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Abstract

We document that the quasi-mandatory U.S. flood insurance program reduces mortgage lending along both the extensive and intensive margins. We measure flood insurance mandates using FEMA flood maps, focusing on the discreet updates to these maps that can be made exogenous to true underlying flood risk. Reductions in lending are most pronounced for low-income and low-FICO borrowers, implying that the effects are at least partially driven by the added financial burden of insurance. Our results are also stronger among non-local or more-distant banks, who have a diminished ability to monitor local borrower adherence to complicated insurance mandates. Overall, our findings speak to the unintended consequences of (well-intentioned) regulation. They also speak to the importance of factoring in affordability and enforcement feasibility when introducing mandatory standards.

Key words: insurance, unintended consequences, regulation, FEMA maps, flooding, mortgage lending, access to credit

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1 Introduction

The National Flood Insurance Act of 1968, which established the National Flood Insurance Program (NFIP), did not formally mandate individual participation. It did, however, deny disaster relief to persons who could have purchased flood insurance, but did not do so. The pressure for communities and people to opt into flood insurance schemes has been growing ever since. From 1994, houses purchased in regions of high flood risk must have insurance so as to be eligible for GSE underwriting. We make use of FEMA flood maps, which are designed to communicate the need for flood insurance to market participants, to identify the impact of such quasi-mandatory insurance on mortgage lending. In so doing, we shed valuable light on the fact that mandates can be costly and that regulation may have unintended consequences.

It is ex-ante unclear how quasi-mandatory flood insurance should affect mortgage lending behaviour. On the one hand, insurance coverage in areas with flood risk may alleviate bank concerns over possible flooding. After all, insurance may lower the residual risks to which lenders are exposed and thereby lower the riskiness of investing in an area. Given that subsidized NFIP flood insurance becomes available to inhabitants in a flood zone, the risk of catastrophic flooding can be transferred away from banks and borrowers.[1]

On the other hand, banks may experience reduced incentives to lend. NFIP flood insurance, while subsidized, still represents a substantial cost to borrowers. Households with marginal income-to-loan payment levels may become unable to borrow as the additional prospect of paying for insurance forces them out of the mortgage market. Banks may gravitate toward ’safe’ borrowers with high incomes and relatively small loan-to-value ratios, thus minimizing the risk to themselves.[2]

A bank may additionally be unwilling to lend to borrowers in flood zones if it has a small local footprint and commensurately limited knowledge of an area. The NFIP puts the onus of ensuring that borrowers buy the adequate flood insurance for the property in question on mortgage lenders. This may involve a detailed understanding of NFIP policies available in a given region (these policies can vary based on property type, local topography, and community compliance with the NFIP). The ability to monitor adherence to the NFIPs requirements may be beyond a ’distant lender’. Especially non-local banks may be unable or unwilling to engage with the oversight burden imposed by mandatory

[1] Private insurance against flood risk for conforming properties is virtually nonexistent in U.S. markets.

[2] The ability to securitize certain loans – and thereby remove the exposure to a borrower from the bank’s balance sheet – may attenuate this effect, but not resolve it completely. As we discuss, banks are still liable for loans they securitized if it can be shown that borrowers failed to purchase the required flood insurance.

insurance.[3]

In this paper, we use confidential HMDA data, which includes applicant location information, natural disaster data, as well as nationwide flood maps for the years 2013-2020. This data set allows us to test bank lending responses to (i) the presence of and (ii) changes in insurance requirements as dictated by flood maps. Changes to the flood maps are especially important, as these lag behind real developments in an area and can be made quasi-exogenous to any actual flood risk. This exogeneity is key in isolating the causal effect of insurance requirements. To explore relevant sensitivities, we distinguish between different types of borrowers and bank-types. Naturally, we condition our analyses on a host of region, borrower, and bank controls and fixed effects.

We find that the chance of a loan being accepted – as well as the size of loans that are accepted – are smaller in flood zones. The effect is particularly pronounced after a flood zone is extended and new borrowers are forced to buy insurance. Commensurate with the hypothesis that the **costs** of flood insurance reduce the ability of households to borrow; we find the reduction in lending is strongest for households with lower relative income and lower FICO scores. Similarly, we find that new contracts, which cannot be 'grandfathered in' to older rates and usually represent a significant cost, drive our results.

We also find that local banks – and banks with branches in the area affected by flood zone changes – respond less to these changes than large national banks, banks without local branches, or banks without links to local borrowers. These finding are in keeping with the fact that a greater physical distance between borrowers and lenders, limited pre -existing relationships, or other differences between borrower and lender can exacerbate information asymmetry issues. "Distant" lenders may find it difficult to monitor an unknown borrower's adherence to mandatory insurance requirements (or simply find such a task to costly) and therefore choose to forego lending.

While our results depict a host of negative – and likely unintended – consequences that arise as a result of mandatory insurance requirements, it is worth noting that our results do not speak to the overall *aggregate* welfare-effects of updating flood maps or of requiring insurance. Bank decisions to forego lending in areas designated a flood risk may be prudent in some cases. As such, we abstain from a welfare evaluation of bank decisions. Instead, our paper highlights the degree to which insurance mandates change and the the ability of different borrowers to access mortgage credit. However, it is unlikely to be the intention of flood-maps and the associated flood insurance requirements to exclude

[3] In our paper, we define a bank as local if it has more than 40% of all outstanding mortgage loans in a single county.

certain buyers or lenders from the waterfront mortgage market. As such, our paper ultimately quantifies possibly unintended consequences of mandating insurance. We therefore also reveal the importance of combining mandatory flood insurance with an affordability program, particularly when flood insurance is fairly priced.

