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Household, Bank, and Insurer Exposure to Miami Hurricanes: a flow-of-risk analysis

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Abstract

We analyze possible future financial losses in the event of hurricane damage to Miami residential real estate, where the hurricane's destructiveness reflects climate-change. We focus on three scenarios: (i) a business-as-usual scenario, (ii) a Hurricane-Ian-spillovers scenario, and (iii) a cautious-markets scenario. We quantify bank exposures and loss rates, where exposures are proportional to the size of real estate markets and loss rates depend on post-hurricane devaluations and insurance coverage. This quantitative methodology could complement modeling of local economy impacts, stress on public finances, asset market losses, and other financial developments that will also affect banks.

*The views expressed in this paper should not be attributed to the Federal Reserve Board and are the sole responsibility of the author. The scenario analysis in this paper is a research effort and is unrelated to the Federal Reserve Board's recently announced Pilot Climate Scenario Analysis. This paper builds on contributions by my colleagues in S&R Policy Planning and Strategy to a review of Miami climate risks, including Joseph Cox, Jonathan Loritz, Jacy Su, Nick Tabor, Justin Warner, and Aurite Werman. Other participants in the Miami study included Brian Bailey, Kyle Binder, Saba Haq, Nick Klagge, Andy Polacek, John Schindler Jr., Solomon Tarlin, Lauren Terschan, and James Wang. I thank Liz Marshall and Roisin McCord for their review of the code. Jake Clark was instrumental in applying the Hazus tool. I also thank Benjamin Kay for many helpful comments. While the insights of these individuals were instrumental in shaping this analysis, all errors and omissions remain my own.

Contents

1 Introduction

The accelerating impact of climate change has added urgency to efforts to understand how severe weather events might affect the safety and soundness of the financial system.[1] This paper takes a bottom up approach by investigating the impact of sea level rise on the vulnerability of banks to losses on their residential real estate portfolios in Miami. The defining feature of this analysis is that it traces what we define as the *flow-of-risk* across entities. Pozsar (2014) [31] introduced the term flow-of-risk as a means of taking derivatives and other risk shifting mechanisms into account when quantifying exposure to specific financial risks in the shadow banking sector. We similarly use the term as a means of identifying true exposure to climate risks taking into account all known loss allocation arrangements. In the event of a hurricane in Miami, insurance companies take the first loss (net of deductables). When insurance coverage does not exist or is insufficient, losses spill over to homeowners. If homeowners default for whatever reason, losses accrue to mortgage originators or purchasers depending on their exposure. Thus, the model shares a kinship with waterfall models developed to understand loss distributions across asset managers in the wake of the Global Financial Crisis. This kinship extends to the recognition that institutional and contractual details matter in the passthrough of losses from one party

[1]See, for example, the most recent Sixth Assessment of the Intergovernmental Panel on Climate Change (IPCC): https://www.ipcc.ch

to another, and the degree to which losses are contingent on complementary factors.

The focus on residential real estate is an attractive starting point given the significant role of banks in mortgage lending and the availability of bank balance sheet data that can be matched against hurricane and flood risks. While exposure to residential real estates in Miami is admittedly a small fraction of any large national bank's portfolio, this exercise provides a template that can be extended to other assets and regions. With a suitable methodology for aggregating across these assets and regions, taking into account correlations between climate events and spillovers across regions, a given bank's total exposure to climate risk can be evaluated.

We choose Miami given that its unique exposure to sea level rise has received a lot of interest. The high risk to Miami from sea level rise combined with its susceptibility to hurricanes imply that homeowners might have a markedly higher incentive to strategically default on their mortgages in the event of climate-related losses. There are two recent books that cover real estate markets in Miami in the context of sea level rise (Ariza 2020 [1], and Goodell 2017 [20]). Each city-region is distinguished by unique set of physical and transitional climate risks. Miami is wedged between two large bodies of water that will overwhelm the city if sea levels rise. Complicating decision-making, local climate officials must coordinate across 34 municipalities in Miami-Dade County alone. In addition, Miami is built on porous limestone through which water can infiltrate. Not only does this allow water to bypass seawalls, but saltwater infiltration is also degrading Miami's freshwater aquifers.

In the flow-of-risk framework, a climate-linked natural disaster leads to insurable claims for covered homeowners, generating losses for insurers.[2] To the extent that insurance policy premiums accurately reflect climate risks and homeowners are appropriately insured against those risks, insurance should be sufficient to prevent any losses from passing through to banks. Yet not all households have insurance, especially if they are not required to have it, and those that do may not be fully insured. This applies both to flood and wind insurance which are sold by different insurance companies in separate markets (whether wind is bundled into general homeowner's insurance

[2]The flow-of-risk considerations examined here are a subset of the effects described by Batten et al. (2016) [5], who provide a comprehensive mapping of direct and indirect impacts of a climate-linked natural disaster on the financial system.

automatically or is required as a separate rider depends on the insurers assessment of wind vulnerability within the policy-holders vicinity). Potential homeowners looking to take out a mortgage to purchase property located in FEMA-designated flood plains are often formally required to purchase flood insurance by lenders. However, there are concerns that lenders may be exempting as many as half of these borrowers from this requirement.[3] For those with insurance, coverage may not be sufficient to replace the home, especially if it is now necessary to elevate the home on pilings, construct private water drainage infrastructure, or build to higher local construction codes. Policies written to cover the actual depreciated value of structures may fall far short of the necessary reconstruction funds, and homeowners may often insure themselves to the minimum required level. As discussed in Section 3.1, property-level data on insurance coverage is limited or unavailable.

Insurance losses only pass through to banks if homeowners do not in turn absorb uninsured losses. Losses to homeowners include two distinct components: losses due to damage to structures, and losses due to devaluation of the land parcel. For residential mortgages, the historical record on price devaluation is limited. Many homeowners have benefitted from some form of insurance or disaster relief and strategic default rates have been low. In many cases, property values have rebounded from isolated natural disasters within three to seven years. When authorities have determined that a land parcel is no longer suitable for habitation, the government has often acted to buy out homeowners and make them whole.[4] However, if the number of at-risk properties becomes too large, governments may not be able to absorb these losses. A scenario that produces the trifecta of uninsurability, large and unexpected adaptation costs (such as for condominium owners in the wake of the Surfside tragedy), and losses too large to be absorbed by the government could produce a large impact on prices. Although some research has found an impact of climate change on home prices, it does not seem likely that prices fully reflect climate risks (see, e.g., Dennis, 2022, [9]).

Section (2) describes the flow-of-funds analytical approach, with a description of how losses are calculated for each loss-absorption layer. Section (3) describes the data, assumptions, and design of each of our three scenar-

[3]This point, initially raised in informal discussions with insurance experts, is supported by coverage data from NFIP as described in Section 3.1.

[4]See, e.g., NYT, "U.S. Flood Strategy Shifts to 'Unavoidable' Relocation of Entire Neighborhoods": https://www.nytimes.com/2020/08/26/climate/flooding-relocation-managed-retreat.html

ios, and presents results. Section (4) concludes. Addition details on model calculations and other information are provided in the appendix.

2 Analytical approach

We model hurricanes at each boundary of the Saffir-Simpson Hurricane Wind Scale – Categories 1 through 5 – that follow a predetermined path through the heart of Miami-Dade County using the HAZUS FEMA physical modeling tool.[13][5] This tool uses the physical characteristics of both a defined hurricane system and Miami to determine damage rates on a census tract basis. These damage rates are then applied to properties.

The HAZUS software takes into account various factors such as windspeed, track speed, tidal elevation, width of hurricane, etc. to calculate wind and flood damage in a combined model. The relative balance of flood and wind damage will depend on many factors, including storm characteristics in addition to the characteristics of built structures in the storms path (e.g., frame vs. masonry, age, height, purpose, etc.). For example, a wide, slow-moving storm with slower winds will create a high ratio of flood to wind damage. A narrow, fast-moving Category 5 hurricane will primarily cause wind damage (although flooding due to storm surge will depend on the topography of the shoreline). These many features are captured by the HAZUS model.

HAZUS provides a series of wind and flood loss rates as a fraction of replacement value for single family homes, multifamily dwellings, and mobile homes by census tract. Replacement values are also available from HAZUS, allowing us to calculate losses. Actual property values are equal to the replacement value plus the value of the land parcel. Although it is generally the case that the land parcel adds value to the structure, this is not always the case. Local amenities may have a negative value that lowers the sales price of a property below the replacement value, especially in areas in which climate risks are rising sharply.

We then map census tracts to flood zones using FEMA National Risk Index data and use U.S. Census data to identify areas of high-to-medium income owners, lower-income owners, and primarily rental properties. These

[5]The boundaries are given by the following maximum sustained wind speeds: Category 1 = 74 mph, Category 2 = 96 mph, Category 3 = 111 mph, Category 4 = 130 mph, and Category 5 = 157 mph.

distinctions are used to impute the amount of insurance coverage likely to prevail by census tract. We assume that floodplain homes are more likely to carry flood insurance as a condition of securing a mortgage. Evidence suggests that this coverage is only around 50 percent, however, given that half of homeowners allow their flood coverage to subsequently lapse.[6]. We also assume that lower income households are less insured relative to high-to-middle income households, again most likely due to lapses in renewing policies. Analysis of the aftermath of Hurricane Ian will provide much more information about how well insured Florida households are, and whether insurance will remain within the reach of most households.

We derive the mortgage exposure of banks to each census tract, and therefore each of the six homeowner categories, using Home Mortgage Disclosure Act (HMDA) data. HMDA mortgage data provides information on the type of borrower, the location of the property, the loan-to-value ratio, and many other factors for a wide variety of financial institutions. However, it does not provide the stock of mortgage assets on these institutions? balance sheets. We get information on the stock of mortgages from Y-14M data. One benefit of Y-14M data is that it apportions bank-originated mortgages into mortgages held by banks, mortgages sold to the GSEs, mortgages that are securitized and sold, and mortgages sold in the interbank market. Bank-originated mortgages account for only a third of all mortgages, with the majority of mortgages offered through non-bank financial institutions (NBFIs) such as Rocket Mortgage. Banks tend to keep around half of the mortgages they originate and sell the rest, and the choice of which mortgages to retain will reflect a risk management strategy. Lacking data on which mortgages are retained and held on banks' own books, we assume that mortgage retention and sales are proportional to the stock of mortgage loans in each of the six categories. This assumption will overstate the risk to banks (and understate the risk to purchasers) if banks retain the least risky categories of mortgages for their portfolios.

2.1 Loss absorption by insurers

The first layer of loss absorption is insurance, net of deductible. Because homeowners insurance deductibles are so small, typically $500 to $2,000, we

[6] There are no comprehensive datasets on insurance coverage of households. We base our estimates of coverage rates on reporting on the impact of Hurricane Ian, see, e.g., Rozsa and Werner (2022) [33], and Flavelle (2022b) [15]

do not model them in our simulations. There are three types of homeowner policies in the model: (i) National Flood Insurance Program (NFIP), (ii) private flood insurance, and (iii) homeowners insurance. The first two types of insurance are specific to flooding, while the latter covers damage by wind. In the event that wind and flood damage coincide, we assume that homeowner insurers will insist that the damage be classified as flood damage.

Most homeowners lack flood insurance. Recent reporting in the wake of Hurricane Ian suggests that only half of homes in floodplain areas in the counties evacuated for Hurricane Ian had flood insurance, while only 20 percent in non-floodplain areas had flood insurance (see, e.g., Rozsa and Werner (2022) [33], and Flavelle (2022b) [15]). It is unclear why so many mortgage borrowers lack flood insurance, which is a requirement of securing a mortgage in designated floodplain areas. Most likely flood policies are allowed to lapse after the original mortgage is secured.

