = (1+r)a + y_j + (1-ltv - \theta)p_{at-risk},$$

where  $p_{rental}$  is the periodic rental payment, and the agent again has to pay a moving cost.

The household optimally decides whether to move to the safe region or rental housing, based on condition (2)

$$V_{move}^{at-risk}(j, a, oltv, fico, n, \theta) = \max \begin{cases} V_{move-safe}^{at-risk}(j, a, oltv, fico, n, \theta) & \text{move to safe region,} \\ V_{move-rent}^{at-risk}(j, a, oltv, fico, n, \theta) & \text{move to rental housing.} \end{cases} \quad (2)$$

**Interim at-risk homeowner: default** Lastly, a homeowner considering defaulting on their mortgage solves the following problem

$$V_{default}^{at-risk}(j, a, oltv, fico, n, \theta) = \max_{a'} u^{at-risk}(c, \theta) + \beta V^{rental}(j+1, a', fico = 500),$$

$$s.t. \quad c + a' + p_{rental} + \text{moving cost} = (1+r)a + y_j,$$

where the agent can only move to rental housing and their FICO score is set to 500, the lowest possible score. The homeowner does not receive any equity payout in this case.

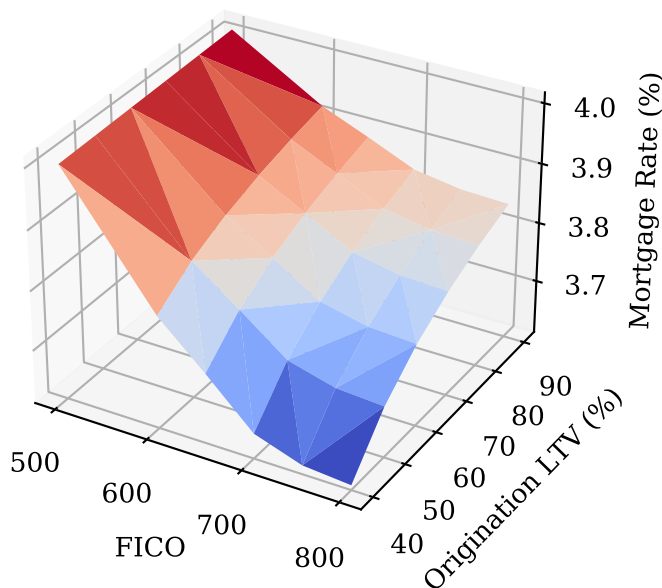
**Optimal household behavior** Having considered all their options, the homeowner chooses the best course of action as embodied in condition (3).

$$V^{at-risk}(j, a, oltv, fico, n, \theta) = \max \begin{cases} V_{current}^{at-risk}(j, a, oltv, fico, n, \theta) & \text{stay current} \\ V_{refinance}^{at-risk}(j, a, oltv, fico, n, \theta) & \text{refinance} \\ V_{move}^{at-risk}(j, a, oltv, fico, n, \theta) & \text{move} \\ V_{default}^{at-risk}(j, a, oltv, fico, n, \theta) & \text{default} \end{cases} \quad (3)$$

In particular, the household chooses the option that brings them the most value.

## 2.4 Mortgage Lender

In the model economy, mortgages are supplied elastically by a lender. Given a household's FICO score, the lender offers a menu of mortgage contracts. Each mortgage contract consists



**Figure 3: The Credit Surface.** This figure depicts the credit surface in 2012. For a detailed description of the credit surface and its construction, see Geanakoplos and Panjwani (2021).

of an origination loan-to-value ratio,  $oltv$ , and a corresponding mortgage rate,  $m$ . This menu of mortgage contracts is called the credit surface, see Figure 3.

I model the credit surface using the strategy laid out in Geanakoplos and Panjwani (2021). The lender prices mortgage contracts using a double-binomial tree. It assumes that house prices and the risk-free interest rate follow geometric Brownian motion processes, projecting these variables into the future for 30 periods. At each node of the tree, the borrower makes the optimal decision between prepaying, defaulting, or continuing. By backward induction along the tree, the lender can compute the present value of the mortgage for a given mortgage rate. It pins down the mortgage rate by setting the present value of the mortgage equal to the origination balance of the mortgage. The lender does this calculation for each FICO and origination LTV pair and creates the credit surface as a result.

In the baseline specification, the credit surface is the same for the safe and risky region. However, one of the policy responses I consider is that mortgagors in the at-risk area are charged a flood risk premium as part of their mortgage. In this counterfactual world, the lender charges mortgagors in the at-risk area  $\phi_m$  basis points more. Thus, there would be two credit sur-

faces, one for each region, with the surface for the risky area being a level shift up (by  $\varphi_m$ ) relative to the surface for the safe region.

## 2.5 Housing Supply

In the model, a construction sector provides housing for safe and at-risk regions. There is a representative firm in the sector. It provides safe housing perfectly elastically at a price  $p_{safe}$ .

Moreover, the firm uses capital  $k$  at cost  $r$  to produce at-risk housing using the technology  $q = (Ak)^{\alpha_c}$ . Thus, the firm solves the static problem

$$\max_k (Ak)^{\alpha_c} - rk$$

Solving this problem yields the supply function for at-risk housing

$$q = \bar{A} p_{at-risk}^{\frac{\alpha_c}{1-\alpha_c}}$$

where  $\bar{A} \equiv \left(\frac{\alpha A}{r}\right)^{\frac{\alpha_c}{1-\alpha_c}}$  and  $\frac{\alpha_c}{1-\alpha_c}$  is own-price elasticity of at-risk housing.

Lastly, rental housing is provided elastically by a deep-pocketed landlord at rental price  $p_{rental}$ . The landlord bears the brunt of disasters as opposed to the tenant. Rental housing is effectively nested in the safe region.

## 2.6 Market Clearing and Equilibrium

I now describe the equilibrium for the model economy. Given housing prices for safe, at-risk, and rental housing,  $(p_{safe}, p_{at-risk}, p_{rental})$ , the credit surface  $\mathcal{C}$ , government policies  $(\tau, \varphi_m, \lambda)$ , and initial distributions over endowment and FICO, agents solve their household problem and calculate their optimal policy functions. Moreover, the construction sector optimally decides how much at-risk housing to supply,  $q_{construction}$

Newly entering households opting for and renters moving to the at-risk region form the demand side for at-risk housing. The supply side for at-risk housing consists of at-risk residents moving to either the safe or rental sectors or defaulting on their mortgage, terminally old at-risk residents, and the construction sector. Defaulters do not sell their own home, instead the lender forecloses and sells the home. In equilibrium, the at-risk housing market clears at



price  $p_{at-risk}$ . The market clearing condition for at-risk housing is

$$\int q^h(j=1, a, fico) dh + \sum_j \int q^h(j, a, fico) dh = \sum_j \int q^h(j, a, oltv, fico, n, \theta) dh + q_{construction} \quad (4)$$

where  $q^h(\cdot)$  represents the action of the household for a given set of state variables, one if they decide to buy or sell, zero otherwise. The first term on the LHS is the demand for at-risk housing from newborns, and the second term is the demand for at-risk housing from renters of all ages. On the RHS, the first term is the supply due to all the existing at-risk homeowners, and the second term is the supply from the construction sector.  $p_{at-risk}$  adjusts, so the equation holds. There is a perfectly elastic supply of safe and rental housing and mortgage credit. Thus, only  $p_{at-risk}$  is determined in equilibrium.

The disaster shock,  $\theta$ , is idiosyncratic and the only source of uncertainty in the economy. In particular,  $\bar{\theta}$  fraction of the at-risk population gets flooded. Thus, there is a stationary distribution of households that is consistent with individual behavior and disaster shock. There are no transition dynamics in the model, and I compare policy outcomes across two equilibria.<sup>10</sup>

### 3 Quantifying Distortions

#### 3.1 Overview

How would

1. limiting government assistance after a disaster ( $\tau$ )
2. pricing flood risk into mortgage rate ( $\varphi_m$ )

reduce the number of homeowners exposed to disaster risk by living in the risky region? To answer this question, I need to quantify these distortions first. Specifically, how much is the assistance after a disaster,  $\tau$ ? Moreover, how much should mortgage rates for the risky region increase by,  $\varphi_m$ ?

**Assistance after a disaster ( $\tau$ )** In response to the devastation wreaked by Sandy, FEMA and HUD jointly spent \$5.9 billion in New Jersey alone, see Table 1.<sup>11,12</sup> Moreover, the FHFA

<sup>10</sup>The policy thought experiment is that if certain policy regimes were implemented by the policymaker today, how would the composition of at-risk homeowners change in the long run.

