Who Bears Flood Risk?
Evidence from Mortgage Markets in Florida*

Parinitha Sastry†
MIT Sloan School of Management

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Abstract

This paper explores how residential mortgage contracts distribute flood risk exposures across banks, households, and the government flood insurer. I merge newly digitized flood maps with geo-located mortgage data to obtain loan-level classifications of flood risk. Strict flood insurance coverage limits and staggered flood map updates provide plausibly exogenous variation in flood risk exposures and assessments. I find that banks manage flood risk by rationing credit through lower loan-to-value (LTV) ratios, which reduces negative borrower equity after floods. However, banks only adjust LTVs when flood insurance coverage limits bind, showing that they offload flood risk to the government flood insurer. Increased credit rationing after flood map updates shifts the composition of mortgages towards richer and higher credit quality borrowers. I conclude that lenders screen for flood risk when sufficiently incentivized to do so, and that their credit rationing has distributional consequences for who moves into flood zones.

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†Sloan School of Management, Massachusetts Institute of Technology. Contact: psastry@mit.edu.

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 (Newburger, 2021). These costs are expected to rise further, with climate change bringing rising sea levels, heavier rains, and stronger hurricanes (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). Despite recent policy actions, there is limited empirical evidence related to how flood risk is managed by mortgage lenders and distributed in the U.S. economy.[2]

In the market for flood risk, there are three primary players: households, mortgage lenders, and the government flood insurer. 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). Flood insurance payments can be used to repair damaged homes, changing household default incentives and lender risk exposures.

This paper studies how flood risk exposures are distributed across banks, households, and the government flood insurer through residential mortgage contracts in Florida. There are three key findings. First, lenders account for flood risk in the mortgage contract, the primary margin of adjustment being downpayments rather than interest rates. This is con-

[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)

[2]Ouazad and Kahn (2021) which explores securitization activity after hurricane events is a notable exception.

sistent with lenders rationing credit to decrease the likelihood of negative equity, as higher downpayments lower delinquency rates and expected losses. On average, banks reduce loan-to-value ratios by 85 basis points (0.85 percentage points) in flood zones, while interest rates do not significanty 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. For underinsured homes, a 1 percentage point increase in the insurance gap brings a 1 percentage point decline in loan-to-value ratios. Third, this credit rationing has distributional consequences and shifts the composition of borrowers to richer, higher credit quality individuals. Higher downpayments and flood insurance requirements seem to deter more liquidity-constrained borrowers from purchasing homes in flood zones.

Estimating the impact of flood risk on mortgage markets and household location choices is challenging for two reasons. First, obtaining data on flood risk 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). 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. I then combine the current and historical flood maps with a novel dataset that geo-locates individual mortgages and thereby obtain the property's flood zone classification at origination. This creates both cross-sectional and time-series variation in flood risk classifications.

The second challenge is that flood zone status may be correlated with unobserved location-specific characteristics. For example, if homes in flood zones are disproportionately likely to have water views that attract wealthier borrowers, then differences in loan characteristics may reflect the tendency of wealthier individuals to have lower LTVs rather than lender risk management. I use three empirical strategies to address this concern. First, I control directly for borrower incomes and FICO credit scores at origination. Second, strict coverage limits of flood insurance contracts create plausibly exogenous variation by changing banks' residual flood risk exposure within flood zones. Third, periodic flood map updates change risk assessments while keeping underlying amenities fixed. The results of these alternate specifications confirm that unobserved amenities only partly explain the observed correlation between flood zone status and loan-to-value ratios, the rest driven by lender rationing.

I begin the paper with suggestive descriptive evidence of credit rationing in flood zones. I find that loan-to-value ratios are on average 85 basis points lower in flood zones, even after including zipcode-year fixed effects and controlling for the borrower's income, FICO credit score, and property value. With the same set of fixed effects and controls, interest rates are only 1 basis point higher in flood zones, whereas delinquency rates are roughly equal in and out of flood zones. Lower loan-to-value ratios without lower interest rates suggests lender credit rationing rather than borrower preferences. Borrowers who choose higher downpayments usually do so to obtain an interest rate advantage, which would lead mortgages in flood zones to have lower interest rates than mortgages outside of flood zones.

The effect of flood insurance on loan-to-value ratios also supports a supply-side explanation. Flood insurance is required by law for most mortgage borrowers in flood zones, and government flood insurance has a 95% market share. This insurance only covers up to $250,000 in flood damage, and there is limited availability of private top-up insurance for borrowers in high risk flood zones. As a result, smaller homes are fully insurable, and larger homes are under-insured. This feature of flood insurance allows comparisons of mortgage contracts by flood zone status and by whether the insurance cap binds. I find that flood zone status has no effect on loan-to-value ratios when the loan can be completely insured, that loan-to-value ratios are lower in flood zones when the coverage limit binds, and that the relationship between flood zone status and loan-to-value ratios changes around the insurance coverage limit. Furthermore, loan-to-value ratios are reduced more in flood zones when a greater share of the home is uninsurable. A 1 percentage point increase in the insurance gap leads to a 1 percentage point decline in loan-to-value ratios, suggesting that banks are particularly likely to screen on flood risk when sufficiently incentivized to do so.

Staggered difference-in-differences estimates from flood map updates support the cross-sectional evidence of lender credit rationing. 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.[3] While these updated flood maps change flood risk assessments, they hold fixed unobserved location-specific characteristics. I find that banks dynamically respond to the flood zone expansions by reducing loan-to-value ratios. Average interest rates are higher, though not significantly so. The results are not likely to be driven by unobserved county-year shocks since mortgage terms do not change after map updates which leave flood zone boundaries unchanged.

Furthermore, the composition of mortgage borrowers changes after the 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. Transacted properties themselves are more than 100 square feet larger after the remapping. The combination of lower loan-to-value ratios and unchanged interest rates suggests that the change in composition towards richer, higher credit quality individuals buying larger homes is most likely

[3] Private sector measures of flood risk, such as those from CoreLogic, use the FEMA data and flood maps as an input.

driven by higher down payment requirements deterring liquidity constrained borrowers.

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 lives in flood zones. However, much of this risk is offloaded to the government through flood insurance contracts. 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.

Floods create financial losses, implying that lenders 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. They find that lenders change where they originate mortgages (Cortés and Strahan, 2017) and their securitization activity (Ouazad and Kahn, 2021), but there is limited evidence that lenders adjust interest rates or loan-to-value ratios (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. Variation from insurance contracts and updated maps allow for directly measuring the independent effect of risk exposure and risk assessments on mortgage terms. Using these sources of variation, I show that banks manage flood risk by adjusting loan-to-value ratios.[4]

The large literature on household default and negative equity explains why adjusting loan-to-value ratios is a powerful risk management tool. Default behavior can be described by 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.[5] Importantly, in both

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

[5]See, for example, Bhutta et al. (2017); Scharlemann and Shore (2016); Fuster and Willen (2017); Gerardi

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.[6] Loan-to-value ratios at origination affect the borrower's equity position throughout the life of the loan, making it an important risk management tool for lenders.[7]

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 to take on less leverage in flood zones.

Lasly, the literature shows that the ability to offload risk changes lender screening incentives. Downing et al. (2009), **?**, Purnanandam (2011), and Keys et al. (2012) find strong evidence that lenders securitize mortgage 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 also diminish underwriting standards. I contribute to this literature by exploring how government flood insurance changes banks incentives to manage risk. Consistent with this literature, I find that flood insurance reduce banks' incentives to ration credit in flood zones.

The remainder of the paper is organized as follows. Section 2 develops the key hypotheses that will be tested. Section 3 describes the institutional setting. Section 4 describes the data and presents the descriptive evidence. Section 5 shows the effect of flood insurance availability on bank risk management. Section 6 confirms the cross-sectional patterns using a difference-in-differences design, and explores the real effects of credit rationing in flood zones. Section 7 concludes.

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

et al. (2018); Ganong and Noel (2020))

[6]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.

[7]Lenders also increase borrower skin-in-the-game to mange 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).

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. 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. In both the strategic default (Foster and Van Order, 1984) and double trigger (Foote and Willen, 2018) 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 rates 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).[8]

This leads to the following hypotheses:

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

[8]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.

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 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 model also does not generate clear predictions for the relationship between delinquency rates and flood risk exposures.

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 are similar or higher interest rates as homes outside of flood zones.

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.[9] Furthermore, mortgage borrowers are required to by flood insurance in flood zones (see Section 3). As a result, only large underinsured homes in flood zones are exposed to flood risk because the coverage limit binds. Therefore, there should be no difference in mortgage terms for observably-equivalent borrowers with small homes in and out of flood zones. Loan-to-value ratios and interest rates should only be different in flood zones when homes are underinsured. In other words, I use both the insurance gap and flood zone status as measures of flood risk exposure.

The third source of variation considers changes in flood risk assessments rather flood risk exposures directly. I assume that changes in the flood maps can be used to proxy changes in risk assessments, even if flood risk itself does not change. Thus, expanded flood zone boundaries suggest an increase in expected flood risk exposure. Therefore, under Hypothesis 1 and Hypothesis 2, loan-to-value ratios and interest rates should change after new maps expand flood zone boundaries.

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

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 be explained by 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. In this scenario, Hypothesis 2 is not likely to hold. 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, interest rates would also decrease in flood risk exposure.

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 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.[10]

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 map information describes the location of streams, roads, buildings, dams, administrative

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

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. This 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 technological 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).

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.

3.2 Mandatory Purchase Requirements

Mortgage lenders must require borrowers in high risk flood zones to purchase flood insurance. The requirement stipulates that federal agencies, federally regulated lending institutions, 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.[11] 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 market are excluded from this requirement; however, in my sample between 2010-2016, the private label markets have mostly disappeared. 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. 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 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 knowing (Gallagher and Hartley, 2017). In the event of foreclosure,

[11] 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.