Methodologically, our paper makes use of data at the census tract level, given we do not have applicant-level street address information. A census tract contains on average 4000 inhabitants and substantially fewer households, meaning the granularity of our estimates is extremely high. Our methodology is based on measuring average effects for the treated which can be used to infer treatment effects for the individual. First, we determine the degree to which a census tract is covered by a flood map and assume that, in a census tract which is X% covered by a flood map, a household has an X% chance of being in the flood zone and requiring insurance. Given the propensity of homes to cluster close to waterways or the waterfront, this is likely to be an underestimation. In order to ensure our results are not driven by changing neighbourhood characteristics, we account for census-tract level characteristics that include average income and neighbourhood composition.

Finally, we want to ensure that any effect we measure is independent of actual natural disasters. It may be the case, after all, that disasters, which are higher in areas zoned as flood risks, are driving any lender reactions. For this reason, we control for actual cumulative weather-related damages as well as county*year fixed effects. This removes the impact of actual flooding risk. Moreover, flood maps are known to be updated slowly. The chance of any one community's map being updated in a given year is conditionally random – after we control for a host of local characteristics. As such, we can make use of changes to flood maps as quasi-exogenous shocks to the need for individual mortgage applicants to buy insurance.

Our paper is related to the literature on the unintended effects of regulations or more generally governmental policies. For example, while it is widely acknowledged that bank capital regulation has played an important contribution to the financial stability of banks, Acharya et al. (2013) and Demyanyk and Loutskina (2016) show that the inconsistent application of the regulation across all of the activities of bank holding companies led to the migration of risk to off-balance conduits and mortgage companies' subsidiaries, respectively. Similarly, while it is well established that deposit insurance has been effective at protecting banks from depositor runs, there is also substantial evidence it has afforded banks the opportunity to take on additional risk.[4]. Kim, Plosser, and J. Santos (Kim et al.), in turn, document that

[4]See Calomiris and Chen (2020), Bonfim and Santos (2021), and Blickle et al. (2021) for a review of this literature

the introduction of the leverage lending guidance in 2013 did reduce banks' riskier lending, but this activity migrated to nonbanks which in turn increased borrowing from banks. Lastly, Fuster et al. (2021) show that the Consumer Financial Protection Bureau created in 2011 did offer borrowers protection but this came at a cost to mortgage supply particularly to the Federal Housing Administration market, where mortgage borrowers are typically lower-income and often first-time homebuyers. Our paper is closer to this last study in the sense that we are also interested in understanding the unintended effects of an arrangement — the mandated flood insurance program — that was institutionalized to offer protection to consumers (and lenders).

Our paper is also related to the recent body of research on banks' responses to climate risks. A branch of this literature focuses on banks' ex ante responses to changes in these risks. For example, Sastri (2021) finds that banks manage flood risk, as captured by on changes in FEMA's flood maps in Florida, by rationing mortgage credit through lower loan-to-value (LTV) ratios when flood insurance coverage limits bind, suggesting that they offload flood risk to the government flood insurer. Keenan and Bradt (2020) document that banks, particularly concentrated local lenders, transfer risk from mortgages collateralized by properties in high-risk coastal geographies in the Southeast Atlantic and Gulf Coasts through securitization, consistent with them being better informed about local risks than larger lenders with diversified portfolios. This contrasts with Keys and Mulder (2020) finding that mortgage lenders have not meaningfully changed their rate of refinancing, loan denial, or securitization in the most-sea-level-rise-exposed areas of Florida between 2013 and 2018. Another branch of the literature investigates banks' ex post responses to climate disasters. Cortes (2015), Chavaz (2016) and Schüwer et al. (2018) document that local banks increase corporate lending following natural disasters, consistent with an increase in credit demand to rebuild. Cortes and Strahan (2017), Rehbein and Ongena (2020), and Ivanov et al. (2022) document that banks cut lending to unaffected regions in the aftermath of disasters, possibly to accommodate the additional credit demand in affected regions. Ouazad and Kahn (2019), in turn, find that lenders are more likely to securitize mortgages in areas hit by hurricanes that lie outside of federal flood zones, suggesting that lenders rely on securitization to lay off their riskier exposures.[5]

Our paper is some ways closest to the studies of banks' ex ante responses to changes in climate risk, in particular Sastri (2021). Like Sastri (2021), we too build on changes in FEMA's flood maps and banks' responses in the mortgage market. In contrast to her, we consider changes in flood maps throughout

[5] This contrasts with ?? (Gar) finding that UK banks do not adjust interest rates or loan amounts following a severe flood event in England notwithstanding the decline in local property prices, suggesting they underestimate long-term risks from climate change.

the entire U.S., highlighting differences between different types of regions or states. An important differentiation, for example, lies in the degree to which regions may 'expect' flooding to occur, based on past events. Secondly, we differentiate our results along both borrower and lender dimensions. Finally, and perhaps most crucially, we differ in our interpretation of what flood maps represent. Unlike Sastri (2021), we do not use updates to flood maps as expressions of changing flood risk. Maps, after all, are by FEMA's definition outdated lower bound designations of possible flooding zones. Instead, we account for true risk in our regressions through other measures. Far rather, we use changes in maps to isolate the effect of mandatory insurance requirements from a bank's possible flood-risk aversion.

The remaining paper is structured as follows. Section 2 provides a detailed overview of flood maps and the NFIP. We also use this section to build hypotheses that relate to the impact of mandatory flood insurance on lending. Section 3 outlines our data as well as our data collection and digitization process. Section 4 presents our methodology. Section 5 showcases our main findings, and Section 6 offers a series of robustness tests and extensions. Section 7 confirms our findings hold at the aggregated level. Finally, section 8 concludes.