Homeowners insurance, which typically covers wind damage, is available for the replacement cost of the home's structure. The combined value of the home's structure and the land parcel on which the home sits is equal to the price of the home. If the land value does not change in the wake of a hurricane, it is possible for insurance to make the homeowner whole, which seems to be the historical norm. However, climate change may cause a climate event to lead to a devaluation of the land parcel in addition to structural damage to the home. This potential devaluation is most likely if insurers are led by climate change to withdraw coverage by declining to renew insurance policies (or to increase premiums beyond the reach of most homeowners). There is no practical method for insuring land value, so some homeowner losses are not covered by the insurance loss absorption layer.

Our specific insurance assumptions are discussed further below.

2.2 Loss absorption by borrowers

Borrowers are next in line to absorb losses not covered by insurers. Borrower equity will vary by many different factors including tenure in the home. We assume that all borrowers purchase their homes initially with a 30-year fixed rate mortgage and a 20 percent down payment. We assume that there is a constant rate at which homes are sold, which allows us to solve for the cohort distribution where cohorts are defined by the number of years since purchase. To the extent that uninsured structural damage and land devaluation caused by a hurricane reduces homeowner equity, homeowners may owe more on their mortgages than their homes are worth. Recent cohorts, who have newly purchased their homes, will have a large loan-to-value ratio and will consequently be more likely to default.

The literature on post-natural disaster home values tends to find that home values recover with three to seven years of the disaster implying that land values are typically durable. Homeowners who expect the eventual recovery of their home values will be less likely to default, viewing any devaluation as temporary. However, for Miami, climate change is likely to permanently devalue properties in harms way through at least three channels. The first is the carrying cost of modifying the property to withstand higher sea levels and enduring more frequent or damaging storms. The second is the cost in reduced amenities values caused by eroding public services, higher taxes, and other community effects of climate-induced changes. The third is the increased difficulty of insuring property, including reduced availability of insurance or increased premiums.

This implies that studies that tie default rates to negative equity need to be modified for land value devaluation in addition to considerations such as whether the state has non-recourse laws in which the lender cannot go after more than the collateral of the home itself. Florida is a recourse state. We use an adaptation from Bhutta et al. (2010) [6], which focuses in part on Florida default rates, to impose a linear relationship between negative equity and default probability with an ad hoc adjustment to capture the expectation of permanent devaluation.

For each cohort of each type of borrower, we then apply the non-default rate times the homeowner's loss (both uninsured damage and devaluation) to determine the amount of loss absorbed by homeowners. Remaining losses pass through to the next loss absorption layer.

2.3 Loss absorption by creditors

Credit originators include both banks (which originate roughly one-third of mortgages) and non-bank financial institutions (NBFIs). However, banks only retain a portion of the loans that they originate on their balance sheets. The remainder are securitized, sold to government-sponsored entities such as Fannie Mae or Freddie Mac, or sold to other banks. Confidential Home Mortgage Disclosure Act (HMDA) data can track annual mortgage originations and sales by homeowner type and location, allowing us to calculate the exposure of different creditors and purchasers to homeowner type and climate-vulnerable locations. We assume that the share breakdown of these mortgage flows is equivalent to the balance sheet composition for these institutions, with some institutions carrying a heavier exposure to climate risk.

For each housing type (single, multi, mobile homes)/homeowner type (high/middle income, low income, investor)/locational vulnerability/cohort quad in each census tract (where census tracts differ in the mix of housing type – single family homes, multi-family homes, and mobile homes – and home prices), we apply the appropriate default rate (the portion of borrowers in that category who default) times 80 percent of the net value of outstanding principle minus the ex-post collateral value of the home. The percentage represents an assumption that there is a foreclosure friction for the bank of 20 percent of value of the home.

Once we have the total quad losses, we allocate them across creditor institutions using the share exposures of each institution to each quad. For example, suppose net default losses for low-income homeowners in mobile homes in flood-prone census tract X total $100 across all cohorts, and Bank Y accounts for 50 percent of low-income, mobile home mortgages in this census tract. We would calculate that Bank Y experiences losses of $50.

3 Scenarios

Scenario design is complicated due to the many different exogenous variables not calculated within the model. This iteration of the flow-of-risk model takes home price levels and growth rates, turnover rates, interest rates, insurance rates, sea level rise, home construction rates, and other factors as exogenous. These factors interact, however, and so they cannot be chosen completely independently. Ideally, consistency across exogenous variables could be enforced through an asset valuation model (or module) that would complement the flow-of-risk analysis. For example, if insurance premiums were to rise sharply (or if insurance is no longer available for some homes), we would expect a "syndrome" to follow in which insurance coverage falls, home construction slows, home prices decrease, and mortgage interest rates rise (if for no other reason than a rising risk premium). We also, critically, assume post-hurricane devaluation rates in which the amenities value (or the value of the land parcel of the property distinct from the value of the built structure) falls by a fixed amount. Historically, land parcel devaluation in the wake of a climate disaster has not played a significant role. However, climate change impacts may lead to permanent revaluations of certain locations, and we allow for it. At the very least, the scenarios that we develop need to follow a consistent narrative. With this in mind, we construct four scenarios to explore how bank losses respond to the following conditions:

- Business-as-Usual (BAU)
- Hurricane Ian Spillover Effects
- Cautious Markets

3.1 Data

First, we discuss the key data sources for our analysis. From the Home Mortgage Disclosure Act (HMDA) dataset, we obtain the following data on Miami mortgages on an institution level basis by census-tract: combined loan-to-value ratio, whether within limit for conforming loans, lien-status, loan amount, loan purpose, loan term, loan type, property type, property value, purchaser type, name of lending institution, whether sold/guaranteed/transfered to another institution, occupancy, construction method, dwelling category, debt-to-income ratio of borrower, business/commercial purpose, applicant income, median census-tract family income, ratio of average tract income to MSA income (as percentage), number of units in tract, number of owner occupied units in tract, action type, and applicant race. From Y14M data, we obtain the names of covered banks, their category (e.g., LISCC, RBO, etc.), total mortgage holdings, and custodial holdings for GSEs and securities-holders.

From Elliot et al. (2017) [10], we obtain by neighborhood: the number of housing units, the number of occupied units, the number of low-middle income (LMI) households, the number of very-low-income (VLI) plus (LMI) households, population, the number of households, the number of white/black/other race residents, the number of hispanic residents, the labor force unemployment rate, the poverty rate, the share of renter-occupied housing, the share of LMI renter-occupied housing, the share of VLI renter-occupied housing, the share of owner-occupied housing under $200 thousand, the share of rental occupied housing where rent is less than $1,000 per month, the amount of single family housing, the median home value, and whether housing is flood prone.

We match the flow data from HMDA with the stock data from Y14M to generate the stock-flow figures from appendix section (A) in combination with the following assumptions. Downpayments are assumed to be 20 percent of the value of the loan in all cases. Low-income households are defined as having no more than $117 thousand in income.[7]. Unoccupied or renter-occupied homes are classified as other (i.e., "OX"). The number of "LX" homes is calculated as the share of sub-$200K owner-occupied homes (from Elliot et al., 2017, [10]) times the number of primary occupancy homes (from HMDA). The number of "HX" homes the therefore the total of primary occupancy homes minus "LX" homes. "OX" homes are all non-primary residence homes (from HMDA).

Home prices are taken from the Zillow Home Value Indices (bottom-, middle-, and top-tier homes in the Ft. Lauderdale/Miami region) and the National Association of Realtors (median price of existing one-family homes for Miami-Ft. Lauderdale and West Palm Beach) as reported in HAVER. We use an average of top- and middle-tier home values for the price of "HX" homes, the value of low-tier homes for the price of "LX" homes, and the NAR median price for "OX" homes.

Initial turnover rates are given by the number of home mortgages from HMDA divided by existing housing stock net of new home construction[8] We also use data from the American Enterprise Institute on *months supply of existing homes* to calculate the turnover as follows: (12/months supply of housing) * MSA housing inventory * (Miami-Dade County home sales/MSA home sales).[9]

We use the best 30-year housing market growth rate (for the years 1976-2005) to project a 2.2 percent annual growth rate for the business-as-usual (BAU) scenario described below. We use the methodology described in section (G.2) to generate price trends for floodplain homes. We assume flood plain homes grow at the rate of population growth (1.16 percent), and stop growing thereafter. We do not model the destruction of housing stock. However, as described above, we do assume that floodplain homes lose 80 percent of their value in the wake of a severe hurricane.

[7]Miami-Dade defines low-income households as $73.1 thousand in income for a family of four, or 80 percent of AMI as of April 2020)

[8]While this neglects cash-only sales, this is the turnover rate that is relevant for financial institutions' financial health.

[9]Available on Haver at US Regional ⇒ Selected Regional Indicators ⇒ Housing Market Statistics.

We use newspaper reporting on flood insurance coverage in the wake of Hurricane Ian to condition our scenario insurance assumptions (e.g., Flavelle, 2022b, [15]). Home replacement cost values are taken from the Hazus model. See appendix section F for alternative calculations for both the NFIP flood coverage rate and replacement cost values.

3.2 Assumptions

Each scenario will share some common parameter values as shown in Table 1. We assume that both investors and owner-occupiers purchase their homes with mortgages with a 20 percent downpayment.[10] Banks' share of mortgage originations is 34 percent.[11] If a home is foreclosed, the unrecoverable costs of foreclosure are 20 percent.[12] Lastly, the nominal interest rate is 1.5 percent throughout the period of analysis.

Table 1: Universal parameter values

Investor downpayment rate	0.2
Owner-occupier downpayment rate	0.2
Bank share of mortgage originations	0.34
Foreclosure recovery share	0.8
Nominal interest rate	1.5

We now discuss each scenario in turn. For more information on the choices for scenario parameters, see appendix section G.

[10] Although a downpayment rate of 20 percent is ideal, the typical downpayment for first-time homebuyers was 7 percent in 2021 and 17 percent for repeat buyers according to the National Association of Realtors. https://www.nar.realtor/blogs/economists-outlook/tackling-home-financing-and-down-payment-misconceptions . Our assumption of 20 percent is therefore conservative.

[11] According to 2021 Home Mortgage Disclosure Act (HMDA) data, non-depository, independent mortgage companies accounted for 63.9 percent of first lien, 1-4 family, site-built, owner-occupied, closed-end home-purchase loans, an increase from 60.7 percent in 2020. https://www.consumerfinance.gov/data-research/hmda/summary-of-2021-data-on-mortgage-lending/

[12] Frame, 2010, [17], e.g., surveys foreclosure discount estimates that range from 22 to 50 percent. Pennington-Cross, 2006, [29] links the discount to loan size, time in real-estate-owned (REO) status, local house price movements, and being located in a judicial foreclosure state.

3.3 The Business-as-Usual (BAU) Scenario

We simply extrapolate current growth rates, turnover rates, home construction rates, interest rates, etc. We also set post-hurricane devaluation rates at their highest levels given that major hurricane damage was not expected. While this may represent the expectations of many (most?) home buyers in Florida, the BAU assumption is also unrealistic in light of climate change. This scenario may plausibly represent losses in distant future years out to 2050 only if Florida is enormously lucky in avoiding hurricanes between now and then.

The BAU scenario assumes rapid annual growth in both prices and home units at growth rates of 2.2 and 1.6 percent, respectively. Properties in both flood and above-flood plain areas experience similar price and construction trajectories. In addition, historical turnover rates continue unabated. We use the estimated share of homeowners within and outside of flood plains that had flood insurance to proxy for well- and poorly-insured homes (See Rozsa and Werner, 2022, [33], Flavelle, 2022b, [15].)