<sup>11</sup>Breakdown of expenses for FEMA: <https://www.fema.gov/disaster/4086>

<sup>12</sup>Breakdown of expenses for HUD CDBG-DR Program: <https://www.renewjerseystronger.org/transparency/sandy-recovery-program-dashboard/>

Agency	Program	Amount Spent (millions of dollars)
FEMA	Individual & household program	422
	Public assistance	2,016
HUD	Homeowner assistance	1,607
	Rental assistance	835
	Economic development	263
	Infrastructure programs	290
	Miscellaneous (admin, planning, etc.)	465
Total		5,897

**Table 1: FEMA and HUD Spending on Relief Measures after Sandy.** This table shows money spent by FEMA and HUD for various relief measures in the aftermath of Hurricane Sandy in New Jersey alone.

and the GSEs — Fannie Mae and Freddie Mac — offer forbearance as a temporary relief measure for flooded mortgagors. They also suspend credit reporting for missed payments and provide loan modifications on a case-by-case basis. These forms of relief are difficult to measure in dollar terms because they are not direct cash transfers. So how large is the total average transfer, combining direct pecuniary and indirect non-pecuniary forms of relief? To estimate this transfer amount, I proceed in two parts. First, I estimate the effect of this transfer on flooded homeowners’ probability of staying current on their mortgage. Then I use the model to infer the magnitude of the transfer needed to achieve this effect.

I use difference-in-differences to estimate the effect of the disaster and the assistance on homeowners’ mortgage-related decisions, e.g., staying current, prepaying, becoming delinquent, or defaulting. I find that flooded homeowners were 74 basis points more likely to remain current than their non-flooded counterparts (who did not receive any aid). In the model, I calibrate mean assistance per household,  $\tau$ , to target this moment from the natural experiment. I infer that  $\tau$  is equal to \$48,000.

**Flood risk premium ( $\varphi_m$ )** Agency mortgage rates in the US do not price in flood risk, see Appendix A for details. Specifically, the GSEs guarantee the investor that the latter will receive the principal and interest payments due to them. In turn, the GSEs charge the mortgagor a guarantee fee to cover for default risk. This fee does not account for location-specific climate risk, in particular flood risk.<sup>13</sup> How large is this flood risk premium? I estimate that the mean spread between actual mortgage rates and mortgage rates that account for flood risk was 26 basis points in New Jersey between 2010 and 2015.

<sup>13</sup>Although the homeowner is expected to carry flood insurance, the implementation of this mandate is lax (NRC, 2015). Moreover, only homeowners living in certain high-risk areas are required to carry flood insurance. This geographic classification is based on FEMA’s flood maps which may be outdated and not reflect the true extent of the threat (NYC, 2013).

### 3.2 Institutional Details for Mortgages

After a lender originates a mortgage, it can sell the mortgage to government-sponsored entities (GSEs), Fannie Mae and Freddie Mac. The GSEs purchase these mortgages from lenders as long as the mortgage meets specific preset criteria. In particular, the borrower must have a credit score above 620 and carry private mortgage insurance if the loan-to-value ratio is above 80%.<sup>14</sup> The agencies pool these mortgages together, creating mortgage-backed securities, which are then sold to investors. The agencies promise to make the investor whole if a mortgage in the pool defaults to maintain market liquidity. Thus, the GSEs shield investors from credit risk and only pass on prepayment risk — the risk of a homeowner paying off the mortgage ahead of schedule, usually due to refinancing or moving.

In return for the guarantee against credit risk, Fannie and Freddie collect a guarantee fee from the borrower, which covers projected losses due to borrower defaults in addition to administrative expenses. In 2019, the average fee was 58 basis points (FHFA, 2020). This fee is determined by the borrower's FICO score, loan-to-value ratio, the loan's purpose, and the term of the mortgage. Currently, GSEs charge the same fee nationwide, regardless of spatial variation in risk. In 2012, the Federal Housing Finance Agency, the conservator for Fannie and Freddie, published a notice in the Federal Register proposing higher guarantee fees on mortgages originating in states with stringent foreclosure laws like Florida and New York. Prolonged foreclosure proceedings mean the GSEs have to carry defaulted loans on their books for much longer before they can sell off the collateral and recover the investment. Meanwhile, the GSE, being the investor, has to pay for maintenance, taxes, and legal fees as the borrower is delinquent. Various stakeholders pushed back the proposal, and FHFA dropped the idea (FHFA, 2013). Likewise, the guarantee fee does not account for region-specific risk like flood or wildfire risk, or, as Hurst et al. (2016) find, economic downturn risk.

### 3.3 Hurricane Sandy and Government Assistance

Using multi-period difference-in-differences based on Callaway and Sant'Anna (2020), I identify the average treatment effect on the treated (ATT) for mortgages affected by Hurricane Sandy. While Sandy impacted multiple states, I restrict attention to New Jersey. Zip codes in New Jersey that witnessed residential property damage based on FEMA's surveys and received assistance are assigned to the treatment group, while all other zip codes in New Jersey serve as the control group, see Figure 4. Thus, the counterfactual is not being flooded *and* not receiving any government assistance.

<sup>14</sup>Exact requirements vary by debt-to-income and purpose of the loan, see <https://selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/Subpart-B3-Underwriting-Borrowers/Chapter-B3-5-Credit-Assessment/Section-B3-5-1-Credit-Scores/1032996841/B3-5-1-01-General-Requirements-for-Credit-Scores-08-05-2020.htm>

**Data** Hurricane Sandy made landfall in New Jersey on October 29th, 2012. I track mortgages in the entire state starting in January 2012 through December 2013. The event study period is 24 months with ten pre-treatment periods and 14 post-treatment periods. Using CoreLogic’s Loan-Level Market Analytics dataset, I observe agency and non-agency mortgages in New Jersey at the five-digit zip code level for the entire duration of the study. To determine whether a mortgage in a zip code was treated or not, I use FEMA’s Individual Assistance Registrant Inspection Data used by HUD to create damage estimates due to Sandy (HUD, 2014). Since this data is at the block group level and mortgages are at the zip code-level, I aggregate up the damage estimates data from block group to five-digit zip code-level using HUD’s Crosswalk files (HUD, 2012).

**Econometric specification** My main econometric specification is based on Callaway and Sant’Anna (2020)’s difference-in-differences framework. I estimate

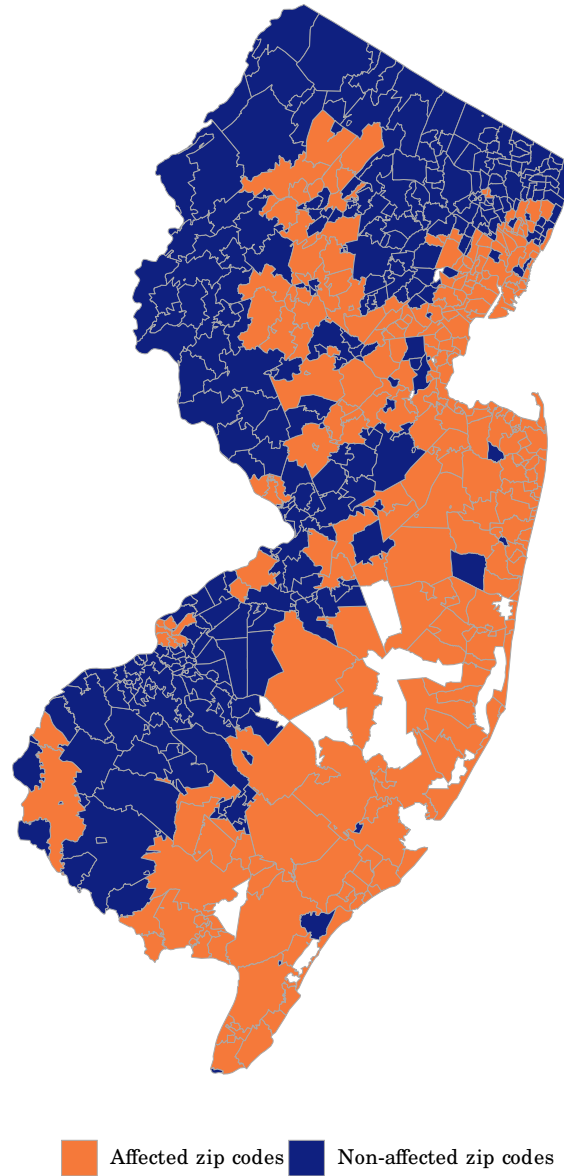
$$\text{outcome}_\ell^t = \alpha_0^t + \alpha_1^t \mathbf{1}\{\text{treated}\}_\ell + \alpha_2^t \cdot \mathbf{1}\{T = t\} + \beta^t \cdot (\mathbf{1}\{\text{treated}\}_\ell \times \mathbf{1}\{T = t\}) + \text{flood\_risk}_\ell + \gamma X_\ell + \varepsilon_\ell^t, \quad (5)$$

where  $\text{outcome}_\ell^t$  is the outcome of interest for loan  $\ell$  in month  $t$ .  $\mathbf{1}\{\text{treated}\}_\ell$  is an indicator variable that is one if the loan is in a flooded zip code that (eventually) receives assistance.  $\mathbf{1}\{T = t\}$  is the relevant time dummy while  $(\mathbf{1}\{\text{treated}\}_\ell \times \mathbf{1}\{T = t\})$  is the difference-in-differences term. The coefficient of interest is  $\beta^t$  which captures the change in probability of a homeowner’s mortgage outcome due to flooding and assistance in month  $t$ . Thus,  $\beta^t$  is the average treatment effect on the treated (ATT) in month  $t$ .  $\text{flood\_risk}_\ell$  is the (zip code level) flood risk of the loan and  $X_\ell$  are other loan-level controls like FICO and LTV. I estimate  $\beta^t$  for each month, starting nine months before Sandy and ending 14 months after.