2 Institutional Setting and Hypotheses

2.1 Historical Background on NFIP

Insurance Mandate

The National Flood Insurance Act of 1968 established the National Flood Insurance Program (NFIP) to "promote the public interest by providing appropriate protection against the perils of flood losses and encouraging sound land use by minimizing exposure of property to flood losses." In other words, the program targeted two interrelated policy purposes: (i) to provide access to primary flood insurance (allowing for the transfer of some of the financial risk of property owners to the federal government) and (ii) to mitigate and the nation's overall flood risk through the development and implementation of floodplain management standards. This followed evidence that post-disaster flood losses, and the subsequent federal disaster relief assistance to help communities recover from those losses, were posing an increasingly larger burden on the Nation's resources. Further, there was a growing belief that it was uneconomic for the private sector to make flood insurance available to those in need of it on reasonable terms and conditions.

The 1968 Act did not mandate community participation in the NFIP; instead, it gave communities the opportunity to participate in the program and obtain subsidized flood insurance with the completion of a Flood Insurance Rate Map (FIRM). Communities, in turn, would adopt and enforce floodplain management standards aimed at reducing flood damages.[6] A FIRM is an official map of the community. It primarily marks the 100-year flood risk – the Special Flood Hazard Areas (SFHAs) – which are regions that have a chance of flooding "at least" once in 100 years. The maps also show the risk premium zones applicable to the community (usually referred to as the 500-year flood zone). As we discuss below, while informative, flood maps are not accurate reflections of flood risk. They represent a lower bound of risk that a community may face due to coastal or river flooding. It is therefore possible that two communities with the same "flood map" coverage experience a very different number of floods.

Even though the 1968 did not initially mandate the purchase of flood insurance by home owners, it denied disaster relief to persons living in a 100 year flood zone who could have purchased flood insurance for a year or more and did not do so. Further, over time, Congress increasingly put pressure on communities and residents of flood risk zones to buy flood insurance. For example, the Flood Disaster Protection Act of 1973 made three important amendments to the 1968 Act to "promote" enrollment in the NFIP. It required states and communities to participate in the NFIP as a condition for future financial assistance.[7] Additionally, it required property owners in participating communities to purchase flood insurance as a condition of receipt of federal or federally related financial assistance for acquisition, construction, or the improvement of structures in SFHAs.[8] Lastly, it mandated that federally regulated lending institutions could not make, increase, extend, or renew any loan on a property located in a SFHA without requiring flood insurance.

The trend towards the mandatory purchase of flood insurance continued after 1973. The National Flood Insurance Reform Act of 1994 expanded the insurance purchase requirements to apply to mortgages underwritten by the government sponsored enterprises; required lenders to ensure coverage was maintained over the life of the loan; required escrow of flood insurance payments if escrows were already in use; required the purchase of flood insurance by lenders if a borrower failed to obtain the necessary coverage; and required prudential regulators to impose civil penalties on lenders that were found to have a pattern of violating certain flood insurance requirements, among others. Note

[6]The Act required that flood-risk zones be established in all flood-prone areas and that rates of probable flood-caused losses be estimated for the various flood-risk zones for each of these areas within 15 years (i.e., by August 1,1983) following enactment.

[7]Participation had to begin by July 1, 1975, or one year after notification that a community had flood-prone areas.

[8]The purchase of flood insurance also became a requirement before property owners were eligible to obtain federal disaster assistance for construction or reconstruction purposes.

that despite these changes, not all mortgages in the SFHA were subject to the mandatory purchase requirement. For example, a personal mortgage loan between two private parties (such as between family members), or a mortgage issued by a private mortgage company that is not then sold on the secondary market, to a bank, or government entity, may not require flood insurance. Further, FEMA has processes which allow properties to request, upon providing certain mapping and survey information, the removal of the SFHA status (and thus, the requirement to purchase flood insurance). These changes came in response to criticism levied on the effectiveness of the purchase requirement.[9]

Further, the Biggert-Waters Flood Insurance Reform Act of 2012 instructed lenders to escrow borrowers' flood insurance premiums and increased the civil penalties that the prudential regulators could levee against non-compliant lenders.[10] The Homeowner Flood Insurance Affordability Act of 2014 amended the escrow requirements to require lenders to escrow flood insurance premiums for all mortgages, except if the lending institution fell below a certain size or the loan was a subordinate to another loan. This broader implementation of the escrowing provision, which began in January 2016, likely increased compliance with the mandatory purchase requirement.

NFIP's maximum coverage limit for single-family residential policyholders is $250,000 per unit for buildings and $100,000 per unit contents. It should be noted, however, that even homes significantly more valuable may be "fully" insured. After all, the property and residual structures on a property may retain value after a catastrophic flood. A house might be rebuilt for significantly less than $250,000. Finally, it should be noted that insurance is– in aggregate– associated with somewhat fewer delinquencies following a disaster. We detail this in Appendix A.4.

Insurance Rates

To attract enrolment in the program, the National Flood Insurance Act of 1968 stipulated that occupants of structures in floodplains would have their premiums subsidized. Structures built in floodplains after the Act's passage would pay actuarial premiums. To further attract participation, and realizing that raising rates would run counter to that goal, NFIP rates remained low for several years. In fact, subsidized rates for flood insurance were lowered in 1972 and again in 1974.

However, the declining trend in insurance premiums began to reverse in 1981, when rates increased

[9] In 1990, while investigating the Mandatory Purchase Requirement, the GAO identified high levels of noncompliance in parts of the two states it examined, Maine (22 percent) and Texas (79 percent) and in a subsequent study in 2002, the GAO noted that there had not been a definitive analysis measuring the extent to which property owners, who were required to maintain insurance, actually did so, but concluded that noncompliance was low at loan origination. See GAO (1990) and GAO (2002).