Table 2: Scenario – Business as Usual

	Floodplain Homes	Above-floodplain Homes
Devaluation		
Cat 3	0.4	0.3
Cat 4	0.6	0.4
Cat 5	0.8	0.5
Price Growth		
Through 2035	0.22	0.22
2040 plus	0.22	0.22
Unit Growth		
Through 2035	0.16	0.16
2040 plus	0.16	0.16
Turnover Rate Change		
Through 2035	0	0
2040 plus	0	0
Well-insured share	0.5	0.2
Additive propensity to default		0.4

We develop insurance profiles for well- and poorly insured homes for each of our six different homeowner types, given in Table 3. Beyond the higher insurance coverage of well-insured homeowners, who have NFIP flood insurance, high-income and investor properties in floodplains are assumed to have additional private flood insurance given that NFIP policies are capped at $250,000. Well insured homes' wind coverage is 80 percent of replacement cost of the structure of the home (where the cost of the structure is provided in HAZUS data), while that of poorly-insured homes covers only 55 percent of the replacement cost.

Table 3: BAU-Scenario Insurance Assumptions

Type	Well-insured? (y/n)	NFIP ($K)	Private Flood ($K)	Private Wind (% structure val.)
HA	y	233	0	0.80
HF	y	233	40	0.80
LA	y	233	0	0.80
LF	y	233	0	0.80
OA	y	233	0	0.80
OF	y	233	40	0.80
HA	n	0	0	0.55
HF	n	0	0	0.55
LA	n	0	0	0.55
LF	n	0	0	0.55
OA	n	0	0	0.55
OF	n	0	0	0.55

Notes: Homeowner types are: HA = high/mid income, above-floodplain, HF = high/mid income, floodplain, LA = low income, above-floodplain, LF = low income, floodplain, OA = other, above-floodplain, and OF = other, floodplain.

Simulation results are given in Table 4. We calculate losses in billions of dollars resulting from a single incidence of the relevant simulated for the years 2025, 2030, 2035, 2040, 2045, and 2050. The local economy evolves over time according to each scenario's assumptions in ways that may make it more or less vulnerable, depending on the scenario. These losses are reported for each loss-absorbing agent for each category on the Saffir-Simpson scale from Cat 1 to Cat 5. Although we can disaggregate the data extensively, we report category totals as well as the share of the banking sector's Miami-Dade mortgage portfolio that is lost. It is important to note that these damage estimates are for a specifically-parameterized hurricane and should not be viewed as representative of all possible hurricanes. For example, a moderately fast and narrow Cat 1 hurricane will cause far less damage than a wide and slow-moving Cat 1 hurricane.

All parties suffer significant loss from Cat 3 or higher hurricanes. For a Cat 5 hurricane that strikes in 2050, the losses for insurers could rise to as much as $89 billion, with losses to banks on mortgages held on their balance sheet of $ 6.3 billion (or 54.8 percent of their Miami portfolio).[13] Given that Miami-area mortgages constitute a small fraction of the overall asset portfolio of large banks, these losses in isolation are not likely to threaten bank solvency. But for smaller banks that are more heavily concentrated in the area, there might be significant distress. The exposure of the various creditors to our six different types of homeowners differs, and HMDA data allow us to draw distinctions between creditors based on relative exposure to the most risky households. Loss rates for other holders of bank-originated mortgages are 28.7 percent for GSE's, 19.7 percent for securitized mortgage purchasers, and 19.3 percent for interbank purchasers.[14]

3.4 The Hurricane Ian Spillover Effects Scenario

The next scenario postulates a strong reaction to Hurricane Ian that dramatically alters real estate and insurance markets in Florida.[15] The continued existence of insurance as an initial loss buffer (after deductables) is question-

[13]RMS Moody's best estimate of private insurance losses from Hurricane Ian is $67 billion, with an additional $10 billion loss to NFIP for a total of $77 billion. https://www.rms.com/newsroom/press-releases/press-detail/2022-10-07/rms-estimates-us67-billion-in-insured-losses-from-hurricane-ian .

[14]We ignore the possibility of 'put-back' risk, or the potential that purchasers of securitized mortgages might have a contractual right to return mortgages that fall below a performance standard to the banks that sold the mortgage. We also assume that the homeowner-type shares of the mortgages sold by banks matches the distribution of these shares held on the banks' own balance sheets. In other words, we do not allow for the adverse selection or moral hazard that has been investigated by [21] (for securities) and [27] for GSE purchases.

[15]See, e.g., Flavelle (2022a) [14] which describes potential consequences of out-of-reach insurance for Florida's housing market.

Table 4: Scenario – Business as Usual

	2025	2030	2035	2040	2045	2050
Cat 1						
Insurers	1,422,105	1,540,548	1,668,856	1,807,850	1,958,420	2,121,532
Homeowners	71,806	78,293	90,530	107,396	126,787	150,556
Bank held	24,326	29,734	36,311	43,856	53,261	64,442
% of mortage portfolio	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%
Bank-originated but not held	37,661	46,035	56,241	67,904	82,477	99,792
Bank-originated other	25,564	31,249	38,177	46,094	55,986	67,741
Non-bank originated	169,951	207,741	253,769	306,423	372,170	450,304
Total	1,751,413	1,933,600	2,143,884	2,379,524	2,649,102	2,954,366
Cat 2						
Insurers	3,707,877	4,016,694	4,351,233	4,713,635	5,106,219	5,531,502
Homeowners	226,653	249,923	275,385	308,828	342,464	389,847
Bank held	24,326	29,734	36,311	43,856	53,261	64,442
% of mortage portfolio	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%
Bank-originated but not held	37,661	46,035	56,241	67,904	82,477	99,792
Bank-originated other	25,564	31,249	38,177	46,094	55,986	67,741
Non-bank originated	169,951	207,741	253,769	306,424	372,171	450,304
Total	4,192,032	4,581,376	5,011,115	5,486,742	6,012,578	6,603,627
Cat 3						
Insurers	7,871,837	8,527,459	9,237,687	10,007,066	10,840,525	11,705,182
Homeowners	19,300,000	23,300,000	28,100,000	33,900,000	40,900,000	49,300,000
Bank held	151,784	181,464	217,225	260,555	312,840	384,027
% of mortage portfolio	3.5%	3.4%	3.4%	3.3%	3.3%	3.4%
Bank-originated but not held	127,474	152,663	183,073	219,409	263,595	332,123
Bank-originated other	95,795	114,684	137,482	164,778	197,927	247,924
Non-bank originated	728,044	871,220	1,043,926	1,251,558	1,503,173	1,871,438
Total	28,274,934	33,147,490	38,919,393	45,803,366	54,018,060	63,840,694
Cat 4						
Insurers	20,037,181	21,715,237	23,499,792	25,391,391	27,590,618	29,898,111
Homeowners	28,200,000	33,900,000	40,800,000	49,100,000	59,100,000	71,200,000
Bank held	871,819	1,057,617	1,258,331	1,497,623	1,785,934	2,132,540
% of mortage portfolio	20.2%	20.0%	19.5%	19.2%	18.9%	18.6%
Bank-originated but not held	628,287	756,040	897,038	1,064,928	1,267,365	1,510,590
Bank-originated other	489,774	590,572	701,090	832,728	991,412	1,182,083
Non-bank originated	3,862,709	4,667,033	5,544,892	6,590,835	7,851,498	9,366,589
Total	54,089,771	62,686,499	72,701,144	84,477,505	98,586,827	115,289,912
Cat 5						
Insurers	59,675,523	64,673,429	69,979,489	75,794,383	82,118,846	88,953,676
Homeowners	38,700,000	46,200,000	55,300,000	66,200,000	79,400,000	95,200,000
Bank held	2,658,525	3,129,476	3,753,645	4,454,419	5,281,918	6,271,536
% of mortage portfolio	61.5%	59.2%	58.2%	57.2%	55.8%	54.8%
Bank-originated but not held	2,001,947	2,341,945	2,769,197	3,252,756	3,824,587	4,507,738
Bank-originated other	1,548,189	1,813,848	2,151,897	2,533,719	2,984,721	3,523,673
Non-bank originated	12,100,000	14,100,000	16,800,000	19,900,000	23,500,000	27,800,000
Total	116,684,185	132,258,697	150,754,229	172,135,277	197,110,073	226,256,623

able. In the wake of Hurricane Andrew, some insurers went bankrupt, and several withdrew from the Florida market altogether (see, e.g., MGI 2020 [25]). The state set up a Florida taxpayer-backed supplemental insurance vehicle to fill the gap, and private captive re-insurance companies emerged in the Cayman Islands to backstop Florida insurers after more well-known re-insurers increased rates or left the market. It is possible that private insurance options may cease to exist or that new insurance company entrants are unreliable. Moreover, the patchwork regulation of insurance by local, state, and federal regulators implies different outcomes by region that challenge a one-size-fits-all model to metro region flow-of-risk analysis.

We therefore model a stark reaction to Hurricane Ian in which insurers flee the state causing insurance coverage to decline sharply. The lack of insurability causes home price trends to turn negative and brings new home construction to a halt for floodplain housing. Table 5 displays our assumptions. We lower the ex-post devaluation for floodplain homes from the BAU scenario given that homeowners are already aware of the potential for hurricane damage. Prices for floodplain homes begin to fall at half the rate of recent increases through 2035, after which climate change leads them to fall even more sharply. For above floodplain homes, prices rise at half their previous rate through 2035, after which they plateau. Home construction in floodplain zones ceases (beyond replacement) while construction in above-floodplain zones proceeds at half its previous rate. Greater difficulty in selling floodplain homes leads to a decrease in the turnover rate that intensifies slightly in 2040 and beyond. The well-insured share of both homeowner types drops severely, and homeowners are more likely to default for a given loss of equity.

We also make adjustments to insurance coverage for well- and poorly-insured homeowners. Well-insured now means the homeowner in all six categories is covered by NFIP flood insurance up to $233,000, and wind damage of up to 60 percent of the value of the structure. For poorly-insured homeowners, there is no flood insurance coverage (NFIP or private) and homeowners insurance only covers 30 percent of wind damage.

Simulation results are given in Table 7. In this scenario, mortgage portfolios are much smaller given lower turnover rates and smaller mortgages (due to reductions in home prices over time). So the loss rates are applied to smaller balances. In this way, the reaction to Hurricane Ian can be seen as corrective, helping to right-size the real estate market relative to climate risks. For example, bank-held mortgages in this scenario reach only $7.4 billion by

Table 5: Scenario – Hurricane Ian Spillovers

	Floodplain Homes	Above-floodplain Homes
Devaluation		
Cat 3	0.2	0.10
Cat 4	0.3	0.15
Cat 5	0.4	0.20
Price Growth		
Through 2035	-0.014	0.11
2040 plus	-0.080	0.00
Unit Growth		
Through 2035	0	0.008
2040 plus	0	0.008
Turnover Rate Change		
Through 2035	-0.2	0
2040 plus	-0.3	0
Well-insured share	0.25	0.10
Additive propensity to default		0.55

Table 6: Hurricane Ian Spillovers Insurance Assumptions

Type	Well-insured? (y/n)	NFIP ($K)	Private Flood ($K)	Private Wind (% structure val.)
HA	y	233	0	0.6
HF	y	233	0	0.6
LA	y	233	0	0.6
LF	y	233	0	0.6
OA	y	233	0	0.6
OF	y	233	0	0.6
HA	n	0	0	0.3
HF	n	0	0	0.3
LA	n	0	0	0.3
LF	n	0	0	0.3
OA	n	0	0	0.3
OF	n	0	0	0.3

Notes: Homeowner types are: HA = high/mid income, above-floodplain, HF = high/mid income, floodplain, LA = low income, above-floodplain, LF = low income, floodplain, OA = other, above-floodplain, and OF = other, floodplain.

2050 compared with \$11.5 billion in the BAU scenario. The distribution of those mortgages is also more skewed towards non-floodplain properties in the Hurricane Ian spillover scenario.