For the primary specification, the outcome variables of interest are binary variables for various mortgage statuses. I estimate (5) with the following outcome variables

1. current: 1 if borrower has made the mortgage payment for the month on time, 0 otherwise
2. delinquent: 1 if borrower has not made the mortgage payment by the due date, 0 otherwise
3. prepayment: 1 if borrower has paid off the full outstanding balance of the mortgage, 0 otherwise
4. foreclosed: 1 if the home has been foreclosed upon by the lender after the grace period has elapsed, 0 otherwise

## Zip codes affected by Sandy in New Jersey



**Figure 4: Spatial Variation in the Impact of Hurricane Sandy on New Jersey** This figure shows a choropleth map of New Jersey with zip codes that witnessed residential property damage due to Hurricane Sandy based on FEMA surveys (orange). These zip codes form the treatment group. All other zip codes are assigned to the control group (blue).

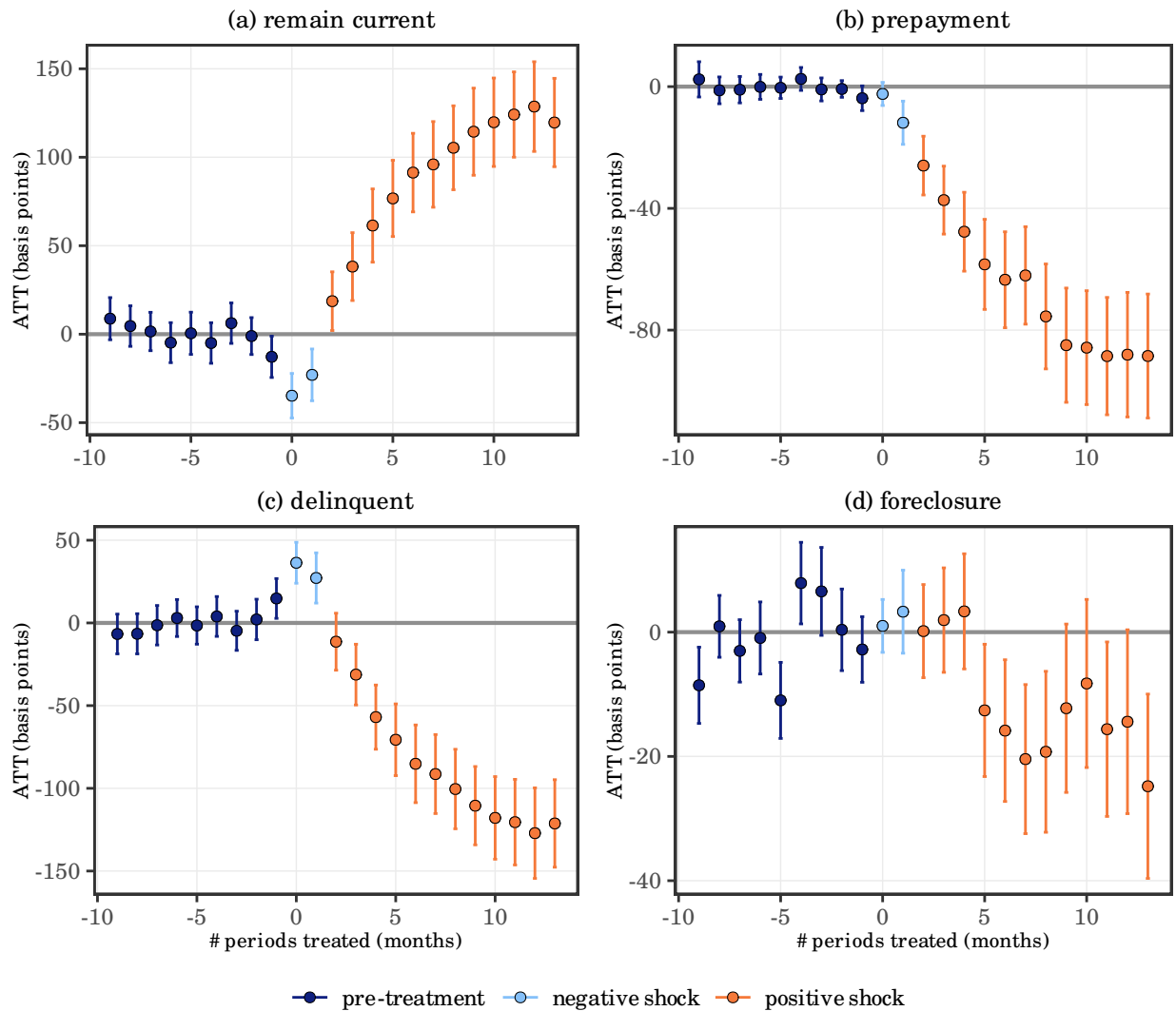
Outcome Variable	Current	Delinquent	Paid Off	Foreclosed
	(1)	(2)	(3)	(4)
Overall ATT (basis points)	74*** [63, 85]	-70*** [-82, -58]	-59*** [-67, -51]	-12*** [-16, -3]
Baseline Probabilities (%)	95.0	0.03	4.90	0.07
Covariates	N	N	N	N
Clustered	N	N	N	N
Observations	695,180	695,180	695,180	695,180

**Table 2: Average effect of Hurricane Sandy and Government Assistance on Mortgage Outcomes** This table shows the overall effect of Hurricane Sandy on mortgage performance. Mortgages in effected zip codes were 74 basis points more likely to remain current on their monthly dues, 70 basis points less likely to become delinquent, 59 basis points less likely to prepay, and 12 basis points less likely to be foreclosed upon in the 14 months following the flooding. Standard errors are reported in parenthesis while 95% confidence intervals based on simulated bootstrap are included in square brackets. Standard errors are non-clustered and no covariates were included in the baseline specification. \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01

Mortgage delinquencies are recorded in levels: a mortgage can be 30, 60, 90, 120, 150, or 180+ days delinquent. If a homeowner has not made a payment in 90 days, the mortgage is considered seriously delinquent and unlikely to become current again. Prepayment occurs when a homeowner wishes to refinance or move. In this case, they close out of their existing mortgage by paying the remaining balance and start afresh (usually with a lower mortgage rate, or a higher loan-to-value ratio, or with a new home altogether). Lastly, foreclosure is the legal process by which the lender sells the house to recover their investment after legal proceedings have concluded and the homeowner has relinquished their property rights. Foreclosure happens after the borrower has been unable to pay their dues for many months. The exact time duration before delinquency leads to foreclosure varies by state.

**Identification** I assume that the parallel trends assumption is satisfied conditional on the flood risk of a loan. If high-risk mortgagors tend to live in flood-prone areas, there would be more defaults and delinquencies in that region regardless of flooding. The objective is to capture the effect of flooding and government assistance on whether a mortgagor pays their mortgage or not, not the impact of creditworthiness on mortgage performance. Thus, I condition on flood risk using First Street Foundation’s flood risk score at the zip code-level.

**Results** For the baseline specification, I find that mortgagors who were flooded and received government assistance were more likely to stay current on their mortgage, see Figure 5a. In



**Figure 5: The Effect of Hurricane Sandy and Ensuing Government Assistance on Homeowners' Mortgage Decisions.** This figure shows the monthly average treatment effect on the treated for mortgage outcomes in zip codes impacted by Hurricane Sandy in New Jersey. The horizontal axis refers to months before and after Hurricane Sandy. The vertical axis indicates the change in the probability of an affected mortgage being classified as current, delinquent, prepaid, or foreclosed upon. Panels (a), (b), and (c) show that mortgages in effected zip codes were more likely to stay current, less likely to prepay or become delinquent in the months following the disaster, respectively. Panel (d) suggests the foreclosure rate also declined, albeit marginally. Negative shock refers to the initial impact of the hurricane when government assistance had not made its way to households. Positive shock refers to ensuing months when households had access to various relief programs. The error bars represent the 95% confidence intervals.

particular, Sandy made landfall on October 29th, 2012, and most mortgage payments are due at the start of the month. As a result, affected homeowners were more likely to miss their mortgage payments in November and not stay current. However, as relief measures made their way through, affected homeowners were more likely to remain current. Likewise, Figure 5c shows that delinquencies rose initially among affected homeowners, but as assistance reached them, they were less likely to be delinquent. I also find that affected mortgagors were less likely to prepay their mortgage and less likely to be foreclosed upon, see Figures 5b and d, respectively.