[10] The Act increased the maximum civil monetary penalty that regulators could impose per flood violation from $350 to $2,000 and eliminated the $100,000 limit they could levee on a lender in a given year.

for the first time in the NFIP's history. In that year, FEMA established a goal for the NFIP to achieve self-supporting status for an average historical loss year by 1988. This would mean the elimination of subsidies for pre-FIRM and grandfathered properties.[11] Despite several increases in premiums after 1981, FEMA concluded in the late 1980s that to eliminate subsidized flood insurance, the average premiums for residential properties subject to substantial flood risk would still have to rise from $585 to about $2,000 annually.

The 2012 Biggert-Water Act required the subsidies that pre-FIRM properties enjoyed to be progressively phased out. Further, and in contrast to this gradual approach, the 2012 Biggert-Water Act eliminated subsidies for a range of properties, including any property purchased after the date of enactment of the act. As a result, starting in the fall of 2012, prospective mortgage borrowers for residential properties in high-risk flood zones were required to buy flood insurance at unsubsidized rates. This led to a significant increase in the cost of flood insurance, with potentially adverse effects on the affordability of mortgage financing for low- and medium-income borrowers. The Homeowner Flood Insurance Affordability Act of 2014 presented a partial reversal of this trend. It alleviated the rate problem – to a certain extent. It still allowed policy premiums to rise by up to 18% per year (from their pre-2012 levels) until they reached their risk-based rates.

Updating Outdated Maps

the National Flood Insurance Reform Act of 1994 required FEMA to review and assess the need to update and revise FIRMs every five years. Further, the 2012 Biggert-Waters Act directed FEMA to rely on accurate and comprehensive flood hazard data while maintaining its floodplain maps. For example, it required FEMA, when updating floodplain maps, to use the most accurate topography and elevation data available. It also directed FEMA to include any relevant information or data from the National Oceanic and Atmospheric Administration and the U.S. Geological Survey related to the best available science regarding future changes in sea levels, precipitation, and intensity of hurricanes.

FEMA, however, has not been able to meet these goals. For example, in February 2020, FEMA estimated that roughly 3,300 communities (out of approximately 22,500) had maps that were over 15 years old (GAO (2021)). There is still no consistent and definitive timetable for when a community will have its map revised and updated. FEMA uses a process called the Coordinated Needs Management Strategy to identify flood maps in need of revision. Generally, flood maps may require updating when

[11] Pre-FIRM properties are those built before FEMA mapped flood risk in a community. Grandfathered properties are those that were built in compliance with the local FIRMS in effect at the time of construction and they are allowed to maintain a lower rate, even if a new FIRM reclassifies the property into a higher risk zone.

there have been significant new building developments in or near the flood zone, changes to flood protection systems (e.g., levees and sand dunes have been erected), and environmental changes in the community have taken place. Importantly, map updates take a long time to complete. Given the many different inputs – that vary from community to community – the process is not uniform across the country. As such, the timing of when new maps become available can be quasi random for many neighbourhoods – especially if local wealth and past disaster exposure are accounted for. We exploit the randomness of map updates in our investigation below.

2.2 Possible Consequences of Insurance Requirements: Hypotheses

To the extent that borrowers can afford the cost of mandated flood insurance and access to it does not negatively impact their behavior, then demanding borrowers exposed to flood risk to buy flood insurance should **increase** their access to mortgage finance. This follows from the reduction in residual risk to mortgage lenders. This is the first hypothesis that one could postulate in regards to the presence of flood insurance requirements. **Hypothesis 1**: Mandated flood insurance improves access to mortgage financing.

However, mandated flood insurance – if too expensive – may have the unintended effect of inhibiting access to mortgage funding. This may hold particularly for low- and medium-income borrowers. Especially mortgages taken out after the 2012 Biggert-Waters Act had to buy insurance at close to fair market prices. Based on NFIP insurance rates, an average house may pay several hundred dollars per month for insurance. While it may make economic sense from the perspective of a bank to curtail lending to borrowers with low income who are unable to afford the mortgage costs, including the flood insurance premium, it is unlikely to be desirable for a society to limit coastal living to only the wealthy. This brings us to the second hypothesis we investigate. **Hypothesis 2**: Mandatory flood insurance when too costly can have the unintended effect of limiting access to mortgage financing to poorer households.

A second channel through which the NFIP might negatively affect access to mortgage credit is via the regulatory burden that enforcing and monitoring mandatory insurance requirements represent for banks. Recall that the National Flood Insurance Reform Act of 1994 put the onus of ensuring that mortgage owners had the appropriate flood insurance coverage not only at the time of the mortgage origination but also during the life of the mortgage on lenders. Consequently, some banks, especially non-local banks, unfamiliar with an area, may be unwilling to take on such a risky burden. On the one hand, NFIP insurance can be complicated. Coverage requirement will depend on the exact property in question (and can be affected by construction, number of stories, and the presence of additions) as well as the communities compliance with the NFIP regulations. The understanding required to monitor borrower adherence to insurance requirements may be beyond large national banks with limited local presences. In fact, available evidence continues to show that despite the mandatory purchase requirement, not all mortgages on properties located in SFHAs actually carry flood insurance. A study by the GAO reports that the four prudential regulators (FED, FDIC, NCUA, and OCC) detected violations related to the mandatory purchase requirement which ranged from 2 percent to 23 percent between 2016 and 2019.[12]

Given the expenses – which have risen over time – associated with banks failing to ensure their borrowers carry insurance, large banks may be unwilling to dedicate resources to the issue. It may simply be safer to forego lending in these regions. This is the final possible hypothesis we investigate.