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). As of July 2018, Florida's admitted insurers had only 5,983 excess flood insurance policies in force (Lingle and Kousky, 2018). 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 (Flavelle, 2019).

The literature implies that insurer exit from high-risk areas arises from a combination of state-level price controls on private insurers 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 worry that they may be restricted from raising premiums after updates in risk assessments (Kousky et al., 2018).

4 Data and Descriptive Evidence

The paper's empirical analysis considers how mortgage terms vary with flood zone status and insurability. To do so, I construct a novel data set that combines geospatial data from flood maps with geo-located data on mortgage characteristics and performance and granular data on property attributes. 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 are available in Appendix Section A.

4.1 FEMA Flood Maps

My primary measure of flood risk comes from FEMA's flood maps. Digitized flood maps for the latest flood maps and for some historical ones can be downloaded directly from FEMA's Map Service Center. The digitized files can be downloaded for an entire 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.

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 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 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 FIRMS for these counties myself using ArcGIS Pro.

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.

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 a 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.

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.

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 1500 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 to complement my flood risk classification 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.[12]

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 construction costs and flood insurance take-up rates at the zip-code level. In 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 300,530 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 the final estimation sample is a small subset of the input datasets, it 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.

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.

[12]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.

Figure 1 shows the spatial distribution of flood risk and the ratio of down payments to property values across Florida in 2013. Flood risk in Panel A is defined as the share of homes located in a high risk flood zone. Unsurprisingly, flood risk is mostly concentrated in coastal counties. The down payments ratio in Panel B is defined as one minus the loan-to-value ratio at origination. There is a strong positive relationship between flood risk and downpayment ratios, with the highest risk counties also having the higher average down payments.

Table 2 shows summary statistics on mortgage characteristics at the loan-level. 20% of the 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% versus 87%), slightly higher interest rates (4.19% versus 4.2%), and lower delinquency rates (1.51% versus 1.14%) than borrowers outside flood zones. Flood zones also have a different types of borrowers on the basis of observables. Borrowers in flood zones on average have higher FICO credit scores (720 versus 726), higher incomes ($76,253 versus $99,944), and are more likely to be purchasing second homes. Additionally, the characteristics of the properties securing the mortgages also differ by flood zone. Property values are higher in flood zones ($206,531 versus $281,755), and these properties are larger (1,968 square feet versus 1,869 square feet). Another key difference is that loan sizes are almost $50,000 higher in flood zones, and the share of jumbo loans jumps from 1.69% to 4.55%.

Table 3 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. Claim probabilities are higher in flood zones, though average claims 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 this pattern.

Table 2 shows that it is important to control for differences in the composition of borrowers in flood zones. Flood zones have richer and higher credit quality borrowers who buy larger homes. The empirical analysis in Section 5 will control for these observable differences in composition when establishing lender-driven risk management in flood zones. The empirical analysis in Section 6 will establish that the differences in flood zone composition are partly driven by lender credit rationing.

One way to address the interaction of flood zone status and borrower composition is to examine whether the relationship between mortgage terms and flood zone status is uniform across the distribution of income. Figure 2 plots the average loan-to-value ratio, interest rate, and delinquency rate by flood zone and log income. For each ventile of log income in flood zones, loan-to-value ratios are lower, interest rates are higher, and delinquency rates are roughly the same. The plots look similar using breakouts by log property value (see Figure B.1) and by credit score (see Figure B.2). The fact that the relationship is uniform across the distribution of income, credit scores, and house prices is strongly suggestive that composition differences may not explain the entirety of the relationship between flood zone status and mortgage terms.

In Table 4, I show that the broader patterns hold even after controlling for credit score, income, and property values. Panel A shows the regression with just the three controls, and Panel B shows the regression including zip code-year fixed effects. Loan-to-value ratios are almost 85 basis points (or 0.85 percentage points) lower in flood zones, and interest rates are higher by 1 basis point (.01 percentage point). Delinquency rates are 6 basis points lower, though the difference is not statistically significant. These patterns are consistent with Hypothesis 1 and Hypothesis 2, outlined in Section 2.

4.6 Unobserved Amenities

Differences in equilibrium mortgage terms may be driven driven by borrowers in flood zones demanding different mortgage terms rather than banks offering different contracts. Ideally, to identify lender credit rationing, I would consider how mortgage terms vary in and out of flood zones for the same individual buying the same exact property. While these descriptive evidence is certainly not definitive, it helps narrow down what types of endogeneity issues could arise.

The patterns are unlikely to be explained by adverse selection in flood zones. Similar ex-post mortgage performance combined with higher incomes and credit scores does not suggest that flood zones attract lower quality borrowers. Furthermore, all-else equal, the literature suggests that individuals with riskier collateral would prefer larger loan-to-value ratios rather than smaller loan-to-value ratios (Hertzberg et al., 2018; Bailey et al., 2019).

However, the cross-sectional patterns can be explained by positive selection (also called 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 4 by controlling for applicant incomes, property values, and credit scores directly. Additionally, as argued in Section 2, wealthier people in equilibrium would not optimally 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 amenities. In Sections 5 the 6, I consider two sources of variation in flood risk that are plausibly exogenous to unobserved amenities.

5 Effect of Flood Insurance on Bank Credit Rationing

In this section, I utilize the fact that government flood insurance contracts only cover damages up to $250,000 to identify lender credit rationing. Smaller homes can be completely insured, whereas larger homes are only partially insurable. 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 unobserved amenities or a demand-side explanation.

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 this 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 the mortgage contract 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.[13] 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

[13] 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).

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 90 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, 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 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 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 to rebuilding the home and the home insurance claim pay out. 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 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 3 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. In Figure B.3, I plot the distribution of flood insurance claims for each replacement cost value. While large floods are rare, they certainly occur, and therefore large floods do pose a real risk to the bank.

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:

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

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 $\phi_{k+\$25{,}000} < \phi_k < 0$.

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:

$$Y_{izt} = \alpha_{zt} + \beta_1 FloodZone_{it} + \beta_2 logInsGap_{it} + \beta_3 FloodZone_{it} \times \log InsGap_{it} + \gamma' X_{it} + \eta_{izt} \tag{3}$$

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.

Identifying Assumptions: They 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. Wealthier people are more likely to live in flood zones because of unobserved amenities, and wealthier people are more likely to live in larger homes with higher replacement costs. The correlation between unobserved wealth and replacement costs violates the identifying assumptions of regression kink designs, which would require exogeneity of unobserved wealth to replacement costs within the chosen bandwidth around the threshold. I do not have enough observations to choose a bandwidth where this assumption is likely to hold.

Instead, I rely upon a weaker identifying assumption that accommodates a correlation between unobserved wealth and floodzone as well as unobserved wealth and replacement cost. I assume 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. This assumes that I do not have any differential omitted variables bias for replacement costs by flood zone status, meaning that I can use homes outside of flood zones with a given replacement cost as a control group for homes inside of flood zones with that same replacement cost. That is to say, I account for the correlation between unobserved wealth and replacement cost using homes outside of flood zones as a control group. In summary, the ordinary least squares exogeneity assumption behind Equation 1 is that, in the absence of flood risk, the average difference in mortgage terms for homes in flood zones and outside of flood zones would be constant across replacement cost categories. The identifying assumption would be violated if borrowers in flood zones with homes of a given replacement cost tend to be unobservably wealthier than borrowers outside of flood zones who purchase a home with the same replacement cost.

Like a parallel trends assumption in the standard difference-in-differences context, this exogeneity assumption cannot be tested directly. However, it can be partially evaluated by observing whether the relationship between mortgage terms and replacement costs for homes below the insurance cap are similar in and out of flood zones. 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 support the identifying assumption.

5.2 Results

Table 5 reports the estimation results for Equation 1 for loan-to-value ratios. In Column (1), I run the regression without zip code - year fixed effects, and in Column (2) I include zip code - year fixed effects. Both specifications imply that there is no significant effect of being in 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 according to my preferred specification in Column (2). The magnitude of the coefficient is higher in Column (1), suggesting that there is some variation across loan-to-value ratios across zip codes and years. In Column (3), I restrict the sample to consider houses with replacement costs within \$100,000 of the flood insurance cap. I obtain that the results continue to hold, although the coefficient roughly halves to 47 basis points (0.47 percentage points). This suggests that the reduction of loan-to-value ratios in flood zones may be larger for homes with higher replacement costs.

Table 6 reports the estimation results for Equation 1 for interest rates and delinquency outcomes. Columns (1) and (2) consider the full sample, and columns (3) and (4) consider the restricted sample for homes with replacement costs within \$100,000 of the flood insurance cap. In both samples, interest rates do not respond to flood zone status, regardless of whether homes are above or below the insurance cap. Similarly, Columns (2) and (4) show that delinquency outcomes are also not significantly different in flood zones, regardless of whether the insurance cap binds.

I next consider how the effect of flood zone status on mortgages varies by the replacement cost of the home. Panel A of Figure 4 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. For example, for homes with replacement cost of \$300,000, loan-to-value ratios are 1 percentage point lower in 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 Panel B of Figure 4, 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.

In Panel C of Appendix Figure B.4, I also show that delinquency rates are on average a few basis points lower in flood zones across replacement cost categories, though again not significantly so.

Column (4) of Table 5 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 0.5% decline in loan-to-value ratios at origination.

Figure 4 affirm Hypothesis 1 and 2 from Section 2. Banks respond to uninsurable exposures in flood zones by lowering loan-to-value. Interest rates are on average higher, though not significantly so. And delinquency rates are equalized in and out of flood zones for each replacement cost category. This is not consistent with a demand-side phenomenon where richer borrowers trade of smaller loan sizes to obtain lower interest rates. This provides strong evidence 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.