I calculate the time averages of the average treatment effect on the treated for each period and outcome to summarize these findings, see Table 2. I find that affected homeowners were i) 74 basis points more likely to stay current, ii) 70 basis points less likely to be delinquent, iii) 59 basis points less likely to prepay, and iv) 12 basis points less likely to be foreclosed upon. I conduct robustness checks by clustering the standard errors at the zip code level and including loan-level covariates such as FICO score and the loan-to-value ratio at origination. Additionally, I use different measures to determine whether the loan is current or not. I describe these checks in Appendix C.

Why are homeowners more likely to stay current following a superstorm and less likely to become delinquent or prepay? Sugarman (2016) documents the legal framework that FEMA, HUD, FHFA, and the state government of New Jersey used to implement a host of relief measures. For example, using federal funding from HUD through the Community Development Block Grant for Disaster Relief, the state government offered grants of up to \$150,000 for qualifying households. Moreover, HUD put a moratorium on foreclosures for 90 days following the landfall. Fannie and Freddie worked with servicers to allow up to 12 months of forbearance for seriously flooded homes without affecting the borrowers' credit score. An amalgam of such measures explains the lower delinquency rate in affected areas.<sup>15</sup>

### 3.4 Flood Risk Premium and Mortgages

How large is the flood risk premium not charged by the GSEs despite differential exposure to climate-credit risk across space? I define the flood risk premium as the difference between flood risk-adjusted mortgage rates and the actual mortgage rates. To compute this spread, I start by calculating the median flood insurance premium in a given zip code,  $z$ , in year  $t$  in New Jersey. The flood risk-adjusted mortgage payment for loan  $\ell$  in zip code  $z$  originated in

<sup>15</sup>For details on these relief measures, see <https://www.renewjerseystronger.org/homeowners/> and <https://www.fanniemae.com/newsroom/fannie-mae-news/fannie-mae-delivers-help-homeowners-affected-hurricane-sandy>



year  $t$ ,  $\hat{x}_{\ell z t}$ , is given by

$$\hat{x}_{\ell z t} \equiv x_{\ell z t} + (\text{origination loan-to-value}_{\ell z t} \times \text{median insurance premium}_{z t}),$$

where  $x_{\ell z t}$  is the original mortgage payment. The GSEs' exposure to climate risk is captured by the fraction of the house that serves as collateral. Thus, I scale the median flood risk in zip code  $z$  by the loan's origination loan-to-value ratio. Given the counterfactual mortgage payment and the loan's original principal, I back out the implied mortgage rate if the mortgagor had to pay flood insurance as part of their mortgage payment

$$\hat{m}_{\ell z t} \equiv m(\hat{x}_{\ell z t}, \text{original principal}_{\ell z t}).$$

Then the flood risk premium is

$$\varphi_{m, \ell z t} \equiv \hat{m}_{\ell z t} - m_{\ell z t},$$

where  $m_{\ell z t}$  is the original mortgage rate. In my policy experiments, I use the mean flood risk premium,  $\varphi_m$ , in the policy experiments.

Given the flood risk premium, I also calculate the dollar value of the implicit subsidy as

$$\text{subsidy}_{\ell z t} = \varphi_{m, \ell z t} \times \text{original principal}_{\ell z t}.$$

Assuming that on average, a mortgage has a lifespan of seven years, I calculate the present value of the subsidy over the life of the loan.

Using mortgage origination data from CoreLogic for 30-year fixed-rate mortgages originating in New Jersey between 2010 and 2015, I calculate the mean flood risk premium to be 26 basis points. This estimate serves as the additional mortgage interest rate at-risk homeowners should be charged in the model counterfactual with different credit surfaces for safe and at-risk areas. I also estimate the mean subsidy as \$610 per year per mortgage. Moreover, the present value of the mean subsidy is \$3,572, which is 1.54% of the mortgage's principal, assuming the average mortgage prepays after seven years, see Table 3.

## 4 Calibration for the Model

### 4.1 Overview

I internally calibrate seven parameters: i) assistance after a disaster ( $\tau$ ), ii) utility from homeownership in the at-risk region ( $\alpha_{at-risk}$ ), iii) utility from homeownership in the safe region ( $\alpha_{safe}$ ), and iv) price of safe housing ( $p_{safe}$ ), v) production technology ( $A$ ), vi) strength of the

	Median	Mean	Sum
Flood risk premium (basis points)	21	26	—
Subsidy at origination (\$)	517	610	230 million
PV of subsidy (\$)	3,024	3,572	1.35 billion
PV of subsidy / Loan amount (%)	1.23	1.54	—

**Table 3: Flood Risk Premium and Implicit Mortgage Subsidy.** This table shows the mean and median value of the flood risk premium not priced into mortgages. Additionally, the table also shows the same statistics for the dollar-value of the subsidy in the first year of the mortgage, the present value of the subsidy assuming that the average mortgage prepays after seven years, and the present value of the subsidy as a fraction of the loan amount.

bequest motive ( $\psi$ ), and vii) bequest motive shifter ( $\xi$ ). Let

$$\xi \equiv \{\tau, \alpha_{at-risk}, \alpha_{safe}, p_{safe}, A, \psi, \xi\}$$

be a vector of the parameters that have to be internally calibrated. Let  $m(x)$  be the empirical moments that I target and let  $\widehat{m}(x|\xi)$  be the model moments given parameters  $\xi$ . Using a simulated method of moments approach, I find  $\widehat{\xi}$  such that  $\widehat{\xi}$  minimizes the distance between the model moments and its empirical counterparts, i.e.,

$$\widehat{\xi} = \underset{\xi}{\operatorname{argmin}} \|\widehat{m}(x|\xi) - m(x)\|.$$

Other parameters are externally calibrated given their typical values common in the macroeconomic and housing finance literature

## 4.2 Internally Calibrated Parameters

**Current rate and government assistance ( $\tau$ )** The difference-in-difference exercise showed that affected homeowners were 74 basis points more likely to remain current on their mortgage than the control group. This finding serves as one of the empirical moments I target in the simulated method of moments exercise. Specifically, I calibrate the transfer,  $\tau$ , each homeowner receives such that the difference in the current rate in the two regions is 74 basis points. I find that  $\tau = \$48,000$  in the model and affected homeowners are 62 basis points more likely to remain current on their mortgages in the model, compared to the empirical target moment of 74 basis points.

**Homeownership and Home Prices** The overall homeownership rate in the US in 2011 was 65.5% based on quarterly estimates from the Census Bureau. Additionally, three percent more mortgages were originated in at-risk areas than the safe regions in New Jersey. Likewise, housing price in at-risk areas was 4% higher relative to the safe areas. In addition to the staying current moment from the natural experiment, these three moments serve as targets for the simulated method of moments exercise.

I calibrate  $\alpha_{at-risk}$ ,  $\alpha_{safe}$ ,  $p_{safe}$  to target the above moments.<sup>16</sup> In the model, the overall homeownership rate is 65.1% as compared to 65.5% in the data. Moreover, there are 13% more homeowners in the at-risk region relative to 3% more in data. Lastly, housing in the at-risk regions sells at a 24% premium relative to the 4% premium observed in the data. In the model, the incentive to live in the at-risk region is slightly higher than what I find in the mortgage origination data due to amenity value. However, the calibrated values are within a reasonable bandwidth, and the overall distance between the model and empirical moments is sufficiently small.

### 4.3 Externally calibrated parameters

**Disaster risk ( $\theta$ )** Ortega and Taspinar (2018) estimate that homes impacted by Sandy lost about 22% of their value in the immediate aftermath before recovering to a degree. Thus, in the baseline specification I set  $\bar{\theta} = 0.22$ .

**Other parameters** Households enter the economy at age 25 and die at age 75. The discount factor,  $\beta$ , is 0.97, and the CRRA parameter,  $\gamma$ , is 2.

The ratio of the rental rate to median income ( $p_{rental}/y$ ) is 28%, embodying the rule-of-thumb that rent be 28% of income. Maintenance is equal to 3.0% of the home value. The closing cost for mortgages is 5% of home value. Moving costs are 12% of the home value. FICO scores range from 500 to 850 in reality but are scaled to the unit interval in the model. The loan-to-value ratio at origination ranges from 0 to 1 as well. Table 4 reports these parameters and their calibrated values.

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<sup>16</sup>Along with internally calibrating  $A$ ,  $\psi$ , and  $\xi$ .