Hypothesis 3: The NFIP, by requiring lenders to ensure borrowers adhere to flood insurance requirements, may make lending by non-local banks, who do not wish to dedicate resources to understanding the insurance situation in hundreds of communities, less likely.

3 Data

The two main data sources we use for this project are Federal Emergency Management Agency's (FEMA) flood maps and mortgage applications from the confidential version of the Home Mortgage Disclosure Act (cHMDA) database available to the Federal Reserve. We complement these datasets with information on natural disasters from the Spatial Hazard Events and Losses Database (SHELDOS) and on mortgage delinquency from the Consumer Financial Protection Bureau (CFPB). We describe next the data we use from each of these sources.

3.1 Flood Maps

We obtain archived maps of the "national flood hazard risk" from the Federal Emergency Management Agency (FEMA). National flood hazard layers highlight the regions that are at risk of experiencing a 100 year (or a 500 year) flood. An area considered part of a 100-year flood zone is reasoned to have at least a 1% chance of experiencing a severe flooding event in a given year. These are the regions in which borrowers are required to maintain flood insurance. The maps are built as part of FEMA's support for

[12] The most commonly identified violation (42 percent) was related to a lack of flood insurance coverage. These figures account only for violations identified for mortgage loans that examiners tested during examinations – and therefore may not capture the full universe of violations that have occurred for all mortgage loans over the time period, GAO (2021).

the National Flood Insurance Program (NFIP) and are available to the public. Historical maps are hard to come by because they are retired once a map has been updated. However, we were able to gather information on U.S.-wide maps for 2013, 2014, 2015, 2016, 2017, 2020, and 2021. Our maps cover all 50 states but exclude territories, dependencies, and the District of Columbia.

As we discussed in Section 2, although some exemptions can apply, for the most part new mortgages in a 100 year flood zone have to buy protection in the form of flood insurance. Flood insurance can be bought at subsidised rates from the NFIP as long as the community of the borrowing applicant participates. Participation involves meeting certain requirements and can present a regulatory burden. As such, some communities with very few inhabitants forego participation. Conversely, communities can qualify for NFIP subsidies if they actively engage with the NFIP, including helping inhabitants be aware of flood risks. We merge in data on all counties that are either sanctioned by the NFIP, removed from the program due to noncompliance, and obtain additional insurance subsidies. This data is at the level of the participating community and usually subsumes several census tracts at once.

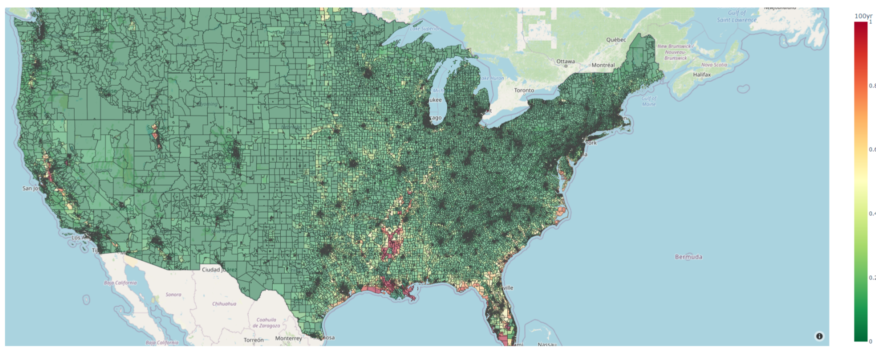
We digitize historical FEMA flood maps and overlay them with U.S. census-tract maps. We are thereby able to determine the share of each census tract that is covered by a 100 year (and 500 year) flood hazard layer over time. Our operating assumption is that, in a census track which is X% covered by a 100 year flood zone, applicants have an X% chance of applying for a mortgage subject to the flood insurance requirement. Recall that being in 100 year flood zone is associated with the requirement to purchase insurance. Given that census tracts are geographically small, and contain around 4000 inhabitants, this distinction seems suitable to our purposes. Further, given that low-lying coastal zones are more densely inhabited, our estimates are unlikely to be upward biased.

Figure 1, Panels a and b, are examples of digitized flood maps. They depict the entire U.S. as well as the area around New Orleans in Louisiana, respectively. Areas in dark red are considered to be 100% covered by flood zones. Areas in dark green, on the other hand, are at most 5% covered by a flood zone. Most areas in the U.S. are nominally classified as being either at risk of flooding or not. By area, most of the U.S. is not considered a flood risk. However, as noted above, the most populated regions lie along the coast or close to rivers – these census tracts are geographically small but numerous. Based on HMDA mortgage data, we estimate that around 48% of all mortgage applications for new single family (primary residence) homes in the U.S. over the past ten years occurred in census tracts that were at least partially covered by flood hazard zones. This represents around 50 million applications.

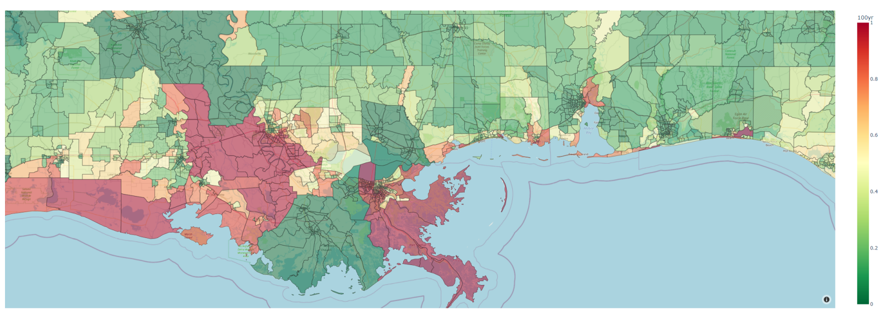
It is important to note that flood maps, while communicating some information about flood risk to