Consequently, instantaneous losses are smaller for all parties, despite the relative high rates of default and lack of insurance. Again, focusing on a Cat 5 hurricane that hits in 2050, total losses are \$63.3 billion in this scenario compared with \$226.3 billion in the BAU scenario. Insurer losses fall from \$95.2 billion to \$31.8 billion, and bank-held mortgage losses fall from \$6.3 billion (54.8 percent of the Miami mortgage portfolio) to \$2.2 billion (or 29.5 percent of the portfolio). Milder hurricane scenarios due lead to higher losses under this scenario than the BAU scenario, however. The assumed deterioration in price trends and turnover rates beginning after 2035 lead to higher percentage losses on banks' mortgage portfolios under the Hurricane Ian Spillover scenario for Cat 1 through 3 hurricanes from 2040 onwards. In a sinking real estate market, moderate shocks will lead to higher rates of default. However, once shocks become sufficiently large, the sinking-market-fragility effect is overwhelmed by the generally poor level of resilience of the entire market.

3.5 The Cautious Markets Scenario

Our final scenario envisions real estate markets turning cautious while insurance coverage rates rise significantly. Agents take maximum action to anticipate and prepare for climate risks under this scenario, with specific assumptions given in Table 8. In many aspects, the parameter assumptions are similar to those of the Hurricane Ian Spillovers scenario. The main differences are that almost all households, regardless of floodplain status, are well-insured; that even prices for above-floodplain homes eventually begin to decline, and that propensity to default is lower given that expectations are better calibrated towards climate risks.

The definition of well-insured now means 90% coverage of structural damage, full NFIP insurance, and an additional \$40,000 of private flood insurance, as shown in Table 9. Poorly-insured is almost identical except for the absence of flood insurance.

Simulation results are given in Table 10. Given that insurers now absorb the bulk of losses, loss rates fall for all other parties. Even so, insurer losses are roughly comparable to the BAU losses and are even lower in extreme cases, such as a Cat 5 hurricane in 2050, despite the far higher insurance

Table 7: Scenario – Hurricane Ian Spillovers Effect

	2025	2030	2035	2040	2045	2050
Cat 1						
Insurers	684,771	697,443	697,443	697,443	697,443	697,443
Homeowners	110,766	113,524	119,671	129,330	139,392	151,368
Bank held	51,053	55,810	58,355	58,480	151,444	249,823
% of mortage portfolio	0.8%	0.7%	0.7%	0.7%	2.0%	3.4%
Bank-originated but not held	64,971	72,138	76,427	77,942	144,086	213,125
Bank-originated other	42,141	46,886	49,760	50,894	98,952	149,601
Non-bank originated	307,027	339,385	358,229	363,613	765,759	1,189,066
Total	1,260,730	1,325,187	1,359,886	1,377,703	1,997,076	2,650,426
Cat 2						
Insurers	1,867,320	1,903,494	1,903,494	1,903,494	1,903,494	1,903,494
Homeowners	363,299	375,052	380,256	391,229	399,174	416,154
Bank held	51,053	55,811	58,355	60,202	175,490	293,667
% of mortage portfolio	0.8%	0.7%	0.7%	0.8%	2.3%	4.0%
Bank-originated but not held	64,972	72,139	76,428	79,073	160,323	242,720
Bank-originated other	42,141	46,886	49,760	51,786	111,214	171,957
Non-bank originated	307,029	339,386	358,231	370,885	867,759	1,375,022
Total	2,695,814	2,792,768	2,826,524	2,856,671	3,617,454	4,403,015
Cat 3						
Insurers	4,034,063	4,116,560	4,116,560	4,116,560	4,116,560	4,116,560
Homeowners	7,370,094	7,459,375	7,437,682	6,470,597	5,828,364	5,406,228
Bank held	53,633	58,976	62,276	302,479	605,080	748,601
% of mortage portfolio	0.8%	0.8%	0.8%	3.8%	7.8%	10.1%
Bank-originated but not held	66,777	74,341	79,144	248,691	461,308	566,296
Bank-originated other	43,646	48,720	51,987	175,705	331,205	408,183
Non-bank originated	318,463	353,368	375,438	1,410,992	2,712,975	3,344,802
Total	11,886,676	12,111,341	12,123,087	12,725,024	14,055,492	14,590,670
Cat 4						
Insurers	10,362,955	10,623,717	10,623,717	10,623,717	10,623,717	10,623,717
Homeowners	12,400,000	12,600,000	12,600,000	11,100,000	10,100,000	9,500,216
Bank held	217,369	244,060	251,394	820,514	1,198,659	1,266,701
% of mortage portfolio	3.2%	3.3%	3.2%	10.4%	15.5%	17.1%
Bank-originated but not held	186,410	208,434	215,371	618,625	885,641	933,088
Bank-originated other	130,698	146,923	152,227	445,024	639,499	675,121
Non-bank originated	1,037,514	1,163,575	1,201,573	3,657,495	5,287,376	5,580,707
Total	24,334,946	24,986,709	25,044,282	27,265,375	28,734,892	28,579,549
Cat 5						
Insurers	31,028,955	31,834,483	31,834,483	31,834,483	31,834,483	31,834,483
Homeowners	20,200,000	20,500,000	20,400,000	18,500,000	17,200,000	16,200,000
Bank held	1,073,418	1,253,443	1,321,399	2,168,634	2,387,930	2,187,986
% of mortage portfolio	15.8%	16.8%	16.8%	27.5%	30.9%	29.5%
Bank-originated but not held	940,160	1,073,457	1,115,956	1,743,196	1,899,883	1,751,174
Bank-originated other	652,266	747,185	778,090	1,224,745	1,341,413	1,241,419
Non-bank originated	5,174,873	5,967,342	6,241,746	9,970,999	10,900,000	10,100,000
Total	59,069,671	61,375,911	61,691,674	65,442,057	65,563,710	63,315,062

Table 8: Scenario – Cautious Markets

	Floodplain Homes	Above-floodplain Homes
Devaluation		
Cat 3	0.2	0.10
Cat 4	0.3	0.15
Cat 5	0.4	0.20
Price Growth		
Through 2035	-0.02	0.00
2040 plus	-0.08	-0.02
Unit Growth		
Through 2035	0	0.008
2040 plus	0	0.008
Turnover Rate Change		
Through 2035	-0.3	0
2040 plus	-0.3	0
Well-insured share	0.9	0.9
Additive propensity to default		0.4

Table 9: Cautious Markets Insurance Assumptions

Type	Well-insured? (y/n)	NFIP ($K)	Private Flood ($K)	Private Wind (% structure val.)
HA	y	250	40	0.9
HF	y	250	40	0.9
LA	y	250	40	0.9
LF	y	250	40	0.9
OA	y	250	40	0.9
OF	y	250	40	0.9
HA	n	0	0	0.9
HF	n	0	0	0.9
LA	n	0	0	0.9
LF	n	0	0	0.9
OA	n	0	0	0.9
OF	n	0	0	0.9

Notes: Homeowner types are: HA = high/mid income, above-floodplain, HF = high/mid income, floodplain, LA = low income, above-floodplain, LF = low income, floodplain, OA = other, above-floodplain, and OF = other, floodplain.

coverage rates. This is due to a smaller amount of home construction in floodplain areas over our study period. Banks hold far smaller real estate portfolios, with a combined total of $5.9 billion in mortgage loans held in 2050, compared to $7.4 billion and $11.5 billion in the IAN and BAU scenarios respectively. Loss rates for banks are much smaller, with maximum losses of 19.3% in the 2050 Cat 5 outcome, compared with 29.5% and 54.8% in the IAN and BAU scenarios respectively. Total losses under the Cautious Markets scenario amount to $98.9 billion, compared with $63.3 billion and $226.3 billion in the IAN and BAU scenarios respectively.

4 Conclusion

This paper simulates a flow-of-risk approach to a specific climate event that affects strategic mortgage defaults. Its value lies in the various considerations that affect insurance, homeowner, and creditor decisions in the presence of diversity in borrower charactistics and climate risk. However, even in the narrow confines of the exercise, this flow-of-risk model does not consider market, counterparty, or operational risks, nor does it endogenously model real economy impacts. Moreover, even though hurricanes of different categories are considered under conditions of a rising sea level, there are in principle an infinite number of, say, Category 5 hurricanes that could be designed that differ by track speed, width, shear, and other characteristics. Each of these theoretical hurricanes could lead to different levels of damages and loss. For these reasons, the flow-of-risk model should be thought of as a module in a larger suite of models that could help evaluate climate risk to financial institutions. We now turn to several possible paths forward.

As mentioned, Miami mortgages are likely to be a limited portion of any large bank's balance sheet implying that even momentous losses in Miami are manageable in isolation. However, the correlation of climate events across both time and space is rising significantly.[16] If a given bank faces repeated climate disasters affecting a portion of its portfolio, or simultaneous climate events across all regions of its business footprint or asset types, losses might add up sufficient to threaten distress. One approach might be to repeatedly conduct joint flow-of-risk-type analyses across a bank's major business

[16] See, for example, the increase in both the number and the joint occurrences of large climate disasters in NOAA's Billion Dollar Disasters data. https://www.ncei.noaa.gov/access/billions/mapping

Table 10: Scenario – Cautious Markets

	2025	2030	2035	2040	2045	2050
Cat 1						
Cat 1						
Insurers	3,054,115	3,128,427	3,128,427	3,128,427	3,128,427	3,128,427
Homeowners	16,189	16,604	17,365	18,606	19,905	21,474
Bank held	50,973	54,387	55,017	52,522	115,595	179,885
% of mortage portfolio	0.7%	0.7%	0.7%	0.7%	1.7%	3.0%
Bank-originated but not held	63,943	69,217	70,812	68,686	107,556	146,145
Bank-originated other	41,463	44,966	46,068	44,776	73,083	101,529
Non-bank originated	303,559	327,226	333,682	322,204	575,042	829,967
Total	3,530,242	3,640,828	3,651,371	3,635,221	4,019,607	4,407,428
Cat 2						
Insurers	6,188,516	6,328,672	6,328,672	6,328,672	6,328,672	6,328,672
Homeowners	54,480	56,093	56,760	58,178	59,236	61,449
Bank held	50,973	54,387	55,017	52,611	118,437	185,168
% of mortage portfolio	0.7%	0.7%	0.7%	0.7%	1.8%	3.1%
Bank-originated but not held	63,943	69,217	70,812	68,738	109,278	149,338
Bank-originated other	41,463	44,966	46,068	44,814	74,369	103,918
Non-bank originated	303,559	327,226	333,683	322,551	586,398	851,058
Total	6,702,934	6,880,561	6,891,011	6,875,563	7,276,388	7,679,603
Cat 3						
Insurers	11,785,069	12,051,615	12,051,615	12,051,615	12,051,615	12,051,615
Homeowners	6,288,613	6,092,540	5,808,625	4,636,502	3,785,778	3,157,120
Bank held	50,992	54,420	55,076	191,105	374,898	456,171
% of mortage portfolio	0.7%	0.7%	0.7%	2.7%	5.6%	7.7%
Bank-originated but not held	63,954	69,236	70,847	157,592	273,523	326,250
Bank-originated other	41,471	44,980	46,093	108,466	192,494	231,269
Non-bank originated	303,633	327,353	333,914	887,434	1,632,365	1,967,752
Total	18,533,732	18,640,144	18,366,170	18,032,714	18,310,673	18,190,177
Cat 4						
Insurers	28,232,298	28,888,386	28,888,386	28,888,386	28,888,386	28,888,386
Homeowners	9,676,562	9,388,947	8,962,466	7,200,111	5,919,813	4,972,503
Bank held	116,142	120,848	116,936	421,167	656,459	729,795
% of mortage portfolio	1.7%	1.6%	1.6%	5.9%	9.9%	12.3%
Bank-originated but not held	105,926	111,977	110,612	305,499	454,178	497,932
Bank-originated other	71,438	75,567	74,582	214,570	322,714	355,708
Non-bank originated	569,747	598,642	586,487	1,827,106	2,782,389	3,073,727
Total	38,772,112	39,184,366	38,739,468	38,856,839	39,023,939	38,518,051
Cat 5						
Insurers	82,381,354	84,440,942	84,440,942	84,440,942	84,440,942	84,440,942
Homeowners	13,500,000	13,100,000	12,500,000	10,200,000	8,453,299	7,176,015
Bank held	336,820	394,137	388,143	885,749	1,173,052	1,144,842
% of mortage portfolio	4.9%	5.3%	5.2%	12.3%	17.7%	19.3%
Bank-originated but not held	250,641	291,023	288,556	611,340	794,921	774,158
Bank-originated other	173,863	202,510	200,789	431,884	564,813	551,489
Non-bank originated	1,477,863	1,723,123	1,703,357	3,744,476	4,916,584	4,795,656
Total	98,120,540	100,151,734	99,521,786	100,314,390	100,343,610	98,883,102

regions for different climate event severities and correlations supported by climate modeling. The output could be used to develop a probability distribution of losses. Similar to stress-testing methodologies, a focus on a pre-specified level of tail risk might be used to judge safety and soundness.

