Who Bears Flood Risk?

Evidence from Mortgage Markets in Florida

Abstract

This paper exploits strict flood insurance coverage limits and staggered flood map updates to show that mortgage lenders offload flood risk to the government through flood insurance contracts, and to households through higher down payment requirements when borrowers are not fully insured. Lender risk management is effective and equalizes delinquency rates inside and outside of flood zones. Rationing shifts the composition of mortgages in flood zones towards richer and higher credit quality borrowers. In conclusion, lenders screen for flood risk when they retain residual exposures to it, and their credit rationing has distributional consequences for flood zones.

1 Introduction

In the United States, 35.8 million homes with a combined market value of $6.6 trillion are exposed to natural disaster risk (RealtyTrac, 2015). Floods are the most costly natural disasters, having caused hundreds of billions of dollars in damage over the past few decades (See Figure 1). These costs are expected to rise further, with climate change bringing rising sea levels, heavier rains, and stronger hurricanes (Newburger, 2021; Davenport et al., 2021). By some estimates, flood-related property damage could increase by more than 60% over the next 30 years due to climate change (Duguid, 2021). Given the large scale of potential financial losses, it is important to know who bears flood risk in mortgage markets.

Financial regulators worry that banks may neglect or offload flood risk to the government, possibly threatening financial stability.[1] Mortgage lenders originate more than $200 billion annually in flood zones, representing roughly 10% of total bank equity (Ouazad, 2020). Bank regulators in Canada, France and the United Kingdom are already conducting climate-related stress tests, and the U.S. Federal Reserve is considering a similar approach (Brainard, 2021).

Similarly, climate activists worry about over-development in high risk coastal areas and the role played by financial markets. If lenders neglect to incorporate flood risk into mortgage terms, then borrowers may not bear the true costs of flood risk. The effects could be similar to a mispricing of insurance, where borrowers are shielded from risks and therefore are incentivized to move into high risk areas (Froot, 1999, Bagstad et al., 2007).

Despite recent policy actions, there is limited empirical evidence related to how lenders adjust mortgage terms to manage flood risk, which affects how these risks are distributed in the U.S. economy.

[1] Fed Governor Lael Brainard says in her December 18, 2020 speech: "It is vitally important to strengthen the U.S. financial system to meet the challenge of climate change... We are already seeing elevated financial losses associated with an increased frequency and intensity of extreme weather events... Mortgages in coastal areas are vulnerable to hurricanes and sea level rise... Recent research argues that lenders hit by hurricanes, particularly in areas not typically affected by natural disasters, tend subsequently to securitize more of their mortgage loans, which could have higher climate risks, higher borrower defaults, and lower collateral values." (Brainard, 2020)

In the market for flood risk, there are three primary players: households, mortgage lenders, and the government. Households bear flood risk because flood damage can directly affect home values. Lenders bear flood risk because households purchase their homes using mortgages. The mortgage's loan-to-value ratio at origination is a key determinant of how this risk is shared between them. Households and banks may transfer flood risk to the government through the publicly-run National Flood Insurance Program (NFIP), which is the dominant player in this market. Flood insurance payments can be used to repair damaged homes, changing household default incentives and lender risk exposures. Flood insurance is required by law for most mortgage borrowers in flood zones. Importantly, these government insurance contracts have strict coverage limits, meaning that some flood risk can be transferred to the NFIP, but not all flood risk.[2]

This paper studies how flood risk exposures are distributed across banks, households, and the government flood insurer through residential mortgage contracts in Florida. To explore this question, I consider how mortgage interest rates, loan-to-value ratios, and delinquency outcomes vary with flood risk. There are four key findings. First, lenders account for flood risk in the mortgage contract, the primary margin of adjustment being down payments rather than interest rates. This is consistent with lenders rationing credit to decrease the likelihood of negative equity, as higher down payments improve lender recovery rates. On average, banks reduce loan-to-value ratios by 83 basis points (0.83 percentage points) in flood zones, while interest rates do not significantly change. Second, lenders only ration credit when they retain direct exposure to flood risk; there is no evidence of rationing when risks are fully covered by government flood insurance. Third, these loan-to-value adjustments appear to be effective, with delinquency rates being roughly equal for both fully insured and under-insured homes in and out of flood zones. Fourth, lender credit rationing has distributional

[2] Ouazad and Kahn (2021) show that the ability to securitize mortgages plays less of a role in federal flood zones where flood insurance is required. Most of the increase in securitization following hurricanes occurs in areas outside of federal flood zones, suggesting lenders rely on securitization as a substitute for flood insurance.

consequences and shifts the composition of borrowers in risky areas to richer, higher credit quality individuals. Higher down payments and flood insurance requirements seem to deter more liquidity-constrained borrowers from purchasing homes in flood zones.

Data is a key challenge with estimating the impact of flood risk on mortgage markets and household location choices. Obtaining data on each mortgage's flood risk exposure is difficult. Flood maps produced by the Federal Emergency Management Authority (FEMA) are the most widely used measures of flood risk (Kousky et al., 2018).[3] Although current flood maps are available digitally as a database from FEMA, historical flood maps are not, making it difficult to identify a mortgage's flood zone classification at origination. I address this issue by digitizing historical flood maps that were previously unavailable. Additionally, standard mortgage datasets do not include property characteristics, such as the address. To geo-locate individual mortgages, I employ a fuzzy merge between mortgage datasets and property deeds data. I then combine the current and historical flood maps with the geo-located mortgage data to obtain each property's flood zone classification at mortgage origination. This creates both cross-sectional and time-series variation in flood risk classifications. I supplement the flood risk data with information from public and commercial sources, allowing me to obtain a a rich set of borrower and property-level characteristics including applicant income, credit score, property value, replacement cost, and securitization status, as well as the subsequent performance of the mortgage. The data I assemble covers single-family purchase mortgages in Florida originated between 2010 and 2016.

With this novel dataset, I begin the paper with descriptive evidence on how mortgage characteristics vary with flood zone designations. I find that loan-to-value ratios are on average 83 basis points lower in flood zones, even after including zip code-year fixed effects and controlling for the borrower's income, FICO credit score, and property value. With the

[3]Today there are many commercial providers of flood risk information, such as the First Street Foundation and CoreLogic, but during my sample period of 2010-2016, there were few alternatives to the government flood maps. I focus on government flood maps since that information could feasibly be in lenders' information sets.

same set of fixed effects and controls, interest rates are only 1 basis point higher in flood zones, and delinquency rates are roughly equal in and out of flood zones.

These descriptive facts are consistent with two competing interpretations. The first is a supply-side story: lenders manage their exposure to flood risk by adjusting down payments in flood zones, which leads delinquency rates to equalize. The second is a demand-side story: flood zones are disproportionately likely to have water views which attract wealthier borrowers who tend to have higher down-payment mortgages. I use two empirical strategies to address these competing stories.

In my first empirical approach, I exploit strict flood insurance coverage limits that leave some borrowers in flood zones under-insured. Flood insurance is required by law for most mortgage borrowers in flood zones. Government flood insurance has a 95% market share, and these contracts only cover up to $250,000 in flood damage. There is limited availability of private top-up insurance for borrowers in high risk flood zones in Florida. As a result, smaller homes are fully insurable, and larger homes in flood zones are under-insured. This feature of flood insurance allows comparisons of mortgage contracts by flood zone status and by how much of the home can be insured against flood risk. I find that loan-to-value ratios are only lower in flood zones when the insurance coverage limit binds, by 81 basis points. Flood zone status has no effect on loan-to-value ratios when the loan can be completely insured. Loan-to-value ratios are reduced more in flood zones when a greater share of the home is un-insurable. Most importantly, the relationship between flood zone status and loan-to-value ratios changes at the insurance coverage limit. Average interest rates and delinquency rates are roughly equal in and out of flood zones for each replacement cost category. These facts suggest that lenders screen on flood risk when they are sufficiently incentivized to do so, and that their loan-to-value ratio adjustments are effective at equalizing delinquency rates.

In my second empirical approach, I exploit periodic flood map updates which change risk assessments while keeping underlying amenities (such as water views) fixed. Updating a community's flood map often requires an engineering study that produces new data on elevation and the location of dams and levees. FEMA partners with local communities to conduct these studies, and it can take up to five years to release an updated flood map.[4] All zip codes in a county receive updated flood maps at the same time, although some zip codes have expanded boundaries while others have unchanged or contracted boundaries. Importantly, these updated flood maps change flood risk assessments while holding fixed unobserved location-specific characteristics like water views. I find that banks dynamically respond to the flood zone expansions by reducing loan-to-value ratios by 2 percentage points. Average interest rates do not significantly change, and delinquency rates decline by 1 percentage point. The results are not likely to be driven by unobserved county-year shocks since mortgage terms do not significantly change for zip codes with map updates that leave flood zone boundaries unchanged. Furthermore, the composition of mortgage borrowers changes after these flood zone expansions. I find that average mortgagor incomes increase by 10% in the years following a flood zone expansion, and average credit scores increase by over 5 points. The results suggest that higher down payment requirements deter more liquidity constrained individuals from borrowing in high risk areas.

Taken together, these results show that banks internalize flood risk when they have direct exposures to it, and this credit rationing has strong distributional consequences for who can purchase homes in flood zones using a mortgage. Importantly, flood risk is partially offloaded to the government through flood insurance contracts for homes that can be fully covered, and to households for homes that cannot be completely covered. In the absence of mandatory government flood insurance, lenders would likely ration credit for all borrowers in flood zones.

Related Literature: This paper lies at the intersection of household and climate finance, and makes a number of contributions to the existing literature.

The literature shows that floods create financial losses for lenders, implying that lenders

[4]Private sector measures of flood risk, such as those from CoreLogic or the First Street Foundation, use the FEMA data and flood maps as an input.

should adjust mortgage terms to manage this risk. Hurricanes increase household delinquency and insolvency, and these rates rise with property damage (Bleemer and van der Klaauw, 2019; Kousky et al., 2020). Insurance payouts offset some of the rise in delinquencies after disasters (Billings et al., 2019; Issler et al., 2019; Kousky et al., 2020). A handful of papers have explored whether lenders screen for flood risk by exploring the effects of natural disasters on mortgage pricing. After hurricanes, lenders change where they originate mortgages (Cortés and Strahan, 2017; Gropp et al., 2019), using geographic diversification to manage their exposures. Ouazad and Kahn (2021) find that lenders are more likely to securitize loans in areas hit by hurricanes that lie outside of federal flood zones, which are areas where flood insurance is not required by law for mortgage borrowers. They suggest that lenders rely on securitization as a substitute for flood insurance. However, there is limited evidence that lenders adjust interest rates or loan-to-value ratios after storms (Garbarino and Guin, 2021).

While these papers have explored the causal effect of realized natural disasters on mortgage originations, I consider new sources of variation in ex-ante flood risk from updated flood maps and insurance coverage limits. This approach has two main advantages. First, large natural disasters often directly affect municipalities, firms, banks, and households financially in addition to changing assessments of risk (Nordhaus, 2010; Deryugina, 2017; Boustan et al., 2020). Second, it is difficult to ascertain how much risk assessments should change in response to the experience of a natural disaster. Third, hurricane strikes may increase the salience of flood risk even for borrowers in high risk areas that are not directly hit. Variation from insurance contracts and updated maps allow for directly measuring the independent effect of risk exposure and risk assessments on mortgage terms for a given location. Using these sources of variation, I show that banks manage flood risk by adjusting loan-to-value ratios.[5]

[5]Insurance availability is likely to grow in importance as private insurers exit other key natural disaster markets (Garmaise and Moskowitz, 2009; Flavelle, 2019; Oh et al., 2021).

In a contemporaneous paper, Santos and Blickle (2022) use restricted HMDA data and flood map updates to study the effect of government insurance requirements on lender credit supply. While similar in spirit, they focus on the extent to which flood insurance requirements in flood zones may lead poorer households to take on smaller loans, independent of what flood zone designations may convey to banks about risk. In contrast, my paper focuses on a different but complementary question, which is how lenders use interest rates and loan-to-value ratios to manage their exposure to flood risk, particularly when borrowers are not completely insured in flood zones. Unlike their study, I look at both quantities and prices, and I supplement the flood map event study with a cross-sectional difference-in-differences design based on the insurance coverage limit to establish the credit rationing interpretation. Both my paper and Santos and Blickle (2022) are consistent with the relatively growing literature showing that climate risk has become increasingly capitalized in house prices in recent years.[6]

The large literature on household default and negative equity explains why lenders adjust loan-to-value ratios to manage risk. The literature describes default behavior using either a pure "strategic default" model where default is entirely triggered by negative equity (Foster and Van Order, 1984) or a "double-trigger" model where household default is triggered by both negative equity and cash-flow shocks (Foote and Willen, 2018). Much of the literature finds limited evidence of pure strategic default behavior.[7] Importantly, in both the pure strategic default and double-trigger models, negative equity is a necessary condition of default, since borrowers with positive equity are better off repaying loans using the proceeds from selling the home and keeping any remaining balance.[8] Loan-to-value ratios at origination affect the borrower's equity position throughout the life of the loan and therefore

[6]See, for example, Baldauf et al. (2020); Bernstein et al. (2019); Gibson and Mullins (2020); Giglio et al. (2021b); Keenan et al. (2018); Murfin and Spiegel (2020); Keys and Mulder (2020).

[7]See, for example, Scharlemann and Shore (2016); Bhutta et al. (2017); Fuster and Willen (2017); Gerardi et al. (2018); Ganong and Noel (2020).

[8]Low (2018) and Ganong and Noel (2020) note that frictions in housing markets can make it difficult to sell homes, explaining some observed defaults from borrowers with positive equity experiencing cash-flow shocks.

serve as a useful tool for managing collateral risk. Lenders also rely on loan-to-value ratio adjustments to manage default risk in other secured lending markets, such as in corporate lending markets (Benmelech et al., 2005; Benmelech and Bergman, 2009) and in derivatives markets (Capponi et al., 2020).

There is also evidence that households with riskier collateral tend to prefer loans with higher loan-to-value ratios (Lamont and Stein, 1999; Hertzberg et al., 2018; Bailey et al., 2019), consistent with notions of adverse selection in Stiglitz and Weiss (1981) and Finkelstein and Poterba (2014). My results imply that banks are aware of household preferences for larger loans and respond by actively requiring riskier households in flood zones to take on less leverage.

Lasly, this paper joins a large literature which shows that the ability to offload risk changes lender screening incentives. Downing et al. (2009), Keys et al. (2010), Purnanandam (2011), and Keys et al. (2012) find strong evidence that lenders securitize mortgages that are of lower credit quality than the ones they retain on balance sheet. Campbell and Dietrich (1983) and Park (2016) suggest that government and private mortgage insurance diminish lender underwriting standards. I contribute to this literature by showing that government flood insurance reduces lender incentives to ration credit in flood zones.

2 Hypothesis Development

In this section, I consider a conceptual framework to derive two hypotheses of how banks should manage their flood risk exposure which can be tested in the data. The stylized model in Appendix C formalizes these intuitions.

The conceptual framework considers a borrower who has decided to purchase a home and then applies to a bank for mortgage financing. In the two-period model, the mortgage is originated in the first period and repaid in the second period. Between those two periods, a flood can occur with some positive probability. A flood causes some property damage, where property damage follows some probability distribution and impacts the second-period liquidation value of the home. After the flood, the household can choose to repay the loan or default. The borrower incurs some loss of utility from defaulting, reflecting the costs associated with financial distress. The probability of a flood, the distribution of flood damage, and default costs are known to both the borrower and the bank. Both the borrower and the bank are risk-neutral, but there are gains from trade because the lender is assumed to be more patient than the borrower.

After a flood, the borrower decides whether to default or repay the loan. The borrower's default rule will compare the outstanding balance of the mortgage with the value of the flooded property and the costs of default. If the property is worth less than what is owed to the banks and the costs of default, the borrower optimally defaults. The default rule is consistent with both the strategic default (Foster and Van Order, 1984) and double trigger (Foote and Willen, 2018) models, since in both models negative equity is a necessary condition of default. Given their default rule, households will therefore maximize their expected utility subject to a lender zero profit constraint.

Because delinquency depends on the borrower's equity position, lenders adjust both loan sizes and interest rates to manage delinquency risk. A smaller loan size at origination will imply that the borrower owes less to the bank after a flood, thereby giving the borrower a lower incentive to default. However, a smaller loan size will also lead to reduced repayments when households do not default. Loan sizes will trade off the effect of lower repayment and lower default probabilities.

If delinquency rates did not depend on loan sizes, then lenders could increase interest rates to manage flood risk. However, in this setting, a higher interest rate without a smaller loan size increases the amount owed to the bank, thereby increasing delinquency risk. The interest rate will be determined by the trade off between increased returns and increase delinquency rates. Adjustment through both quantities and prices is a general result that be shown in a broad class of models with moral hazard (e.g. Stiglitz and Weiss, 1981).[9]

This leads to the following hypotheses:

Hypothesis 1: Loan-to-value ratios are decreasing in flood risk exposure.

Hypothesis 2: Interest rates are not decreasing in flood risk exposure.

In the model, the magnitude of the loan-to-value and interest rate adjustments, as well as the pass-through to delinquency rates, depend on parameters that determine the risk-return relationship, such as the shape of the distribution of flood damages, lender and borrower discount rates, and borrower default costs. Outside the model, the competitive structure of lending markets also plays a role. The direction of the relations, however, are unambiguous.

2.1 Testing the Hypotheses

I use three sources of variation in flood risk exposure to test these hypotheses. The first approach uses a mortgage's flood zone status under FEMA flood maps as a proxy for its flood risk exposure. Hypothesis 1 and 2 thus imply that observably-equivalent homes in flood zones should have lower loan-to-value ratios and similar or higher interest rates as homes outside of flood zones. These results are presented in Section 4.

The second source of variation considers both flood zone status and insurance availability to measure a lender's residual exposure to flood risk. As formalized in Appendix C.2, a fully insured mortgage is not exposed to flood risk because each dollar of flood damage is offset by an insurance payment.[10] Furthermore, mortgage borrowers are required to by flood insurance in flood zones (see Section 3). As a result, only large under-insured homes in flood zones are exposed to flood risk because the insurance coverage limit binds. Therefore, there

[9] A positive relationship between delinquency and loan sizes is similar to moral hazard in health insurance markets, where more insurance coverage causes more healthcare spending.

[10] This result relies on the assumption of frictionless insurance markets.

should be no difference in mortgage terms in and out of flood zones for observably-equivalent borrowers that are fully insurable. Loan-to-value ratios and interest rates should only adjust in flood zones when homes are under-insured and banks retain residual flood risk exposure. I therefore test Hypothesis 1 and 2 by estimating the effect of flood zone status on loan-to-value ratios and mortgage terms when homes are not fully insurable. These results are presented in Section 5.

The third source of variation considers changes in flood risk assessments rather than flood risk exposures directly. I assume that changes in federal flood maps can be used to proxy changes in risk assessments, even if fundamental flood risk itself does not change.[11] Thus, expanded flood zone boundaries suggest an increase in lender's expectation of flood risk exposure. Therefore, I test Hypothesis 1 and Hypothesis 2 by analyzing how loan-to-value ratios and interest rates adjust following the release of new maps that expand flood zone boundaries and bring heightened risk assessments. These results are presented in Section 6.

2.2 Demand-side Explanations

Importantly, both Hypothesis 1 and Hypothesis 2 are required to establish that lenders manage flood risk. For example, Hypothesis 1 can also hold in a model of advantageous selection where homes with more flood risk exposure tend to have less risky borrowers who demand smaller loan-to-value ratios. This can occur if, for example, areas with more flood risk are also areas with better waterfront amenities, and therefore attract unobservably higher credit quality borrowers that choose mortgages with higher down payments. In this scenario, Hypothesis 2 is not likely to hold because, all else equal, for a given loan-to-value ratio, borrowers would be better off financially with a lower interest rate. If the correlation between loan-to-value ratios and flood risk exposures were entirely driven by advantageous selection, we would expect interest rates to also decrease in flood risk exposure, thus violating

[11] To be clear, fundamental risk itself my change; my strategy cannot distinguish between risk and information about risk.

Hypothesis 2.

Therefore, I examine how both interest rates and loan-to-value ratios change using each empirical strategy.

3 Institutional Setting

FEMA's flood maps are the most widely used measures of flood risk (Kousky et al., 2018). FEMA's flood zone designations determine flood insurance premiums and have regulatory consequences for mortgage borrowers and lenders. In this section, I provide more background on FEMA's flood maps, these regulatory requirements, and the flood insurance market.