Figure 1: ***Digitized Flood Maps***

(a) *U.S.-Wide Flood Maps at Census Level*



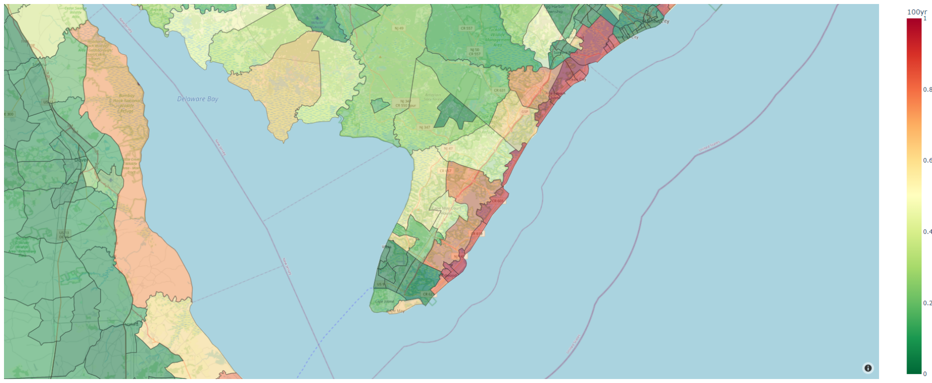
(b) *Flood Maps of New Orleans and Surrounding Areas*



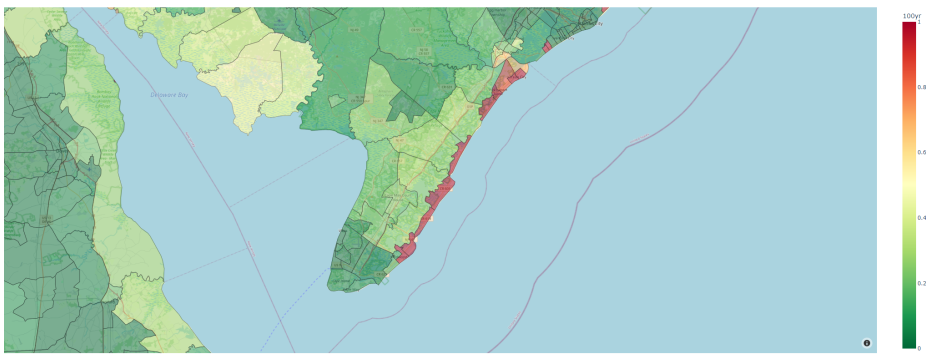
Notes: This Figure shows examples of Flood maps in 2021. Green areas are not or barely covered by flood maps. Panel (a) shows flood maps at the U.S.-level. By size, the uncovered census tracts are the majority of the country though this obscures more densely populated census tracts, which are much smaller and more likely to be mapped. Panel (b) shows the area around New Orleans, much of which is considered a high flood risk.

Figure 2: *Changes in Flood Maps*

(a) *2021*



(b) *2018*



Notes: Flood map updates visualized for Delaware Bay area

market participants, are not actually accurate gauges of such risks. Firstly, maps express a lower bound of risk. 100 year flood zones denote an area that is expected to flood "at least" once every 100 years. Many flood regularly. Secondly, maps are known to be outdated and are often not reflective of the most recent risks – or of the countermeasures that a community may have taken. To address this second issue, maps are updated occasionally.

Figure 2 shows changes in flood maps around the Delaware bay area between year-end 2018 and 2021. It is apparent that flood risks have increased. A number of previously 'safe' areas have been rezoned and are at least partially (in some cases substantially) covered by a flood hazard risk in 2021. It is unlikely that the underlying flood risk changes substantially within such a short period of time.

Flood map updates are infrequently and FEMA attests to a long backlog of maps that require updating.[13] Map updates can increase the degree to which an area is considered at risk of flooding

[13] These updates are set to occur at regular intervals, though communities can attempt to expedite the process. For a discussion of the backlog see for instance Scata (2020). FEMA also details the lengthy process that underpins flood map changes here: https://www.fema.gov/flood-maps .

or they can reflect efforts taken by the community to manage flood risk. In the latter case, the share of the census tract liable to flood can decrease.[14] Map updates are somewhat more frequent in the years following a major disaster as well as for more affluent communities. However, even after a major disaster an update usually takes several years to complete. This has an important implication for our purposes. Using community, historical disaster damage, income and population-composition controls, flood map updates can be made quasi exogenous to local house purchase applications in any given year.

We compute year-on-year changes of the degree to which census tracts are covered by flood maps in our data. Changes are bounded between -1 and 1. A change of 1, which can occur, indicates a census track that was not covered by any flood map in the year prior but considered to be fully in a flood zone the following year. A change of -1 (which we do not observe in our data) indicates a census track that was considered a flood risk and subsequently removed.

3.2 HMDA Data

Our primary data on mortgage applications comes from the confidential version of the Home Mortgage Disclosure Act (cHMDA) database available to the Federal Reserve. Unlike the standard HMDA database, the confidential data includes origination month and – most importantly – the applicant's census tract. Given that census tracts are designed to encompass around 4000 people, they are often small in size. We are thus more accurately able to ascertain the flood risk of individual applicants than when using county-level data.

Similar to the public version, the cHMDA contains information on loan amount, applicant income, applicant race, applicant gender, and several census-tract level characteristics. These include census tract composition and average local income. For a subset of applications in later years (2017+) we are able to track property values and thereby compute Loan-to-Value (LTV) ratios. Finally, the confidential data includes information on applicant credit scores after 2018. This is an important additional control and we make use of separate specifications that contain these scores.