Parameter	Description	Internal	Value
<b>Demographics</b>			
$J$	Length of life (years)	N	50
<b>Preferences</b>			
$\beta$	Discount factor	N	0.97
$\gamma$	CRRA	N	2
$\alpha_{at-risk}$	Utility from homeownership in at-risk region	Y	0.42
$\alpha_{safe}$	Utility from homeownership in safe region	Y	0.20
$\psi$	Strength of bequest motive	Y	5
$\xi$	Bequest motive shifter	Y	0.57
<b>Prices</b>			
$p_{at-risk}$	Price of at-risk housing (\$)	N	285,000
$p_{safe}$	Price of safe housing (\$)	Y	230,000
$p_{rental}$	Annual rent (\$)	N	28,000
$r$	Interest rate (%)	N	3
<b>Costs &amp; Transfers</b>			
Maintenance	% of home value	N	3
Closing cost	% of home value	N	5
Moving cost	% of home value	N	12
<b>Disaster risk</b>			
$\bar{\theta}$	Damage to home due to disaster (Ortega and Taspinar, 2018)	N	0.22
<b>Construction Sector</b>			
$A$	Construction technology	Y	0.07
$\alpha_C/(1 - \alpha_C)$	Housing supply elasticity	N	1.5
<b>Policy Levers</b>			
$\tau$	Government assistance (\$)	Y	48,000
$\lambda$	Tax on at-risk homeowners (\$)	N	564
$\varphi_m$	Flood risk premium (basis points)	N	26

**Table 4: Model Parameters.** This table summarizes the key parameters that are calibrated in the model. Tax on at-risk homeowners ( $\lambda$ ) and flood risk premium ( $\varphi_m$ ) are empirically estimated and do not play a role in the baseline calibration process. They are only used in counterfactual policy experiments.

## 5 Results

### 5.1 Model Fit

Before presenting the results for the policy experiments, I describe the fit of the model to the data.

**Targeted moments** The model matches the homeownership rate well: 65.5% empirically compared to 65.1% in the model across both regions, see Table 5.

In New Jersey in 2012, there were 3% more mortgages in the at-risk region than the safe region. In the model, there are 13% more mortgagors in the at-risk area. Likewise, the price of at-risk housing was 4% higher in New Jersey in 2012 relative to the safe region. In the model, the price of at-risk housing is 24% higher.

Moments of interest	Empirical Target	Calibrated Value
Overall homeownership rate (%)	65.5	65.1
$\frac{\# \text{ homeowners in at-risk}}{\# \text{ homeowners in safe}}$ (%)	103	113
$\frac{P_{at-risk}}{P_{safe}}$ (%)	104	124
$\Delta$ prob. of flooded homeowner staying current (bps)	74	62

**Table 5: Targeted Moments.** This table shows the empirical values for the targeted moments and their in-model counterparts.

Moments of interest	Empirical Value	Calibrated Value
Price of at-risk housing (\$)	296,000	285,000
$\Delta$ prob. of flooded homeowner prepaying (bps)	-59	-167
$\Delta$ prob. of flooded homeowner defaulting (bps)	-12	2

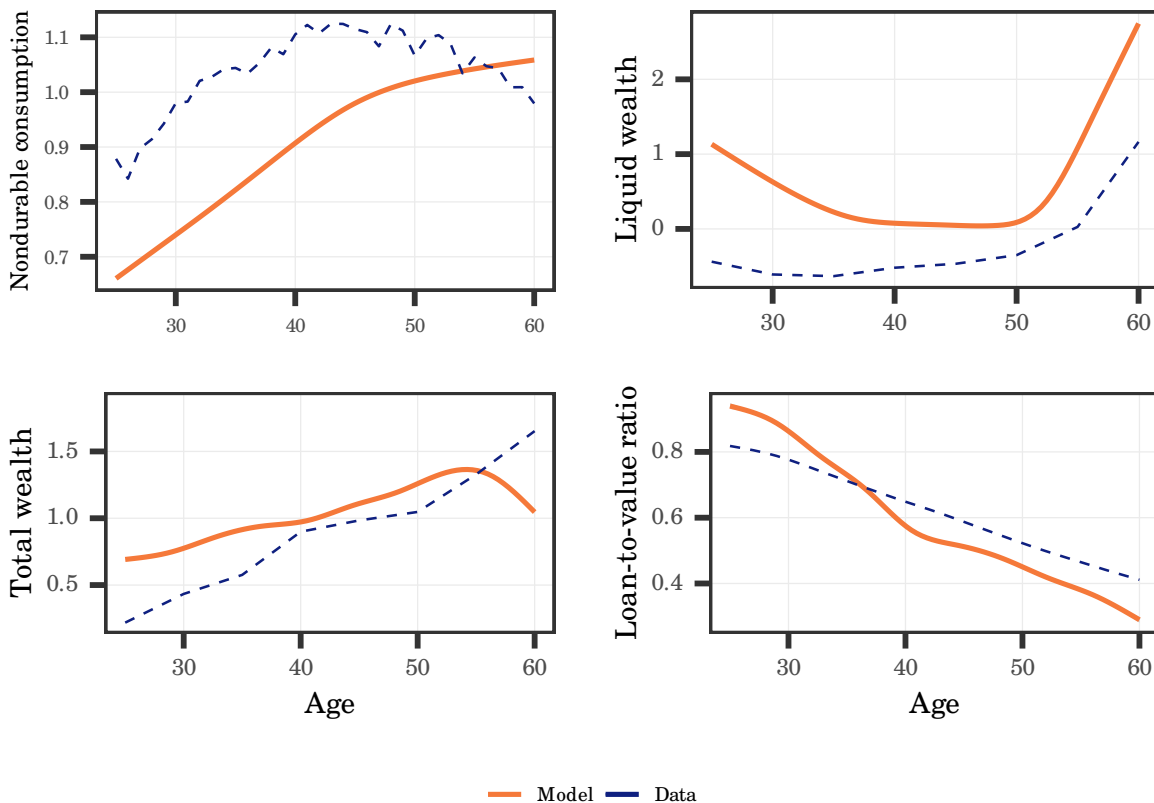
**Table 6: Untargeted Moments.** This table shows the empirical values for untargeted moments and their in-model counterparts.

Lastly, flooded homeowners are 74 basis points more likely to remain current based on the difference-in-differences exercise. In the model, flooded homeowners are 62 basis points more likely to stay current on their mortgage. Thus, the model does a reasonable job of matching critical moments.

**Untargeted moments** In the model, the price of at-risk housing is determined in equilibrium by market clearing. In dollar terms, the market-clearing price of at-risk housing is \$285,000. Rao (2017) finds that the median house price at risk of being underwater is \$296,000, see Table 6.

In the difference-in-difference exercise, I found that flooded homeowners were 59 and 12 basis points less likely to prepay and default, respectively. In the calibrated model, flooded homeowners are 167 basis points less likely to prepay and 2 basis points more likely to default. That the model moments are in line with untargeted moments reassures me of the policy experiments that I conduct.

**Lifecycle profiles** In the model, as in the SCF data, consumption increases over the course of a household's life, albeit plateauing close to retirement as income declines. Likewise, liquid asset holdings increase with age. However, in the model, middle-aged households run down their liquid asset holdings to pay a downpayment to buy a home. Once they become a home-



**Figure 6: Lifecycle Profiles.** This figure provides a comparison of the lifecycle profiles in the model to the SCF data. In the model, as in the SCF data, consumption of nondurable goods, liquid wealth, and overall wealth (inclusive of home equity) generally increase with age. Loan-to-value ratio (equivalently, leverage) declines with age.

owner, the build-up of liquid wealth continues, see Figure 6.

Similarly, the household's total wealth—wealth inclusive of home equity—also increases with age. Conversely, the average leverage (equivalently contemporaneous loan-to-value ratio) declines as households age. This decline in housing debt is reflected in the increase in housing equity and overall wealth.

## 5.2 Policy Experiments

I conduct two policy experiments using the quantitative model. First, I estimate the effect of removing both distortions on homeowners' exposure to climate risk. Specifically, suppose the policymaker i) committed to not providing assistance to flooded homeowners and ii) charged mortgagors a flood risk premium as part of the mortgage. How many fewer households would live in the at-risk area? This experiment serves as a benchmark.

Description	Baseline (1)	Benchmark (2)	Taxing At-Risk Homeowners (3)
<u>Government policies</u>			
Government assistance after disaster, $\tau$ (\$)	48,000	0	48,000
Flood risk premium in mortgage, $\varphi_m$ (basis points)	0	26	26
Tax on at-risk homeowners, $\lambda$ (\$)	0	0	564
<u>Magnitude of change</u>			
Number of homeowners exposed to climate risk	350,000		
Number of fewer homeowners exposed to climate risk		73,000	57,700
Residential losses due to Hurricane Sandy (\$)	7.8 billion		
Residential losses prevented (\$)		2.95 billion	2.34 billion
<u>Economic attributes of movers</u>			
Average annual consumption of nondurable goods (\$)		40,900	27,100
Average liquid wealth (\$)		26,500	26,400
Average wealth including housing equity (\$)		112,000	111,000
Average FICO score		686	644

**Table 7: Effect of Various Policy Regimes on Households' Exposure to Climate Risk.** This table summarizes the results for two policy experiments: i) removing both distortions which serves as a benchmark, and ii) continuing government assistance for flooded homeowners while charging at-risk homeowners a 26 basis point flood risk premium as part of their mortgage and a tax equal to the median flood insurance premium in New Jersey between 2010 and 2015, \$564.