3.1 Flood Maps

The National Flood Insurance Program (NFIP) was established in 1968 to provide insurance that had been historically unavailable through the private sector. Flood risk is carved out of standard homeowners insurance, and until very recently private flood insurance was rare (Kousky et al., 2018). FEMA administers the flood insurance program and today, the NFIP covers 95% of all residential flood insurance policies in the United States. To administer the insurance program, FEMA produces flood maps that define its classification of flood risk, with homes located in high risk flood zones facing higher flood insurance premiums.[12]

In 1970, Congress required FEMA to produce flood maps that delineate the boundaries of high, moderate, and low risk flood zones. High risk flood zones are defined as areas which have at least a 1% chance of flooding in a given year. These flood maps are extremely data-intensive to produce. Creating a new flood map or updating an existing flood map often requires a new engineering study, and can take as long as five years or more. These flood maps have two key data requirements: base map information, and elevation data. Base

[12]In Florida, moving from a low or moderate risk to a high risk classification leads to a $400 increase in annual premiums.

map information describes the location of streams, roads, buildings, dams, administrative boundaries, etc. This information is widely available from a number of sources (such as Google Earth or the U.S. Geological Survey). The second data requirement is information on land and water surface elevation. Elevation data is then used as an input into hydrological models that define the direction, velocity, and depth of flood flows (National Research Council, 2007). These models require highly accurate elevation information that are reliable up to one-tenth of one foot. FEMA supplements elevation data from the U.S. Geological Survey with data compiled by land surveys and by remote sensing techniques from aircraft or satellites to meet its vertical accuracy standards (FEMA, 2019).

By law, FEMA is supposed to review its flood hazard engineering studies every five years and decide whether to update or change the flood maps which rely on those studies. This is because flood hazards and our measurement of flood risk both change over time. Water flow and drainage patterns can change due to new land use and infrastructure development or by natural forces such as changing weather, terrain changes, hurricanes, or wildfires. For example, about 17,000 square miles of land in California, Texas, Louisiana, and Florida sinks a few inches every year, rendering old elevation data obsolete (National Research Council, 2007). Furthermore, improved data availability and methodological advancements also necessitate the development of new flood maps.

In reality, most flood maps are older than five years. Starting in 2000, FEMA faced Congressional pressure to update, modernize, and digitize its maps, and it began its Flood Map Modernization program with a pledge of $5 million per year from Congress to fund the efforts, but funding tapered off in 2003 (National Research Council, 2007). This program was rebranded in 2009 as the Risk Mapping, Assessment, and Planning program (Risk MAP) with renewed Congressional funding (FEMA, 2012). As a result of these investments, FEMA's digitized flood maps now cover more than 90% of the U.S. population, though many are still quite old.

FEMA prioritizes when and where map updates should occur by determining how likely it is that existing maps are out of date (National Research Council, 2007). As FEMA writes, "Risk MAP's primary areas of focus include coastal flood hazard mapping, areas affected by levees, and significant riverine flood hazard data update needs" (FEMA, 2012). Relevant parameters for remapping prioritization include the age of the prior flood risk study, historical flood damage occurring outside of previously mapped flood zones, and magnitude of new dam and levee construction. FEMA partners with individual communities to run the elevation studies and produce the maps. All communities within the same county receive finalized flood insurance studies and flood maps at the same time.

Today, there are a number of alternative measures of flood risk, such as from commercial data providers like the First Street Foundation. While these providers use state-of-the-art risk classification techniques (Mulder, 2022), they also rely on methodologies, flooding events, and other information that occur after 2016, meaning that they incorporate information that would not have been available to the lenders in my sample. For this reason, I do not use their classifications. That said, when comparing FEMA maps to the First Street Foundation for Florida, I find that only 10% of homes outside of official flood zones are mis-classified and should be included in a FEMA flood zone.[13] It seems that map inaccuracy is less of an issue in Florida. Separately, starting in 2021, FEMA began to move away from its map-based classification system, in an attempt to measure flood risk for each home incorporating the unique features of each parcel. These effects are underway as part of the Risk Rating 2.0 system.

3.2 Mandatory Purchase Requirements

Most mortgage lenders must require borrowers in high risk flood zones to purchase flood insurance. The requirement stipulates that federal agencies, federally regulated lending in-

[13]To obtain this number, I consider parcels outside FEMA flood zones for which the First Street Foundation's probability of flooding events that exceed 30 centimeters of water depth in the year 2030 exceeds 1%. There are 26,262 homes in my dataset outside of FEMA flood zones for which this holds; there are 242,259 homes overall outside of FEMA flood zones.

stitutions, and the GSEs must require borrowers in high risk flood zones to purchase flood insurance for every mortgage that these entities originate, guarantee, or purchase.[14] Furthermore, lenders must force-place flood insurance on behalf of the borrower if the borrower does not comply. Mortgages originated by state-regulated lenders and securitized in private label markets are excluded from this requirement; however, in my sample between 2010-2016, the private label markets have less than a 5% market share. Insurance is required throughout the life of the loan and should cover the full loan balance up to FEMA's maximum coverage limit of $250,000.

Direct estimates of lender compliance with the mandatory purchase requirement are difficult to ascertain because FEMA does not systematically record whether the insurance policy holder has a mortgage that is subject to the mandatory purchase requirement, and their publicly available data does not include addresses so it cannot be combined with other data sources. However, FEMA recently conducted a study where they matched policy-holder information with data from the American Community Survey at the address level to obtain estimates of lender compliance. Their calculations suggest that, in 2015, 60% of mortgage borrowers in high risk flood zones had a flood insurance policy (FEMA, 2018). Furthermore, their estimates also suggest that 67% of all non-renter flood insurance policy holders had mortgages.

Some recent papers have explored the dynamics of flood insurance take-up. Wagner (2021) looks at insurance purchase behavior inside flood zones and finds limited evidence of private information. Bradt et al. (2021) find some evidence of adverse selection in flood insurance purchases outside of flood zones, in that only people with high flood risk purchase flood insurance.

When mortgage borrowers purchase flood insurance, their policy includes the name of

[14]This requirement was first implemented by Congress in the Flood Disaster Protection Act of 1973, which applied to mortgages originated by federally regulated institutions or backed by federal agencies, such as the Federal Housing Authority. Congress extended the flood insurance requirement to the government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, in the National Flood Insurance Reform Act of 1994.

their lender, and insurance claim checks are written to both the borrower and the lender. Flood insurance premium payments are managed similarly to homeowners insurance and property taxes; premium payments are usually made to the lender and held in an escrow account, after which the lender transfers the payment to the insurer. Flood insurance claim checks are written to both the borrower and the lender, with payouts typically held in an escrow account with the lender. The homeowner must receive the signature of the lender to release insurance claim payments, meaning they cannot abscond with insurance payments without the lender's knowledge (Gallagher and Hartley, 2017). In the event of foreclosure, lenders are entitled to keep the proceeds of insurance claims (Issler et al., 2019; Hoberock and Griebel, 2018)

3.3 Flood Insurance Coverage Limits

A key feature of the federal flood insurance program is that NFIP coverage is capped at $250,000 for residential structures. The private markets do provide excess flood coverage beyond the NFIP limit, but the availability of such products is be limited for properties in high risk flood zones, especially in the states of Florida and Louisiana (Wells, 2006; Goldberg, 2005). For example, the company Bankers Insurance says in a publicly available manual that they do not underwrite excess flood policies in coastal FEMA flood zones at all (Bankers Insurance Company, 2014). Only six companies are even admitted to write excess flood policies in Florida (Florida Office of Insurance Regulation, 2021). Recent survey data suggest that, as of July 2018, Florida's admitted insurers had only 5,983 excess flood insurance policies in force (Lingle and Kousky, 2018).

The limited availability of top-up private flood insurance is consistent with the documented evidence of a general unavailability of private insurance in Florida's property and casualty segment. After Hurricane Andrew in 1992, Florida created a state-run reinsurance fund called the Hurricane and Catastrophe Fund, to stymie further private insurer exit. Florida's state-run re-insurer now has a 50% market share in the re-insurance sector.

Furthermore, the market share of Florida's state-run private insurer of last resort increases each year, now covering 8.2% of the market.[15] Even when excess coverage is provided by private markets, there is anecdotal evidence of insurer-driven policy cancellations for properties deemed too risky or after flood events (Coueignoux, 2021). The limited availability of private flood insurance in the highest risk segments is consistent with documented evidence of insurer exit for other natural disasters, such as wildfires in California (Flavelle, 2019). Florida's potential for large-scale insurer exit has resurfaced in the aftermath of Hurricane Ian.

The literature implies that private insurer exit from the highest-risk areas in Florida arises from a combination of state-level price controls which limit premium increases and other capital market frictions that restrict the availability of reinsurance (Oh et al., 2021). In Florida, premium increases for private flood insurance, including excess flood insurance, must be approved by the state insurance regulator. Insurers have raised concerns about being unable to raise premiums after new information leads to updated risk assessments (Kousky et al., 2018).

4 Data and Descriptive Evidence

The paper's empirical analysis considers how mortgage terms vary with flood zone classification and insurability. To do so, I construct a novel data set that combines geo-spatial data from flood maps with geo-located data on mortgage characteristics and performance. The final dataset focuses on the state of Florida and spans 2010-2016. The sample is restricted to purchase mortgages for single-family homes. In this section, I describe the key datasets and how I merge them. I then show some descriptive facts using the raw data, which help set-up my identification approaches in Section 5 and 6. Further details on the data merge

[15] Barry Gilway, the president and CEO of Citizens, the state insurer-of-last-resort, recently testified that the marketplace in Florida is "shutting down," and that ""The capacity in the marketplace has shrunk to the point where, unfortunately, Citizens is becoming not the market of last resort, but, in many cases, the market of first resort, and that was never intended for a residual market mechanism."

are available in Appendix Section A.

4.1 FEMA Flood Maps

My primary measure of flood risk comes from FEMA's flood maps. In Florida, the latest flood maps and some historical ones can be downloaded directly from FEMA's Map Service Center as a geo-spatial database called the National Flood Hazard Layer. The digitized maps can be downloaded for an entire county, including all the individual maps for each community in that county. I obtain archived FEMA flood maps from geospatial libraries at Princeton, University of Texas, University of Florida, Harvard, and Berkeley, which saved snapshots of FEMA's floodmaps for various counties in Florida from 1996, 2001-2009, and 2011.[16]

FEMA releases a flood insurance study whenever it produces a new flood map. These studies list when flood maps are revised for each community before county-wide flood maps were introduced. The studies also include when county-level flood maps are introduced and any subsequent revisions at the county-level. These two sets of information can be combined to obtain the revision dates of the community's current and historical flood maps.

For some zip codes in Levy, Calhoun and Clay counties, digitized flood maps that would be valid at the beginning of my sample were not available from FEMA or in the university repositories, so I digitized the floodmaps for these counties using PDFs of the historic map boundaries for each community, which are also available from FEMA's map service center.

4.2 Mortgage and Housing Data

I combine mortgage and housing data from BlackKnight McDash, HMDA, and ZTRAX to obtain granular loan-level information on housing characteristics, mortgage characteristics, and mortgage performance.

[16]When I asked FEMA, they said archived flood maps were unavailable to be shared, which is why I compiled snapshots from these alternate sources.

BlackKnight McDash: Black Knight is a private company that produces the McDash dataset, a comprehensive, loan-level dataset on mortgages that includes information on mortgage characteristics, borrower characteristics, and mortgage performance. The data is compiled from mortgage servicers and accounts for approximately two-thirds of the overall mortgage market. Mortgage characteristics in the data include the origination month, interest rate, loan-to-value ratio, debt-to-income ratio, maturity, property value, and type of mortgage (e.g. FHA, VA, Jumbo, etc.). The data also include select borrower characteristics such as FICO credit score. Location information is limited to 3-digit or 5-digit zip codes. Importantly, this data includes information on the performance of the mortgage from origination to its final payment. This includes whether the mortgage is current or in delinquency status, as well as events such as prepayment, default or foreclosure.

Home Mortgage Disclosure Act (HMDA): I obtain additional mortgage characteristics from the Home Mortgage Disclosure Act, which is administrative data on the universe of mortgage applications and originations. HMDA data include the lender name, loan amount, property type, loan purpose, and the applicant's income, gender, and race. Location information is limited to the census tract of the house.

Zillow ZTRAX: Zillow produces the Zillow Transaction and Assessment Dataset (ZTRAX), which includes historical tax assessment records as well as information on home sales and loan records from deeds stored in county clerk offices. Each housing transaction includes the date, sales price, mortgage loan amount, mortgage lender's name, and the precise location of the property. The tax assessor data includes basic characteristics for each parcel, including assessed land values, total assessed values, and square footage. The transactions and assessor data within ZTRAX can be merged together with a unique parcel-level identifier created by Zillow.

4.3 Additional Data

Flood Insurance Policies and Claims: I obtained data directly from FEMA on the universe of flood insurance policies and claims through a Freedom of Information Act request. Policies data includes insurance contract information such as the premium and coverage level of individual policies. The claims data include FEMA's property damage assessments, claims paid out, and FEMA's estimates of building replacement values. Location information in both the policies and claims datasets is limited to the zip code and flood zone classification. Some of this data is now available publicly through FEMA's OpenFEMA API, but my data includes some variables which are not in the public dataset, such building value assessments as property damage assessments.

Construction Costs: I obtain data on construction costs from R.S. Means, a consulting company and data provider for the construction industry. The dataset includes estimates of annual construction costs at the 3-digit zipcode level, which can vary by the size of the home and other characteristics such as whether the home has a basement. I use construction costs for a 1000 square foot, average quality home without a basement. Because not all 3-digit zipcodes are available, I average across locations to obtain a state-level measure of annual construction costs.

First Street Foundation Flood IQ Model: I obtain parcel-level estimates of flood probabilities from the First Street Foundation Flood IQ dataset as an independent assessment of flood risk that complements my flood maps from FEMA. This dataset includes estimates of the projected depth of flooding based on past major flood events, local adaptation measures such as the construction of dams/levees, and various scenarios for sea level rise.

4.4 Merge and Sample Selection

I merge both the McDash and HMDA datasets with Zillow ZTRAX to obtain the latitude and longitude coordinates of each property, as well as other characteristics of the properties which secure the mortgages. I first limit each dataset to purchase mortgages for single-family homes. To merge the McDash data with the ZTRAX deeds data, I conduct a fuzzy merge via the zip code of the house, origination date, the loan amount, the property value, and the maturity of the mortgage. For merging the HMDA data to the ZTRAX deeds data, I do a fuzzy merge via the zip code of the house, origination year, loan amount, and lender name. I followed closely the method outlined in Bayer et al. (2016), though with some modifications. This merging process is described in detail in Appendix A. I was able to merge 339,471 loans, representing approximately 75% of the McDash data, 50% of the ZTRAX data, and 30% of the HMDA data.[17]

With each mortgage geo-located in the merged sample, I can overlay the historic and current FEMA flood maps to obtain the mortgage's flood zone classification at origination. I then incorporate data on annual construction costs and flood insurance take-up rates at the zip code - flood zone - year level. I incorporate alternative flood risk measures from Flood IQ using a fuzzy match on addresses.

To construct the final sample, I drop any missing observations for interest rates, applicant income, property tax assessment values, building size, and construction costs. The final sample covers 299,907 mortgages over 837 zip codes, representing all 67 counties. Table 1 provides summary statistics for the analysis sample and the full HMDA, McDash, and ZTRAX samples. Although a subset of the input datasets, the final estimation sample appears fairly representative of the input data sets, even for the variables in McDash that were not used in the merge, such as credit scores, debt-to-income ratios, and interest rates.

[17] My match rates are slightly lower than those in Gerardi et al. (2020), which uses the matching algorithm by the Federal Reserve Bank of Philadelphia. They incorporate information from the restricted HMDA data, including the exact origination date (rather than origination year), and can match approximately 34% of mortgages in McDash, whereas I can only match 30%.

4.5 Descriptive Evidence

In this section, I show some initial cuts of the main sample by FEMA flood zone status. A striking pattern which emerges is that loan-to-value ratios are much lower in flood zones. I use the differences in the composition of flood zones to help motivate the empirical strategies in Sections 5 and 6.

Panel A of Table 2 shows summary statistics on mortgage characteristics at the loan level. Approximately 20% of the sample of mortgages are located in flood zones. A few notable patterns emerge when comparing mortgage characteristics by flood zone status. Mortgages in flood zones have lower loan-to-value ratios (89.3% versus 86.6%), slightly higher interest rates (4.19% versus 4.2%), and lower delinquency rates (3.79% versus 3.07%) than borrowers outside flood zones. Flood zones also have observably different composition of borrowers. On average, borrowers in flood zones have higher FICO credit scores (721 versus 728) and higher incomes ($76,000 versus $100,000). Additionally, the characteristics of the properties securing the mortgages also differ by flood zone. For example, property values are higher in flood zones ($205,000 versus $278,000). Appendix Table B.1 shows that flood zones have larger property sizes (1,869 square feet versus 1,967 square feet), a higher share of second homes, and a higher share of jumbo loans (1.69% versus 4.56%). There are therefore significant average differences in mortgage terms, borrower composition, and property characteristics.

Looking at distributions, Figure 2 shows that the distribution of mortgage terms in and out of flood zones. The distribution for interest rates looks very similar in and out of flood zones (2a). However, the distribution for loan-to-value ratios differs significantly (2b), with a much lower fraction of loans with high LTV lending (LTV > 85%).

Panel B of Table 2 shows zip code-level characteristics on flood insurance. Flood insurance takeup rates are much higher in flood zones, consistent with the mandatory purchase requirement and the fact that flood zones have more flood risk.[18] Claim probabilities are

[18] One may wonder why this number is not closer to 100%. This is because houses without a mortgage do not require flood insurance. In my sample, Florida's average mortgage share is about 40%, which implies a 63% takeup rate in flood zones assuming that the mortgage share is similar in and out of flood zones.

higher in flood zones, though average payouts conditional on filing a claim are roughly similar. This is consistent with documented evidence that individuals who voluntarily buy flood insurance outside of flood zones are likely to also face high flood risk (Bradt et al., 2021). The empirical analysis in Section 5 controls for flood insurance take up rates at the flood zone - zip code - year level to account for these patterns.

One may wonder whether the differences in mortgage terms are entirely driven by the observable differences in borrower composition and property values. In Table 3, I show that the broader patterns for LTV ratios (Column 1), interest rates (Column 2) and delinquencies (Column 3) hold even after including zip code - year fixed effects and controlling for credit score, income, and property values. With no controls or fixed effects, loan-to-value ratios are approximately 2.7 percentage points lower in flood zones. Including zip code-year fixed effects lowers the coefficient to approximately 1.9 percentage points, showing that much of the variation in loan-to-value ratios is across zip codes. Controlling for income, property value, and credit score further lowers the coefficient to approximately 87 basis points, showing that much of the reduction of LTVs in flood zones can be explained by observable differences in composition, but not all of it. With the fixed effects and controls, LTVs are 83 basis points lower in flood zones. All standard errors are clustered at the county level.

Column (2) shows that interest rates are only 1 basis point higher in flood zones, even after including the full set of controls and fixed effects. Column (3) shows that delinquency rates are on average 72 basis points lower in flood zones when we do not include any controls or fixed effects; however, after including the controls and fixed effects, delinquency rates are virtually the same in and out of flood zones, and the standard errors indicate this is a precisely estimated zero. These patterns are consistent with Hypothesis 1 and Hypothesis 2, outlined in Section 2.

A natural question is whether lenders have any motivation to screen for flood risk if

This estimate is consistent with FEMA's estimate of compliance as being close to 67%. Exact compliance is difficult to measure because flood insurance policies do not contain addresses.

mortgages are ultimately backed by the government-sponsored enterprises. Consistent with this intuition, Figure 3 shows that the effect of flood zone status on mortgage terms depends heavily on whether the mortgage is retained by the originating bank. Panel A shows that there is no statistically significant difference in loan-to-value ratios by flood zone when loans are purchased by government entities. However, loan-to-value ratios are on average more than 1.2 percentage points lower in flood zones when loans are kept by the originating bank. Panel B shows that interest rates are about 2 basis points higher on average for government-backed loans, but that they are not significantly different for loans retained by the originating bank.