We restrict our sample to new primary home-purchase applications. As such, we do not consider refinancings or home improvement applications, but look solely at households buying a new home. We further remove any applicant with negative income or negative loan amounts, as these indicate errors in

[14]Reductions in the degree to which regions are considered a flood risk can occur for a number of reasons. Primarily, communities and individual households can petition FEMA to be removed from a flood map. This requires the input of (structural) engineers who attest that (i) improvements to infrastructure have been made that reduce the risk of flood damage or (ii) dwellings are actually located/built in such a way as to not be at risk of flooding. FEMA can also suspend mapping activity in certain communities for their failing to comply with requirements. This can result in the removal of maps.

Table 1: *Summary Statistics*

Variable	N	Mean	Std. Dev.	P10	P90
		Full Sample			
Share of Loans Accepted	45,781,878	0.747	0.433	0	1
Loan Amount ('000 USD)	45,781,878	249.7	222.3	74.7	450.1
Applicant Income ('000 USD)	45,781,878	83.63	74.02	1.2	181
Log Loan to Income	45,781,878	1.945	2.63	0.15	7.77
Med. Family Income ('000 USD)	45,781,878	76	32	43	117
Minority Applicant	45,781,878	0.26	0.44	0	1
Female Applicant	45,781,878	0.297	0.457	0	1
Jumbo Loan	45,781,878	0.05	0.22	0	1
Loan-to-Value Ratio	16,112,510	0.89	0.12	0.74	1
FZ-Coverage	45,781,878	0.10	0.17	0	0.26
FZ-Coverage (excl. unmapped)	31,070,120	0.15	0.19	0.02	0.36
Δ FZ-Coverage (changes only)	5,576,271	0.01	0.02	-0.01	0.05
		Accepted Loans			
Loan Amount ('000 USD)	40,801,868	254.8	216.7	83	450
Applicant Income ('000 USD)	40,801,868	86.28	74.28	31	185
Log Loan to Income	40,801,868	1.92	2.60	0.18	7.77
Med. Family Income ('000 USD)	40,801,868	78	32	44	118
Minority Applicant	40,801,868	0.24	0.43	0	1
Female Applicant	40,801,868	0.29	0.45	0	1
Jumbo Loan	40,801,868	0.05	0.23	0	1
Loan-to-Value Ratio	14,045,646	0.88	0.12	0.73	0.99
FZ-Coverage	40,801,868	0.10	0.17	0	0.26
FZ-Coverage (excl. unmapped)	26,809,286	0.13	0.19	0.01	33
Δ FZ-Coverage (changes only)	4,208,545	0.01	0.02	-0.01	0.04

Note: This table depicts summary statistics for our sample. We include our full sample as well as our sample of accepted loans in panel B. LTV rates are calculated for applicants for whom we can track LTV. Flood zone coverage is shown for our full sample as well as for areas that have non-zero flood zone coverage. Flood zone changes are shown for all areas with flood zone coverage and all areas with non-zero changes in flood zone coverage.

recording. Finally, we match our sample of applicants with our flood map data (see above), as well as disaster data (see below). Since we do not observe PR or Washington DC in our flood map data, we drop applications in these areas. Our final sample includes over 45 million applications for which we have flood map data and over 40 million applications for whom we can calculate year-on-year changes in flood map coverage.

Table 1 shows summary statistics for key variables in our sample. We show both our raw sample – which we use to measure the impact of flood zones on mortgage rejections – and our sample of accepted loans – which we use to measure the impact of flood zones on loan to value ratios. The average loan acceptance rate is nearly 75%. We see that the average loan-to-value ratio in our sample is just below 90% for both applications and accepted loans, implying an average 10% down-payment.

The relatively high acceptance rate in our data follows form the fact that many applicants are "soft rejected" by a bank before completing the official application process. It should be noted that we consider a loan accepted only if both parties agree to the terms. We deal with the issue of soft rejections in two ways. Firstly, we look at both the intensive and extensive margin of lending. By looking at the loan-to-value ratios of accepted loans – i.e. the intensive margin – we learn something about bank risk avoidance in regions with higher flood risk. A second way we deal with soft rejections is by looking at aggregate application data. With it, we are able to identify whether applications – as a whole – are reduced in flood zones. We are careful in interpreting these latter results as reductions may be representative of soft rejections as well as reduced borrower demand.

Table 1 shows that the average income of applicants in our data is just over 80,000 USD, while the average loan application seeks around 250,000 USD. Both figures are somewhat higher in our pool of accepted loans. Importantly, the average neighbourhood is 10% covered by a flood map. This rises to 15% if we exclude those regions that remain un-mapped throughout our sample. The flood zone coverage is lower among accepted loans– a first possible indication of banks avoiding flood zones. For most neighbourhoods, the changes in flood zones are small and incremental. The average neighbourhood experiences just under 2% flood zone increases in a given period. However, the small average belies that some regions saw larger and more substantial increases. Finally, it is worth noting that some regions experienced a decrease in flood zone coverage as flood mitigation measures were assessed and attested to by FEMA.

3.3 Additional and Supplemental Data

We make use of additional data in key analyses or robustness tests. We obtain disaster data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[15] SHELDUS tracks USD damage estimates for every weather event in the U.S. The data is aggregated at the county and month level. SHELDUS relies on insurance and weather station data. For smaller disasters, damages are estimated by local officials and may be somewhat inaccurate. In fact, there are known measurement

[15]SHELDUS was first developed at the University of South Carolina. Since 2018, the Arizona State University and the department of Homeland Security have maintained it.

errors (Roth Tran and Wilson, 2020).[16] Differences in how damages are estimated typically follow state lines, which can be accounted for in regressions (see below). Larger events – especially events that elicit a FEMA declaration as a national emergency – are likely to include more accurate estimates of damages. We use historical flood damages (including both coastal and riverine flooding) to account for realized flood risk.