In addition, while the scenario inputs are chosen to be plausible, a better approach would be to derive them from a companion model that integrates regional economic outcomes with home prices, incomes, and other key variables. For example, we have modeled the default decision as strategic (based on the willingness of borrowers to repay their debts). However, even willing borrowers will not be able to repay if they lose their jobs and are unable make their payments. A companion model that provides estimates of the impact on incomes can factor in how changes in the ability to pay might change default rates. It would also be useful to include expected public support, which is currently absent from the model. A more holistic approach would also address market, counterparty, and operational risks in addition to the credit-risk outcomes addressed by the flow-of-risk model.

Appendix

A Model

To set up the modeling framework, we first establish the flow and stock relationships for the adding, financing, and distributing of real estate equity. Prices and price trends are taken as exogenous to the model. Two important distributional concerns are tackled here. First, homeowners are separated into six categories reflecting income, purpose of homeownership, and exposure to flood risk. Second, homeowners are divided into cohorts that reflect the amount still owed on mortgages relative to the value of the original loan. Both of these factors will influence the decision to default in the event of hurricane damage.

A.1 Homeowner types

We will exploit the homeowner type to distinguish between high- and low-income residents, and outside investors. We will also distinguish between homes built inside and outside high-risk flood plains. This in turn gives six separate types of homeowners. Let the first character denote identity (H=high-income, L=low-income, O=outside investor) and the second character denote location (F=floodplain, A=above floodplain). Thus, we have:

$$j \in \{HF, LF, OF, HA, LA, OA\}.$$

We do not count low income households who rent as part of the "LF, LA" category, as they do not hold mortgages. Properties that are rented to low-income households are assumed to be part of the high-income, "OF, OA", category, whereby the owner will presumably have engaged in the same investor-motivated behavior that characterizes outside owners.

A.2 Residential real estate dynamics

Homeowner exposure to real estate is determined by the rate at which the homeowners' home equity grows. Home equity, E, grows with:

1. The degree of *price appreciation* realized by (all) homeowners of type j, which is $\gamma_t^j \cdot H_{t-1}^j \cdot p_{t-1}^j$, where γ_t^j is price appreciation between time $t-1$

and t of the average home of homeowner type j, H_{t-1}^j is the number of properties of type j, and p_{t-1}^j is the $t-1$ price of the average home of type j;

2. The routine payment of *mortgage principal* based on the book value of the home at the time of purchase, which is $\pi_t^j \cdot H_{t-1}^j \cdot p_{t-1}^j$, where π_t^j reflects a steady-state relationship calibrated to represent principal payments relative to the overall level of the housing stock at time $t-1$, exclusive of prepayment;

3. The *deacquisition of homes* by selling existing properties, which is $-\omega_t^j \cdot H_{t-1}^j \cdot p_{t-1}^j$, where ω_t^j is the rate of turnover of homes of type j between times $t-1$ and t;

4. The *prepayment of mortgage debt*, which we will associate with turnover of properties, given by $\hat{\pi}_t^j \cdot \omega_t^j \cdot H_{t-1}^j \cdot p_{t-1}^j$, where $\hat{\pi}_t^j$ is a steady-state adjustment factor that calibrates prepayments to the home's book value;

5. *Home acquisition* as homeowners of type j purchase existing housing stock, which is $\psi_t^j \cdot \omega_t^j \cdot H_{t-1}^j \cdot p_{t-1}^j$, where ψ_t^j is the rate of downpayment as a fraction of the home's value;

6. Purchase of *new housing stock*, which is $\psi_t^j \cdot \Delta H_t^j \cdot p_t^j$, where ΔH_t^j represents the increase in the housing stock between times $t-1$ and t.

Putting this together, home equity changes according to:

$$\Delta E_t \;=\; \sum_{j=1}^{J} \left\{ \left[\gamma_t^j + \pi_t^j - (1 - \hat{\pi}_t^j - \psi_t^j)\omega_t^j \right] H_{t-1}^j p_{t-1}^j + \psi_t^j p_t^j \Delta H_t^j \right\}.$$

where E_t represents housing equity owned by all homeowners at time t.

A.3 Equity held by non-homeowners

Changes in home equity not held by homeowners, Q_t, is equal to:

$$\Delta Q_t \;=\; \sum_{j=1}^{J} \Delta \left(H_t^j p_t^j \right) - \Delta E_t.$$

The amount of this home equity *initially* held by banks is given by the following elements:

1. Reductions based on the payment of *mortgage principal* based on the book value of the home at the time of purchase as described above, which is $-\pi_t^j \cdot H_{t-1}^j \cdot p_{t-1}^j$;

2. Reductions based on the *prepayment of mortgage debt*, as described above, which is $-\hat{\pi}_t^j \cdot \omega_t^j \cdot H_{t-1}^j \cdot p_{t-1}^j$;

3. The *financing of home purchases*, both existing and new, equal to: $(1-\psi_t^j) \cdot (\omega_t^j H_{t-1}^j \cdot p_{t-1}^j + \Delta H_t^j \cdot p_t^j)$, where ω_t^j is the rate of turnover of homes of type j between times $t-1$ and t;

Thus:

$$
\begin{aligned}
\Delta Q_t &= \sum_{j=1}^{J} \left\{ \underbrace{(1-\psi_t^j)(\omega_t^j H_{t-1}^j p_{t-1}^j + \Delta H_t^j p_t^j)}_{\text{New mortgages}} - \underbrace{(\pi_t^j + \hat{\pi}_t^j \omega_t^j) H_{t-1}^j p_{t-1}^j}_{\text{Repayments}} \right\}, \\
&= \sum_{j=1}^{J} \sum_{k=1}^{K} \left(m_t^{jk} - o_t^{jk} \right).
\end{aligned}
$$

where the k superscript refers to lender type, m_t^{jk} is new mortgages, and o_t^{jk} is repayments.

A.4 Ensuring consistency between stocks and flows

In order to make the parameterization as tractable as possible, we will assume that the shares of financing across homeowner types and lender types are stable over time. Thus:

$$Q_t^{jk} = \varpi^{jk} Q_t.$$

where j is homeowner type and k is lender type, and ϖ is the appropriate fixed share value and $\sum_{jk} \varpi^{jk} = 1, \ \forall\ jk \in J \times K$.

We will also assume that the distribution of originations remains fixed such that:

$$
\begin{aligned}
m_t^{jk} &= \chi^{jk} m_t^j, \\
o_t^{jk} &= \chi^{jk} o_t^j.
\end{aligned}
$$

where χ is another fixed share such that $\sum_k \chi^{jk} = 1, \ \forall\ k \in K$.

This implies that repayments are given by:

$$\chi^{jk} o_t^j = \chi^{jk} m_t^j - \varpi^{jk} \Delta Q_t.$$

Summing over k:

$$o_t^j = m_t^j - \varpi^j \Delta Q_t.$$

where $\varpi^j = \sum_k \varpi^{jk}$.

We can then solve for:

$$\underbrace{(\pi_t^j + \hat{\pi}_t^j \omega_t^j)}_{\text{Unknown}} = \underbrace{\frac{m_t^j - \varpi^j \Delta Q_t}{H_{t-1}^j p_{t-1}^j}}_{\text{Known}}. \tag{A.1}$$

The right hand side of this equation is composed of known variables. In order to address the left hand side of the equation, we take the following approach. We determine the amount of mortgage prepayment (the second term on the RHS), by making use of the turnover rate, the average length of a mortgage, the historical interest rate, and the average historical value of a mortgage. More specifically, we determine the average amount of mortgage remaining for each cohort of each homeowner type, the number of homes for each cohort-homeowner dyad, and finally the amount of prepayment *due to the selling of existing homes* by homeowner type. The method described below does not include prepayment for other motives, such as refinancing at a lower interest rate, which could in principal be included in equation (A.1).

A.5 Average size of mortgage by cohort

Let M_t^j be the amount remaining on mortage j, with M_0^j equal to the original loan amount and the subscript 0 referring to the first year of the mortgage. For simplicity, we assume that interest is compounded annually. At the end of the first year, the amount owed will be:

$$M_1^j = M_0^j(1 + r_0^j) - F^j.$$

where F^j is the fixed (annual) payment (interest and principal) on the mortgage, and r_0^j is the contractual interest rate on the mortgage.

Likewise, in the second period:

$$\begin{aligned} M_2^j &= M_1^j(1+r_0^j) - F^j, \\ &= M_0^j(1+r_0^j)^2 - F^j(1+r_0^j) - F^j. \end{aligned}$$

and so on. In general, if M_0^j is the original value of the mortgage, than at any time t:

$$M_t^j = M_0^j \left(1+r_0^j\right)^t - F^j \left[\sum_{i=0}^{t-1}(1+r_0^j)^i\right]. \tag{A.2}$$

where T is the total number of years of the original mortgage (e.g., 30 years). We can determine F^j as a function of the initial mortgage amount and interest rate by noting that at the end of the life of the mortgage (at time T), the principal has to be equal to zero, i.e., $M_T^j = 0$. Thus:

$$F^j = \frac{M_0^j(1+r_0^j)^T}{\left[\sum_{i=0}^{T-1}(1+r_0^j)^i\right]}$$

The amount of principal at any given time 1 can be calculated as:

$$P_1^j = P_0^j - (F^j - M_0^j r_0^j).$$

where P_t^j is principal remaining at time t. At time 2, we have:

$$\begin{aligned} P_2^j &= P_1^j - (F^j - M_1^j r_0^j), \\ &= P_0^j - 2F^j + r_0^j(M_0^j + M_1^j). \end{aligned}$$

In general, we will have:

$$P_t^j = P_0^j - t \cdot F^j + r_0^j \left(\sum_{i=0}^{t-1} M_i^j\right). \tag{A.3}$$

The average mortgage for each homeowner type j is calculated from HMDA data. We impose this mortgage on all homeowners of type j. We assume that there is a constant probability (equal to the turnover rate for homeowner of type j) that any homeowner cohort sells their home in any given time t. This will then drive the size distribution of cohorts of homes with mortgages and those that have been paid off. We then take the value of average outstanding mortgage principal for each cohort times the amount of homes remaining in each cohort and multiply it times the turnover rate to get the overall principal repayment for that cohort in a given year t. Summing over cohorts in j gives us $\widehat{\pi_t^j \omega_t^j}$. This allows us to solve for the one remaining free variable in equation (A.1), which is π_t^j.