4.6 Limitations of Descriptive Evidence

Taken together, the descriptive evidence shows that loan-to-value ratios are lower in flood zones, interest rates are slightly higher, and that delinquency rates are the same (with a precise zero). These patterns hold even after controlling for observable differences in the composition of mortgage borrowers, and are stronger for mortgages that are retained on lenders' balance sheets. This tells us that lenders bear less exposure to housing collateral in flood zones, and that lending in flood zones is not observably riskier than lending outside of flood zones.

What the descriptive facts do not tell us is why loan-to-value ratios are lower in flood zones. There are two possible explanations: a supply-side one, and a demand-side one. The supply-side explanation, consistent with the conceptual framework, is that lenders require higher downpayments in flood zones to manage their exposure to flood risk. Higher downpayments are effective because they lower expected losses by both lowering the probability of negative equity as well as the loss given default. On the other hand, there could also be a demand-side explanation driven by advantageous selection. In this channel, wealthier individuals who tend to have smaller loans also prefer to live in flood zones. This can occur because flood zones have unobserved amenities, such as water views and beach front access, which disproportionately attract wealthy people. I partly address this concern in Table 3 by controlling for applicant incomes, property values, and credit scores directly. Additionally, as argued in Section 2, wealthier people in equilibrium would not choose both lower LTVs and higher interest rates, which is what I find in the cross-section. However, the best way to address this demand-side explanation would be to obtain variation in flood risk that is exogenous to unobserved wealth. In Sections 5 the 6, I consider two sources of variation in flood risk that are plausibly exogenous to unobserved wealth.

5 Effect of Flood Insurance Cap on LTVs

In this section, I utilize the fact that government flood insurance contracts only cover up to $250,000 in damages to identify lender credit rationing in flood zones. The key intuition is that smaller homes can be completely insured, whereas larger homes are only partially insurable and therefore expose lenders to residual flood risk. I show that LTVs are insensitive to flood risk when the home can be completely insured, and are sensitive to flood risk when homes can only be partially insured. I also show that the relationship between flood zone status and LTVs changes at the flood insurance coverage limit, a result which is unlikely to be driven by other demand-side explanations.

5.1 Empirical Strategy

As discussed in Section 3, mortgage borrowers in flood zones are required to purchase flood insurance, and FEMA's NFIP insurance program dominates the market. The NFIP only provides up to $250,000 in coverage, and there are limited private options for excess flood coverage in Florida's highest risk flood zones. This leaves a large segment of homeowners in flood zones under-insured. I will exploit this setting to consider how access to full insurance changes mortgage contracts in flood zones.

Banks are not exposed to flood risk when homes are fully insurable because every dollar of flood damage is offset by a dollar of insurance payments and flood insurance is mandatory.[19] Therefore, banks do not need to adjust mortgage terms in flood zones when homes can be fully insured.

In contrast, when homes cannot be fully insured, banks retain exposure to flood risk because flood damages can exceed the flood insurance cap. Therefore, banks only have an incentive to ration credit in flood zones for under-insured homes. I formalize this point in Appendix Section C.2.

This leads to the following specification:

$$Y_{izt} = \alpha_{zt} + \beta_1 FloodZone_{it} + \beta_2 CapBinds_{it} + \beta_3 (FloodZone_{it} \times CapBinds_{it}) + \gamma' X_{it} + \varepsilon_{izt} \quad (1)$$

for a mortgage i originated in year t in a zip code z. The dependent variable Y_{izt} is either the loan-to-value ratio at origination, the interest rate at origination, or an indicator for whether the mortgage becomes delinquent by more than 30 days within the first three years of origination. The indicator $FloodZone_{it}$ equals one when the property is located in a FEMA-defined flood zone, and zero otherwise. The indicator $CapBinds_{it}$ equals one when the replacement cost of a home exceeds the flood insurance coverage limit, and 0 otherwise. The specification includes zip-year fixed effects in α_{zt}. These are important since they absorb any time-varying local shocks at the zip code level which could also influence loan-to-value ratios. I also include a rich set of mortgage and borrower controls in X_{it} to separate the independent effect of being in a flood zones from any effects due to differences in the composition of flood zones. Borrower characteristics include the borrower's FICO credit score and annual income at origination. Mortgage characteristics include the property value, maturity, debt-to-income ratio, and combined loan-to-value ratio for other liens on the property. I also include indicator variables for mortgage type, such as whether it is a first mortgage, second home, low grade mortgage, full document mortgage, jumbo loan, or

[19]Even if insured homeowners in flood zones choose to default after floods, lenders are still entitled to receive insurance proceeds in foreclosure (Hoberock and Griebel, 2018; Issler et al., 2019).

an adjustable rate mortgage. Finally, I control for flood insurance take-up rates which vary at the flood zone - zip code - year level. Standard errors are clustered at the county level.

The key parameters of interest are β_1 and β_3. For homes that can be fully insured ($CapBinds_{it} = 0$), loan-to-value ratios in and out of flood zones should be the same because banks are no longer exposed to flood risk and therefore do not need to ration credit. This suggests that the estimated coefficient $\beta_1 = 0$. For homes that cannot be fully insured ($CapBinds_{it} = 1$), loan-to-value ratios should be lower in flood zones, because banks retain exposure to flood risk. This suggests that the estimated coefficient $\beta_3 < 0$.

Measuring Whether the Insurance Cap Binds: To determine whether the insurance cover limit can bind, I consider whether a home's replacement costs at origination exceed the \$250,000 insurance cap. Replacement costs are defined as the cost of rebuilding the exact same home if it is totally destroyed, and are ubiquitously used by insurers to determine appropriate coverage amounts for an insurance policy. The idea behind this measure is that, if the home is completely destroyed, the homeowner pays the difference between the cost of rebuilding the home and insurance claim pay outs. The replacement cost depends on a variety of factors, including local construction costs, square footage, the quality of materials used to build the home, and other home features. I develop a proxy for this measure by multiplying construction costs for an average quality home (dollar per square foot) and the size of the home (square feet). I obtain annual construction costs for Florida from the R.S. Means company, and I obtain the building size from Zillow ZTRAX's assessment dataset (see Section 4 for more details). Figure 4b plots a histogram of this variable in and out of flood zones; the distribution is smooth through the \$250,000 coverage limit.

One might worry that floods do not cause high enough levels of damage for the insurance coverage limit to be relevant to banks. In Figure 4a, I plot the distribution of flood insurance claims for each replacement cost value. While large floods are rare, flood damages exceed the insurance for large homes roughly 10 percent of the time, showing that uninsurable damages are a relevant consideration for lenders.

Next, I estimate whether the effect of flood zone on loan-to-value ratios is larger for homes that have a larger portion of the home uninsured. To do so, I replace the $CapBinds_{it}$ indicator in Equation 1 with an indicator for replacement cost categories $RepCost_{k,it}$. I create these k categories using replacement cost increments of size \$25,000; for example, homes with an estimated replacement cost of \$100,000 and \$125,000 will be included in the same replacement cost category. I then estimate the following specification:

$$\begin{aligned} Y_{izt} = \alpha_{zt} + \delta FloodZone_{it} + \sum_{k \neq 75{,}000} \theta_k RepCost_{k,it} \\ + \sum_{k \neq 75{,}000} \phi_k (FloodZone_{it} \times RepCost_{k,it}) + \gamma' X_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

for a mortgage i originated in year t in a zip code z. As earlier, $FloodZone_{it}$ is an indicator variable which equals one for homes that are located in a FEMA-defined flood zone and zero otherwise. I include zip-year fixed effects α_{zt} and the same set of loan-level control variables in X_{it} that I used in Equation 1. The key parameters of interest here are the ϕ_k coefficients, which show the average reduction of loan-to-value ratios in flood zones for that replacement cost category relative to the omitted category of homes with replacement costs less than \$75,000. For homes with replacement costs less than \$250,000, I expect $\phi_k = 0$. For homes with replacement costs above \$250,000, I expect $\phi_k < 0$. Furthermore, I expect the effect of being uninsured to increase with how much of the home remains uninsured, with $\phi_{k+\$25{,}000} < \phi_k < 0$. Standard errors are clustered at the county level.

Finally, I seek to obtain an estimate of how much loan-to-value ratios respond to uninsurable risk in flood zone that can be interpreted as an elasticity. To do so, I estimate the following specification for those mortgages where replacement costs exceed the flood insurance cap:

$$
\begin{aligned}
Y_{izt} = \alpha_{zt} &+ \beta_1 FloodZone_{it} + \beta_2 \log InsGap_{it} \\
&+ \beta_3 (FloodZone_{it} \times \log InsGap_{it}) + \gamma' X_{it} + \eta_{izt}
\end{aligned} \tag{3}
$$

The dependent variable of interest Y_{izt} in this specification is the log loan-to-value ratio. The variable $InsGap$, or the insurance gap, is the uninsurable share of the home, defined as the replacement cost minus $250,000 divided by the property value. The key parameter of interest is β_3, which can be interpreted as how much loan-to-value ratios change with respect to a 1 percent change in the uninsurable share of the home for properties located in flood zones. This is a measure of the pass-through of insurance availability into mortgage contracts. Standard errors are clustered at the county level.

5.2 Identifying Assumptions

The key omitted variable in this setting is unobserved wealth, because wealthier people tend to choose mortgages with higher down payments. As a result, any trend in loan-to-value ratios may be driven by borrower preferences rather than lender risk management. I argue in Section 2 that this issue can be addressed by looking at both loan-to-value ratios and interest rates, since borrowers are less likely to choose higher down payments if they do not receive an interest rate advantage. However, here I try to deal with this endogeneity concern more directly by exploiting variation in flood risk exposure this is plausibly exogenous to unobserved wealth.

There are two particular endogeneity issues which arise because of unobserved wealth. First, wealthier people are more likely to live in flood zones because of unobserved amenities. Second, wealthier people are more likely to live in larger homes with higher replacement costs.

Equation 2 is a cross-sectional difference-in-differences design. The key identifying assumption is that, conditional on controls, there is no differential sorting of wealthy people into flood zones by home values. This approach accommodates a correlation between unobserved wealth and flood zone, as well as unobserved wealth and replacement costs. The key functional form assumption is that these biases are additive, meaning that the expected value of loan-to-value ratios for homes with no flood risk exposure can be written as the sum of a flood zone fixed effect and a replacement cost fixed effect.

To better understand this identifying assumption, consider the following stylized example, outlined in Appendix Figure B.1. There are four borrowers, A, B, C, and D. Borrower A buys a house in a flood zone with a replacement cost of $100,000, meaning that he is fully insured. Borrower B buys a house in a flood zone with a replacement cost of $300,000, meaning that borrower B is underinsured. The loan-to-value ratios of borrowers A and B differ primarily for two reasons; first, because B is likely to be wealthier than A, and second, because B has uninsurable flood risk while A does not. Thus a comparison of borrowers A and B does not identify the causal effect of interest. Now consider borrowers C and D. Suppose borrower C buys a $100,000 house outside a flood zone, and borrower D buys a $300,000 house outside a flood zone. Now, the loan-to-value ratios of borrowers C and D differ because D is wealthier than C–these homes are not in a flood zone and therefore have limited exposure to flood risk.[20] The difference-in-differences estimate of $LTV_A - LTV_B$ minus $LTV_C - LTV_D$ thus obtains the effect of flood risk on LTVs under the following key assumptions: that the effect of wealth on LTVs is the same in and out of flood zones, and that $\Delta Wealth_{A,B} = \Delta Wealth_{C,D}$. The latter assumption requires that the relationship between unobserved wealth and replacement costs is parallel in and out of flood zones.

Like most empirical designs, this exogeneity assumption cannot be tested directly because wealth is unobserved. However, it can be partially evaluated by observing whether the parallel relationship holds for income, the idea being that if there is no differential sorting by income, there is also unlikely to be differential sorting by wealth. Figure 4c is a binscatter

[20]Here this relies on the accuracy of the flood map. Comparisons with other private sources of information, such as the First Street Foundation, indicate that for Florida, more than 90% of homes are correctly classified.

plot showing how the relationship between income and replacement costs differs in and out of flood zones. The figure illustrates a few key points. First, the red diamonds representing homes in flood zones are always higher than the blue circles represents homes outside of floodzones, indicating that borrowers in flood zones tend to be richer than borrowers outside of flood zones. Secondly, we can see that both lines are upward sloping, that is richer people tend to buy larger homes with higher replacement costs. Most importantly, however, is that these two lines are parallel; for any two replacement costs, the income difference in flood zones is equal to the income difference outside of flood zones. This means that the line for flood zones is a level shift up of the line for homes outside of flood zones. If the relationship is similar for unobserved wealth, then the cross-sectional difference-in-differences design will obtain the causal effect of flood risk.

Similarly, another key implication of this design is that the relationship between mortgage terms and replacement costs for homes below the insurance cap are similar in and out of flood zones. This is because homes in flood zones below the insurance cap are fully insured against flood risk. In other words, I can check whether the coefficients for ϕ_k in Equation 2 equal to zero for homes with replacement costs less than 250,000. This would also support the identifying assumption.

5.3 Results

Table 4 reports the estimates of Equation 1 for loan-to-value ratios, interest rates, and delinquency outcomes. Column (1) shows that there is no significant effect of flood zone on loan-to-value ratios when homes can be completely insured. However, for homes that are under-insured, being in a flood zone leads to a 81 basis point (0.81 percentage point) reduction in loan-to-value ratios. For interest rates, Column (2) shows that interest rates do not do not respond to flood zone status, regardless of whether homes are above or below the insurance cap. Similarly, for delinquency rates, Column (3) shows there is no significant difference by flood zone regardless of whether borrowers are fully insured or under-insured.

Column (4) of Table 4 shows the results of estimating Equation 3. I find that in flood zones, a 1% increase in the share of the home that is uninsurable leads to a 0.87% decline in loan-to-value ratios at origination.

To test whether the results are driven by the flood insurance coverage limit, I consider how the effect of flood zone status on mortgages varies by the replacement cost of the home. Figure 5a plots the ϕ_k coefficients obtained by estimating Equation 2 for loan-to-value ratios. There is no average difference in loan-to-value ratios in and out of flood zones when replacement costs are lower than the \$250,000 coverage limit. However, once replacement costs pass the insurance coverage limit, loan-to-value ratios are significantly lower in flood zones. Furthermore, the magnitude of the coefficient increases with how much of the home remains uninsured. Homes with replacement cost of \$300,000 in flood zones have loan-to-value ratios are 1 percentage point lower than homes in the same group outside of flood zones. For homes with a replacement cost of \$425,000, loan-to-value ratios are more than 2.5 percentage points lower in flood zones.

In Figure 5b, I plot the ϕ_k coefficients obtained by estimating Equation 2 for interest rates. Interest rates are on average a few basis points higher in flood zones, although they are never significantly different in flood zones at any replacement cost level.

Figure 5c shows that on average delinquency rates are the same in and out of flood zones for each replacement cost category, conditional on observables. This suggests that loan-to-value ratios are reduced to the point that delinquency rates are equalized in and out of flood zones.

Taken together, Figure 5 and Appendix Figures 5c affirms Hypothesis 1 and 2 from Section 2 and are not consistent with a demand-side phenomenon where richer borrowers trade off smaller loan sizes to obtain lower interest rates. This shows that banks offer different mortgage terms to borrowers in flood zones, and that their primary margin of adjustment is through lower loan-to-value ratios rather than interest rates.

5.4 Robustness and Alternative Explanations

These results are robust to a number of alternate specifications. Appendix Table B.2 shows that these results hold even when restricting the sample to homes with replacement costs with \$100,000 of the flood insurance cap. In Appendix Table B.3 I report results for loan-to-value ratios using alternate measures of whether the flood insurance cap binds. The first measure considers whether the house price exceeds \$250,000, and the second measure uses property tax assessments to calculate the value of the structure, defined as the difference between the total assessed value of the home and the assessed value of the land. The results are similar using both measures of whether the flood insurance cap binds.

Another possibility is that the flood insurance coverage limit lines up with the conforming loan limit, which determines whether a mortgage is eligible to be securitized. The baseline conforming loan limit in my sample period is \$417,000, well above the insurance coverage limit of \$250,000. While there have been changes to the conforming loan limit in recent years, the FHFA did not make any changes to the conforming loan limit between 2006 and 2016, which covers the entirety of my sample. Appendix Figure B.2 shows that the conforming loan limit does not line up with the flood insurance coverage limit.

6 Real Effects of Updated Flood Maps and Bank Credit Rationing

This section employs a second source of variation in flood risk to investigate whether the lenders ration credit in flood zones. Rather than looking at insurance coverage limits, I use a difference-in-differences strategy which utilizes the staggered release of updated flood maps from FEMA that expand the boundaries of high risk flood zones. This leads to changes in flood risk assessments while fixing unobserved location-specific characteristics. I show that banks respond to the updated maps by requiring lower loan-to-value ratios, which in turn changes the composition of borrowers in flood zones towards richer people.

6.1 Background

In Section 4, I document that loan-to-value ratios are significantly lower in flood zones, even after controlling for the credit score, income, property value, and zip code-year fixed effects. In Section 5, I document that the cross-sectional relationship between loan-to-value ratios and flood zone status changes around the flood insurance coverage limit. This empirical strategy address the endogeneity of unobserved wealth under the identifying assumption that the relationship between unobserved wealth and replacement costs is the same in and out of flood zones. While I provide evidence from the cross-section, in this section I consider a second source of variation from the time series that does not rely on this identifying assumption.

In particular, I consider an experiment in which flood risk assessments are updated while other aspects of an area remain fixed, thus allowing me to obtain variation in flood risk assessments that are exogenous to unobserved amenities in a flood zone. Obtaining random variation in fundamental flood risk is challenging because flood risk changes extremely slowly over time. In this section, I follow the literature and consider variation in information about flood risk (Giglio et al., 2021a). I look particularly at information contained in the release of updated flood maps from FEMA. As discussed in Section 3.1, FEMA produces updated flood maps that include new data on elevation on land erosion which are essential inputs for modeling flood risk (National Research Council, 2007).

The release of an updated map has two effects. First, banks must update their compliance systems and notify any mortgage borrowers in newly mapped flood zones to buy flood insurance; this applies to both existing and new borrowers. In Appendix Table B.5, I verify that new borrowers in flood zones do also purchase flood insurance, showing evidence of lender compliance with the flood insurance mandatory purchase requirement.[21] Second,

[21] This is consistent with flood insurance take up evidence from Mulder, 2022.

these maps arguably provide new information that change flood risk assessments without changing other features of an area that can induce borrower selection, such as coastal amenities. These new flood maps are extremely costly to produce, and they often produce new data that are subsequently used by the private sector to model flood risk. I argue that banks free-ride on FEMA for this information, and in the rest of this section, I explore the informational effect on mortgage terms.

6.2 Empirical Specification

New flood maps do not always lead to heightened perceptions of risk. Some maps expand the boundaries of flood zones in a zip code while others may keep boundaries the same or even contract them. For example, flood boundaries may contract because communities construct levees and dams to manage water flow. On the other hand, flood boundaries may expand if new development raises the surface elevation of water. To understand in which direction the maps change risk assessments, I classify each zip code by whether the new maps expand flood zone boundaries or contract them. I make this determination by comparing the share of homes in a flood zone under the old map to the share of homes in a flood zone under the new map for a given zip code. I also check to make sure that the updated map is actually the expansion of an existing flood zone rather than a shift in the location of the flood zone by checking that homes in a flood zone under the old map are also in a flood zone under the new map. On average, for new maps that expand flood zone boundaries in a zip code, the zipcode share of homes in a flood zone increased by 30% (or by 4 percentage points).

To implement the difference-in-differences design, I restrict the sample and define treatment as follows. I first exclude any counties that are re-mapped multiple times in sample. Second, if a county c receives a new map, I classify a zip code z in that county as "treated" if the new map expands that zip code's flood zone boundaries. I exclude zip codes that do not change or have contracted boundaries because I want to isolate areas that lead to a heightened assessment of flood risk; I consider these zip codes in a robustness check. Third, because my sample spans 2010-2016, I limit to counties that are remapped in 2012, 2013, and 2014 to ensure I have enough years before and after the remappings. Appendix Figure B.3 shows which counties were remapped in which year. I exclude counties that do not receive an updated map between 2005 - 2016, but show in a robustness test that the results are not affected by including this never-treated group.