Appendix Figure B.4 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.

5.3 Robustness

In Appendix Table B.1 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.

One may wonder whether the results are driven by a formal or informal rule from the government-sponsored enterprises. I address this concern in three ways. First, I check GSE underwriting manuals and confirm that they do not require loan-to-value ratio adjustments in flood zones. Their only discussion of flood risk relates to the mandatory flood insurance purchase requirements. Second, I look at how flood zone status affect loan-to-value ratios when loans are immediately sold to government-sponsored enterprises. Appendix Figure B.5 shows that loan-to-value ratios are only lower in flood zones when loans are kept by the originating bank. For loans which are sold to Fannie Mae or Freddie Mac, loan-to-value ratios in flood zones are not significantly different, and in some cases are significantly higher. Third, in Appendix Table B.2, I show that flood insurance coverage limits do not matter for mortgage pricing when loans are immediately sold to the government-sponsored enterprises.

One may wonder whether 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 if $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. Of the 68,604 loans that are immediately purchased by the GSEs, 29,768 are above the flood insurance cap.

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 this information about flood risk by requiring lower loan-to-value ratios, and that this 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 zipcode-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. While suggestive, the cross-sectional patterns alone may not necessarily reflect a causal effect of flood risk if there are omitted variables that are correlated with an area's flood zone status and insurability that also affect loan-to-value ratios.

Unobserved amenities in flood zones are a particularly important omitted variable; if wealthier borrowers are attracted to coastal amenities, are more likely to purchase larger homes, and also prefer lower loan-to-value ratios, then the cross-sectional results could still be driven by borrower selection rather than bank rationing.

I therefore seek to randomly vary flood risk without changing any other aspect of an area. Obtaining random variation in fundamental flood risk is challenging because flood risk changes extremely slowly over time. Furthermore, it is not obvious how individuals should react to experiencing a natural disaster. In this section, I follow the literature and consider variation in information about flood risk (**?**). 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.3, I verify that new borrowers in flood zones do also purchase flood insurance. Second, 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.

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.

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. Figure 5 shows which counties were remapped in which year. Fourth, I include counties that do not receive an updated map between 2005 - 2016 as a control group.

I estimate the following specification at the mortgage level:

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

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 The variable is only defined for zipcodes where updated flood maps expanded flood zone boundaries and for mortgages in the untreated control group. The variable equals zero for these never-treated counties. I include year fixed effects δ_t and county fixed effects $\alpha_{c(z)}$ which control for any unobserved year or county shocks. The staggered difference-in-difference design compares treated counties to the not-yet-treated counties and never-treated counties (Callaway and Sant'Anna, 2021). In some specifications, I also include FICO score and debt-to-income ratios as loan-level controls, represented by X_i. 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 consider loan-to-value ratios as the dependent variable. 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 considering interest rates as the dependent variable. Under Hypothesis, 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 also equals 0 for those counties that are never remapped and serve as controls. 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 validate this assumption, I check that most socio-demographic characteristics related to a mortgage fail to predict when a new map is released. 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 are endogenous to loan-to-value ratios.

6.3 Results on Mortgage Terms

Panel A of Figure 6 shows the difference-in-differences estimation results for loan-to-value ratios and plots the β_h coefficients from Equation 4. Consistent with Hypothesis 1, loan-to-value ratios decline in the years following the introduction of the updated map. The results are robust to including credit scores, debt-to-income ratios, and interest rates as loan-level controls, as shown in Appendix Figure B.6. In the year of the remapping, loan-to-value ratios In the first year, 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.

Panel B of Figure 6 shows the difference-in-differences estimation results for interest rates and plots the β_h coefficients from Equation 4. Consistent with Hypothesis 2, interest rates are higher on average in the years following the introduction of the updated map though these results are not statistically significant. In terms of magnitudes, interest rates are on between 5-10 basis points higher after the remapping. Importantly, the coefficients estimates from both regression support the parallel trends assumption. Taken together, the results suggest lenders reduce loan-to-value ratios and keep interest rates mostly the same, or if anything slightly higher.

Figure 7 shows the decomposition of loan-to-value ratios for loan sizes (Panel A) and property values (Panel B) 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 in the first year after the remapping. Importantly, this result does not imply that flood risk is positively capitalized into house prices. Panel C of Figure 7 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.

In Figure 9, I run the regression for loan-to-value ratios separately by high and low credit score groups. Individuals with credit scores about 740 are referred to as superprime borrowers and rarely default on their mortgages or in credit card markets. For super prime 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 not superprime.

Table 7 shows the results for Equation 5. Column (2) 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 (2) shows that average mortgage maturity reduces by less than one month after the remappings, though this is also not significant. The results suggest that loan-to-value ratios are the key margins of adjustment.

Column (1) of Table 7 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.

6.4 Results on Borrower Composition

Figure 8 shows the effects of the remappings on the composition of borrowers in flood zones. Panel A shows the effects on log income. This variable is the annual applicant income reported by 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 12% 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 5 points higher, and three years after the remappings they are 8 points higher. There are also no visible pre-trends in either variables.

Why do we observe a change in borrower income and credit scores? There could be a supply-side explanation or a demand-side one. After the remapping, homeowners are required to purchase flood insurance, and downpayment requirements increase. The combination of these two requirements can prevent more liquidity-constrained borrowers from moving into a zip code, because they cannot afford the out-of-pocket payments. This could lead to the observed change in borrower composition. Importantly, these results cannot be driven by unobserved amenities driving higher quality borrowers into flood zones, since location-specific coastal amenities are kept fixed by the difference-in-differences design.

However, an alternative explanation could be advantageous selection on flood risk. In this story, only richer individuals that can bear flood risk are willing to move to an area with a perceived increase in flood risk. Lower loan-to-value ratios could then reflect the preferences of these richer individuals. I show that advantageous selection is unlikely to drive these results for two reasons. First, in Panel A of Appendix Figure B.6, I show that loan-to-value ratios decline even after controlling for credit scores and debt-to-income ratios. Furthermore, in Panel (B) of Appendix Figure B.6, I add interest rates as a control. This shows that loan-to-value ratios decline even when comparing individuals with the same credit scores, debt-to-income ratios, and interest rates. As argued in Section 2, a smaller loan size with no offsetting benefit in terms of rates is a worse financial deal for the borrower. Taken together, the results are most consistent with bank credit rationing.

6.5 Robustness

The staggered difference-in-differences design compares treated counties with not-yet-treated counties and untreated counties. One possible identification-related 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 re-run the same staggered difference-in-differences specification, except I limit to zipcodes that do not change flood zone boundaries or contract flood zones by a small amount (less than a 2% change). More specifically, I run the following model:

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

The event-time variable $E^{Contract}_{i,t,c(z)} = t - \tau_{c(z)}$ will be defined for never-treated counties and zip codes which receive updated maps that do not change flood zone boundaries. The idea behind this robustness check is that county-year shocks would affect both zip codes with expanded boundaries and zip codes where boundaries do not change.

Figure 10 plots the β_h coefficients of Equation 6. 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.

Another possible concern is that the results may be driven by unobserved zip code - year shocks. To address this concern, I defer to the results from Section 5, which relied on within zip code - year variation.

Lastly, the recent econometrics literature suggests that staggered difference-in-differences design can be biased when treatment effects are heterogeneous by cohort and 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 remapped counties to never-treated counties. This approach has the disadvantage that I cannot include year fixed effects. However, the results are consistent with what I find in my staggered setting, such helps alleviate some of these concerns.

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. The cross-sectional evidence in Sections 4 and 5 suggests that the reduction in loan-to-value ratios leads to equal delinquency rates in and out of flood zones. For example, Table 4 shows that delinquency rates in and out of flood zones are the same even though loan-to-value ratios in flood zones are lower. While not definitive, Table 7 suggests that the delinquency rates decline after the remappings due to the reduction in loan-to-value ratios. Taken together, this shows 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.

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. With the exception of Ouazad and Kahn (2021), there is limited empirical evidence on how flood risk is distributed among in residential mortgage markets.

This paper shows that lenders manage uninsurable flood risk by reducing loan-to-value ratios. To establish this result, I first show that lenders do not adjust mortgage terms in flood zones when they are fully covered by insurance, relying on insurance payments to offset any property damage from floods. This suggests that banks transfer flood risk exposures to the government through flood insurance contracts. For any residual uninsured flood risk exposure, they require lower loan-to-value ratios. Requiring higher downpayments, in effect, shifts some flood risk back to borrowers by increasing their equity positions.

I confirm the cross-sectional results in the time series by showing that loan-to-value ratios respond to the release of updated flood maps that expand flood zone boundaries. This result cannot be driven by unobserved amenities since the identification strategy fixes unobserved location-specific attributes. In turn, these higher required down payments change the composition of borrowers towards richer, higher credit quality individuals. This suggests that the decisions made by lenders have real effects by deterring liquidity constrained borrowers from flood zones.