A.6 Number of homes in each mortgage cohort

Let us define $H_t^{j,s}$ as the number of homes owned by homeowners of type j at time t who took out mortgages s number of years ago. From the HMDA data, we know the average loan term for homeowners of type j and assume this is constant. Furthermore, we assume that the turnover rate of home ownership, ω_t^j is the same across all cohorts. Homeownership will then be distributed across cohorts as:

$$H_t^j \;=\; \sum_{s=1}^{S} \sum_{r=t-s}^{t} H^{j,s}(1-\omega_r^j)^{t-r} + H_{t-1}^{j,0}(1-\omega_t^j). \tag{A.4}$$

where S is the loan term of the typical mortgage for homeowner type j (e.g., $S = 30$ if the typical mortgage was a 30-year loan), $H^{j,s}$ is the original amount of households taking out mortgages at time $t = s$, the number of cohort s households of type j at time t will be equal to $H_t^{j,s} = H^{j,s}(1-\omega_t^j)^{t-s}$, and $H_t^{j,0}$ are homes owned by homeowners of type j that are fully owned. The amount of homes funded by mortgages taken out s years ago is given by total loans to homeowners of type j found in the HMDA data. We impute turnover rates from HAVER data provided by Zillow, although we cannot determine these rates by year. Finally, we know the total amount of homes held by homeowers of type j at time t. Using this information, we can calculate $E_{t-1}^{j,0}$.

Let $A_t^{j,s}$ be equal to the average mortgage taken out by a homeowner of type j who bought a home $t-s$ years ago, which we assume to be equal to $(1-\psi_{t-s}^j)p_{t-s}^j$. Using equations (A.2) and (A.3), the amount of mortgage principal remaining at any given time t will be equal to:

$$\begin{aligned}\frac{P_t^{j,s}}{A_t^{j,s}} &= \frac{P_t^{j,s}}{P_0^{j,s}}, \\ &= 1-(t-s)\frac{F_0^{j,s}}{P_0^{j,s}} + r_0^{j,s}\left\{\sum_{i=0}^{t-s-1}\left[\left(1+r_0^{j,s}\right)^i - \frac{F_0^{j,s}}{P_0^{j,s}}\left[\sum_{k=0}^{i-1}\left(1+r_0^{j,s}\right)^k\right]\right]\right\}.\end{aligned}$$

where $F_0^{j,s}/P_0^{j,s}$ is purely a function of the contractual interest rate:

$$\frac{F_0^{j,s}}{P_0^{j,s}} = \frac{\left(1+r_0^{j,s}\right)^T}{\left[\sum_{i=0}^{T-1}\left(1+r_0^{j,s}\right)^i\right]}.$$

Let:

$$\Upsilon_t^{j,s} = \frac{P_t^{j,s}}{A_t^{j,s}} = F\left(r_0^{j,s}\right).$$

A.7 Solving for mortgage repayments

We can now write our expression for prepayments due to home sales.

Some fraction of each cohort of each homeowner type, equal to the turnover rate at time t, will sell their home and retire (prepay) their mortgage. To determine the amount of total repayments by homeowner type, we need to: (i) determine the contemporary number of borrowers in each homeowner type-cohort dyad, (ii) apply the appropriate (time-sensitive) turnover rate to determine the number of homeowners retiring their mortgages, and (iii) calculate and aggregage the amount of principal left on the mortgages by homeowner type.

Consider the case of a single homeowner type and set aside the j superscript. Designate the amount of homeowners in the present cohort $s = t = 0$ as H^0. The one-period-earlier cohort $s = -1$ will have a total size equal to $H^{-1}(1-\omega_{-1})$ at time t, where ω_{-1} is the turnover rate of the prior period. Likewise, the remaining number of cohort $s = -2$ households will be given by $H^{-2}(1-\omega_{-2})(1-\omega_{-1})$. In general, the amount of cohort s remaining at the beginning of time t will be given by: $H^s\Pi_{r=s}^{t-1}(1-\omega_r)$. The share of this cohort that sells their home will be given by the present turnover rate and will equal: $\omega_t H^s\Pi_{r=s}^{t-1}(1-\omega_r)$. The value of the mortgages that they prepay will be equal to the share of principal left to repay times the value of the original mortgage times the remaining size of the cohort, $\Upsilon_t^s A^s\omega_t H^s\Pi_{r=s}^{t-1}(1-\omega_r)$. Summing across cohorts gives us the total amount of prepayment: $\sum_{s=1}^S \Upsilon_t^s A^s\omega_t H^s\Pi_{r=s}^{t-1}(1-\omega_r)$.

Finally, we acknowledge the different homeowner types j to get:

$$\hat{\pi}_t^j\omega_t^j = \frac{\sum_{s=1}^S \Upsilon_t^{j,s}A^{j,s}\omega_t H^{j,s}\Pi_{r=s}^{t-1}(1-\omega_r^j)}{H_{t-1}^j p_{t-1}^j}. \tag{A.5}$$

where the prepayment rate is calibrated to the current value of type-j homeowner housing stock.

We can solve for repayments in two ways. We can calculate repayments directly using the mortgage rates and principal owed by each homeowner type and cohort, or we can use the following relationship:[17]

$$\pi_t^j = \frac{m_t^j - \varpi^j \Delta Q_t}{H_{t-1}^j p_{t-1}^j} - \hat{\pi}_t^j \omega_t^j. \tag{A.6}$$

There is a continuum of choices for the turnover rate ω_t^j that lead to corresponding repayment rates π_t^j in equation (A.6). In principle, a unique combination of repayment rate and turnover rate can be calibrated to mortgage income reported on the income statement, but this is beyond the scope of the paper. Rather, we use information on historical turnover rates, and consider the future path of turnover rates one of the key scenario choices of the modeler.

A.8 Determining equity holdings by banks, securities purchasers, and GSEs

Although these mortgages initially sit with banks, banks will securitize and sell mortgages on to other parties. These shares are obtained for *flows* from HMDA data and Y14M data provide custodial holdings of GSE and securitized mortgages by LISCC institutions for *stocks*.

We can therefore represent the change in home equity held by investment funds and other parties as:

$$\begin{aligned} \Delta Q_t &= \Delta B_t + \Delta G_t + \Delta F_t + \Delta NBFI_t, \\ Q_t &= B_t + G_t + F_t + NBFI_t. \end{aligned}$$

where B_t is bank holdings of home equity, G_t is GSE holdings of bank-originated mortages, F_t is investment fund holdings of bank-originated mortgages, and $NBFI_t$ is holdings of all non-bank financial institution (NBFI) originated mortgages. Note that NBFI-originated mortgages account for the majority of new mortgages (as high as two-thirds).[18]

[17]Note: Detailed historical data on home sales are provided by Miami-Dade Office of Appraisal - See bbs.miamidade.gov.

[18]https://www.wsj.com/articles/nonbank-lenders-are-dominating-the-mortgage-market-11624367460

B Climate Change Damage Generation Process

For each scenario, we model five hurricanes at the boundary of each Saffir-Simpson category using the FEMA Hazus tool. We choose a track that carries the hurricanes through the main business district using the "near wave surge model" approach.

B.1 Apportioning flood and wind damage

The total amount of structural damage that a homeowner can experience is limited to the replacement cost value of the unit structure. In many cases the sum of flood and wind damage exceeds the replacement value. It is common to hear stories of homeowners struggling to get flood and wind insurers to pay claims because each has determined that the primary damage was inflicted by the condition that they do not insure (e.g., flood insurers insist that the damage was caused by wind, whereas homeowners insurers insist that the damage was caused by flooding).[19] We assume that flood insurance stands first in line, such that if flood damage alone is equal to the replacement cost of the property, wind damage is equal to zero. In general, wind damage will be limited to the difference between the replacement value and flood damage if wind and flood damage together exceed the replacement cost value.

C Insurance as the first loss-absorbing layer

The degree to which insurance absorbs risk depends on the nature of the damage (flood or wind, as described above) and the number of households with coverage (the *extensive* margin) and the extent to which those households are insured (the *intensive* margin). These two margins will vary significantly across our six different household categories. We therefore adopt a two-step procedure in which the first step is to model the specific type of loss (either actualized or anticipated), followed by determining the size of the loss and the amount that would be covered by insurance.

[19] See, e.g., https://www.nytimes.com/2021/09/10/your-money/ida-flood-damage-insurance-policy.html.

In general, the analysis will determine each entity's exposure, and then apply loss rates. These loss rates will be dependent on an ordering of priority in claims on the underlying asset. The first losses will be borne by insurers up to the limits of their obligations (or their resources). Any losses above these amounts will spill over to homeowners. Whether homeowners will completely absorb remaining losses will depend on the share of ownership of the home's equity, and their ability and willingness to continue to honor mortgage obligations. Under circumstances in which they cannot or do not honor these obligations and default, losses will spill over to banks, investment funds, and GSEs in proportion to their share of the mortgage pool. This *pari passu* assumption may be incorrect if, say, securitization contracts allocate first losses to different tranches of blended assets (circa 2008 CDOs) or require the securitizer to take first losses.

Insurance coverage for a shock occurring between times $t-1$ and t will equal:

$$I_t^j = \sum_{r \in N,F,W} \left(\lambda_{I,Z,t}^{j,r} \cdot R_I^{j,r} \right) \tag{C.1}$$

where $\lambda_{I,Z,t}^{j,r}$ is *Type* r insurers' loss rate as a share of total exposure for a shock of *Type* Z at time t of coverage of homeowners of *Type* j (covered in detail in section (E)); and $R_I^{j,r}$ is exposure of insurers of *Type* r to homeowners of *Type* j.[20]

In matrix notation:

$$\mathcal{I}_t = \mathcal{L}_{I,Z,t} \times \mathcal{R}_{I,t}.$$

where $\mathcal{I}_t$ is a $j \times 1$ vector given by:

$$\mathcal{I}_t = \begin{bmatrix} I_t^{HF} \\ I_t^{LF} \\ \vdots \\ I_t^{OA} \end{bmatrix}.$$

$\mathcal{L}_{I,Z,t}$ is a $j \times 3 \cdot j$ matrix of insurance sector loss rates applicable to each

[20] Congressional Budget Office. (2019) [8]

of our $3 \cdot j$ combinations:

$$\mathcal{L}_{I,Z,t} = \begin{bmatrix} \lambda^{HF,N}_{I,Z,t}, & \lambda^{HF,F}_{I,Z,t}, & \lambda^{HF,W}_{I,Z,t} & 0, & 0, & 0 & \cdots & 0, & 0, & 0 \\ 0 & \cdots & 0 & \lambda^{LF,N}_{I,Z,t}, & \lambda^{LF,F}_{I,Z,t}, & \lambda^{LF,W}_{I,Z,t}, & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 0 & \cdots & \lambda^{OA,N}_{I,Z,t}, & \lambda^{OA,F}_{I,Z,t}, & \lambda^{OA,W}_{I,Z,t}, \end{bmatrix}.$$

and $\mathcal{R}_{I,t}$ is a $3 \cdot j \times 1$ vector given by:

$$\mathcal{R}_{I,t} = \begin{bmatrix} R^{HF,N}_{I,t} \\ R^{HF,F}_{I,t} \\ R^{HF,W}_{I,t} \\ \vdots \\ R^{OA,N}_{I,t} \\ R^{OA,F}_{I,t} \\ R^{OA,W}_{I,t} \end{bmatrix}.$$

We discuss the determination of the λ terms below.

C.1 The extensive vs the intensive insurance margin

For the extensive insurance margin, or the number of households that have flood insurance, we assume differing NFIP flood insurance coverage rates for occupied floodzone residential units and above-floodplain units (see scenario assumptions). This essentially doubles our homeowner categories as we now have well- and poorly-insured versions of each of our six homeowner classifications. In what follows, the subscript j therefore refers to 12 different homeowner types: the original six as NFIP-insured, and the original six as non-NFIP-insured.