I estimate the following specification at the mortgage level:

$$Y_{i,c(z),t} = \alpha_{c(z)} + \delta_t + \sum_{h=-4}^{-2} \beta_h \mathbb{I}\{E_{i,c(z),t}^{Expanded} = h\} + \sum_{h=0}^{4} \beta_h \mathbb{I}\{E_{i,c(z),t}^{Expanded} = h\} + \gamma' X_{it} + \varepsilon_{i,c(z),t} \quad (4)$$

The dependent variable $Y_{i,c(z),t}$ is the mortgage's loan-to-value ratio at origination, interest rate, and other outcomes of interest. For each mortgage i that is originated at time t, I identify whether its county c receives an updated map, the year of the updated map $\tau_{c(z)}$, and whether it is in a treated zipcode z that has an expanded flood zone. I construct the event-time variable $E_{i,c(z),t}^{Expanded} = t - \tau_{c(z)}$ which reflects the origination year relative to the release of the county's updated map. The variable is defined for zipcodes where updated flood maps expanded flood zone boundaries. I include year fixed effects δ_t and county fixed effects $\alpha_{c(z)}$ which control for any unobserved year or county shocks. In some specifications, I also include FICO score and debt-to-income ratios as loan-level controls, represented by X_{it}. Treatment occurs at the county level since all communities in a county receive a new flood map at the same time. I therefore cluster standard errors at the county level (Bertrand et al., 2004).

The key parameters of interest in Equation 4 are the β_h coefficients on the event-time indicators which estimate the outcome at a given event-time relative to the omitted category $h = -1$, the year prior to the updated map.

Hypothesis 1 can be tested by using loan-to-value ratios as the dependent variable for Equation 4. Under Hypothesis 1, the coefficients on the event-time indicators after the remappings are negative, showing reduced loan-to-value ratios after the release of updated flood maps ($\beta_1, \beta_2, \beta_3, \beta_4 < 0$).

Hypothesis 2 can be tested by using interest rates as the dependent variable for Equation 4. Under Hypothesis 2, the coefficients on the event-time indicators after the remappings should not be negative, showing increased interest rates after the release of updated flood maps ($\beta_1, \beta_2, \beta_3, \beta_4 > 0$).

I also consider following pooled specification:

$$Y_{i,c(z),t} = \alpha_{c(z)} + \delta_t + \beta Post^{Expanded}_{c(z)t} + \varepsilon_{i,c(z),t} \tag{5}$$

The variable $Post^{Expanded}_{c(z)t}$ equals 1 after an area receives a map update and equals 0 beforehand. The variable is not defined for zipcodes who receive an updated floodmap that contracts flood zone boundaries. For my outcome variables $Y_{i,c(z),t}$, I consider delinquency rates, debt-to-to-income ratios, and maturity.

A key assumption of this approach is that loan-to-value ratios among the treated and control groups would have evolved in parallel in the absence of any re-mappings. Under the common trends assumption, for all dependent variables, coefficients on the event-time indicators before the remappings should be zero ($\beta_{-4}, \beta_{-3}, \beta_{-2} = 0$).

This empirical strategy uses variation in both the location and timing of the release of updated maps. Therefore another key assumption of this approach is that the timing of map updates is uncorrelated with other determinants of loan-to-value ratios. To help assess the validity of this assumption, Table 5 shows descriptive statistics on mortgages and flood insurance by remapping year. There are no systematic differences in most socio-demographic characteristics across zipcodes based on when they receive a new map. I also check FEMA's publications on how they prioritize new map updates to ensure their decision rule does not depend on variables that are endogenous to loan-to-value ratios. FEMA chooses to update maps if the prior map is very old or if there is evidence that the prior map is inaccurate, such as large losses or high insurance takeup outside of flood zone boundaries (National Research Council, 2007).

6.3 Main Results

The main results show that the remappings bring a decline in loan-to-value ratios, no change in interest rates, and a decline in delinquencies. The results are robust to a number of alternate specifications.

Figure 6a shows the shows the main difference-in-differences estimation results and plots the β_h coefficients from Equation 4 for loan-to-value ratios. Consistent with Hypothesis 1, loan-to-value ratios decline in the years following the introduction of the updated map. In the first year of the remapping, loan-to-value ratios decline on average by 40 basis points, though this result is not statistically significant. The reduction is larger in the second year, closer to 1.5 percentage points. By the third year, loan-to-value ratios are almost 2 percentage points lower in the treated group. This suggests that after the remappings expand flood zones boundaries in a zip code, borrowers on average receive loans with lower loan-to-value ratios. Importantly, the coefficient estimates from the pre-period support the parallel trends assumption.

Column (1) in Table 6 shows the estimation results for interest rates. Consistent with Hypothesis 2, interest rates are not significantly changed in the years following the introduction of the updated map, and on average slighly increase by 6 basis points. Taken together, the results suggest lenders reduce loan-to-value ratios and keep interest rates mostly the same, or if anything slightly higher.

The next results show the effects of the remappings on borrower composition. Figure 6b report the results using log income as an outcome variable, defined as annual applicant income reported in the HMDA data. In the first year after the remapping, log incomes significantly increase by 5%. In the second year after the remapping, log incomes increase by almost 10%, and this number increases further to 15% in the third year. Panel (B) shows similar results for FICO credit scores. Credit scores increase by 3 points in the first year after the remapping. Two years after the remapping they are 6 points higher, and three years after the remappings they are 8 points higher. There are also no visible pre-trends in either variables.

Table 6 shows the results for Equation 5. Column (3) shows that debt-to-income ratios on average reduce by 15 basis points in the post-remapping period, though not significantly so. The standard errors are less than 1 percentage point, suggesting a fairly precisely estimated zero effect on debt-to-income ratios. Column (4) shows that average mortgage maturity reduces by less than one month after the remappings, and this result is also not significant. The results suggest that loan-to-value ratios are the key margins of adjustment.

Column (2) of Table 6 shows the results for delinquency rates. Delinquency rates reduce on average by 1 percentage point after the mappings, although the result is not statistically significant at the 5% level. The sign suggests that lower loan-to-value ratios do have the intended effect of lowering delinquency rates.

The results for mortgage terms are robust to including credit scores and debt-to-income ratios as loan-level controls, as shown in Appendix Figure B.4. The magnitudes of the coefficient decline, indicating that about half of the decline in LTVs is related to changing borrower composition, but not all it. This implies that two borrowers with the same observable characteristics would indeed receive different mortgage terms after the remapping.

Heterogeneity

Figure 7 explores which types of borrowers have the largest LTV reductions. In Figure 7a, the sample is split into high and low credit score groups. Individuals with credit scores above 740 are referred to as superprime borrowers and rarely default on their mortgages or in credit card markets. For superprime borrowers, loan-to-value ratios actually increase on average after the remapping, though the results are not statistically significant. The reduction in loan-to-value ratios is entirely driven by borrowers with credit scores below 740, and not borrowers that are superprime. Figure 7b looks at income groups, defined as above or below the median income of $60,000, and shows that lower income borrowers experience significant higher downpayments, while loan-to-values do not significantly change for the higher income group. Lastly, Figure 7c shows that loan-to-values decline for borrowers buying lower priced homes, not higher priced ones. These groups of borrowers are less likely to prefer higher downpayments.

Additionally, I also find that the LTV reduction is stronger among mortgages that are above the flood insurance coverage limit (Appendix Figure B.6a) and among jumbo loans (Appendix Figure B.6b). These are mortgages such that lenders bear the residual insured risk, and are held on balance sheet. Though the results are not statistically significant, they qualitatively go in the right direction.

House Prices

An important question is whether the loan-to-value ratio reduction is driven through a property value channel, with property prices declining after the remapping, which in turn leads to an LTV reduction. Appendix Figure B.5 shows the decomposition of loan-to-value ratios for loan sizes (B.5a) and property values (B.5b) separately. Both loan sizes and property values of mortgage transactions begin increasing immediately after the remapping, with loan sizes increasing by less than property values on average. Importantly, this result does not imply that flood risk is positively capitalized into house prices. Figure B.5c shows that the types of homes which are transacted change after the remappings, shifting towards larger homes. Three years after the remappings, transacted homes are on average 100 square feet larger on average. This result is, however, consistent with lender credit rationing, which screens out lower income borrowers, leaving higher income borrowers who buy larger homes.[22]

[22]While the focus of this paper is on lender behavior, other studies have looked directly at the effect of

This is less consistent with a property price channel. Moreover, the literature examining property values mostly finds that house prices start capitalizing flood risk after 2014 (see, for example,bernsteinDisasterHorizonPrice2019 Baldauf et al. (2020)).

6.4 Addressing Remaining Demand Side Explanations

The lender screening argument is that, after remappings, homeowners are required to purchase flood insurance and lenders increase down payments. The combination of these two requirements then prevents more liquidity-constrained borrowers from moving into a zip code, because they cannot afford the out-of-pocket payments, leading to the observed change in borrower composition.

However, an alternative explanation could be that a perceived increase in flood risk following the remappings changes which types of borrowers live in flood zones. For example, only risk-seeking individuals that can bear flood risk may be willing to move to flood zones following a remapping. These individuals may generally prefer lower loan-to-value ratios. Alternatively, the remappings could bring in borrowers who do not believe in climate change. Such borrowers would also prefer lower LTVs if they believe that house prices are too low in flood zones, holding their housing consumption fixed.[23].

While borrower preferences and beliefs are not observed directly, Figure 8 considers three proxies that shed light on this question. First, Figure 8a shows that there is no significant change in the share of Republicans following the remappings, measured as the share of political donations going to the Republican party. The Republican share is a common proxy in the literature for climate change beliefs (for example, Baldauf et al., 2020)[24]. Secondly, I

remappings on the capitalization of flood risk into house prices. The closest in spirit is (Hino and Burke, 2021), who use a panel repeat-sales methodology where they look at home transaction prices for the same property before and after the remapping, and find that being zoned into a flood zone reduces property values by -2.1% on average, but the result is not statistically significant from zero.

[23]The sign for beliefs is less obvious, since an alternate story is that borrowers who do not believe in climate change that believe house prices are too low would prefer max out their leverage constraint and consume as much housing as possible

[24]Baldauf et al., 2020 using voting shares to measure beliefs, but because these do not change annually, I use the annual share of political donations, as done in Meeuwis et al., 2022)

use flood insurance deductibles to proxy for risk aversion, with risk-seeking people preferring lower deductibles, all else equal (Cohen and Einav, 2007). Figures 8b and 8c show that average building and contents deductibles for flood insurance contracts do not significantly change following the remapping.[25] These results suggest that borrower risk preferences and climate change beliefs do not significantly change following the release of the updated maps.

6.5 Robustness

This section of the paper employs a staggered difference-in-difference design, utilizing the variation in the timing of remappings. There are a few possible identification-related concerns about this approach. I consider them one-by-one, and offer robustness checks to address such concerns.

Never-treated counties

In the main specification of Equation 4, I exclude counties which do not receive updated flood maps at all, the so-called never-treated sample. I show in a robustness check that the main results are robust to including never-treated counties in the control group, defined as counties which do not receive updated flood maps between 2005-2016. Here, the event-time variable is defined for zipcodes where updated flood maps expanded flood zone boundaries and equals zero for never-treated counties in the control group which are not re-mapped between 2005-2016. Appendix Figure B.7 shows the main results when including these counties as part of the regression. We can see that the results for loan-to-value ratios, interest rates, incomes and credit scores are very similar in magnitude (in fact, the result for loan-to-value ratios is higher in magnitude).

[25]The results also hold when controlling for flood insurance premiums (not shown).

Unobserved County-Year Shocks

One possible identification-related concern is that the results may be driven by unobserved county-year shocks rather than the causal effect of the remapping. To address this concern, I conduct a placebo test by running the same staggered difference-in-differences specification for zipcodes that receive updated flood maps which do not change flood zone boundaries or slightly shrink them (by less than 1 percentage point). The idea behind this robustness check is that if my results were driven by unobserved county-year shocks that are unrelated to flood risk perceptions, then we would see similar effects in zip codes that receive a new map where boundaries do not change.

More specifically, I run the following model:

$$Y_{i,c(z),t} = \alpha_{c(z)} + \delta_t + \sum_{h=-4}^{-2} \beta_h \mathbb{I}\{E^{Placebo}_{i,c(z),t} = h\} + \sum_{h=0}^{4} \beta_h \mathbb{I}\{E^{Placebo}_{i,c(z),t} = h\} + \gamma' X_i + \varepsilon_{i,c(z),t} \quad (6)$$

The event-time variable $E^{Placebo}_{i,t,c(z)} = t - \tau_{c(z)}$ will be defined for zip codes which receive updated maps that do not change flood zone boundaries.

Appendix Figure B.8 plots the β_h coefficients of Equation 6. The results are starkly different for the placebo zip codes when compared to the zip codes with expanded boundaries. While the placebo group has a slight declines in loan-to-value ratios following the remappings, it is not statistically significant and the reduction never exceeds 1 percentage point. There are no significant changes in credit scores or log incomes following the remappings. Furthermore, the signs switch, with average credit scores and log incomes declining after the remappings. This suggests that unobserved county-year shocks do not drive the earlier results.

Staggered Design

The recent econometrics literature suggests that staggered difference-in-differences designs can be biased when treatment effects are heterogeneous by treated cohort and/or over time. The literature proposes a variety of approaches to address these concerns. Here, I consider the independent effect of the 2012 remappings, which employs a standard difference-in-differences design comparing counties remapped in 2012 to counties that are not remapped. This approach has the disadvantage that I cannot include year fixed effects, but has a straightforward interpretation of the dynamic treatment effects. Appendix Figure B.9 shows that the results for loan-to-value ratios, incomes, and credit scores are consistent with what I find in my staggered setting, and that there are parallel trends, helping to alleviate the concerns about the staggered design.

6.6 Magnitudes

One may wonder whether the observed reduction loan-to-value ratios is an over- or under-reaction relative to the true delinquency risk that banks face from floods. There are two pieces of evidence which suggest that the adjustjment by lenders is roughly correct.

First, the cross-sectional evidence in Table 3 and Appendix Figure 5c, suggests that the reduction in loan-to-value ratios leads to equal delinquency rates in and out of flood zones. If recovery rates conditional delinquency are equal in and out of flood zones, this result is consistent with a model in which banks adjust mortgage terms to equalize lending risks in and out of flood zones.

Second, a back-of-the-envelope calculation also suggests that the loan-to-value reduction is correct. The results in Section 5 and 6 show that lenders reduce LTVs by roughly 1 percentage point due to flood risk.[26] The key question is whether a 1 percentage point LTV reduction in flood zones effectively improves expected lender recovery enough to offset the

[26] Table 4 shows that LTVs are 81 basis points lower for under-insured borrowers in flood zones. Appendix Figure B.4a shows that, following the remappings, LTVs are 1 percentage lower after controlling for borrower characteristics.

increased risk from lending in flood zones. Lender recovery is unfortunately unavailable, but under the assumption that lender recovery rates and costs in delinquency are similar by flood zone, then one could examine whether the delinquency reduction from lower LTVs is similar to the delinquency risk from floods. The first question is what is the delinquency risk associated with floods? This boils down to obtaining the probability of uninsured losses over the mortgage. Homes in a flood zone have a 1% annual flood probability –this is the estimate provided by FEMA, and this also lines up with the annual probability of filing an insurance claim. Figure 4a shows that, conditional on having a flood, roughly 10% of floods cause damages that exceed the \$250,000 insurance coverage limit. The average mortgage duration in my sample is roughly 5 years (this also matches the national average, according to the Urban Institute). Thus, the probability of uninsured losses over the life of the mortgage is 50 basis points (1% $\times$ 10% $\times$ 5 years).

Now, the question is whether a 1 percentage point LTV reduction can lower delinquencies by 50 basis points. Panel (A) of Figure 6 shows that loan-to-value ratios decline by 2 percentage point after the remappings. Table 6 shows that delinquency rates decline by almost 1 percentage points after the remappings. Since a 2 percentage point LTV reduction is associated with a 1 percentage point decline in delinquency, this suggests that 1 percentage point LTV reduction would reduce delinquency rates by 50 basis points.[27]

Taken together, this suggests that reduced loan-to-value ratios bring lower delinquency rates, and that the level of adjustments successfully equalizes delinquency rates in and out of flood zones. Whether this is the optimal level of adjustment depends on assumptions about the distribution of flood damages, the elasticity of delinquency with respect to loan-to-value ratios at origination, and the competitive structure of lending markets. Future work will bring more evidence to bear on the correct modeling assumptions and parameter estimates.

[27]To know whether the adjustment is correct, one would ideally obtain a precisely estimated elasticity of delinquency with respect to LTV at origination.

7 Conclusion

Climate change is likely to intensify flood damage in the years to come. Policymakers are concerned about what this means for the financial system. Despite the large scale of the potential shock, there is limited empirical evidence on how flood risk is distributed among agents in residential mortgage markets.

To explore this question, this paper exploits two sources of plausibly exogenous variation in flood risk stemming from strict insurance coverage limits that leave some borrowers underinsured, and the release of updated flood maps that change lender assessments of flood risk and flood insurance requirements. I find that lenders adjust mortgage loan-to-value ratios to offload flood risk to the government flood insurer and mortgage borrowers. In turn, tighter credit changes the composition of flood zones to richer, higher credit quality individuals. Taken together, credit markets help to dampen taxpayers' exposure to flood risk by screening out individuals with less risk-bearing capacity away from high risk areas.

The results have several policy implications pertaining to whether climate change poses financial stability risks. The results on delinquencies suggests that the combination of flood insurance and lower loan-to-value ratios effectively protects the traditional banking system from flood risks held on balance sheet. Second, lenders also respond to the release of updated flood maps that change the boundaries of flood zones, showing that they can adapt dynamically to new information about climate risk. For regulators that are concerned about the systemic risk implications of climate change, these results may be heartening.

The results also shed light on the interaction between the government flood insurance program and mortgage markets. Mortgage lenders react optimally to the structure of the insurance program, thereby changing who benefits most from the program. The data shows that fully insurable mortgage borrowers benefit heavily from the flood insurance program because they do not get credit rationed. In contrast, borrowers buying larger homes that cannot be fully insured do get credit rationed. The results suggest that in the absence of a government insurance program, all mortgage borrowers would experience credit rationing, showing how flood insurance supports mortgage lending in high risk areas like flood zones.

While the results show that lenders risk management has real effects in terms of who lives in flood zones, there are several areas which can be addressed in future work. Government flood maps are the most widely agreed-upon measures of flood risk, yet are known to contain important gaps. Furthermore, the analysis sample is limited to the state of Florida, posing questions about whether the results may hold in other states where flood risk is less salient for lenders. I look forward to future work on these questions and more.