However, a commitment from the policymaker to not bail out devastated households would be incredible. In the second experiment, the policymaker i) still charges a flood risk premium as part of the mortgage, ii) taxes at-risk homeowners to fund the public assistance program for flooded homeowners. How does the outcome of this policy regime compare to the benchmark? This regime effectively makes (imperfect) flood insurance mandatory. In fact, I set the tax equal to the median flood insurance premium in New Jersey between 2010 and 2015.

In both experiments, I search for an equilibrium in a world with these alternate policy regimes and compare the outcome to the baseline. Thus, these are long-term outcomes determined by how new entrants into the economy are affected by the policies, not existing homeowners.

**Benchmark** I estimate that removing both distortions, specifically,

1. limiting government assistance following a disaster:  $\tau = 0$
2. charging mortgagors a flood risk premium with the mortgage:  $\varphi_m = 26$  basis points

would reduce the number of homeowners in the risky area by 73,000 households in New Jersey. At baseline, there were 350,000 households in the risky area in the state, so correcting these distortions leads to a 2% reduction in the number of homeowners exposed to climate risk. Halpin (2013) estimates that residential losses due to Hurricane Sandy amounted to \$7.8 billion. With 73,000 fewer households in harm's way, I estimate the losses would be lower by \$2.95 billion, or 37%. Column (2) of Table 7 summarizes these findings.

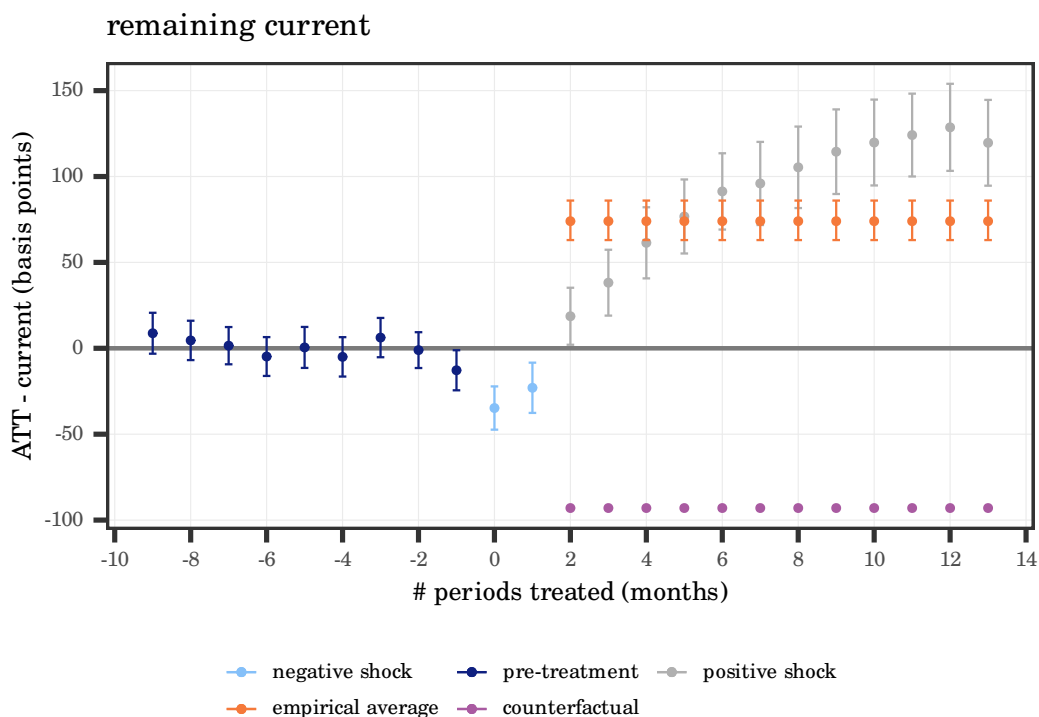
The mean annual consumption of nondurable goods for these 73,000 households is \$40,900. Their liquid wealth is \$26,500 on average. Their total wealth, including their home equity, is \$112,000. Lastly, the average FICO score is 686. Thus, households who change their decision in light of this new policy structure are primarily low- and moderate-wealth, albeit creditworthy, households.

Why do these households choose not to live in the high-risk, high amenity area? First, these are hand-to-mouth households who could not afford to pay for repairs after a disaster if the government did not step in to help. In the absence of government relief after a disaster, these households would default on their mortgage. Their relatively high FICO score would be reset to 500, and they will have to rent for at least one period. Losing their high FICO score makes homeownership in the future more costly since the lender will then charge them a higher mortgage rate for the same loan-to-value ratio. The household preempts these future costs and chooses to live in the safe region in the first place. Additionally, mortgage rates for risky homes are higher by 26 basis points, nudging households towards the safe area. Younger, asset-poor households want to borrow as much as possible and find better credit terms in the safe region.

One assumption I have made is that the policymaker can credibly commit to not helping flooded homeowners. However, limiting assistance may be politically infeasible because it would be morally indefensible. Nonetheless, suppose the policymaker went through with their commitment not to help flooded homeowners. Using the model, I find that in the absence of government relief, affected homeowners would be 93 basis points less likely to stay current on their mortgage, see Figure 7, or 19% more likely to *not* stay current on their mortgage.<sup>17</sup>

<sup>17</sup>I find that in the absence of relief assistance, flooded homeowners are 93 basis points less likely to stay current on their mortgage. The probability of a homeowner not remaining current on their mortgage is 5%. Thus,  $0.93/0.05 \approx 19\%$





**Figure 7: The Effect of No Government Assistance on Homeowners' Mortgage.** This figure shows the effect of no government assistance on homeowners' decision to stay current on their mortgage after a disaster. Empirically, flooded homeowners were 74 basis points more likely to stay current on their mortgage after Sandy because of government relief measures (orange). In the model counterfactual, in the absence of government relief flooded homeowners are 93 basis points *less* likely to stay current on their mortgage (purple).

Such a situation would be untenable for a policymaker. Therefore, we have concrete evidence why the policymaker's commitment to not bailout devastated households is incredible.

**A tax on at-risk homeownership** Instead, suppose the policymaker

1. charged at-risk homeowners a tax equal to the median flood insurance in New Jersey:  
 $\lambda = \$564$
2. charged mortgagors a flood risk premium with the mortgage:  $\varphi_m = 26$  basis points
3. promised to provide relief for flooded homeowners:  $\tau = \$48,000$

My model predicts that this policy regime would lead to 57,700, or 16.5%, fewer homeowners in the risky region relative to baseline. This policy structure nudges 80% of the households who moved to the safe area in the benchmark case without requiring the policymaker to (incredibly) commit to not helping affected homeowners. Similarly, the losses prevented due to Sandy would be \$2.34 billion, or 30%. Column (3) of Table 7 summarizes these results.

The average annual consumption of nondurable goods for these 57,700 households is \$27,100, and their liquid wealth is \$111,000. The average FICO score for the group is 644. Relative to the benchmark, the households who choose to live out of harm's way are less creditworthy and hence poorer. With a per-period tax and higher mortgage rates, the risky area is an expensive place to live. Households with low FICO scores now have a much higher mortgage rate, all else equal. Such households are effectively priced out of this housing market and choose to live in the safe region instead. Households with higher wealth and FICO scores still choose to live in the at-risk area. In fact, households with higher FICO scores do not have to worry about defaulting if they are flooded because they know the government will come to their rescue. The critical takeaway, from a policy standpoint, is that mandatory flood insurance will price out a significant fraction of credit-poor agents from high-risk, high amenity areas.

## **6 Conclusion**

In this paper, I estimated that 20% fewer homeowners would be exposed to climate risk if two existing distortions in the housing market—due to government policies—are removed. Enforcing flood insurance using a tax mechanism would achieve 80% of this reduction. Households not exposed to climate risk due to these policy regimes would primarily be low and moderate-wealth, albeit creditworthy, households. I have quantified how many fewer households would live in at-risk regions as the policymaker alters the policy regime. These estimates and the model I developed are especially timely and relevant: starting in October 2021, FEMA will use a new methodology, Risk Rating 2.0, to determine flood insurance premiums. The tools in this paper can be used to assess the effect of this new risk rating system on households' housing decisions and exposure to climate risk in future work.

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## A Flood Risk and Mortgage Rates

Hurst et al. (2016) show that despite significant variation in predictable default risk at the regional level, there is no spatial variation in mortgage rates for otherwise identical loans. Using a similar econometric strategy, I show that mortgage rates for otherwise identical mortgages do not vary by the flood risk profile of a region.