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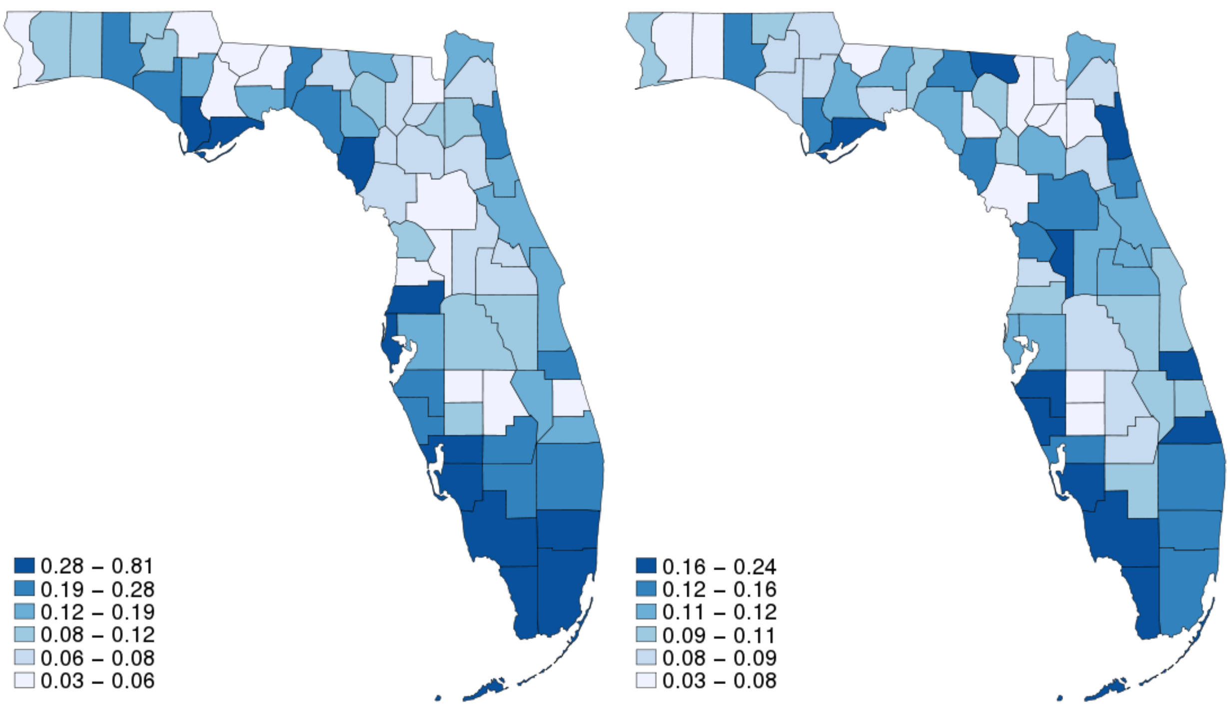
8 Figures and Tables

8.1 Figures

Figure 1: The Spatial Distribution of Flood Risk and Down Payments by County

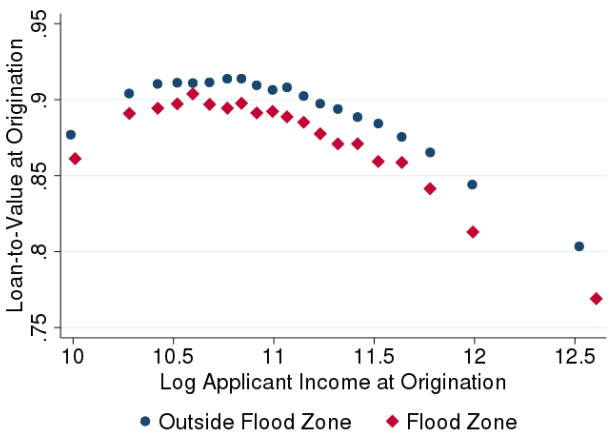
(a) Share of County in a FEMA Flood Zone **(b)** Ratio of Down Payments to Property Value



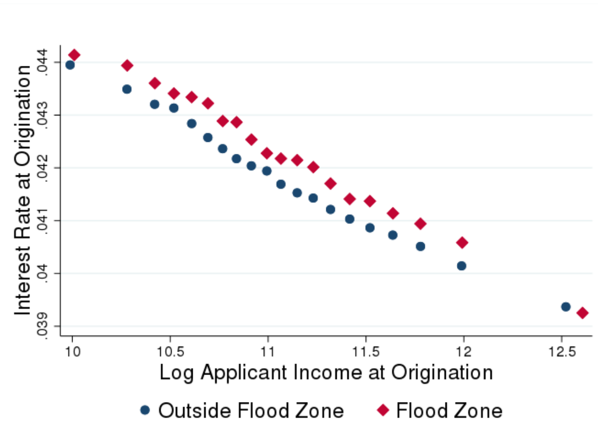
Notes: This figure color-codes counties in Florida based on their FEMA flood zone share and the ratio of downpayments to property values in 2013. Flood zone share is defined as the number of homes in a county mapped by FEMA to be a high-risk flood zone divided by the total number of homes in the county. The underlying data for flood zone share comes from Zillow ZTRAX and FEMA flood maps. Data on the ratio of down payments to property values is calculated as one minus the loan-to-value ratio at origination and comes from the main estimation sample.

Figure 2: The Effect of FEMA Flood Zone on Mortgage Characteristics by Income Ventile

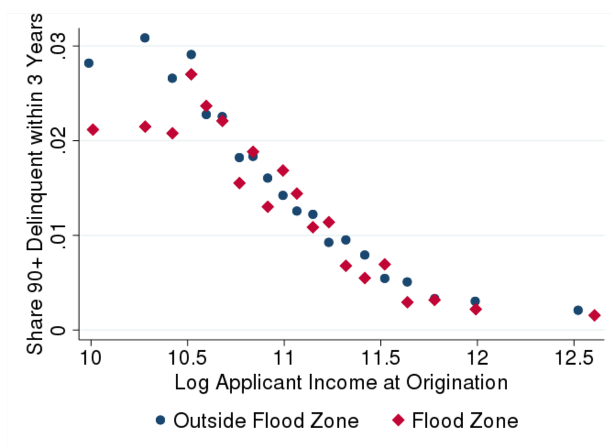
(a) Loan-to-Value Ratios at Origination



(b) Interest Rates at Origination

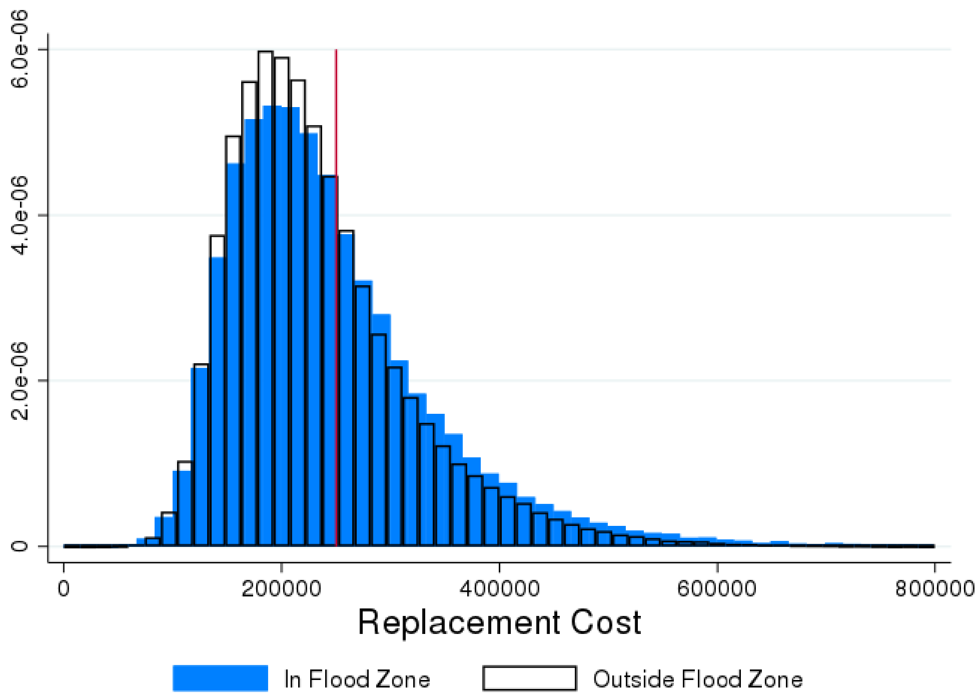


(c) Delinquency



Notes: This figure plots the relationship between mortgage characteristics and log income split by FEMA flood zone status. Delinquency is a dummy variable indicating whether the mortgage becomes delinquent for at least 90 days within the first 3 years of origination. To construct these binned scatterplots, the sample is divided into 20 equal-sized bins based on the ventiles of log income. I then plot the mean of loan-to-value ratios (Panel A), interest rates (Panel B), and the delinquency dummy variable (Panel C) against the mean of log income within each bin separately by whether the mortgage is in a FEMA flood zone.

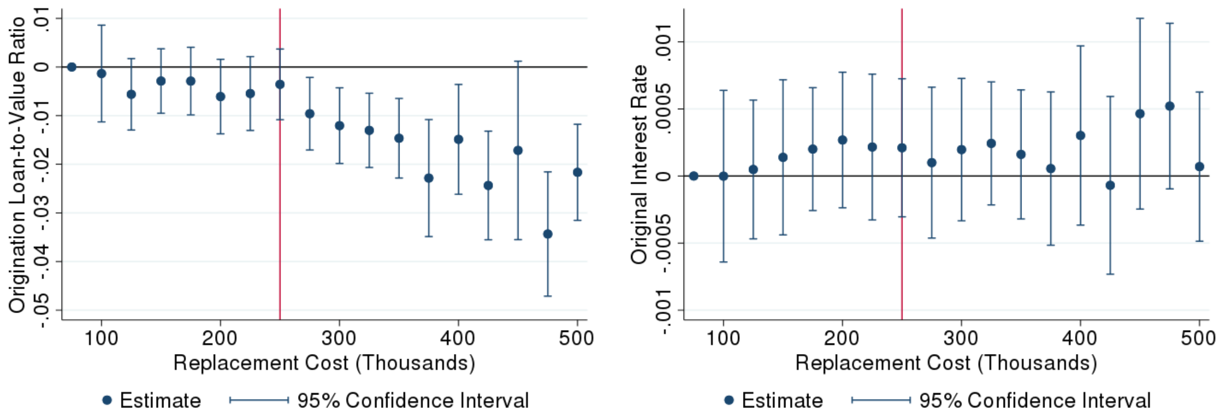
Figure 3: Distribution of Replacement Costs by FEMA Flood Zone



Notes: This graph 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.