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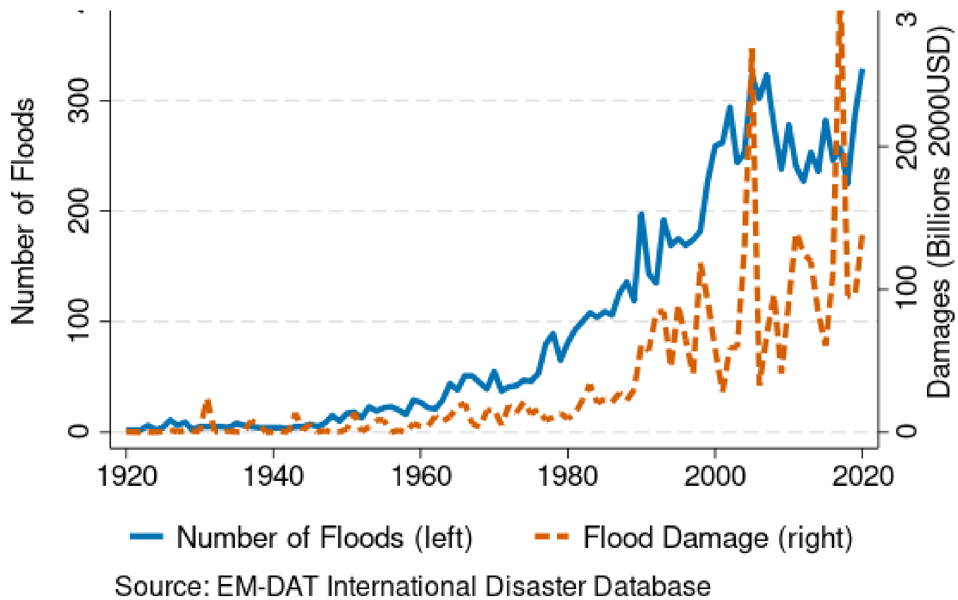
8 Figures and Tables

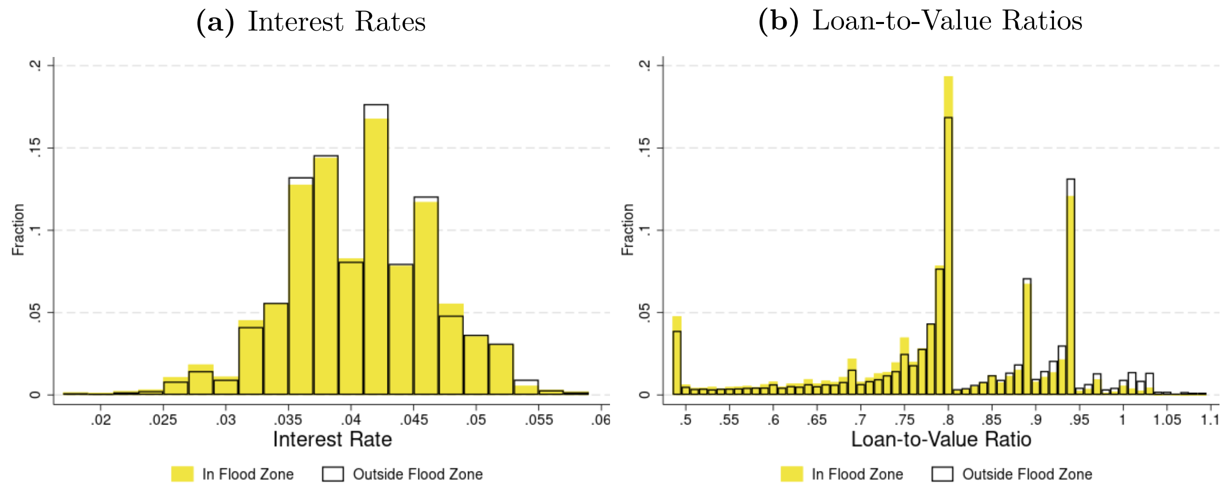
8.1 Figures

Figure 1: Worldwide Flood Disasters Over the Last Century



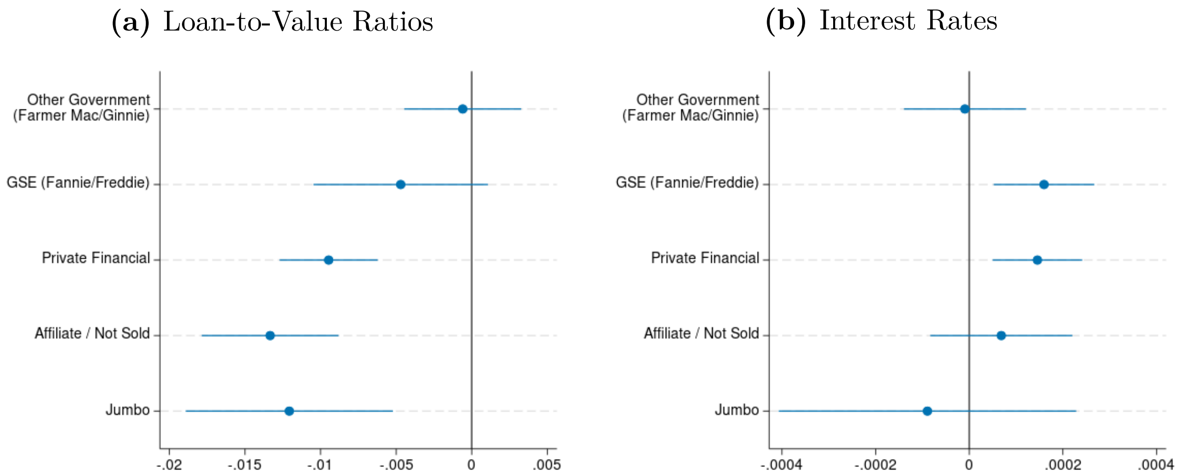
Notes: This graph plots a time series of the number of floods and total property damage caused by floods worldwide, as recorded in the Georeferenced Emergency Events Database (EM-DAT) atlas. To be recorded as a disaster in the database, an event must meet at least one of the following criteria: ten or more people reported killed, 100 or more people reported affected, a declaration of a state of emergency, and/or a call for international assistance.

Figure 2: Histograms of Mortgage Characteristics In and Out of Flood Zones



Notes: This figure plots histogram of interest rates (Panel A) and loan-to-value ratios (Panel B) by FEMA flood zone status for mortgages that are not backed by the Federal Housing Authority or Veterans Affairs.

Figure 3: Effect of Flood Zone on Loan-to-Value Ratio by Purchaser Type



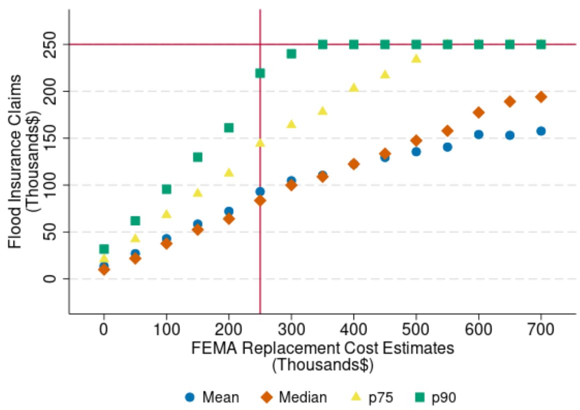
Notes: This figure explores how the effect of flood zone status on mortgage terms varies by who purchases the mortgage in the year it was originated. The figure reports the β_k coefficients from estimating the following specification:

$$Y_{ikzt} = \alpha_{zt} + \sum_k \delta_k Purchaser_{ikt} + \sum_k \beta_k (FloodZone_{it} \cdot Purchaser_{ikt}) + \gamma' X_{it} + \varepsilon_{ikzt}$$

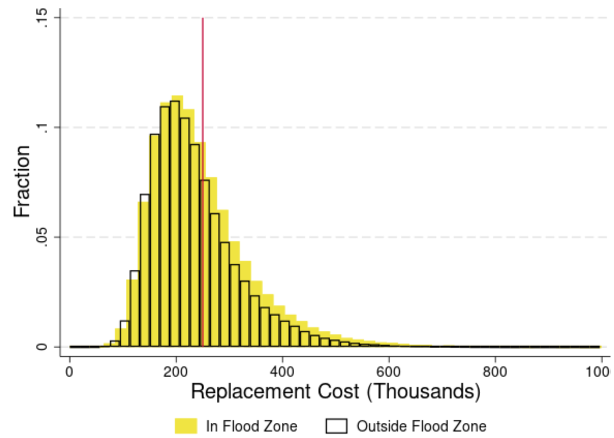
The dependent variable Y_{ikzt} is the mortgage's loan-to-value ratio in Panel (A), and the mortgage's interest rate in Panel (B). $FloodZone$ is a dummy variable for whether the mortgage is located in a FEMA flood zone when it was originated. $PurchaserType_k$ is an dummy variable that indicates whether the originating bank sold the mortgage to an institution of type k within the calendar year. Zip code-year fixed effects are denoted by α_{zt}. Control variables in vector X_{it} include the borrower's FICO credit score, annual income, and property value. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

Figure 4: Descriptive Facts about Replacement Costs

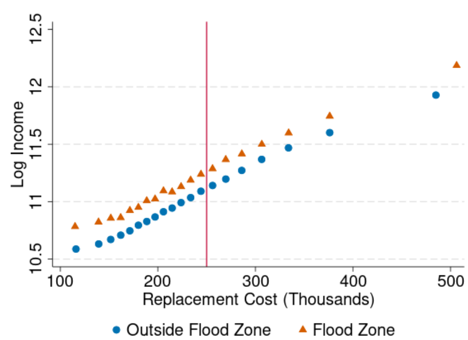
(a) Distribution of Insurance Claims



(b) Distribution of Replacement Costs



(c) Income and Replacement Costs



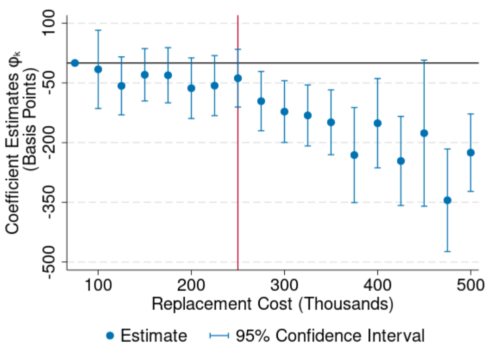
Notes: This figure shows three sets of descriptive facts about the relationship between replacement costs and insurance claims, flood zone, and income. Panel A plots the distribution of FEMA flood insurance claims paid out by building value as assessed by FEMA. To construct this chart, I split FEMA building assessment values into 15 bins using increments of $50,000. For each building value bin, I then calculate the average claim, median claim, and various percentiles of claims. The sample covers the full history of flood insurance claims for the five gulf states (Florida, Texas, Alabama, Mississippi, and Louisiana) spanning 2008-2018.

Panel B plots a histogram of replacement costs by FEMA flood zone status. Replacement costs are proxied as the product of the property's building size in square feet and construction costs for Florida, measured as dollars per square foot. The red vertical line references the $250,000 NFIP flood insurance coverage limit. Data on a property's building size comes from tax assessments in Zillow ZTRAX. Data on construction costs come from the R.S. Means Company.

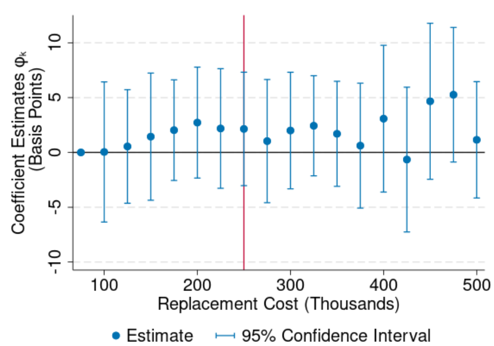
Panel C plots the relationship between log income and estimated replacement costs split by FEMA flood zone classifications for the main sample. To construct these binned scatterplots, the sample is divided into 20 equal-sized bins based on the ventiles of replacement costs. I then plot the mean of log income against the mean of replacement costs within each bin separately by whether the mortgage is in a FEMA flood zone.

Figure 5: Effect of Flood Zone on Mortgage Terms by Replacement Cost

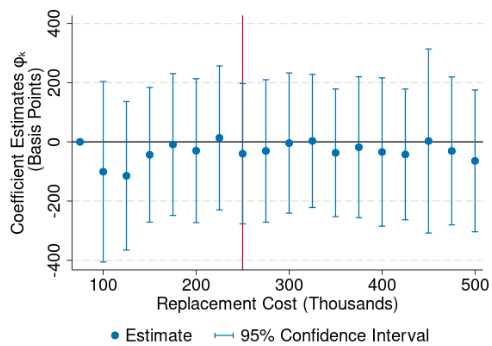
(a) Loan-to-Value Ratios (Basis Points)



(b) Interest Rates (Basis Points)



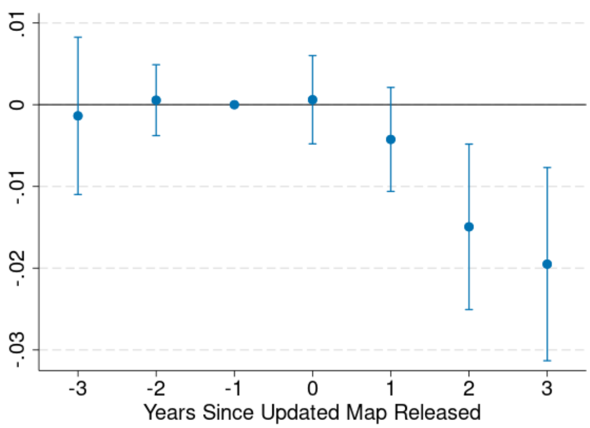
(c) Delinquency (Basis Points)



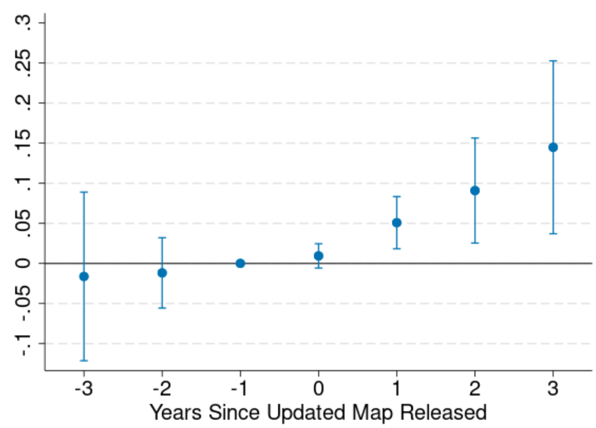
Notes: This figure plots the regression coefficients from Equation 2 in the text for LTVs (Panel A), interest rates (Panel B), and deliqnuency (Panel C). The regression estimates how the effect of FEMA flood zone classification on mortgages varies by the property's replacement cost. *Delinquency* is a dummy variable that indicates whether a mortgage becomes delinquent for at least 30 days within the first three years of origination. Replacement costs are calculated as the product of the property's building size in square feet and construction costs for Florida, measured as dollars per square foot. Replacement costs are grouped into categories by increments of $25,000. Each dependent variable is regressed on a dummy variable indicating that the loan is in a flood zone interacted with a dummy for each replacement cost category. The category for replacement costs lower than $75,000 is omitted. All estimates can be interpreted as the effect of flood zone for that replacement cost category relative to the effect of the omitted category. The regression includes zip code-year fixed effects and a rich set of control variables which include the borrower's FICO credit score, annual income, combined loan-to-value ratio for other liens on the property, property value, maturity, debt-to-income ratio, and dummy variables which indicate first mortgages, second homes, low grade mortgages, full document mortgages, jumbo loans, and adjustable rate loans. I also control for flood insurance take-up rates at the flood zone - zip code - year level. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

Figure 6: Dynamic Effects of Updated Flood Maps on Mortgages and Borrowers

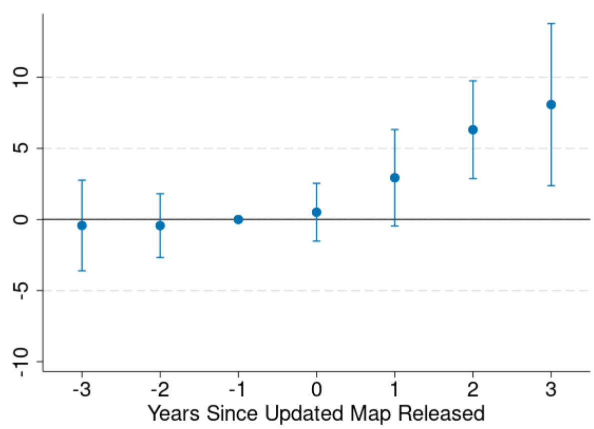
(a) Loan-to-Value (Percentage Points)



(b) Log Income



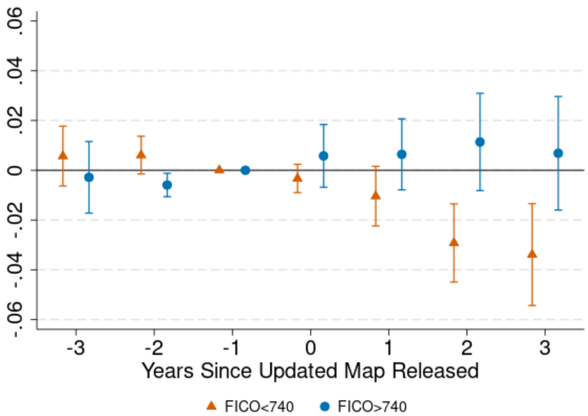
(c) Credit Scores



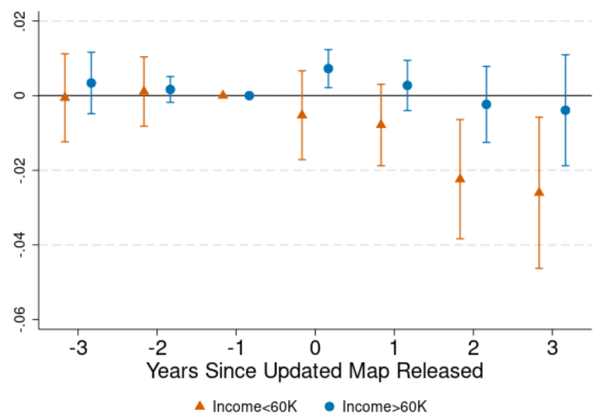
Notes: This figure reports estimates of the effect of updated FEMA flood maps that expand flood zone boundaries and tests Hypotheses 1 and 2 from Section 2. The dependent variables are loan-to-value at origination (Panels A), log income (Panel B), and credit scores (Panel C). The figures report the coefficients from estimating Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released. The regression also includes year fixed effects and county fixed effects. All estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

Figure 7: Dynamic Effects of Updated Flood Maps on Loan-to-Value Ratios: Heterogeneity

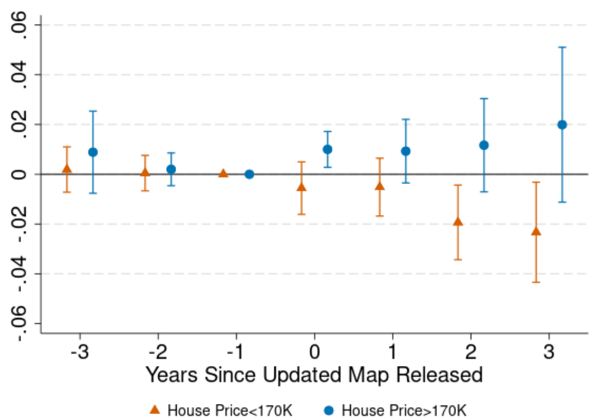
(a) By Credit Score



(b) By Income



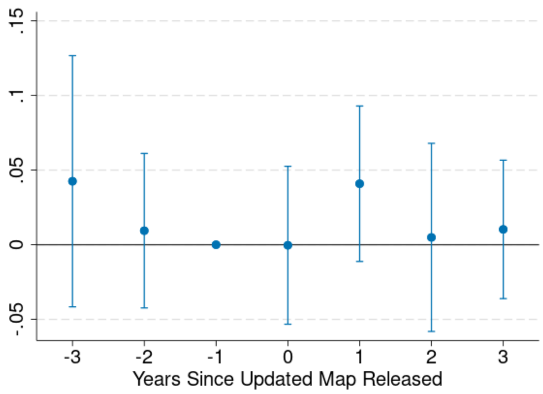
(c) By Property Value



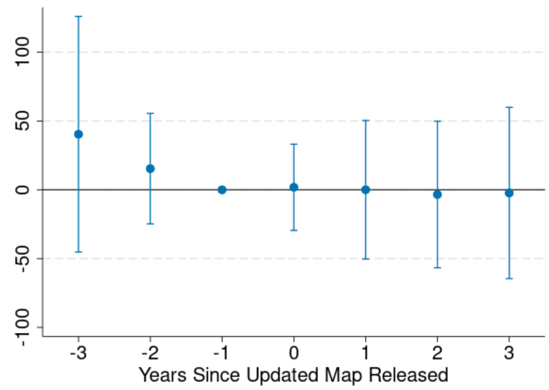
Notes: This figure shows how the effect of updated FEMA flood maps that expand flood zone boundaries on LTVs varies across subsamples. In Panel A, the sample is split by whether the borrower has a FICO score above or below 740. In Panel B, the sample is split by whether borrower income is above or below \$70,000 (the sample median). In Panel C, the sample is split by whether the house price is above or below \$170,000 (the sample median). The figures report the coefficients from estimating Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released. The regression also includes year fixed effects and county fixed effects. All estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

Figure 8: Dynamic Effects of Updated Flood Maps on Borrower Preferences

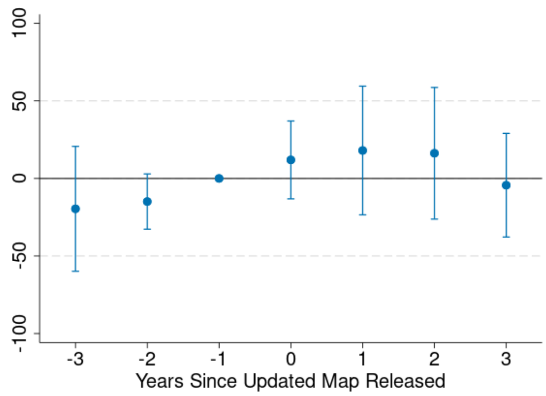
(a) Republican Share



(b) Average Building Deductible



(c) Average Contents Deductible



Notes: This figure reports estimates of the effect of updated FEMA flood maps that expand flood zone boundaries on proxies for borrower preferences. The dependent variables are the share of political donations going to the Republican party in a zip code (Panel A), average building deductibles for flood insurance contracts in a zip code (Panel B), and average content deductibles for flood insurance contracts in a zip code (C). The figures report the coefficients from estimating Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released. The regression also includes year fixed effects and county fixed effects. All estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

8.2 Tables

Table 1: Merge Diagnostics

	Final Sample		McDash		ZTRAX		HMDA	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Applicant Income ($000s)	80.85	99.33					87.91	90.79
Loan Amount ($000s)	187.2	132.7	193.5	113.7	178.1	108.1	199.4	113.5
Property Value ($000s)	219.8	188.4	231.1	155.3	216.7	154.8		
Maturity (months)	354.7	30.18	351.0	39.14	333.3	85.74		
Interest Rate (%)	4.192	0.588	4.172	0.607				
Combined LTV (%)	89.69	11.52	88.06	12.19				
Credit Score	722.5	55.57	725.2	55.78				
DTI Ratio (%)	35.19	14.20	34.74	14.18				
LTV Ratio (%)	88.74	13.22	87.14	13.15				
Obs.	299,907		457,145		683,158		1,128,023	

Notes: This table shows summary statistics for the key mortgage characteristics in the final merged dataset and each of the three input datasets, namely the McDash, Zillow ZTRAX, and Home Mortgage Disclosure Act (HMDA) data. The ZTRAX, McDash, and HMDA datasets are restricted to purchase mortgages for single-family homes for Florida from 2010-2016. The data for ZTRAX, McDash, and HMDA are also trimmed at the 1% level, since there are large outliers in loan amounts, property values, and income which could not be matched.