Empirically, homebuyers with lower FICO scores are charged higher mortgage rates. Likewise, an agent demanding a higher loan-to-value ratio, i.e. wishing to put down a smaller downpayment upfront, will be charged a higher rate. To that end, I want to determine the effect of being located in a high or low flood risk area on mortgage rates, controlling for borrower- and loan-level characteristics like FICO and LTV. Formally, I first estimate the following equation at the individual loan level

$$m_{\ell z t} = \alpha_0 + \alpha_1 X_{\ell t} + \alpha_2 D_t + \varepsilon_{\ell z t} \quad (6)$$

where  $m_{\ell z t}$  is the mortgage rate for loan  $\ell$  in zip code  $z$  in period  $t$ .  $X_{\ell t}$  is a set of loan-level controls, in particular FICO and LTV for loan  $\ell$  at time  $t$ .  $D_t$  is a vector of time dummies based on the month of origination. Estimating equation (6) delivers  $\varepsilon_{\ell z t}$ , the residual of the mortgage rate after controlling for loan-level characteristics and time fixed effects.

I then calculate the average mortgage rate residual for each zip code

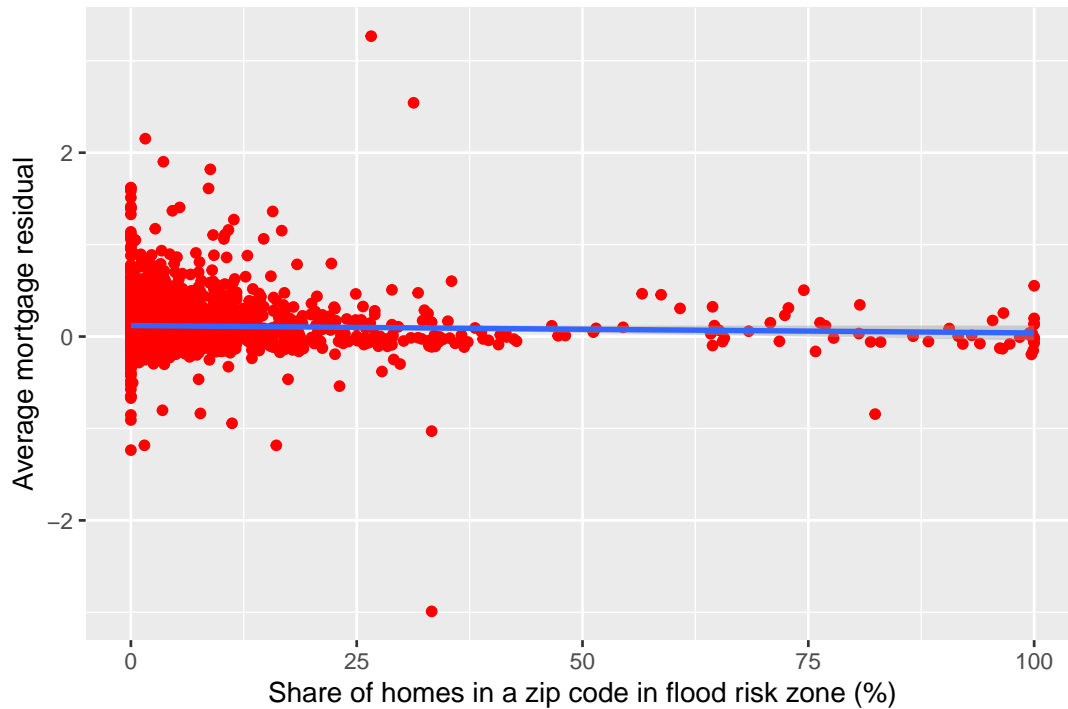
$$M_{z t} = \frac{1}{N_{z t}} \sum_{\ell=1}^{N_{z t}} \varepsilon_{\ell z t}$$

where  $N_{z t}$  is the number of loans in zip code  $z$  in time period  $t$ . Subsequently, I estimate the following equation

$$M_{z t} = \beta_0 + \beta_1 pct\_sfha_{z t} + \eta_{z t} \quad (7)$$

where  $pct\_sfha_{z t}$  is the percentage of homes in zip code  $z$  at time  $t$  that are within the special flood hazard area based on FEMA's flood maps, i.e. the share of homes categorized as being at flood risk.

Table 8 reports the estimates for equations (6) and (7) based on zip codes across New York state and New Jersey. Column 2 shows that zip codes with more homes in flood hazard areas do not have higher mortgage rates, controlling for FICO scores and LTV of the mortgages in the zip code, see Figure 8. This result is an artefact of housing and mortgage policies in the US: mortgage rates should not vary due to spatial factors like state regulations for foreclosures or economic vibrancy as shown by Hurst et al. (ibid.). However, this policy choice has a



**Figure 8:** This figure shows the relationship between the percentage of homes in a zip code that are at flood risk, based on FEMA's flood maps, against the average mortgage residual for the zip code. Current housing policy does not allow for mortgage rates to price in geospatial risk. Consequently, mortgage rates do not increase with higher flood risk.

Outcome Variable:	Mortgage Rate	Average Mortgage Residual
	(1)	(2)
FICO	-0.29*** (0.00)	
LTV	0.48*** (0.00)	
Percentage of homes in a zip code in flood-prone area		0.00 (0.00)
$R^2$	0.47	0.00
Observations	2,988,454	2,355

**Table 8:** This table shows the effect of flood risk on mortgage rates in zip codes across New York state and New Jersey. Column (1) reports the effect of FICO score and LTV on the mortgage rate, in percentage points. A higher FICO score reduces the mortgage rate charged while a higher LTV increases the mortgage rate. Column (2) summarises the relation between the percentage of homes in a zip code that are at flood risk based on FEMA's flood maps and the average mortgage residual across that zip code. By policy design, zip codes with higher flood risk are **not** charged a higher mortgage rate, accounting for variation in FICO and LTV. \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01

	Full-sample (1)	FRM-only (2)
Avg. flood risk at zip code-level	0.003 (0.006)	-0.003 (0.005)
FICO score	-0.188*** (0.010)	-0.174*** (0.008)
Origination LTV	0.027*** (0.004)	0.022*** (0.003)
$R^2$	0.48	0.51
Observations	358,797	224,550

This table shows the effect of flood risk on mortgage rates based on mortgages in New Jersey. I show results for the entire sample of mortgages (FRMs and ARMs combined) and only for 30-year, first lien FRMS. I find that increase in flood risk does not lead to an increase in mortgage rates. \*p < 0.1; \*\* p < 0.05; \*\*\* p < 0.01

key by-product: mortgage rates do not price in regional disaster risk.

Alternatively, as a robustness check, I directly estimate the effect of zip code-level disaster risk on mortgage rates

$$m_{\ell,z,t} = \alpha_0 + \alpha_1 X_{\ell,z,t} + \alpha_2 D_t + \alpha_3 (D_t \times X_{\ell,z,t}) + \varepsilon_{\ell,z,t}$$

where now  $X_{\ell,z,t}$  denotes loan-level characteristics like FICO, origination LTV and also average flood risk by zip code. I use First Street Foundation's measure of flood risk at the five-digit zip code level as a measure of flood risk.

## B Household Problems for Homeowners in the Safe Region, Renters, and Newborns

### B.1 Homeowners in the safe region

First, consider the household's problem in the safe region. Note that a household in safe area does not face any uncertainty (house price is fixed, income is age-dependent, and there is no disaster risk).



**Terminal safe homeowner**

$$V^{safe}(J, a, oltv, fico, n) = \max_b u(c, b)$$

$$c + b = (1 + r)a + y_J + (1 - ltv)p_{safe}$$

**Interim safe homeowner: staying current**

$$V_{current}^{safe}(j, a, oltv, fico, n) = \max_{a'} u^{safe}(c) + \beta V(j + 1, a', oltv, fico, n + 1)$$

$$c + a' + x(oltv) + \text{maintenance} = (1 + r)a + y_j$$

**Interim safe homeowner: refinance**

$$V_{refinance}^{safe}(j, a, oltv, fico, n) = \max_{a', oltv' \in \mathcal{C}_{fico}} u^{safe}(c) + \beta V(j + 1, a', oltv', fico, n + 1)$$

$$c + a' + x(oltv') + \text{maintenance} + \text{closing cost} = (1 + r)a + y_j + (oltv' - ltv)p_{safe}$$

**Interim safe homeowner: optionality**

$$V^{safe}(j, a, oltv, fico, n) = \max \begin{cases} V_{current}^{safe}(j, a, oltv, fico, n) & \text{stay current} \\ V_{refinance}^{safe}(j, a, oltv, fico, n) & \text{refinance} \end{cases}$$

where

- $b$ : bequest
- $ltv$ : contemporaneous loan-to-value ratio
- $x(oltv)$ : mortgage payment as a function of the origination loan-to-value ratio

**B.2 Rental Market**

Now consider the rental market. Again, renters are shielded from disaster risk but don't get any utility from housing either.