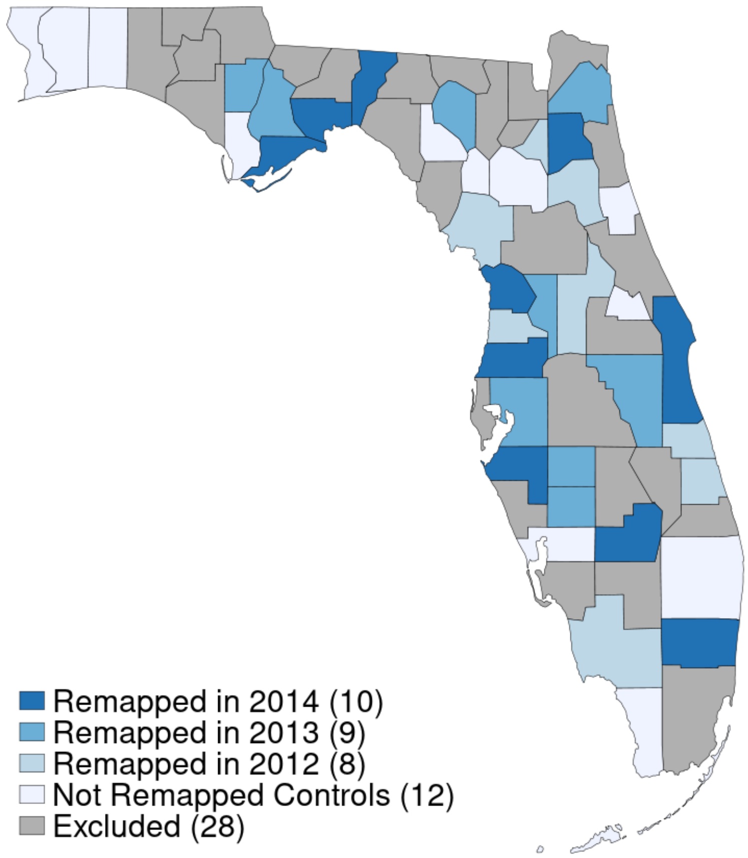
Figure 4: Effect of FEMA's Flood Zone Classification on Mortgage Terms by Replacement Cost

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



Notes: This figure plots the regression coefficients from Equation 2 in the text, which estimates how the effect of being in a FEMA flood zone on mortgage terms varies by the property's replacement cost. Panel (A) shows the coefficient estimates on loan-to-value ratios at origination, and Panel (B) shows the effects on interest rates at origination. 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. 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 homes with replacement costs lower than $75,000 is omitted, so 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.

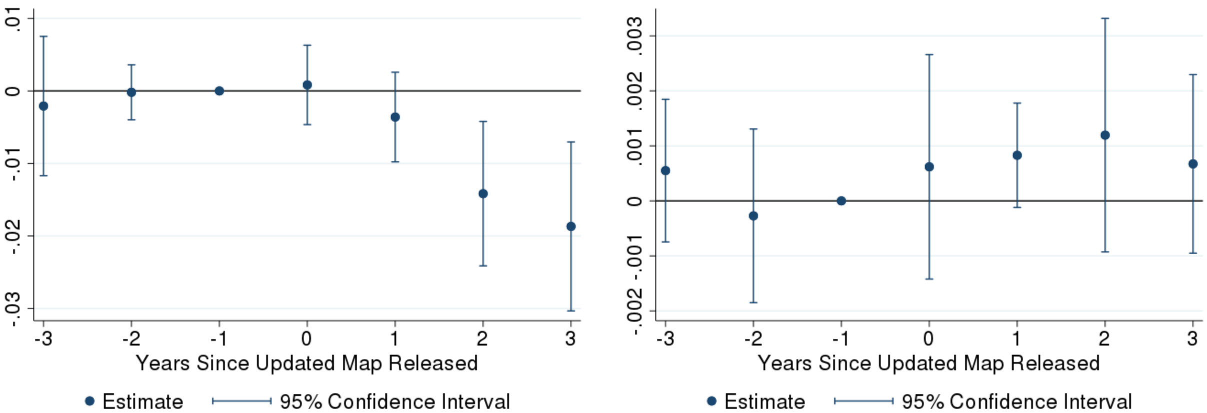
Figure 5: Release Year of Updated Flood Maps by County



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 include as control counties those areas which do not receive any new maps between 2005-2016 (in gray).

Figure 6: Dynamic Effects of Updated Flood Maps on Mortgage Terms

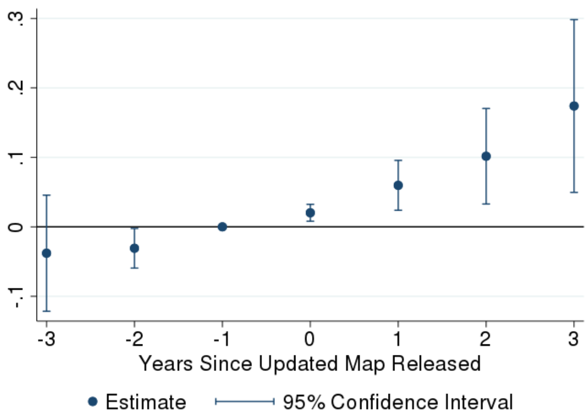
(a) Loan-to-Value Ratios **(b)** Interest Rates



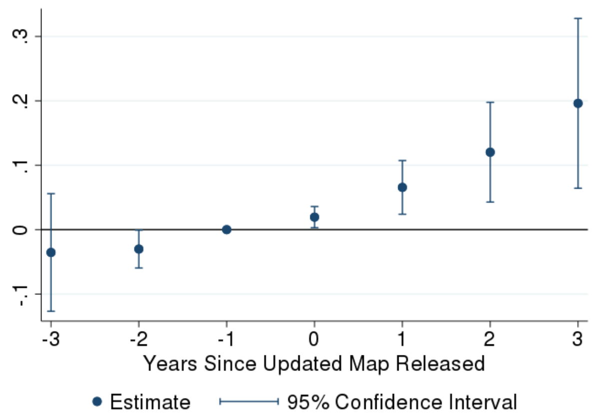
Notes: This figure reports estimates of the effect of updated flood maps from FEMA that expand flood zone boundaries. The dependent variables are loan-to-value ratios at origination (Panel A) and interest rates (Panel B). The figures reports the coefficients from estimating Equation 4 in the text, which is 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 mortgage's loan-to-value ratio and interest 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 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 7: Dynamic Effects of Updated Flood Maps on Mortgages and Transacted Properties

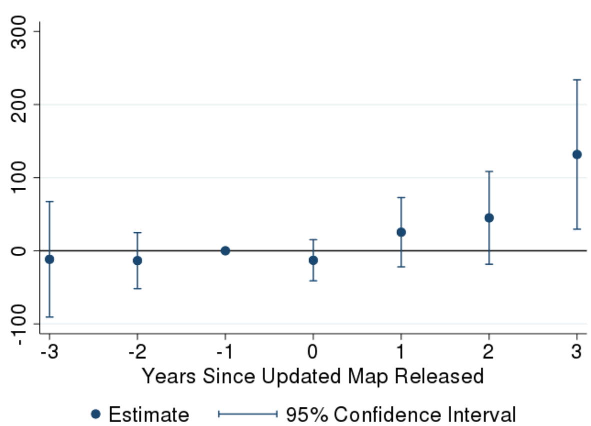
(a) Log Loan Amount



(b) Log Property Value



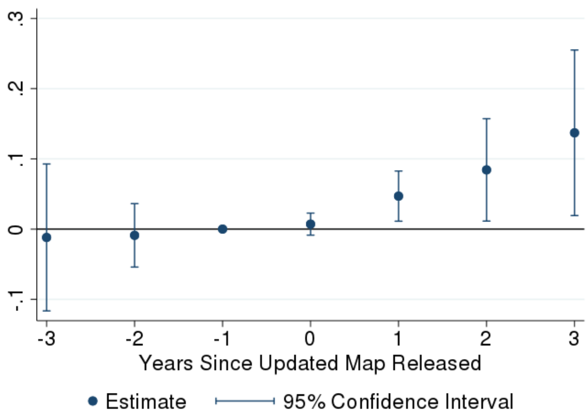
(c) Building Size (Square Foot)



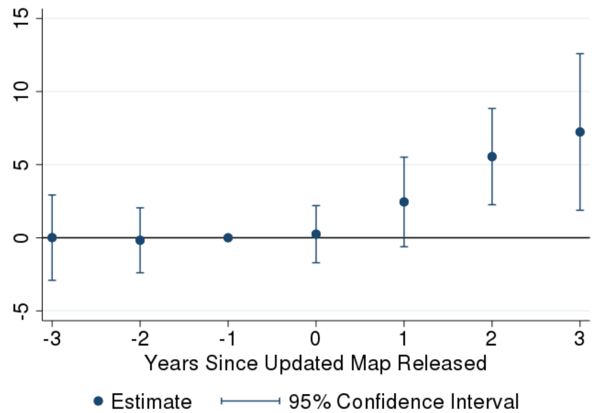
Notes: This figure reports estimates of the effect of updated flood maps from FEMA that expand flood zone boundaries. The dependent variables are log loan amounts (Panel A), log property values (Panel B), and building sizes (Panel C). It reports the coefficients from Equation 4, a difference-in-differences regression that allows the effect to vary by year relative to the release of the updated flood map. Estimates were constructed by regressing each of the three dependent variables 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 8: Dynamic Effects of Updated Flood Maps on Borrower Composition