Table 2: Summary Statistics

	FloodZone		NonFloodZone	
	mean	sd	mean	sd
Panel A: Loan Characteristics				
Credit Score	727.5	54.3	721.3	55.8
Applicant Annual Income ($000s)	100.0	143.4	76.3	84.9
Property Value ($000s)	278.7	291.4	205.7	150.7
LTV (%)	86.6	14.1	89.3	13.0
Interest Rate (%)	4.20	0.60	4.19	0.59
Delinquent Share (%)	3.07	17.3	3.79	19.1
Maturity (months)	354.4	31.0	354.8	30.0
DTI (%)	34.8	14.5	35.3	14.1
Combined LTV (%)	88.0	11.9	90.1	11.4
Observations	57,648		242,259	
Panel B: Flood Insurance Characteristics				
Takeup Rate (%)	25.8	18.4	6.65	8.85
Claim Probability (%)	1.53	4.31	1.16	2.91
Claim ($000s)	13.7	15.4	13.9	17.4
Assessed Building Value ($000s)	192.5	218.9	195.1	198.4
Observations (Zip-Year)	5,598		5,598	

Notes: This table provides summary statistics on mortgage and flood insurance characteristics a for the estimation sample and provides a breakdown by FEMA flood zone status. Panel A focuses on mortgage characteristics. Panel B focuses on flood insurance. The policy-level data from FEMA on flood insurance is anonymized, but includes identifying information about zip code, flood zone classification, and year in force. For each zip code - year combination, I calculate take up rates inside of flood zones and outside of flood zones. To do so, I use Zillow ZTRAX property assessment data to obtain counts of the number of housing units in and out of flood zones. This table presents the overall average and standard deviation for those zip code - year level observations.

Table 3: Descriptive Facts

	(1) Loan-to-Value Ratio	(2) Interest Rate	(3) Delinquency
Panel A: Excludes Controls and Zip-Year Fixed Effects			
FloodZone	-0.0268***	0.0000	-0.0072**
	(0.0054)	(0.0003)	(0.0035)
Adjusted R^2	0.01	0.00	0.00
Panel B: Excludes Controls, Includes Zip-Year Fixed Effects			
FloodZone	-0.0187***	-0.0002***	-0.0040***
	(0.0023)	(0.0000)	(0.0010)
Adjusted R^2	0.13	0.42	0.06
Panel C: Includes Controls, Excludes Zip-Year Fixed Effects			
FloodZone	-0.0087*	0.0007***	0.0014
	(0.0047)	(0.0002)	(0.0023)
Adjusted R^2	0.19	0.09	0.05
Panel D: Includes Controls and Zip-Year Fixed Effects			
FloodZone	-0.0083***	0.0001***	-0.0004
	(0.0016)	(0.0000)	(0.0008)
Observations	299,907	299,907	299,907

Notes: This table shows the results of a cross-sectional linear regression that tests Hypotheses 1 and 2 from Section 2 by exploring the relationship between FEMA flood zone status and mortgage characteristics. The three dependent variables are the mortgage's loan-to-value ratio, interest rate, and delinquency which is a dummy variable that indicates whether the mortgage becomes more than 30-days delinquent within the first three years of origination. *FloodZone* is a dummy variable which indicates whether the mortgage is located in a FEMA flood zone when it was originated. Control variables include the borrower's credit score, income, and property value, and are only included where indicated. Panel (A) runs the regression without any control variables or fixed effects. Panel (B) includes zip code- year fixed effects but no control variables. Panel (C) includes control variables but no fixed effects. Panel (D) includes both fixed effects and the control variables. Standard errors are reported in parentheses and are clustered at the county level. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01)

Table 4: Effect of Capped Flood Insurance on Mortgages in Flood Zones

	Full Sample			Replacement Cost Above 250K Cap
	LTV (1)	Interest Rate (2)	Delinquency (3)	log(LTV) (4)
CapBinds	0.0053***	-0.0001**	-0.0008	
	(0.0012)	(0.0000)	(0.0006)	
FloodZone	-0.0010	0.0000	-0.0007	-0.0176***
	(0.0020)	(0.0001)	(0.0016)	(0.0036)
CapBinds × FloodZone	-0.0081***	0.0000	0.0004	
	(0.0019)	(0.0000)	(0.0011)	
log(InsGap)				0.0087***
				(0.0009)
FloodZone × log(InsGap)				-0.0087***
				(0.0016)
Adjusted R-Squared	0.4756	0.5785	0.1573	0.4307
Zip-Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	299,907	299,907	299,907	104,257

Notes: This table tests Hypothesis 1 and 2 from Section 2 by exploring the effect of flood insurance coverage limits on the relationship between FEMA flood zone status and mortgages. The first three columns report the coefficients estimating Equation 1 for three different dependent variables: the mortgage's loan-to-value ratio (Column 1), the mortgage's interest rate (Column 2), and a dummy variable which indicates whether the mortgage becomes more than 30-days delinquent within the first three years of origination (Column 3). Column (4) reports the coefficients estimating Equation 3 for log LTVs as the dependent variable. *FloodZone* is a dummy variable for whether the mortgage is located in a FEMA flood zone when it was originated. *CapBinds* is a dummy variable for whether the home's replacement cost exceeds the flood insurance coverage limit of \$250,000. *InsGap* is defined by dividing the excess replacement cost above \$250,000 by the property value at origination. Columns (1)-(3) include the full sample. Column (4) restricts the sample to homes with replacement costs that exceed \$250,000. The regression has zip code-year fixed effects where indicated. All specifications control for flood insurance take-up rates at the floodzone-zip code-year level as well as loan-level variables, which include the borrower's FICO credit score, annual income, combined loan-to-value ratio for other liens on the property, property value, maturity, debt-to-income ratio, and dummy variables which indicate first mortgages, second homes, low grade mortgages, full document mortgages, jumbo loans, and adjustable rate loans. Standard errors are reported in parentheses and are clustered at the county level. Significance Levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

Table 5: Descriptive Statistics by Remapping Year for Loans Originated in 2010

	2012		2013		2014		P-
	Mean	SD	Mean	SD	Mean	SD	Value
Panel A: Loan Characteristics							
Number of Loans	2,314		3,015		2,575		.
LTV (%)	89.1	15.4	91.7	11.6	88.1	14.8	.11
Interest Rate (%)	4.93	.45	4.9	.47	4.87	.48	.21
Loan Amount ($000s)	147	102	145	84.2	150	96.4	.95
Property Value ($000s)	176	152	163	116	179	137	.83
Maturity (months)	356	27	356	26.9	355	29.5	.55
Credit Score	645	217	631	220	648	220	.03
Annual Income ($000s)	67.3	81.6	64.7	66.8	67.6	60.2	.96
Combined LTV (%)	17.8	35.5	17.9	36.2	19.3	36.8	.64
Replacement Cost ($000s)	22.6	7.64	21.7	7.99	21.7	8.04	.78
Building Size (Square Feet)	1,913	648	1,837	677	1,839	682	.78
Jumbo Loan Share (%)	1.16	10.7	.56	7.48	1.04	10.2	.64
Panel B: Flood Insurance Characteristics							
Number of Zip Codes	59		54		52		.
SFHA Takeup (%)	19.2	11.8	25.6	12.1	33.9	16.4	.1
Non-SFHA Takeup (%)	7.57	6.69	4.68	3.4	7.37	5.98	.14
SFHA Claim Probability (%)	.08	.43	.05	.21	.01	.07	.14
Average Claim ($000s)	17.5	11.3	21.6	15.6	21.8	13.9	.36
ACS Housing Units (000s)	11.1	5	13.6	6.21	12.1	5.58	.19
Panel C: Other Zip Characteristics							
ACS Population Growth	.05	.11	.1	.29	.04	.15	.27
HMDA Denial Rate (%)	22.4	4.65	22.9	6.6	20.6	5.16	.21

Notes: This table presents average loan-level and zip-level characteristics for mortgages originated in 2010. The sample is restricted to those zip-codes which subsequently receive an updated map that expands flood zone boundaries. Mortgages are grouped by which year the associated county receives an updated map, and statistics on the average and standard deviation are presented. The last column indicates the p-value for the joint test that the means for each remapping year are the same. The acronym "SFHA" refers special flood hazard areas, which are the official names for the FEMA-defined flood zones.

Table 6: Pooled Effect of Updated Maps on Mortgages

	(1) Interest Rate	(2) Delinquency	(3) DTI Ratio	(4) Maturity
Post	0.0006	-0.0098***	-0.2720	-0.0548
	(0.0007)	(0.0024)	(0.2529)	(0.3786)
Adjusted R-Squared	0.39	0.05	0.05	0.00
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	55,692	55,819	19,505	55,819

Notes: This table reports estimates of the effect of updated flood maps that do expand flood zone boundaries on delinquencies, debt-to-income ratios, and maturity. It reports the coefficients from the difference-in-differences regression in Equation 5. $InterestRate$ is the mortgage's interest rate at origination, measured in percentage points. $Delinquency$ is a dummy variable that indicates whether a mortgage becomes more than 90-days delinquent within the first three of origination. $DTIRatio$ is the mortgage's debt-to-income ratio at origination. $Maturity$ is the mortgage's maturity at origination, measured in months. $Post$ is a dummy variable that indicates whether that mortgage is originated on or after the introduction of the updated flood map. Post equals zero in the pre-remapping period. The regression also includes year fixed effects and county fixed effects. Standard errors are clustered at the county level. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

A Internet Appendix: Data

To construct the final dataset, I first processed historical FEMA flood maps, and then I geo-located the BlackKnight McDash mortgage dataset so I could overlay the current and historical flood maps. Finally I geo-located the Home Mortgage Disclosure dataset so I could include borrower's annual income at origination. In this section, I outline the details for each step of the merging process.

A.1 Processing Floodmaps

FEMA Remapping Dates: The first step of the process was to obtain the history of map revision dates for each county in Florida. For each county in Florida, I downloaded the current and historical Flood Insurance Studies from FEMA Flood Map Service Center, a section of FEMA's website. In recent decades, when FEMA chooses to update flood maps, it conducts flood insurance studies for all communities in a given county. The final study is published in a technical report on the same day as the finalized flood maps. Each Flood Insurance Study includes a table titled "Community Map History", which includes the community name, date of the first effective flood map, and subsequent revisions to flood maps at the commmunity level. I supplement the data in this table with the dates of all Flood Insurance Studies, since all the communities in a county receive new maps at the same time and sometimes these tables do not include more recent studies. After these steps, I obtained a data set with the history of flood map revision dates for each county.

Digitizing Flood Maps: The next step of the process is to obtain digitized current and historical flood maps. As explained in Section 4, FEMA's flood maps delineate the boundaries of high and moderate flood risk zones. The highest risk zones are called "special flood hazard areas (SHFAs)", and are denoted as either Zone A or Zone V on maps. For my estimation, I needed flood maps which would be valid for each county throughout my sample period, so that I could correctly define an indicator for a mortgage's SFHA status at origination. Digitized maps refer to georeferenced shapefiles or geodatabases Some current and historic flood maps are available directly from FEMA's Flood Map Service Center. I also downloaded additional FEMA flood maps from online geospatial databases at the University of Texas, Princeton University, Harvard University, Berkeley, and the University of Florida. Specifically, University of Texas, Princeton, and Berkeley's geospatial libraries include snapshots of the "Q3 Flood Data", which digized FEMA flood maps from 1996 for a select number of counties in Florida. Harvard's Geospatial Library include a snapshot of flood maps for Florida from 2011. The University of Florida Geographic Data Library retained digitzed flood maps for a handful of counties in Florida between 2001 and 2009. While some were available for download online, others were shared with me from the library's archives. I then compared my map dates with the list of map revisions to determine which revision date would be reflected by the version of the map I had.

For some zip codes in Levy, Calhoun and Clay counties, digitized flood maps that would be valid at the beginning of my sample were not available from FEMA or in the university repositories. I downloaded PDFs of the paper maps for each community from FEMA's map service center, and digitized the FIRMS for these counties myself using ArcGIS Pro.

After this step, I had shapefiles for each county in Florida which would be valid throughout my sample period of 2010-2016 and a list of each county's flood map revision dates.

A.2 ZTRAX-McDash Merge

The next step is to geo-locate the BlackKnight McDash mortgage data by merging it with Zillow ZTRAX. I first limit both the McDash and ZTRAX data to purchase mortgages. I limit to purchase mortgages because ZTRAX data coverage of refinances is less reliable, and because it is much more difficult to have a good metric of house value for refinances. In McDash, the transaction is a purchase mortgage for single family homes when the variable PurposeOfLoanId equals one and when the variable PropertyTypeCode equals one. In ZTRAX, I identify mortgage transactions by keeping transactions with nonmissing LoanAmounts that are greater than zero, by dropping transactions that are cash sales (SalesPriceAmountStndCode="CS"), keeping deed transfers only (DataClass= "D" or "H"), and dropping arms-length transactions (SalesPriceAmount = 0). I drop refinances and other types of mortgage transactions (defined as LoanTypeStndCode equals "RE", or LoanTypeSt = "AC", "CT","CS", "CC", "CL", "DP", "FO", "FE", "HE", "LC","MD","CM","RM","RD","SM","SE","SL","TR", "PM", or "AS"). In Zillow, single family homes are defined as transactions where PropertyUseStndCode equals "SR", "RR", or is missing.

After limiting both datasets to purchase mortgages, I round loan amounts to the nearest $10,000, and then I merge both datasets on 3-digit zip codes, year of closing, and rounded loan amount. This gives me an m:m match, where each transaction in both datasets are linked to multiple transactions in the other dataset. I then use the following algorithm to choose which match to keep.

First, if the five-digit zip code is available in McDash, then I keep the matches where the zip code is an exact match; otherwise, I keep the three digit match.

Next, I keep the matches with the closest loan amount, house price, and maturity. To do so, I first calculate a distance metric by taking the sum of the squared difference between the McDash and ZTRAX dataset for each variable. Next, I rank each match based on the distance metric for each ZTRAX loan and for each McDash loan. Transactions which are ranked first for both datasets are considered a match. These are then removed from the dataset, and I then redo this step for the remaining unmatched loans. I iterate this process seven times.

Lastly, I remove any matches where the closest house price exceeds $10K or there is more than a 12 month difference in maturity. Because ZTRAX includes a parcel's latitude and longitude, this merge leads to a dataset where mortgages in McDash are geolocated. I am able to merge 83% of transactions in McDash using this algorithm.

Having obtained the latitude and longitude for each mortgage in McDash, I use the stata function geoinpoly to obtain each mortgage's flood zone classification under all available maps of the county. The final flood zones were the classification for under whichever map would have been valid at the time the mortgage was originated.

A.3 ZTRAX-HMDA Merge

For merging the HMDA data to the ZTRAX deeds data, I do a fuzzy merge via the zip code of the house, origination year, loan amount, and lender name. I followed closely the method outlined in Bayer et al. (2016) and Billings (2019), with some minor modifications. I first limit both datasets to purchase mortgages for single family homes, which in HMDA can be obtained by limiting to property types that equal one and loan purposes equal to one. For ZTRAX, I obtain both the 2000 and 2010 census tracts for the loan by overlaying current and historical census shapefiles from the census website. HMDA uses the 2000 census tracts for the 2010 and 2011 LAR files, and uses the 2010 census tracts for the years thereafter.

I then merge the two datasets on the basis of census tract, rounded loan amount, and origination year. The transactions with unique matches are treated as final. For transactions with multiple matches, I keep matches which have the closest lender name and loan amount. I use the stata "matchit" function to develop a similarity score of lender names.

Using this algorithm, I am able to merge 40% of the data in HMDA.

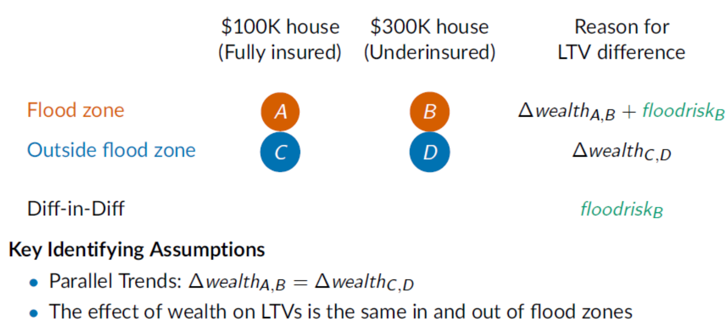
A.4 Validity of ZTRAX data

I use the ZTRAX assessment data to obtain the share of each zip code in a SHFA under each vintage of the county's floodmap. I ensure that the data is reliable by comparing overall numbers to housing unit counts from the American Community Survey. In general, the number of housing units in ZTRAX is close to the American Community Survey data at both the county-year level and at the zip-year level. At the county level, there is a 99.6% correlation between the two datasets. At the zipcode level, there is a 95% correlation between the two datasets.