D Homeowners as the second loss-absorbing layer

Any losses that are not covered by insurance spill over to homeowners. Homeowners must decide whether to absorb these losses in full, or to default on their mortgages. The default choice depends on both the ability of homeowners to service their mortgages (or to reschedule), which has not yet been added to the model, and the willingness to continue servicing their debt (the *strategic default* motive).

D.1 Insurance coverage as a fraction of replacement value vs total property value

Insurance coverage is calibrated to the cost of replacing the structure of the home, which can be either greater or less than the value of the property itself. In expensive real estate markets, the cost of the structure is often small relative to the cost of the land parcel. On the other hand, in declining cities, the cost of rebuilding a structure might be many times greater than the Zillow price of the home. If we differentiate between the land parcel cost and the replacement cost of the structure, it becomes apparent that climate change can damage either or both of these categories. A climate event might reduce the desirability of a parcel of land, leading to a permanent reduction in value even if the structure on that parcel has not experienced damage directly. This kind of loss is uninsurable through homeowner insurance riders for flood and wind damage. Alternatively, a climate event might damage the structure of the home without reducing the desirability of the land parcel itself, leading to a loss in value that is insurable. Of course, a climate event may cause both effects simultaneously. We therefore confine insurance coverage to the replacement value of the home even as we allow climate "damage" to pass through to home prices via a reduction in the desirability of a property.

Denote the damage accruing to each household by $\tilde{s}_t^j \cdot v_t^j \cdot H_t^j$, where v_t^j is the replacement value of the home, and $\tilde{s}_t^j$ is the damage rate as a share of home replacement value. Clearly, homeowners will experience no loss *on the damage to built property* so long as:

$$I_t^j = \tilde{s}_t^j \cdot v_t^j \cdot H_t^j.$$

This equation holds with equality because insurance payouts will never exceed the amount of damage. However, it is possible for $\tilde{s}_t^j$ to exceed unity if, for example, remediation to better protect the property against future climate events is required (by, say, raising the property up on pilings).

Homeowner losses *due to property damages* are therefore equal to:

$$\text{Losses to homeowners of type } j \;=\; \begin{cases} \tilde{s}_t^j \cdot v_t^j \cdot H_t^j - I_t^j, & \text{for} \quad \tilde{s}_t^j \cdot v_t^j \cdot H_t^j > I_t^j \\ 0, & \text{for} \quad \tilde{s}_t^j \cdot v_t^j \cdot H_t^j = I_t^j \end{cases}.$$

To these losses must be added any reductions in the market value of the land parcel:

$$\text{Losses due to land parcel devaluation} \;=\; \Delta p_t^j = \hat{s}_t^j p_t^j = f(S_t^j).$$

where S_t^j is a climate forcing process described below. It is clear that a good proxy for how much residential real estate prices might decline due to unanticipated local developments is needed.

D.2 Keeping track of loss cushions by cohort

Because each cohort will have different amounts of equity at risk, it is likely that different cohorts of homeowners of the same type j will reach the threshold that triggers default at different levels of sustained damage. In general, we would expect default rates to be a function of: (i) home price appreciation since purchasing the home, (ii) the turnover rate, and (iii) the contractual mortgage interest rate, *inter alia*.[21]

For any given cohort s of homeowner type j, the amount of home equity held will equal the value of the home minus the principal owed:

$$h_t^{j,s} \;=\; \frac{E_t^{j,s}}{H_t^{j,s}} = p_t^j - \Upsilon_t^{j,s} A_t^{j,s} \tag{D.1}$$

We can therefore include $h_t^{j,s}$ (or its distribution) as an argument in determining the default rate in the wake of a shock.

Equation (D.1) is extremely useful, however, in showing that financial sector vulnerability to mortgage default will depend in part on the composition of cohorts within a given homeowner type j, the size of the original mortgage relative the the value of the home (which implicates both price appreciation since purchase as well as the prevalance of refinancing), and the mortgage interest rate (with consideration that high interest rates can be refinanced but also that adjustable rate mortgages may trap less wary borrowers into higher interest rate payments).

Now that we have established the amount of losses passing through to homeowners, we focus on the amount of this residual loss that homeowners

[21] There is a large literature on defaults and negative equity that can inform this discussion, including: Bhutta et al. (2010) [6], Scharlemann and Shore (2016) [34], and Foote et al. (2008) [16].

are willing and able to absorb. The ability to continue to service mortgage debt will depend on a homeowner's income and their ability to reschedule their mortgage. These factors are beyond the homeowner's control. However, the homeowner's willingness to default, that is, the strategic default motive, is more complicated. To institutional factors that impose penalties for defaulting (such as whether the state is non-recourse, and the impact on credit scores) must be added homeowner expectations about whether sharp (hurricane-induced) home price devaluations will be reversed. The historical experience is that home prices tend to rebound to their pre-disaster levels after a few years. Under these circumstances, it makes sense for homeowners to hang onto their homes until prices recover. However, this historical tendency may not be a good guide for climate change in that sea level rise or perpetual wildfire risk may make such price recoveries impossible. For example, if the land on which a house is built is permanently submerged due to sea level rise, home prices will not recover.

Based on the previous section, total damages for the homeowner equal:

$$s_t^j p_t = \tilde{s}_t^j v_t^j \varrho_t^j + \hat{s}_t^j p_t. \tag{D.2}$$

where ϱ_t^j is the ratio of home price to replacement cost for homeowner of type j.

D.3 Default risk by segment and cohort

We assume that an increasing fraction χ_t^j of homeowners of type j will walk away from their mortgages as their losses rise. Let losses per household net of insurance be defined as:

$$l_t^j = \underbrace{\left(\tilde{s}_t^j v_t^j - i_t^j\right)}_{\text{Structural damage}} - \underbrace{\hat{s}_t^j p_t^j}_{\text{Devaluation}} . \tag{D.3}$$

where $i_t^j = I_t^j/(H_t^j)$.

D.3.1 Cohort equity and strategic default

Recalling our discussion of cohort equity and equation (D.1), we can write net (post-event) equity holdings by cohort and segment as:

$$e_t^{j,s} = h_t^{j,s} - l_t^j.$$

We follow Bhutta et al. (2010) [6] in estimating the share of homeowners who walk away from their mortgages. Bhutta et al. find support for a dual trigger in which both reductions in the value of the home and reduction in income inform the decision to default. Climate induced damage will likely affect both of these variables, but for now we focus solely on the home price reduction. Florida is a recourse state, meaning that homeowners are still theoretically liable for mortgage debt even if the home is foreclosed. Fortunately, Bhutta et al. [6] focus on Florida as one of the four states in their analysis. According to results presented in their Table 5, it takes a reduction of equity equal to 46 percent of their home's value for 25 percent of Florida homeowners to strategically default (*ceteris paribus*), a reduction equal to 79 percent of their home's value for 50 percent to strategically default, and a decrease in home value equal to 128 percent for all homeowners to strategically default.

However, there is an external validity concern that we must also address. In the case in which a negative event leaves the property intact, an individual homeowner might have some expectation that any decrease in value is temporary. However, a climate event may leave the property unsuitable for reconstruction, in which case it is not a question of 'walking away from your mortgage,' but your 'home walking (floating) away from you.' In other words, strategic default rates are likely to be much higher than those estimated in Bhutta et al. (2010) [6]

After exploring different functional forms, we estimate the percentage of homeowners who walk away from their mortgages by extracting a linear relationship based on the California trend from Figure 6 in Bhutta et al. [6]:

$$\begin{aligned} \chi_t^{j,s} &= 0.6 \times \left| 1 - \left(\frac{P_t^{j,s}}{p_t^j} \right)^{j,s} \right| + W_t^j, \\ & \forall \left[1 - \left(\frac{P_t^{j,s}}{p_t^j} \right)^{j,s} \right] < 0. \end{aligned}$$

where as a reminder $P_t^{j,s}$ is the remaining loan balance and p_t^j is the (post-shock) value of the home. The term W_t^j is a potential adjustment factor to take into account the unsuitability of reconstruction.

The amount of losses absorbed by homeowners of type j will then be equal to the share of homeowners who hang onto their homes and fully absorb losses, plus the share of homeowners who walk away times the amount of positive equity that was destroyed. Thus, for $H^j_{t-1} > 0$:

$$
\begin{aligned}
\lambda^j_{H,Z,t} E^j_{t-1} &= \sum_{s=1}^{S} \epsilon^{j,s}_t (1-\chi^{j,s}_t) l^j_t H^j_t + \sum_{s=1}^{S} \epsilon^{j,s}_t \chi^{j,s}_t E^j_{t-1} \\
\lambda^j_{H,Z,t} &= \underbrace{\sum_{s=1}^{S} \epsilon^{j,s}_t (1-\chi^{j,s}_t) \left[\frac{l^j_t H^j_t}{E^j_{t-1}}\right]}_{\text{Stay}} + \underbrace{\sum_{s=1}^{S} \epsilon^{j,s}_t \chi^{j,s}_t}_{\text{W.A.}}
\end{aligned}
$$

where $\epsilon^{j,s}_t$ is the share of cohort s households in homeowner type j at time t, and the abbreviation "W.A." stands for "walk away." Note that in the case that all homeowners walk away, $\chi^j_t = 1$, and the loss rate is also unity, $\lambda^j_{H,Z,t} = 1$. In other words, homeowners of *Type* j lose all of their equity, but nothing more. In the case in which no homeowners walk away, homeowners may absorb losses greater than the amount of their equity, depending on whether $l^j_t > h^j_t$.

In the case in which there is no positive equity, this approach must be modified. Homeowners who walk away from negative equity lose nothing (note that we address the costs of defaulting separately in the determination of $\chi^{j,s}_t$). The status of those who stay is more complicated. If we adopt a mark-to-market approach, these homeowners lose an amount equal to the devaluation of their homes. However, it is not possible to express this as a 'loss rate' if equity holdings are negative. As an alternative, we think of the choice to stay as maintaining an option to benefit from an upside if home prices were to rise (in addition to the flow of shelter services). The value of this real option is sufficiently low as to change very little with the scale of home devaluation. Consequently, we treat the loss rate $\lambda^j_{H,Z,t}$ as effectively zero when $E^j_{t-1} < 0$.

Define the following net exposure vector (inclusive of unrealized equity gains) for homeowners:

$$\mathcal{R}_{E,t} = \begin{bmatrix} E_t^{HFI} \\ E_t^{LFI} \\ \vdots \\ E_t^{OAI} \\ E_t^{HFU} \\ E_t^{LFU} \\ \vdots \\ E_t^{OAU} \end{bmatrix}.$$

And define the diagonal matrix of homeowner loss rates as:

$$\mathcal{L}_{E,Z,t} = \begin{bmatrix} \lambda_{E,Z,t}^{HFI} & 0 & \cdots & 0 \\ 0 & \lambda_{E,Z,t}^{LFI} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_{E,Z,t}^{OAU} \end{bmatrix}.$$

where $\lambda_{E,Z,t}^j = 0$ if $E_{t-1}^j < 0$.

Losses faced by each homeowner group can thus be represented by the column vector:

$$\mathcal{N}_t = \mathcal{L}_{E,Z,t} \times \mathcal{R}_{E,t}. \tag{D.4}$$

E Non-homeowner asset holders as the final loss-absorbing layer

Non-homeowner asset holders experience losses when homeowners default, and risk-mitigation fails to cover losses.[22] In this section, we combine our loss estimates into a framework that apportions losses between banks, GSEs, and investment funds.