(a) Log Income



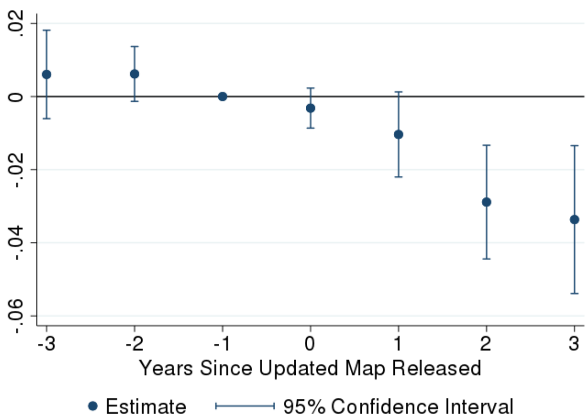
(b) FICO Credit Score



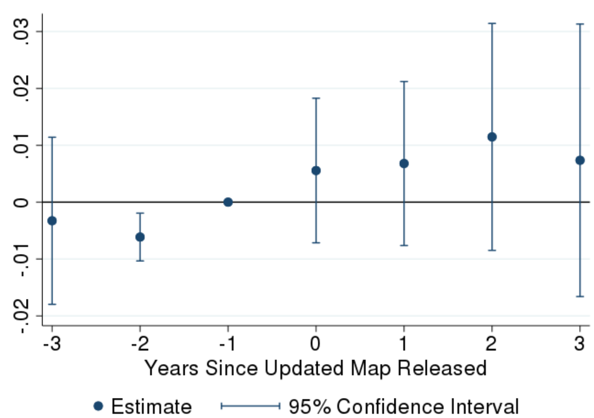
Notes: This figure reports estimates of the effect of updated flood maps from FEMA that expand flood zone boundaries. The dependent variables are the log of the borrower's annual income (Panel A) and FICO credit scores (Panel B) at origination. It reports the coefficients from Equation 4, a difference-in-differences 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 9: Dynamic Effects of Updated Flood Maps on Loan-to-Value Ratios by Credit Score

(a) Regular Borrowers: FICO Scores < 740



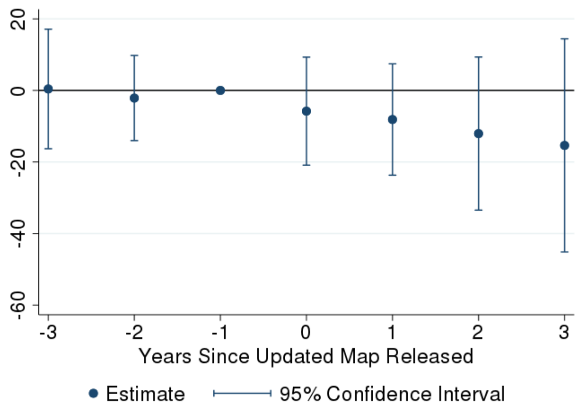
(b) SuperPrime Borrowers: FICO Score $\geq$ 740



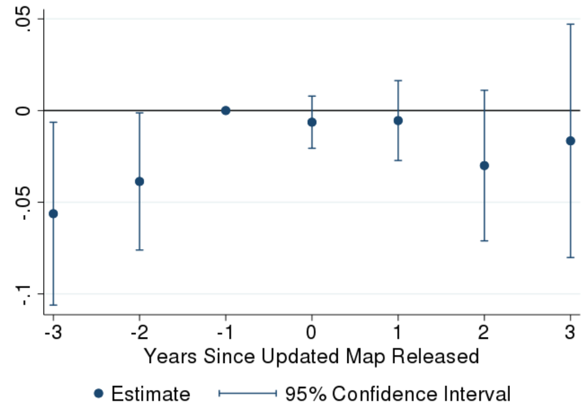
Notes: This figure reports estimates of the effect of updated flood maps from FEMA that expand flood zone boundaries. The dependent variable is the loan-to-value ratio at origination, and the sample is split by whether the borrower has a FICO score below 740 points (Panel A) and whether borrowers are superprime- with FICO scores greater than or equal to 740 points (Panel B). 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 the dependent variable on a series of event-time dummy variables indicating the year relative to the release of the updated map separately for each sub-sample. 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 10: Dynamic Effects of Updated Flood Maps on Borrower Composition when Flood Zone Boundaries Do Not Expand

(a) Credit Scores



(b) Log Income



Notes: This figure reports estimates of the effect of updated flood maps from FEMA that do not expand flood zone boundaries. The dependent variables are the log of the borrower's annual income (Panel A) and FICO credit scores (Panel B) 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 borrower's FICO credit score (Panel A) and log income (Panel B) 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.

8.2 Tables

Table 1: Merge Diagnostics

	Final Sample		McDash		ZTRAX		HMDA	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Applicant Income ($)	80,865	99,282					87,914	90,788
Loan Ammount ($)	187,255	132,633	193,479	113,661	178,124	108,126	199,422	113,537
Property Value ($)	219,788	188,313	231,097	155,295	216,714	154,802		
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	11.51	88.06	12.19				
FICO Credit Score	722.5	55.57	725.2	55.78				
DTI Ratio (%)	35.18	14.19	34.74	14.18				
LTV Ratio (%)	88.74	13.22	87.14	13.15				
Observations	300,530		457,145		683,159		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 winsorized 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 for Mortgage Characteristics

	(1) All		(2) NonFloodZone		(3) FloodZone	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Credit Score	722.5	55.6	721.3	55.8	727.5	54.3
Applicant Annual Income ($)	80,864	99,282	76,318.	84,924	99,966	143,238
LTV (%)	88.7	13.2	89.3	13.0	86.6	14.1
Interest Rate (%)	4.19	0.59	4.19	0.59	4.20	0.60
Loan Amount ($)	187,255	132,633	177,646	112,257	227,625	191149.5
Property Value ($)	219,787	188,313	205,772	150,695	278,673	291116.6
Maturity (months)	354.7	30.2	354.8	30.0	354.4	31.0
DTI Ratio (%)	35.2	14.2	35.3	14.1	34.8	14.5
Combined LTV (%)	89.7	11.5	90.1	11.4	88.0	11.9
First Mortgage Indicator	100.0	0.26	100.0	0.29	100	0
Second Home Indicator	5.20	22.2	4.93	21.6	6.34	24.4
Low Grade Indicator	2.38	15.2	2.39	15.3	2.34	15.1
FHA or VA Indicator	51.0	50.0	52.6	49.9	44.3	49.7
Full Document Indicator	51.6	50.0	51.7	50.0	51.2	50.0
Jumbo Loan Share Indicator	2.24	14.8	1.69	12.9	4.55	20.8
Delinquent Share Indicator	1.44	11.9	1.51	12.2	1.14	10.6
Replacement Cost ($)	237,358	90,388	234,926	87,259	247,574	101,865
Building Size (Square Feet)	1,888.1	710.4	1,869.0	685.5	1,968.1	801.6
Observations	300,530		242,751		57,779	

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

Table 3: Summary Statistics for Flood Insurance Characteristics

	All		NonFloodZone		FloodZone	
	Mean	Sd	Mean	Sd	Mean	Sd
Takeup Rate (%)	10.6	10.9	6.65	8.85	25.8	18.4
Claim Probability (%)	0.82	2.21	1.16	2.91	1.53	4.31
Claim ($)	12,618	14,054	13,933	17,428	13,686	15,352
Assessed Building Value ($)	192,025	199,202	195,081	198,447	192,536	218,862
Observations (Zip-Year)	5,598		5,598		5,598	

Notes: This table provides summary statistics on flood insurance characteristics for the estimation sample and provides a breakdown by FEMA flood zone status. 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 overall take up rates, and then 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 4: Effect of Flood Zone on Mortgages with Controls for Income, Credit Score, and House Prices

	OriginalLTV (1)	Interest Rate (2)	Delinquency (3)
Panel A: Without Fixed Effects			
FloodZone	-0.0087*	0.0007***	-0.0001
	(0.0047)	(0.0002)	(0.0011)
Adjusted R^2	0.19	0.09	0.02
Panel B: With Zip Code - Year Fixed Effects			
FloodZone	-0.0083***	0.0001***	-0.0006
	(0.0016)	(0.0000)	(0.0004)
Adjusted R^2	0.25	0.45	0.06
Observations	300,530	300,530	300,530

Notes: This table shows the results of a cross-sectional linear regression that explores 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 90-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 in all six columns include the borrower's credit score, income, and property value. Panel A excludes zip code - year fixed effects, and Panel B includes zip code - year fixed effects. 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: Effect of Capped Flood Insurance on Loan-to-Value Ratios in Flood Zones

	Full Sample		Replacement Cost within 100K of Cap	Replacement Cost Above Cap
	OriginalLTV	OriginalLTV	OriginalLTV	log(LTV)
	(1)	(2)	(3)	(4)
CapBinds	0.0038***	0.0053***	0.0031***	
	(0.0012)	(0.0012)	(0.0009)	
FloodZone	-0.0021	-0.0009	-0.0023	-0.0116***
	(0.0037)	(0.0020)	(0.0023)	(0.0032)
CapBinds × FloodZone	-0.0095***	-0.0081***	-0.0045***	
	(0.0019)	(0.0019)	(0.0014)	
log(InsGap)				0.0070***
				(0.0010)
FloodZone × log(InsGap)				-0.0055***
				(0.0013)
Controls	Y	Y	Y	Y
Zip-Year FE	N	Y	Y	Y
Adjusted R^2	0.45	0.48	0.47	0.43
Observations	300,530	300,530	234,768	104,483