B Internet Appendix: Supplementary Tables and Figures

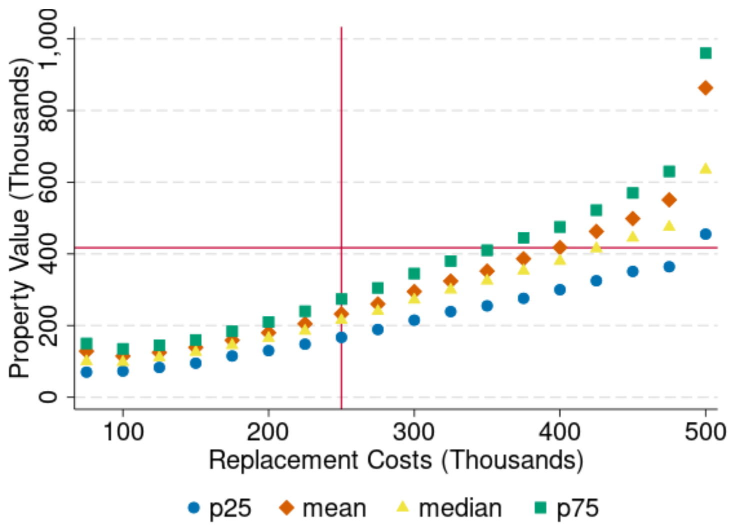
B.1 Figures

Figure B.1: Intuition for Cross-Sectional Difference-in-Differences Design



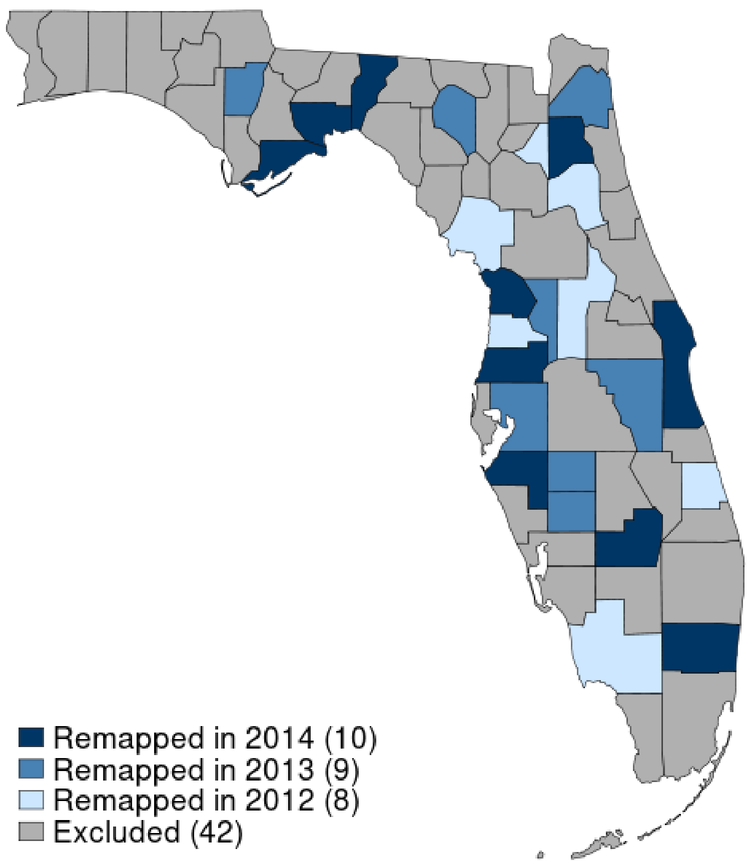
Notes: This figure illustrates the identification strategy and assumptions behind Equation 1, as described in Section 5.2. A, B, C, D represent the loan-to-value ratios of four different borrowers, who differ by whether they live in a flood zone or not, and whether they can be completely insured or not.

Figure B.2: The Distribution of House Prices by Replacement Cost



Notes: This figure plots the relationship between the distribution of house prices and estimated replacement costs. To construct this figure, the sample is divided into 20 equal-sized bins based on the ventiles of estimated replacement costs. I then plot the mean and percentiles of house prices for each separate replacement cost bin. The vertical line indicates the $250,000 flood insurance coverage limit. The horizontal red line indicates the minimum $416,000 conforming loan limit for securitization. Replacement costs are proxied as the product of the property's building size in square feet and construction costs for Florida, measured as dollars per square foot.

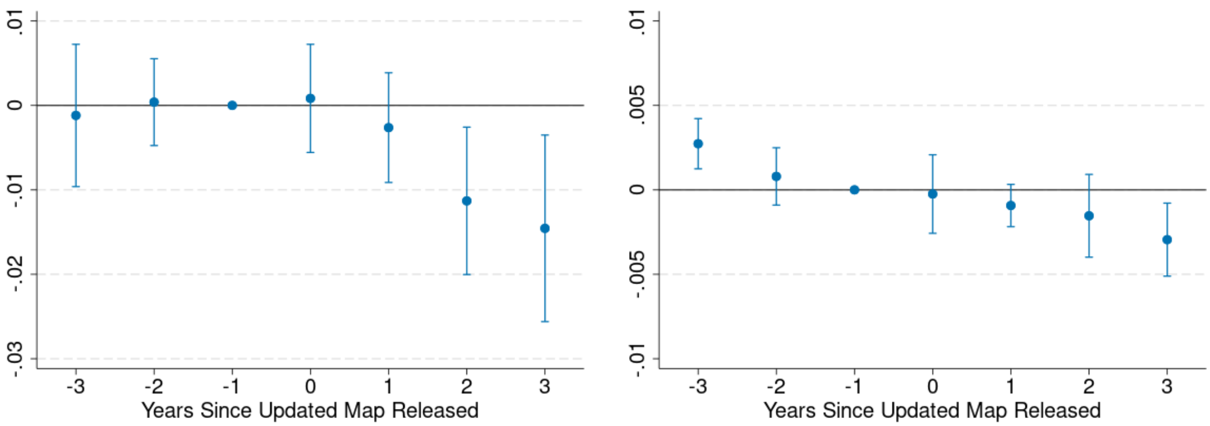
Figure B.3: Release Year of Updated Flood Maps by County



Notes: FEMA issues updated flood maps for all communities within a county at the same time. This map shows the year that each county receives an updated flood map for those areas that are included in my sample as treated counties. I also identify those areas which do not receive any new maps between 2005-2016 (in gray).

Figure B.4: Dynamic Effects of Updated Flood Maps: Robustness to Loan-Level Controls

(a) Loan-to-Value Ratios **(b)** Interest Rates



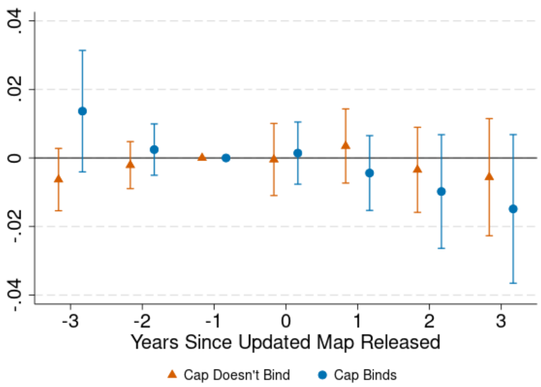
Notes: This figure reports estimates of the effect of updated flood maps that expand flood zone boundaries on loan-to-value ratios (Panel A) and interest rates (Panel B) after including the mortgage's debt-to-income ratio and credit scores as loan-level controls. It reports the coefficients from Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released. The dummy for relative year -1 is the omitted category, so all estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level. The regression also includes year fixed effects and county fixed effects.

Figure B.5: Dynamic Effects of Updated Flood Maps on Transacted Properties

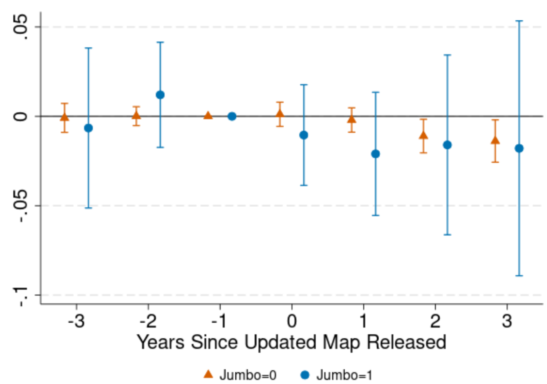
Notes: This figure reports estimates of the effect of updated FEMA flood maps that expand flood zone boundaries. The dependent variables are log loan amount (A), log property value (B), and building size (C). The figures reports the coefficients from estimating Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable rate on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released. All estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level. The regression also includes year fixed effects and county fixed effects.

Figure B.6: Dynamic Effects of Updated Flood Maps on LTV: Heterogeneous Effects

(a) By Whether the Insurance Cap Binds

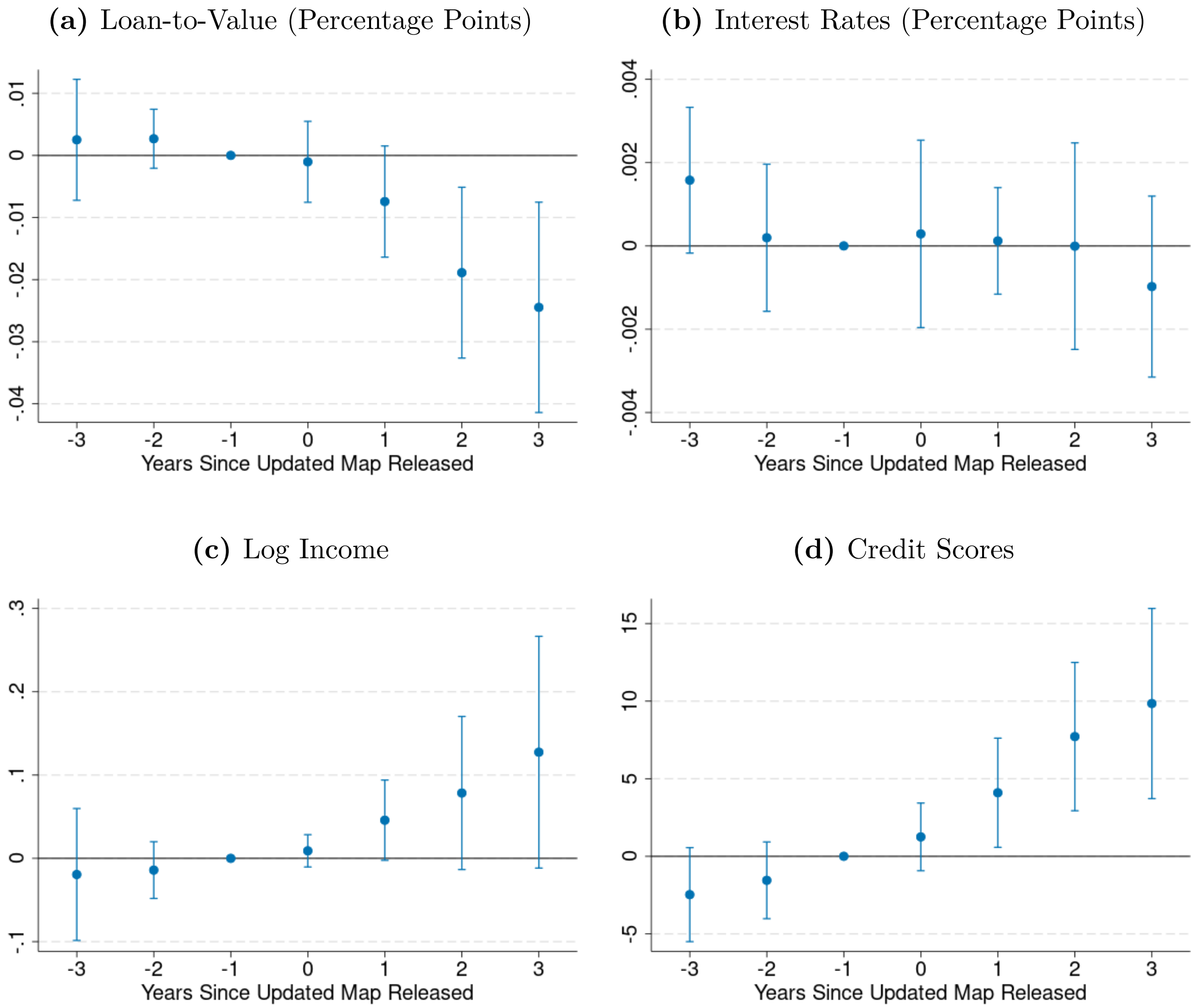


(b) By Jumbo Status



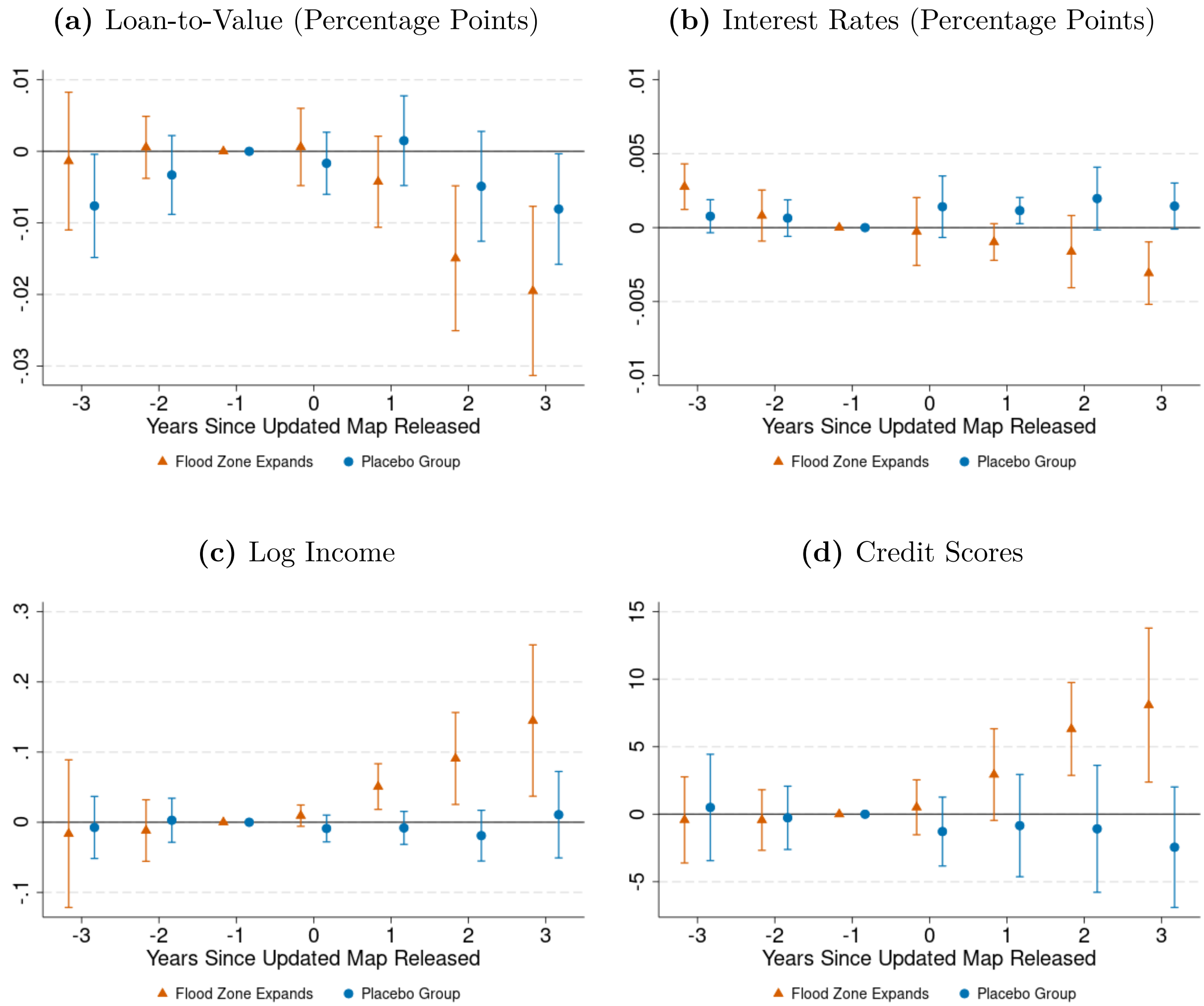
Notes: This figure reports estimates of the effect of updated FEMA flood maps that expand flood zone boundaries on loan-to-value ratios by different subsamples, after including the mortgage's debt-to-income ratio and credit scores as loan-level controls. In Panel A, the sample is split by whether the borrower's estimated replacement cost is above or below the flood insurance coverage limit of $250,000. The sample here is limited to loans with replacement costs between $150,000 and $350,000. In Panel B, the sample is split by whether the mortgage is classified as a Jumbo loan or not, where a jumbo loan is not eligible to be securitized by the government sponsored enterprises. The figures reports the coefficients from estimating Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable rate on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released. The regression also includes year fixed effects and county fixed effects. All estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

Figure B.7: Dynamic Effects of Updated Flood Maps: Robustness to Never-Treated Groups



Notes: This figure reports estimates of the effect of updated flood maps that expand flood zone boundaries on loan-to-value ratios (Panel A), interest rates (Panel B), log income (Panel C), and credit scores (Panel D). It reports the coefficients from Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released or indicates that the county is never treated, meaning it does not receive an updated flood map between 2005-2016. The dummy for relative year -1 is the omitted category, so all estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level. The regression also includes year fixed effects and county fixed effects.

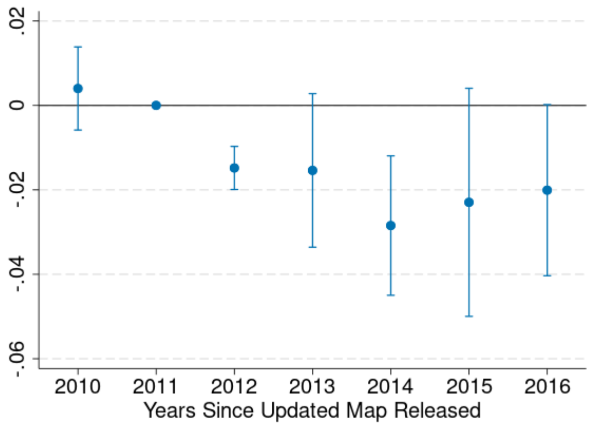
Figure B.8: Dynamic Effects of Updated Flood Maps on Borrowers: Placebo Test



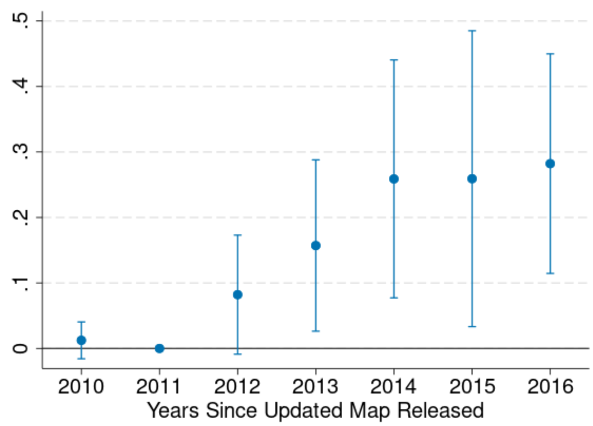
Notes: This figure reports estimates of the effect of updated FEMA flood maps on mortgage borrower characteristics, and splits the sample by whether the updated flood maps expand flood zone boundaries (orange triangle) or leave flood zone boundaries unchanged (blue circle). The dependent variables are the mortgage loan-to-value-ratio (Panel A), interest rate (Panel B), log of the borrower's annual income (Panel C), and FICO credit scores (Panel D) at origination. It reports the coefficients from Equation 6, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each dependent variable on a series of event-time dummy variables indicating the year relative to the release of the updated map. Relative year zero is the year that the map was released. The regression also includes year fixed effects and county fixed effects. All estimates can be interpreted as the effect relative to the year prior to the updated map. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

Figure B.9: Dynamic Effects of Updated Flood Maps: Robustness to Staggered Design

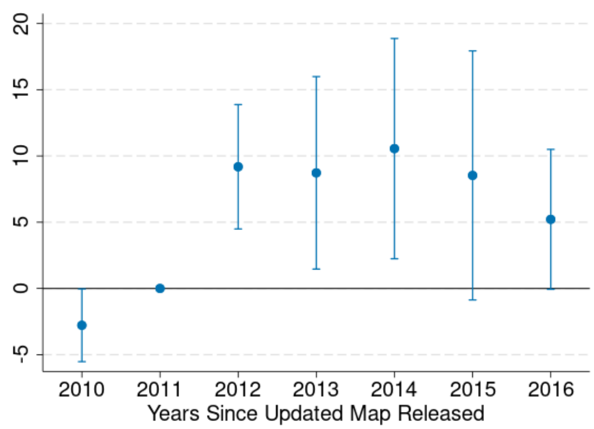
(a) Loan-to-Value (Percentage Points)



(b) Log Income



(c) Credit Score



Notes: This figure reports estimates of the effect of the 2012 FEMA remappings on mortgage borrower characteristics in a standard difference-in-differences design. Estimates were constructed by regressing loan-to-value ratios on a year dummy variables for a treated group that received an updated map, and a control group consisting of counties which do not receive updated maps in my sample (the so-called never-treated groups). The regression includes county fixed effects. All estimates can be interpreted as the effect relative to the year prior to the updated map, 2011. The 95 percent confidence intervals are based on standard errors which are clustered at the county level.

B.2 Tables

Table B.1: Additional Summary Statistics on Loan Characteristics

	FloodZone		NonFloodZone	
	mean	sd	mean	sd
Loan Amount ($000s)	227.6	191.3	177.6	112.3
DTI (%)	34.8	14.5	35.3	14.1
Second Home Share (%)	6.33	24.4	4.93	21.7
Low Grade Share (%)	2.34	15.1	2.39	15.3
FHA or VA Share (%)	44.3	49.7	52.6	49.9
Full Document Share (%)	51.2	50.0	51.7	50.0
Jumbo Loan Share (%)	4.56	20.9	1.69	12.9
Replacement Cost ($000s)	247.4	101.4	234.9	87.3
Building Size (Square Feet)	1966.9	798.0	1869.0	685.6
CapBinds (Yes/No)	39.0	48.8	33.9	47.4
Observations	57,648		242,259	

Notes: This table provides summary statistics on mortgage characteristics for the estimation sample and provides a breakdown by FEMA flood zone status.