**Terminal renter**

$$V^{rental}(J, a, fico) = \max_b u(c, b)$$

$$c + b = (1 + r)a + y_J$$

**Interim renter: remain renter**

The interim renter may chose to stay in the rental or move to at-risk housing; a renter cannot move directly to the safe housing.

$$V_{remain\ renter}^{rental}(j, a, fico) = \max_{a'} u^{rental}(c) + \beta V^{rental}(j+1; a', fico)$$

$$c + a' + p_{rental} = (1+r)a + y_j$$

**Interim renter: become at-risk homeowner**

$$V_{move\ to\ at-risk}^{rental}(j, a, fico) = \max_{a', oltv \in \mathcal{C}_{fico}} u^{at-risk}(c, \theta = 0) + \beta EV^{at-risk}(j+1; a', oltv, fico, n=2, \theta')$$

$$c + a' + x(oltv) + \text{maintenance} + \text{closing cost} + \text{moving cost} + (1-oltv)p_{at-risk} = (1+r)a + y_j$$

**Interim renter: optionality**

$$V^{rental}(j, a, fico) = \max \begin{cases} V_{remain\ renter}^{rental}(j, a, fico) & \text{remain renter} \\ V_{move\ to\ at-risk}^{rental}(j, a, fico) & \text{move to at-risk housing} \end{cases}$$

**B.3 Problems for Newborn Agents**

Newborns are born with an asset endowment and a FICO score. They also receive income,  $y_1$ , in the first period. While newborn agents are heterogeneous in initial endowment of wealth and FICO score, they all receive the same wage. They have two key options: rent or own a home. Furthermore, they can choose to buy a house in the flood-prone at-risk area or the safe region. Thus, they have three possible options to weigh.

**Newborn at-risk homeowner**

A newborn agent considering homeownership in the at-risk solves the following problem.

$$V_{at-risk}^{newborn}(j=1, a, fico) = \max_{a', oltv \in \mathcal{C}_{fico}} u^{at-risk}(c, \theta = 0) + \beta EV^{at-risk}(j+1, a', oltv, fico, n=2, \theta')$$

$$c + a' + x(oltv) + \text{maintenance} + \text{closing cost} + \text{moving cost} + (1-oltv)p_{at-risk} = a + y_1$$

where they have to decide on how much risk-less asset to rollover,  $a'$  while also deciding on their mortgage contract,  $(m, oltv)$  conditional on their FICO assignment.  $(1-oltv)p_{at-risk}$  represents the downpayment they have to make.

### Newborn safe homeowner

On the other hand, a newborn considering homeownership in the safe region solves the following problem.

$$V_{safe}^{newborn}(j = 1, a, fico) = \max_{a', oltv \in \mathcal{C}_{fico}} u^{safe}(c) + \beta V^{safe}(j + 1, a', oltv, fico, n = 2)$$

$$c + a' + x(oltv) + \text{maintenance} + \text{closing cost} + \text{moving cost} + (1 - oltv)p_{safe} = a + y_1$$

The only change relative to the previous problem is that the downpayment is now  $(1 - oltv)p_{safe}$  and the continuation value is deterministic.

### Newborn renter

Lastly, the agent may consider becoming a renter initially. Such an agent would solve the following problem.

$$V_{rental}^{newborn}(j = 1, a, fico) = \max_{a'} u^{rental}(c) + \beta V^{rental}(j + 1, a', fico)$$

$$c + a' + p_{rental} + \text{maintenance} + \text{moving cost} = a + y_1$$

Unlike a newborn becoming a homeowner, a newborn becoming a renter does not have to pay any closing costs nor do they have to make a downpayment.

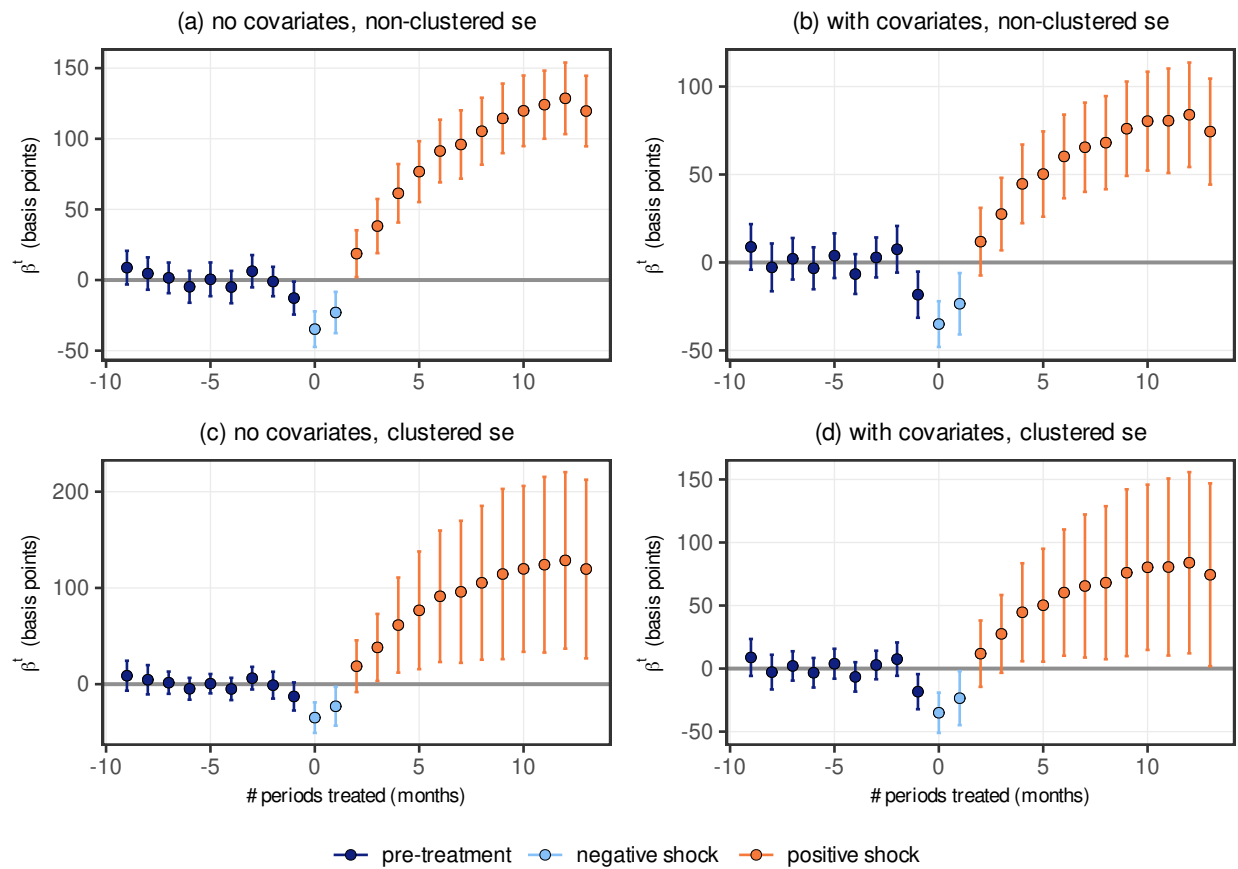
### Newborn: optionality

The agent chooses the best possible course of actions.

$$V^{newborn}(j = 1, a, fico) = \max \begin{cases} V_{at-risk}^{newborn}(j = 1, a, fico) & \text{become at-risk homeowner} \\ V_{safe}^{newborn}(j = 1, a, fico) & \text{become safe homeowner} \\ V_{rental}^{newborn}(j = 1, a, fico) & \text{become renter} \end{cases}$$

## C Robustness Checks for Differences-in-Differences

I also estimate the overall effect of Sandy on the change in homeowners' probability of staying current relative to non-affected homeowners, controlling for FICO and LTV and clustering standard errors at the five-digit zip code level, see Figure 9. I find that the estimate is robust to these alternative specifications, see Table 9.



**Figure 9:** This figure shows the monthly average treatment effect on the likelihood of a homeowner staying current on their mortgage in zip codes impacted by Hurricane Sandy. Panel (a) shows the results for the specification without covariates and without clustered standard error errors. Panel (b) presents the results with FICO and LTV as covariates but without clustered standard errors. Panel (c) displays the results without covariates but with clustered standard errors. Lastly, panel (d) plots the results with covariates and clustered standard errors. In all specifications, the point estimates suggest that number of days a mortgage is delinquent declines in impacted zip codes. The error bars represent the 95% confidence intervals.

Outcome Variable	Remain Current			
	(1)	(2)	(3)	(4)
Overall ATT	74*** [63, 85]	47** [6, 35]	74*** [11, 38]	47*** [18, 77]
Covariates	N	Y	N	Y
Clustered	N	N	Y	Y
Observations	695, 180	615, 591	695, 180	615, 591

**Table 9:** This table summarizes the results of the overall effect of being effected by Hurricane Sandy on the number of days a mortgage in the disaster-struck zip codes. Column (1) reports the overall ATT for the specification without covariates and non-clustered standard errors. Column (2) reports the overall ATT for the specification with FICO and LTV as covariates but without clustered standard errors. Column (3) shows the same estimate for the specification without covariates but with clustered standard errors. Lstly, column (4) shows the estimate of the overall ATT with FICO and LTV as covariates and clustered standard errors. Standard errors are clustered at the zip code level and reported in parentheses. 95% confidence intervals for the point estimates are reported in square brackets. In all of the specifications, the overall ATT is negative at the 95% confidence level. \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01