Notes: This table explores the effect of flood insurance coverage limits on the relationship between FEMA flood zone status and loan-to-value ratios. The first three columns report the coefficients estimating Equation 1. Column (4) reports the coefficients estimating Equation 3. The dependent variable in the first three columns is the 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. *CapBinds* is a dummy variable for whether the home's replacement cost exceeds the flood insurance coverage limit of $250,0000. The dependent variable in Column (4) is the log LTV at origination. *InsGap* is defined by dividing the excess replacement cost above $250,000 by the property value. Columns (1)-(2) include the full sample. Column (3) restricts to homes with replacement costs that range from $150,000 and $250,000. Column (4) restricts the sample to homes where the insurance cap binds. The regression has zip code-year fixed effects where indicated. All specifications control for flood insurance take-up rates at the floodzone-zipcode-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 6: Effect of Capped Flood Insurance on Rates and Delinquencies in Flood Zones

	Full Sample		Replacement Cost Within 100K of Cap	
	InterestRate (1)	Delinquency (2)	InterestRate (3)	Delinquency (4)
CapBinds	-0.0001**	-0.0018***	-0.0001*	-0.0014**
	(0.0000)	(0.0006)	(0.0000)	(0.0007)
FloodZone	0.0001	-0.0006	0.0001	-0.0004
	(0.0001)	(0.0008)	(0.0001)	(0.0009)
CapBinds × FloodZone	0.0000	-0.0005	-0.0000	-0.0007
	(0.0000)	(0.0011)	(0.0000)	(0.0013)
Zip-Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	300,530	300,530	234,768	234,768
Adjusted R^2	0.58	0.08	0.57	0.09

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 two dependent variables are the mortgage's interest rate and a dummy variable which indicates whether the mortgage becomes more than 90-days delinquent within the first three years of origination. *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 $250,0000. 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 7: Pooled Effect of Updated Maps on Mortgage Terms

	(1) Delinquency	(2) DTI Ratio	(3) Maturity
Post	-0.0109*	-0.0015	-0.0843
	(0.0059)	(0.0037)	(0.4520)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Adjusted R^2	0.030	0.048	0.004
Observations	84,968	28,907	84,968

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).

A Data Appendix

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 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 mortgages transactions by keep 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 zone were take the classification for which ever map would be 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 pretty 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%

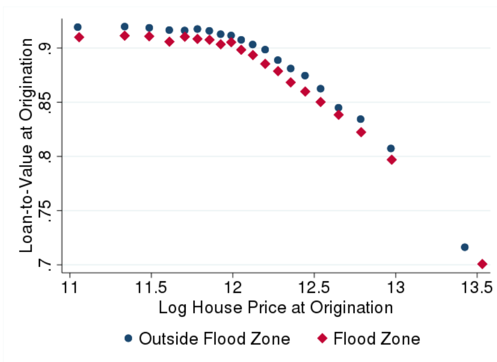
correlation between the two datasets. At the zipcode level, there is a 95% correlation between the two datasets.

B Appendix Tables and Figures

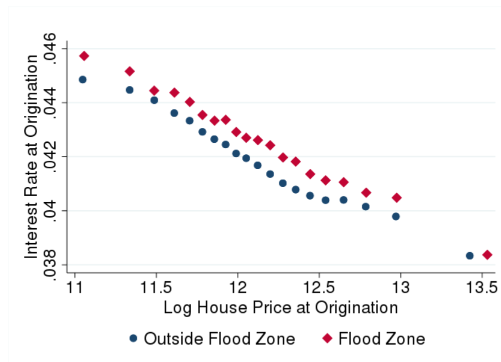
B.1 Figures

Figure B.1: The Effect of Property Value on Mortgage Characteristics by Flood Zone

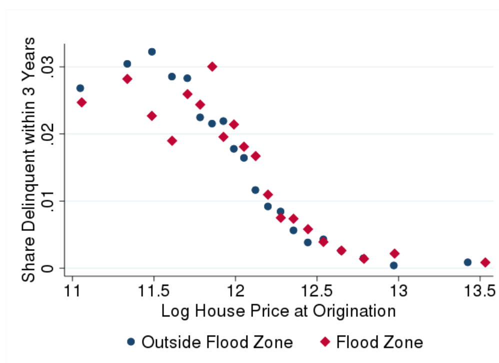
(a) Loan-to-Value Ratios



(b) Interest Rates



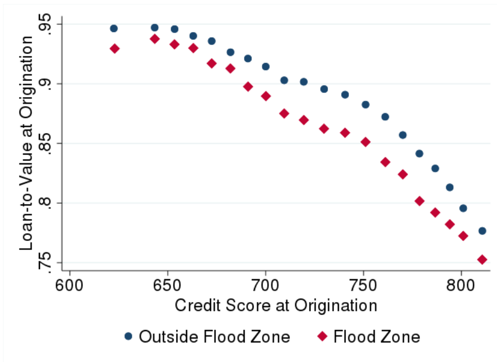
(c) Delinquencies



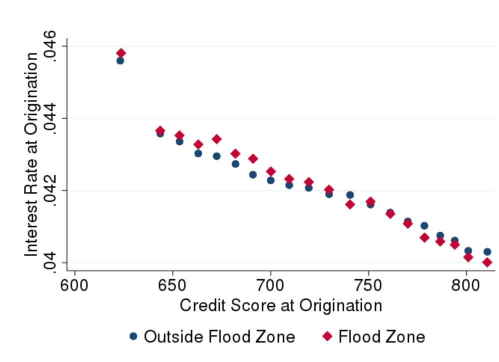
Notes: This figure plots the relationship between mortgage characteristics and log property values split by FEMA flood zone classifications for the main sample. Delinquency is defined as a dummy variable indicating whether the mortgage becomes delinquent for at least 90 days within the first 3 years of origination. To construct these binned scatterplots, the sample is divided into 20 equal-sized bins based on the ventiles of log property values. I then plot the mean of loan-to-value ratios (Panel A), interest rates (Panel B), and the delinquency dummy variable (Panel C) against the mean of log property value within each bin separately by whether the mortgage is in a FEMA flood zone. Since delinquency is an indicator variable, the mean can be interpreted as the share of mortgages that become delinquent for at least 90 days within the first 3 years of origination.

Figure B.2: The Effect of FICO Credit Scores on Mortgage Characteristics by Flood Zone

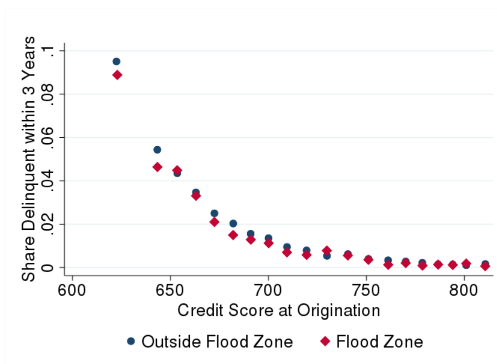
(a) Loan-to-Value Ratios



(b) Interest Rates

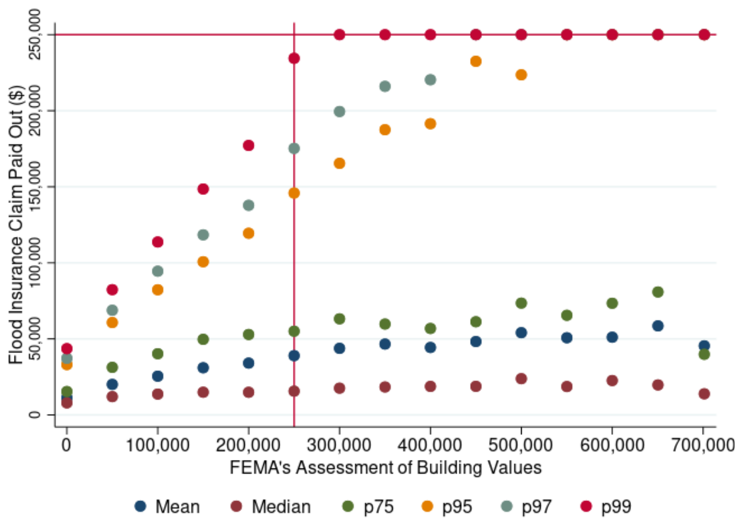


(c) Delinquencies



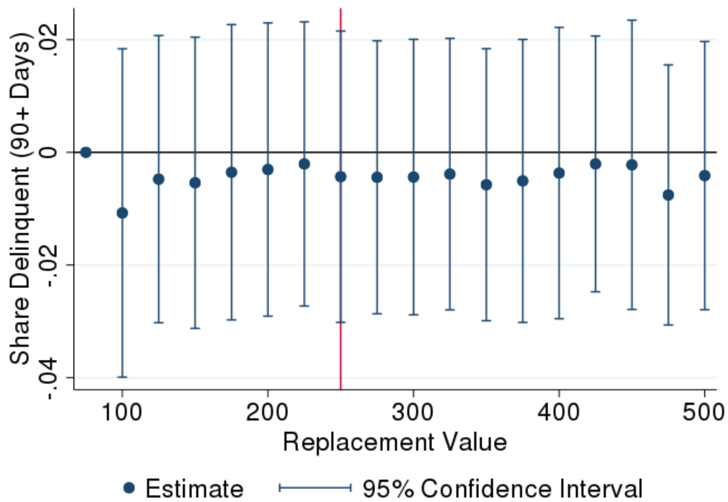
Notes: This figure plots the relationship between mortgage characteristics and FICO credit scores split by FEMA flood zone classifications for the main sample. Delinquency is defined as a dummy variable indicating whether the mortgage becomes delinquent for at least 90 days within the first three years of origination. To construct these binned scatterplots, the sample is divided into 20 equal-sized bins based on the ventiles of credit scores. I then plot the mean of loan-to-value ratios (Panel A), interest rates (Panel B), and the delinquency dummy variable (Panel C) against the mean of credit scores within each bin separately by whether the mortgage is in a FEMA flood zone. Since delinquency is an indicator variable, the mean can be interpreted as the share of mortgages that become delinquent for at least 90 days within the first 3 years of origination.