Table B.2: Effect of Capped Flood Insurance on Mortgages in Flood Zones

	Replacement Costs Between 150K and 350K		
	LTV (1)	Interest Rate (2)	Delinquency (3)
CapBinds	0.0031***	-0.0001**	-0.0002
	(0.0009)	(0.0000)	(0.0007)
FloodZone	-0.0025	0.0001	0.0004
	(0.0023)	(0.0001)	(0.0015)
CapBinds × FloodZone	-0.0044***	-0.0000	-0.0002
	(0.0014)	(0.0000)	(0.0011)
Adjusted R-Squared	0.4718	0.5668	0.1612
Zip-Year FE	Y	Y	Y
Controls	Y	Y	Y
Observations	234,280	234,280	234,280

Notes: This table tests Hypothesis 1 and 2 from Section 2 by exploring the effect of flood insurance coverage limits on the relationship between FEMA flood zone status and mortgages. It reports the same regression as the first three columns in Table 4 but limits the sample to homes with replacement costs that are within $100,000 of the flood insurance cap. The table reports the coefficients estimating Equation 1 for three different dependent variables: the mortgage's loan-to-value ratio (Column 1), the mortgage's interest rate (Column 2), and a dummy variable which indicates whether the mortgage becomes more than 30-days delinquent within the first three years of origination (Column 3). *FloodZone* is a dummy variable for whether the mortgage is located in a FEMA flood zone when it was originated. *CapBinds* is a dummy variable for whether the home's replacement cost exceeds the flood insurance coverage limit of $250,000. The regression has zip code-year fixed effects where indicated. All specifications control for flood insurance take-up rates at the floodzone-zip code-year level as well as loan-level variables, which include the borrower's FICO credit score, annual income, combined loan-to-value ratio for other liens on the property, property value, maturity, debt-to-income ratio, and dummy variables which indicate first mortgages, second homes, low grade mortgages, full document mortgages, jumbo loans, and adjustable rate loans. Standard errors are reported in parentheses and are clustered at the county level. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table B.3: Robustness: The effect of flood zone on LTV by whether the flood insurance cap binds using alternate measures

	(1) OriginalLTV	(2) OriginalLTV
HPriceGt250K	-0.0041	
	(0.0032)	
FloodZone	-0.0018	-0.0010
	(0.0019)	(0.0020)
HPriceGt250K × FloodZone	-0.0067***	
	(0.0017)	
StructValGt250K		0.0053***
		(0.0012)
StructValGt250K × FloodZone		-0.0081***
		(0.0019)
Adjusted R-Squared	0.4756	0.4756
Zip-Year FE	Y	Y
Controls	Y	Y
Observations	299,907	299,907

Notes: This table shows the results of a cross-sectional linear regression that explores the effect of flood insurance coverage limits on the relationship between FEMA flood zone classification and mortgages. The dependent variables is the mortgage's loan-to-value ratio (LTV) at origination. $FloodZone$ is a dummy variable for whether the mortgage is located in a FEMA flood zone when it was originated. $StructValGt250K$ is a dummy variable for whether the home's assessed structure value exceeds the flood insurance coverage limit of $250,0000. To construct this variable, I subtract assessments of land values from assessments of total property value. $HPriceGt250K$ is a dummy variable for whether the house price at origination exceeds the flood insurance coverage limit of $250,000. All specifications include zip code-year fixed effects, a control for flood insurance take-up rates at the flood zone-zip code-year level, and loan-level controls which include the borrower's FICO credit score, annual income, combined loan-to-value ratio for other liens on the property, property value, maturity, debt-to-income ratio, and dummy variables which indicate first mortgages, second homes, low grade mortgages, full document mortgages, jumbo loans, and adjustable rate loans. Standard errors are reported in parentheses and are clustered at the county level. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table B.4: Pooled Effect of Updated Maps on Mortgages: Robustness to Including Never-Treated Groups

	(1) Delinquency	(2) DTI Ratio	(3) Maturity
Post	-0.0139***	-0.2621	-0.0407
	(0.0036)	(0.4505)	(0.3800)
Adjusted R-Squared	0.05	0.05	0.00
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	59,416	20,696	59,416

Notes: This table reports estimates of the effect of updated flood maps that do expand flood zone boundaries on delinquencies, debt-to-income ratios, and maturity. It reports the coefficients from the difference-in-differences regression in Equation 5. *Delinquency* is a dummy variable that indicates whether a mortgage becomes more than 90-days delinquent within the first three of origination. $DTIRatio$ is the mortgage's debt-to-income ratio at origination. $Maturity$ is the mortgage's maturity at origination, measured in months. *Post* is a dummy variable that indicates whether that mortgage is originated on or after the introduction of the updated flood map. Post equals zero in the pre-remapping period and for never-treated counties in the control group that do not receive an update flood map between 2005 - 2016. The regression also includes year fixed effects and county fixed effects. Standard errors are clustered at the county level. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table B.5: Effect of Updated FEMA Flood Maps on NFIP Flood Insurance Takeup Rates

	(1) $\Delta TakeupRates_z$	(2) $\Delta LapseRates_z$
$\Delta FloodZoneShare_z$	0.2410***	-0.3137***
	(0.0113)	(0.0118)
Constant	-0.0157***	-0.0139**
	(0.0024)	(0.0057)
Observations	356	356
Adjusted R^2	0.57	0.39

Notes: This table shows the results of a cross-sectional linear regression exploring the relationship between the change in flood insurance take-up rates ($\Delta TakeupRates_z$) and the change in the number of homes mapped in a flood zone following the issuance of an updated flood map ($\Delta FloodZoneShare_z$). Flood insurance take-up rates are defined as the number of NFIP flood insurance policies divided by the total number of homes according to the Zillow ZTRAX. Flood zone shares are defined as the number of homes mapped in a flood zone under the FEMA valid flood map divided by the total number of homes according to Zillow ZTRAX. I construct the dependent and independent variables as follows. I first construct the flood insurance take-up rate and share of a zip code in a flood zone at the zipcode-year level. I then take the average across years within each zip code to obtain the average in the pre-remapping period and the average in the and post-remapping period for each zipcode. Standard errors are reported in parentheses and are clustered at the county level. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

C Internet Appendix: Model

In this section, I adapt a Holmstrolm and Tirole (1998) model to illustrate this intuition behind the hypotheses in Section 2. This is a special example of a larger class of models based on Stiglitz and Weiss (1981) about credit rationing in the presence of imperfect information. In this setup, the key friction in the model is moral hazard from strategic default. I first consider the case where there is no insurance in Section C.1, and then introduce capped flood insurance in the extension Section C.2.

C.1 Baseline Case: No Insurance

Setup: I consider a static, two-period, partial equilibrium model with three ingredients: household strategic default, costs of financial distress, and endogenous loan sizes and interest rates. The model abstracts from flood insurance; Appendix C.2 considers an extension of the the model with incomplete flood insurance.

In the first period (t=1), a risk-neutral borrower with linear utility purchases a home worth P_0 using a mortgage. The borrower borrows L from the risk-neutral bank, paying a downpayment of $P_0 - L$ from her own income Y. The borrower promises to pay the lender the balance B in the second period (t=2). The fraction $\frac{B-L}{L}$ represents the interest rate on the loan.

Between the first and second period, the household may experience a flood, which occurs with probability q. The flood causes property damage that changes the value of the home from P_0 to $\tilde{P}$, which is defined over the support $[\underline{P}, P_0]$ and follows some distribution F, and density f. With probability $1-q$ there is no flood, and the house price remains P_0.

In the second period, if there is a flood, the household can choose whether to default or repay the loan. If the household chooses to default, the bank receives the flooded home, and the household incurs some utility cost of default $C > 0$. This parameter captures the harm to the borrower's credit rating, the transaction costs of default, and any personal moral or psychological dislike of default. If the household repays, the household keeps the flooded home but pays B to the lender. I assume that if there is no flood, the value of the home stays at P_0 and the household always repays.

To allow for gains from trade, I assume the lender is more patient than the borrower, meaning that the lender's discount rate η exceeds the borrower's discount rate δ. Both discount rates are assumed to be positive and less than 1. For simplicity, the price of the home P_0, the household's income Y, and the costs of financial distress C are assumed to be exogenous to flood risk q.

Default Rule: After a flood, households will strategically default when their payoffs from repaying the loan are less than their utility cost of default, that is when $\tilde{P} - B < -C$. The household's expected utility is given by

$$U(L,B) = Y - \underbrace{(P_0 - L)}_{\text{downpayment}} + \underbrace{\delta q \int_{\underline{P}}^{B-C} (-C) dF}_{\text{flood: default}} + \underbrace{\delta q \int_{B-C}^{P_0} (P - B) dF}_{\text{flood: no default}} + \underbrace{\delta(1-q)(P_0 - B)}_{\text{no flood}} \tag{7}$$

The lender's expected profits are given by

$$\Pi(L,B) = -L + \eta q \int_{\underline{P}}^{B-C} P dF + \eta q \int_{B-C}^{P_0} B dF + \eta(1-q)(B) \tag{8}$$

With perfectly competitive lending markets, households will maximize their expected utility $U(L,B)$ subject to the lender's zero profit constraint $\Pi(L,B) = 0$. The optimal loan repayment B is implicitly defined by the following first order condition:

$$\underbrace{(\eta - \delta)(1-q)}_{\uparrow\text{repayment when there is no flood}} + \underbrace{(n - \delta) q \int_{B-C}^{P_0} dF}_{\uparrow\text{repayment from non-defaulters in a flood}} \underbrace{- \eta q C f(B-C)}_{\uparrow\text{Default}} = 0 \tag{9}$$

The first order condition highlights the key tradeoff in the model. An increase in the repayment amount B

leads to increased payment to the bank from non-defaulters, but at the cost of also increasing the probability of strategic default at the margin.

We can now consider how the optimal loan size (L) and repayment amount (B) change with flood risk q.

Proposition 1 (Credit Rationing): *An increase in the probability of a flood (q) leads to a lower equilibrium repayment balance B and a lower loan amount L.*

Intuition: When the probability of a flood increases, banks lower the repayment amount B to lower the mass of borrowers that strategically default. However, doing so means they also earn less from non-defaulters. Therefore, they must also lower the loan size L in the first period to satisfy their zero profit constraint. Below, I derive the expressions for these two comparative statics ($\partial L/\partial q$ and $\partial B/\partial q$) and discuss the technical conditions for both expressions to be negatively signed. In the above, property values P_0 are fixed, so lowering L is equivalent to lowering the loan-to-value ratio L/P_0.

Proof. In the model, I make two assumptions to ensure the model has an interior solution. First, I assume the lender's profit function increases in loan repayment, that is $\partial\Pi/\partial B > 0$. That is,

$$\eta q(-C)f(B-C) + \eta q\int_{B-C}^{P_0} dF + \eta(1-q) > 0 \tag{10}$$

Secondly, for the first order condition to represent a maximum, I assume that the second order condition holds. That is,

$$-(\eta-\delta)qf(B-C) - \eta qCf'(B-C) < 0 \tag{11}$$

Applying the implicit function theorem to the FOC in Equation 9 yields that $\partial B/\partial q < 0$:

$$\frac{\partial B}{\partial q} = -\frac{-(\eta-\delta)F(B-C) - \eta Cf(B-C)}{-(\eta-\delta)qf(B-C) - \eta qCf'(B-C)}$$

The denominator is negative by the assumption about the second order condition. The numerator is negative because probability distributions and densities are positive, $\eta > \delta > 0$, and because $C > 0$.

Implicitly differentiating the zero profit condition with respect to q yields that $\partial L/\partial q < 0$:

$$\frac{\partial L}{\partial q} = \underbrace{\eta\int_{\underline{P}}^{B-C}(P-B)dF}_{<0} + \underbrace{\frac{\partial B}{\partial q}}_{<0}\underbrace{\left[\eta(1-q) + \eta q\int_{B-C}^{P_0} dF - \eta qCf(B-C)\right]}_{>0}$$

The term in brackets is equivalent to Equation 10 and is therefore positive by assumption. ■

Proposition 2 (Interest Rates): *An increase in the probability of a flood (q) leads to a higher equilibrium interest rate r, because loan amounts L decrease by more than the reduction in the repayment balance B.*

Proof. In light of Proposition 1, to prove that interest rates increase we must show that $\partial L/\partial q < \partial B/\partial q$. Since $1 + r = \frac{B}{L}$, this tells us that loan sizes decrease by more than the reduction in repayment balances.

From earlier, we obtain the relation between the two partial derivatives by implicitly differentiating the zero profit condition with respect to q.

$$\frac{\partial L}{\partial q} = \underbrace{\eta\int_{\underline{P}}^{B-C}(P-B)dF}_{Z} + \frac{\partial B}{\partial q}\underbrace{\left[\eta(1-q) + \eta q\int_{B-C}^{P_0} dF - \eta qCf(B-C)\right]}_{Y} \tag{12}$$

Let us refer to each term in the expression using the following variables:

$$Y := \left[\eta(1-q) + \eta q \int_{B-C}^{P_0} dF - \eta q C f(B-C)\right]$$
$$Z := \eta \int_{\underline{P}}^{B-C} (P-B)dF$$
$$\frac{\partial L}{\partial q} = Z + \frac{\partial B}{\partial q} Y$$

Z represents the net expected gain to the lender when the borrower defaults. This is the mean value of collateral in default less what the lost repayment B, weighted by the probability of default. Y represents the probability of repayment minus what lenders lose from increased defaults on the margin. We first show that $Y < 1$

$$Y = \left[\eta(1-q) + \eta q \int_{B-C}^{P_0} dF - \eta q C f(B-C)\right] < \eta(1-q) + \eta q \int_{B-C}^{P_0} dF < \eta(1-q) + \eta q = \eta < 1$$

We thus know that $\frac{\partial L}{\partial q} < \frac{\partial B}{\partial q}$ since $Y < 1$ and $Z < 0$. Intuitively, this condition represents that the lender's expected losses in default exceed the change in loan repayment. ■

C.2 Model Extension with Capped Flood Insurance

In this section, I extend the model by assuming the borrower has access to flood insurance. Consistent with the institutional details described in Section 3, flood insurance coverage is mandatory and capped at an exogenous amount. Insurance choices are exogenous. Now, if the household chooses to default after a flood, the bank receives the flooded home and the insurance payment. If the household chooses to repay after a flood, the household keeps the flooded home and the insurance payment. Insurance contract $I = \min[P_0 - \tilde{P}, \bar{I}]$, that is insurance pays out the realized flood damage $P_0 - \tilde{P}$ up to some cap $\bar{I}$. Insurance costs a premium X, which is some function of the distribution of flood risk and the insurance cap: $X(q, \tilde{P}; \bar{I}, P_0)$. I do not make any assumptions about whether insurance is priced actuarially correctly or not. Realistically, insurance premia are exogenous to loan terms.

The household will optimally choose to default when her payoff from repaying the loan is less than her cost of default:

$$\tilde{P} + I - B < -C \tag{13}$$

Given the structure of the insurance contract, we have two sub-cases:

- If $P_0 - \underline{P} < \bar{I}$, – then the insurance constraint never binds
- If $P_0 - \underline{P} > \bar{I}$ – then the insurance constraint may bind

The quantity $P_0 - \underline{P}$ can be thought of as the replacement cost of the house when, in the worst case, the flood creates a total loss for the house. In the first case, insurance payments can cover even a total loss of the house. In the second case, for high enough levels of flood damage, insurance payments will not be enough to offset property damage.

Case 1: Insurance Constraint Never Binds: In this case, we know that every dollar of flood damage is completely offset by an insurance payment, and thus the household always repays the loan. It reduces to the case where the household is not exposed to flood risk at all.

$$P_0 - \tilde{P} \leq P_0 - \underline{P} < \bar{I}$$
$$\implies I = P_0 - P \forall \tilde{P}$$

Because the household always repays the loan, her payoffs will always be $P_0 - B$ in every state. The household's problem is now

$$\max_{L,B} Y - (P_0 - L) - X + \delta(P_0 - B) - q\int_{\underline{P}}^{P_0} (P_0 - P)dF(P)$$
$$s.t. - L + \eta B$$

We obtain the corner solution:

$$B^*_{FI} = P_0 + C \tag{14}$$
$$L^*_{FI} = \eta(P_0 + C) \tag{15}$$

Case 2: Insurance Constraint May Bind: Now we know that high levels of damage will not be offset by insurance. In this case, the household will only default when $\tilde{P} + \bar{I} - B < -C$. There may be some regions where flood damage exceeds the insurance payment, but the household still chooses to repay the loan (when $\tilde{P} + \bar{I} - B \geq -C$). Given this default rule, we re-write the borrower's expected utility as:

$$\begin{aligned}
U_{CI}(L,B) =& Y - (P_0 - L) - X + \delta q\int_{\underline{P}}^{B-C-\bar{I}} (-C)dF + \delta q\int_{B-C-\bar{I}}^{P_0-\bar{I}} (P + \bar{I} - B)dF \\
&+ \delta q\int_{P_0-\bar{I}}^{P_0} (P_0 - B)dF + \delta(1-q)(P_0 - B) \\
&- q\int_{\underline{P}}^{P_0-\bar{I}} \bar{I}dF - q\int_{P_0-\bar{I}}^{P_0} (P_0 - P)dF
\end{aligned}$$

The bank's expected profits are thus:

$$\Pi_{CI}(L,B) = -L + \eta q\int_{\underline{P}}^{B-C-\bar{I}} (P + \bar{I})dF + \eta q\int_{B-C-\bar{I}}^{P_0} BdF + \eta(1-q)B$$

Taking first order conditions, the optimal loan repayment B is implicitly defined by the following equation:

$$\underbrace{(n-\delta)q\int_{B-C-\bar{I}}^{P_0} dF(P)}_{\uparrow\text{repayment from non-defaulters,holding constant default}} \quad - \underbrace{\eta q C f(B - C - \bar{I})}_{\uparrow B \implies \uparrow\text{Default}} + \quad \underbrace{(\eta-\delta)(1-q)}_{\uparrow\text{repayment in the no flood state}} \quad = 0$$

We assume that the second order condition holds, which is sufficient for the above to be a maximum.

$$-(\eta - \delta)qf(B - C - \bar{I}) - \eta qCf'(B - C - \bar{I}) < 0$$

Proposition 3: *An increase in the probability of a flood (q) will only lead to a lower equilibrium loan size L when the insurance cap binds, that is when* $P_0 - \underline{P} > \bar{I}$.

Proof. The loan size $L_{FI} = \eta(P_0 + C)$ when the insurance cap does not bind, meaning that loan sizes are independent of q in that case.

When the insurance cap binds, it can be shown that loan sizes L_{CI} will decrease with q. First, applying the implicit function theorem on the FOC obtains:

$$\frac{\partial B}{\partial q} = -\frac{-(\eta-\delta)\int_{\underline{P}}^{B-C-\bar{I}} dF - \eta C f(B - C - \bar{I})}{-(\eta-\delta)qf(B - C - \bar{I}) - \eta qCf'(B - C - \bar{I})} < 0$$

The numerator is negative because probability distributions and the parameters are positively signed. The denominator is negative by the assumption about the second order condition.

From the zero profit condition, we obtain:

$$\frac{\partial L}{\partial q} = \eta \int_{\underline{P}}^{B-C-\bar{I}} (P + \bar{I} - B)dF + \eta q(-C)f(B - C - \bar{I})\frac{\partial B}{\partial q} + \eta(1-q)\frac{\partial B}{\partial q} + \eta q \frac{\partial B}{\partial q}\int_{B-C-\bar{I}}^{P_0} dF \tag{16}$$

$$= \underbrace{\eta \int_{\underline{P}}^{B-C-\bar{I}} (P + \bar{I} - B)dF}_{<0} + \eta \underbrace{\frac{\partial B}{\partial q}}_{<0} \underbrace{\left[(1-q) + q\int_{B-C-\bar{I}}^{P_0} dF - qCf(B - C - \bar{I})\right]}_{>0} \tag{17}$$

The term in brackets is positive and implied by the FOC. ■