Define $\mathcal{S}_t^j$ as the following vector of dollar damages by homeowner type

[22]The model does not consider losses stemming from mark-to-market concerns leading, for example, to collateral calls or other disruptive events.

j:

$$\mathcal{S}_t^j = \begin{bmatrix} S_t^{HFI} \\ S_t^{LFI} \\ \vdots \\ S_t^{OAU} \end{bmatrix}$$

Define $\mathcal{V}_t^j$ as the following (pre-climate event) vector of total home values $p_t^j N_t^j$ for homeowner type j:

$$\mathcal{V}_t^j = \begin{bmatrix} V_t^{HFI} \\ V_t^{LFI} \\ \vdots \\ V_t^{OAU} \end{bmatrix}$$

The net value of mortgages left to banks, funds, and the government after deducting unabsorbed losses will then be given by the $j \times 1$ vector:

$$\mathcal{T}_t = \underbrace{(\mathcal{V}_{t-1} - \mathcal{R}_{h,t-1})}_{\text{Orig. net value}} - \underbrace{(\mathcal{S}_{t-1} - \mathcal{N}_{t-1})}_{\text{Unabsorb. loss}} + \underbrace{\sum_{j=1}^{J}\sum_{s=1}^{S}\chi_t^{j,s}\mathcal{V}_{t-1}^{j,s}}_{\text{Collateral val.}}, \tag{E.1}$$

$$= \underbrace{P_t}_{\text{Outstanding mort.}} - \underbrace{\sum_{j=1}^{J}\sum_{s=1}^{S}\chi_t^{j,s}(P_t^{j,s} - \mathcal{V}_{t-1}^{j,s})}_{\text{Mort. defaults net collateral}}. \tag{E.2}$$

where the first underbraced term is the value of home equity held by parties other than the homeowner, and the second term is the spillover loss not absorbed by homeowners (inclusive of insurance coverage).

We assume that losses are distributed across creditor types on a *pari passu* basis with loss shares equal to:

$$\text{Banks}: \quad \alpha_t^B = \left(\frac{B_t}{Q_t}\right) \tag{E.3}$$

$$\text{Government}: \quad \alpha_t^G = \left(\frac{G_t}{Q_t}\right) \tag{E.4}$$

$$\text{Funds}: \quad \alpha_t^F = \left(\frac{F_t}{Q_t}\right) \tag{E.5}$$

$$\text{NBFI}: \quad \alpha_t^{NBFI} = 1 - \alpha_t^B - \alpha_t^G - \alpha_t^F = 1 - \left(\frac{B_t + G_t + F_t}{Q_t}\right) \tag{E.6}$$

We calculate losses using equation (E.2). We can directly calculate the principle owed by each homeowner type and cohort, $P_t^{j,s}$, using the methods given above and apply our calculations of $\chi_t^{j,s}$ to implement the following for each institution:

$$\mathcal{L}_{Z,t} \;=\; \sum_{j=1}^{J}\sum_{s=1}^{S}\chi_t^{j,s}(P_t^{j,s} - \mathcal{V}_{t-1}^{j,s}). \tag{E.7}$$

F Data addendum

We use NFIP data to generate alternative estimates. The number of NFIP policies per state can be used as a proxy for the number of NFIP policies per municipality. NFIP policies per state (by floodzone designation) are provided by NFIP at: https://nfipservices.floodsmart.gov. The number of Florida occupied residences located in 100-year and combined 100-to-500 year floodplains are provided by FloodZoneData.us [32]. We take the statewide ratio of NFIP policies written on high risk properties (zones A, AE, AH, and AO) per residences located in 100-year floodzones to proxy for the take up rate of NFIP policies by floodzone properties at the municipal level. We likewise take the statewide ratio of non-floodzone NFIP policies to non-floodzone residences to proxy the take up of above-floodplain residences. Data on total occupied residences in Florida is taken from the American Community Survey (https://data.census.gov), as described in Table 11.

Based on these numbers, 84 percent of Miami's NFIP policies should be allocated to floodzone units, or 292,979 policies. Total occupied floodzone units in Miami equal 661,242, for a coverage percentage of 44 percent. The remaining policies, equaling 53,802 cover a total of 222,931 above-floodplain units, for a coverage percentage of 24 percent.

We subtract the number of floodzone properties from the total number of occupied units to arrive at above-floodzone property numbers. We take the ratio of non-floodzone NFIP policies to above-floodzone properties to determine the coverage rate for above-floodzone policies in Miami. We use this ratio in combination with the number of floodzone residences in Miami to estimate the number of NFIP policies going to floodzone residences. We assume identical takeup rates by HF, LF, and OF homeowners. The excess of NFIP policies above this estimated figure is apportioned equally between above-floodplain residences.

Table 11: State-of-Florida NFIP Coverage Data

	100-year	Combined
# of occupied floodzone units	1,893,920	2,611,010
# of NFIP floodzone policies	1,041,842	1,041,842
% of floodzone units NFIP-insured	55.0	39.9
# of occupied above-floodzone units	6,011,912	5,294,822
# of NFIP above-floodzone policies	605,767	605,767
% above-floodzone units NFIP-insured	10.1	11.4
Miami-Dade County		
# of NFIP Policies	346,781	346,781
Avg. policy coverage ($ thous.)	233	233

To perform a consistency check on structural replacement values, we used replacement cost values from Home Construction ProMatcher (https://home-builders.promatcher.com/cost/miami-fl-home-builders-costs-prices.aspx). According to the surveyed construction firms in the Miami area, the cost of custom home building in Miami ranges from $111.35 to $165.33 per square foot. We assume that the average lower-income home is 1,800 square feet (22 percent of new single-family homes completed in the South region of the United States were 1,800 square feet or less according to the US Census 2020 Annual Characteristics of New Housing, which reports data collected by the US Department of Housing and Urban Development (HUD)) which implies a replacement cost value of $\$111.35 \times 1{,}800 \approx \$200{,}000$ for LX homes. Around 65 percent of the total number of homes lie between 1,800 and 3,999 square feet, so we set HX square footage at 2,600 and take a construction cost of $134.61 per square foot to arrive at a replacement cost of $350,000. For OX homes, we take the middle of the cost range, $120, multiplied by the median home square footage (2,261 in 2020) to get approximately $270,000.

G Basis for scenario assumptions

It is widely recognized that: (i) the underlying stationarity required for the application of standard quantitative risk assessments – including the determination of a 'fundamental' price or the assumption of normal statistical moments – is not present with climate change, and (ii) the adjustment of coastal home prices is highly contingent on beliefs about the reality of climate change (see, e.g., Pindyck, 2021, [30], Weitzman, 2011, [37], Bakkensen and Barrage, 2021, [3], and Baldauf et al., 2020, [4]). These factors motivate us to use a scenario analysis approach to our simulations.

There are four main dynamic housing market variables that differ across the two scenarios presented here:

1. The degree to which homes suffer devaluation in the wake of a hurricane of a given strength.
2. The trend growth of home prices in the presence of chronic sea level rise.
3. The growth in the housing stock for different homeowner categories.
4. The rate at which homes turnover.

While each of these variables could in principal be obtained through a dynamic programming solution technique, the stationarity and statistic moment concerns described above make it exceedingly challenging to solve for these variables. Rather, we create scenarios based on knowledge of local characteristics. For example, in localities with ample fiscal resources, the modeler might reasonably expect that the government might build the infrastructure necessary to support continued home price appreciation. Alternatively, if the local economy is highly vulnerable to climate shocks, the degree of local home price devaluation might be much higher as jobs disappear and individuals are no longer able to pay their mortgages. Yet another case is one in which migration from vulnerable to non-vulnerable areas within the same locality is desirable leads to falling home prices in the former and rising home prices in the latter. Whether this last effect dominates is an open question.

We therefore use scenarios to illustrate how the model can be used to process scenarios, where the specific scenario assumptions are given in the text. We describe the basis for some of these assumptions below.

G.1 Hurricane shock devaluation

For our scenarios, we assume that instantaneous devaluations due to a hurricane shock only occur for hurricane categories 3 and above, with the degree of devaluation rising in the strength of the hurricane. The highest devaluation of 80 percent is based on a study by the McKinsey Global Institute.[23]

G.2 Home price depreciation

We follow MGI's projections and set the price trend for homes in floodplains at a pace to bring them to a 30 percent devaluation relative to above-flood-plain homes by 2030, and an 80 percent devaluation relative to above-flood-plain homes by 2050.[24] Sustained home devaluation implies that negative equity will set in at some point depending on the difference between the rate of home price depreciation and the rate of mortgage interest. More generally, if it is clear that prices will face sustained downward pressure, prices should jump to the foreseen lower level immediately consistent with rational pricing models. This is a difficult issue to handle in light of the large empirical literature attempting to explain coastal real estate pricing anomalies. We leave proper consideration of coastal home pricing for future work.

For above-flood-plain homes, let:

$$PI_{2020}^{XA} e^{g_A \cdot 10} \;\; = \;\; PI_{2030}^{XA}.$$

where PI_{year}^{XA} is a price index for a given year for above-flood-plain homes of type XA, and g_A is the annual growth rate of those prices. Likewise:

$$PI_{2020}^{XF} e^{g_F \cdot 10} \;\; = \;\; PI_{2030}^{XF}.$$

If flood plain homes are to depreciate 30 percent relative to above-flood-plain homes, it must be the case that:

$$PI_{2020}^{XF} e^{g_F \cdot 10} = 0.7 \times PI_{2030}^{XA}.$$

Set $PI_{2020}^{XA} = PI_{2020}^{XF} = 1$. Combining this with the above equations, we

[23] McKinsey Global Institute (2020) [25], p. 20.

[24] McKinsey Global Institute (2020) [25], p. 20, maximum devaluation projections.

have the following growth rates for the period 2020-2030:

$$\begin{aligned} g_F &= \frac{\ln(0.7)}{10} + g_A, \\ &= g_A - 0.036, \\ &= 0.022 - 0.036 = -0.014. \end{aligned}$$

where g_A is set equal to 2.2 percent, equal to the best 30 year average growth in the US housing market (1976-2005).

Performing the same exercise for the period 2030-2050, we have:

$$\begin{aligned} g_F &= \frac{\ln(0.7)}{10} + g_A, \\ &= g_A - 0.080, \\ &= 0.00 - 0.080 = -0.080. \end{aligned}$$

where we assume prices for above-flood-plain homes in Miami are flat.

One consideration that sustained home devaluation introduces is that the speed with which negative equity sets in depends on the difference between the rate of home price depreciation and the rate of mortgage interest. More generally, if it is clear that prices will face sustained downward pressure, rational pricing models would generate an immediate jump to a lower price consistent with the fundamentals. However, the empirical evidence on the impact of climate change (particularly sea level rise) on home prices is mixed, with some evidence that greater exposure to climate risk lowers home prices but also evidence that risks are not fully capitalized. Moreover, homeowner beliefs tend to affect the degree to which climate risks are incorporated into prices. Empirical studies of natural disasters suggest that prices tend to rebound, and that homeowners who hold on long enough tend to be rewarded with the recovery of any lost equity. There is always a real options value to waiting to see how uncertainty is resolved before taking an irreversible action. In light of these conflicting factors, we assume that homeowners do not default outside of a hurricane event.

G.3 Housing unit growth

In some scenarios, the housing stock grows at the Miami population growth rate during the 2020s (projected to be 1.16 percent according to the planning horizon figures used by Miami-Dade County).[25]

[25] https://www.miamidade.gov/water/library/reports/reuse-feasibility-iii.pdf

G.4 Turnover rates

Bank vulnerability to climate shocks will depend significantly on the cohort structure of home ownership that in turn depends upon the rate of real estate turnover. Consider the polar case in which turnover is zero, new home construction is zero, and all home equity is fully owned by the homeowners. Under such a scenario, banks and other non-homeowners do not hold risk. It is reasonable to assume that turnover rates will fall in riskier areas as it becomes difficult to see in a sinking market. Add to this the possibility that government programs buy out homeowners living in high risk areas, and the probability of additional lending in these areas declines. There are no clear empirical examples of which we are aware to guide us in our choice of the path of turnover rates.

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