Figure B.3: Distribution of FEMA Flood Insurance Claims Paid out By Assessed Building Value



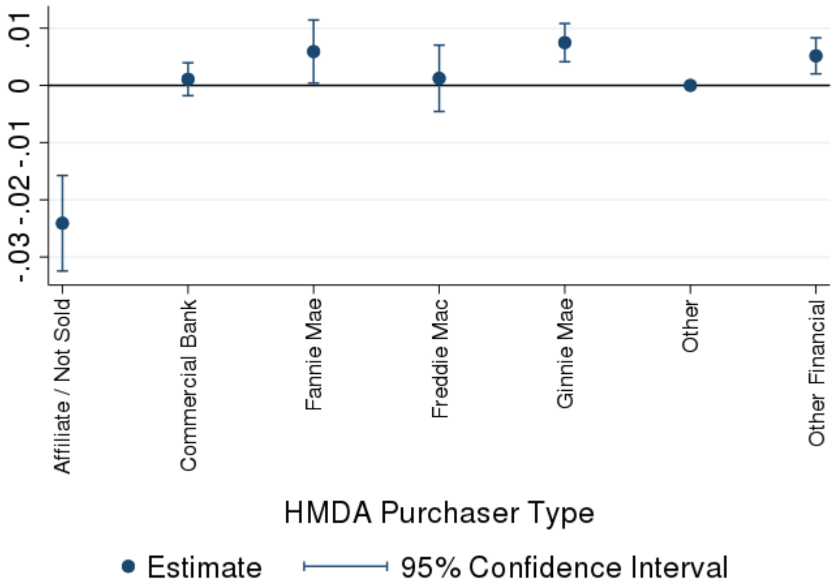
Notes: This graph plots the distribution of FEMA flood insurance claims paid out across for each category of building value as assessed by FEMA. To construct this chart, I split FEMA building assessment values into 15 bins using increments of $50,000. For each building value bin, I then calculate the average claim, median claim, and various percentiles of claims. The sample covers the full history of flood insurance claims for Florida spanning 2008-2018.

Figure B.4: Effect of Flood Zone Status on Delinquency by Replacement Cost



Notes: This figure plots the regression coefficients from estimating Equation 2 in the text, which allows the effect of being in a FEMA flood zone on delinquency to vary by the property's estimated replacement cost. The dependent variable, *Delinquency*, is a dummy variable that indicates whether a mortgage becomes delinquent for at least 90 days within the first three years of origination. 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. Replacement costs are grouped into categories by increments of $25,000. *Delinquency* 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 homes with replacement costs lower than $75,000 is omitted, so 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 B.5: Effect of Flood Zone on Loan-to-Value Ratio by Purchaser Type



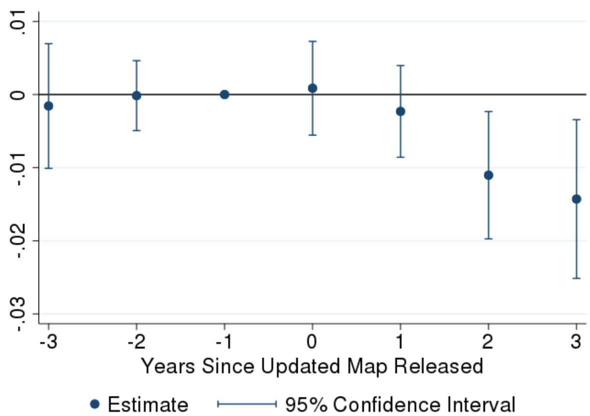
Notes: This figure explores how the effect of flood zone status on loan-to-value ratios varies by who purchases the mortgage in the year it was originated. The figure reports the β_k coefficients from estimating the following specification:

$$LTV_{it} = \alpha_{zt} + \sum_k \beta_k (FloodZone_{it} \times PurchaserType_{k,it}) + \gamma' X_{it} + +\varepsilon_{it}$$

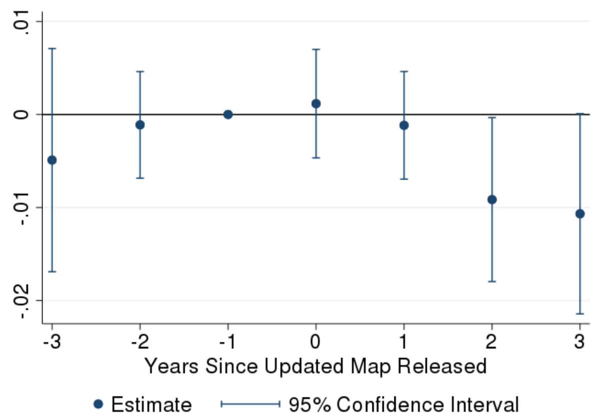
$FloodZone$ is a dummy variable for whether the mortgage is located in a FEMA flood zone when it was originated. $PurchaserType_k$ is an dummy variable that indicates whether the originating bank sold the mortgage to an institution of type k within the calendar year. Zip code-year fixed effects are denoted by α_{zt}. Control variables in vector X_{it} include the borrower's FICO credit score, annual income, 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 B.6: Dynamic Effects of Updated Flood Maps on Loan-to-Value Ratios: Robustness

(a) Controlling for DTI Ratio and Credit Scores



(b) Controlling for DTI Ratio, Credit Scores, and Interest Rates



Notes: This figure reports estimates of the effect of updated flood maps that expand flood zone boundaries on loan-to-value ratios using two sets of loan-level controls. Panel (A) includes the mortgage's debt-to-income ratio and credit scores as loan-level controls. Panel (V) includes debt-to-income ratio, credit scores, and interest rates 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 borrower's loan-to-value ratio 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.

B.2 Tables

Table B.1: Robustness: The effect of flood zone on loan-to-value ratios by whether the flood insurance cap binds using alternate measures

	OriginalLTV (1)	OriginalLTV (2)
HPriceGt250K	-0.0041	
	(0.0032)	
FloodZone	-0.0017	-0.0021
	(0.0019)	(0.0018)
HPriceGt250K	-0.0066***	
× FloodZone	(0.0018)	
StructValGt250K		-0.0086*
		(0.0033)
StructValGt250K		-0.0068***
× FloodZone		(0.0019)
Adjusted R^2	0.48	0.48
Zip-Year FE	Y	Y
Controls	Y	Y
Observations	300,530	300,530

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.2: Effect of Capped Flood Insurance on Loan-to-Value Ratios in Flood Zones by Loan Purchaser Type

	(1) OriginalLTV	(2) OriginalLTV
CapBinds	0.0100***	0.0100***
	(0.0023)	(0.0016)
FloodZone	0.0013	-0.0039
	(0.0034)	(0.0036)
CapBinds ×	-0.0068**	-0.0043
FloodZone	(0.0030)	(0.0031)
Adjusted R^2	0.46	0.36
FE	Zip-Year	Zip-Year
Controls	Y	Y
PurchaserType	OriginatingBank	GSEs
Observations	44,261	68,604

Notes: This table explores the how effect of flood insurance coverage limits on the relationship between FEMA flood zone classification and loan-to-value ratios varies by whether the loan is sold or retained on the bank's balance sheet. The dependent variable is the 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. *CapBinds* is a dummy variable for whether the home's replacement cost exceeds the flood insurance coverage limit of $250,0000. Column (1) restricts the sample to loans which are not sold at all, or sold to an affiliate of the originating bank in the same calendar year as origination. This is constructed using the "purchaser type" variable in HMDA. Column (2) restricts the sample to loans which are sold to the government-sponsored enterprises (GSEs) Fannie Mae or Freddie Mac in the same calendar year as origination. 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.3: Effect of Updated FEMA Flood Maps on NFIP Flood Insurance Takeup Rates

	(1)	(2)
	$\Delta TakeupRates_z$	$\Delta LapseRates_z$
$\Delta FloodZoneShare_z$	0.269***	-0.274***
	(0.0173)	(0.0176)
Constant	-0.0231**	-0.0155**
	(0.0093)	(0.0056)
Observations	382	382
Adjusted R^2	0.1965	0.2954

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 Model Appendix

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 introduced 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. In Appendix **??**, 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,

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

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

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

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 $\partial L/\partial q < 0$:

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

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.

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

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 $\frac{\partial L}{\partial q} < \frac{\partial B}{\partial q}$ if the following inequality holds:

$$Z < \frac{\partial B}{\partial q}(1-Y) \tag{13}$$

Intuitively, this condition requires 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.

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

$$\tilde{P} + I - B < -C \tag{14}$$

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.

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

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

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

We obtain the corner solution:

$$B^*_{FI} = P_0 + C \tag{15}$$

$$L^*_{FI} = \eta(P_0 + C) \tag{16}$$

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:

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

The bank's expected profits are thus:

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

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

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

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

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

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:

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

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:

$$\frac{\partial L}{\partial q} = \eta \int_{\underline{P}}^{B-C-\bar{I}} (P + \bar{I} - B) dF + \eta q(-C) f(B - C - \bar{I}) \frac{\partial B}{\partial q} + \eta(1-q)\frac{\partial B}{\partial q} + \eta q \frac{\partial B}{\partial q} \int_{B-C-\bar{I}}^{P_0} dF \tag{17}$$

$$= \underbrace{\eta \int_{\underline{P}}^{B-C-\bar{I}} (P + \bar{I} - B) dF}_{<0} + \underbrace{\eta \frac{\partial B}{\partial q}}_{<0} \underbrace{\left[(1-q) + q \int_{B-C-\bar{I}}^{P_0} dF - qCf(B - C - \bar{I}) \right]}_{>0} \tag{18}$$

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