We further obtain mortgage delinquency data from the Consumer Financial Protection Bureau (CFPB). CFPB tracks the share of mortgages that are over 90 days in arrears at the county by month level. On the one hand, this allows us to control for delinquencies – and the associated risks from a bank's perspective – in our regressions. On the other hand, we can split areas by mortgage delinquencies in the month prior to lending decisions. This allows us to determine to what extent a bank's reaction to flood map changes is driven by underlying regional risks.

4 Methodology

As we discussed in Section 2, it is ex-ante unclear whether flood zones – and especially the updating of flood zones – should have a negative or positive effect on lending decisions. Therefore, our first set of analyses is based on an ex-ante agnostic tracking of the degree to which bank lending decisions are different, if borrowers are located in a flood zone. This represents a test of Hypothesis 1, as we seek to determine whether the aggregate effect of insurance on lending is negative or positive. We regress the propensity of a borrower receiving a loan (or the LTV of accepted loans) on a host of bank, borrower, and region characteristics. Our main explanatory variable is the degree to which a census tract is covered by a flood map. We assume a uniform risk, so that any given applicant has an X% chance of being in the flood zone, where X is the degree to which a census tract is covered. This assumption is likely to be a lower bound for two reasons. Firstly, populations tend to be clustered along waterways or the coast which are the zoned parts of any census tract. Secondly, a bank may behave differently in a region with *any* flooding potential. As such, the mere presence of a flood map may impact all possible loan applicants in that region as a bank engages in forward-looking planing. Our main equations take the following form:

$$Y_{i,b,c,t} = \alpha + \beta_1 FloodMap_{c,y,t} + X_{i,t} + \gamma_{c,y} + \alpha_b + \omega_{county,y} + \epsilon_{i,b,c,t} \tag{1}$$

[16]This is corroborated in direct discussions with SHELDUS data managers conducted for Blickle and Morgan (2022).

where Y is a dummy denoting whether a loan was accepted (or the LTV of an accepted loan) at the individual borrower (i), census-tract (c), lender (b), and time (t) level. We consider a loan accepted only if both parties agree to the final terms. A lender may otherwise nominally 'accept' a loan at highly unfavourable rates to a borrower. This would constitute a 'defacto rejection' as the bank knows the applicant would refuse the offered terms. In regressions making use of borrower LTV, we are limited to the subset of applications for which the relevant data is recorded. This substantially reduces our sample size. Naturally, we focus only on accepted loans for this type of analysis.

Our coefficient of interest is β_1, which denotes the impact of the degree to which a census tract is covered by a flood map in a given year. It is bounded between 0 and 1. X is a vector of applicant/loan controls including: applicant income, loan amount, income-to-loan ratio, applicant race, applicant gender, and applicant fico credit score, in certain regressions. γ is a vector of census tract level controls for a given year including census tract income, population, and share of minority population. α are bank fixed effects. ω are county*year fixed effects. These would absorb the overall impact of county-level riskiness that lenders may or may not perceive. We further include lagged cumulative flood damages from the last 30 years. Our effect is therefore identified *within* bank, and *within* a county at a given time, after accounting for borrower and past region flood risk. We are ostensibly comparing highly similar borrowers, applying for equally sized loans from the same bank in the same county – differenced by whether applicants live in a census tract considered a flood risk or not. In some analyses we interact our variable of interest, β_1, with either (i) borrower or (ii) bank and loan traits. Through the interaction terms we are able to determine the sub-populations, loan-types or lenders that experience the most pronounced reactions to being in flood zones. In terms of borrower characteristics we are particularly interested in borrower fico scores and whether a borrower is below average income for the count. With these terms we can explore Hypothesis 2 – which states that flood zoning may affect lending to marginally poorer households. In terms of lender and loan characteristics, we are interested in lender type, whether the lender is local to a given county (which we define as >40% of mortgage loans issued in the county in question) , and whether loans are below the insurance limit of 250,000 USD or above the jumbo cutoff. These interactions can help us determine whether flood maps deter certain types of lenders outright, possibly because they reveal information to otherwise less informed participants – such as nation-wide lenders and non-local banks. We are thereby testing Hypothesis 3, which assumes that the costs of enforcing adherence may prevent some (non-local) banks from lending in flood zones or at least forego extending certain types of loans for whom the costs of monitoring exceed the payoff.

The above regressions relate flood map coverage –in levels – to bank lending responses. However, flood maps often remain unchanged for many years. Banks and borrowers have time to adjust their behaviour over the course of time. Moreover, mapped regions experience, on average, more flooding disasters than un-mapped regions. While one can account for the damages of past disasters, it is difficult to claim a causal link between the degree to which a census track is covered by a flood map and bank lending behaviours.

A more causal link can perhaps be established by looking at the changes in maps and the resulting bank lending behaviour. Once we account for county fixed effects, census tract income, demographics, and past disaster damages, we can claim that an update to a map is at least conditionally exogenous to a household's decision to apply for a mortgage at a given point in time. As such, we run analyses of the following type:

$$Y_{i,b,c,t} = \alpha + \beta_1 FloodMap_{c,y-1} + \beta_2 \Delta FloodMap_{c,y,t} + X_{i,t} + \gamma_{c,y} + \alpha_b + \omega_{county,y} + \epsilon_{i,b,c,t} \tag{2}$$

Here, the variable of interest is the *change* in flood map coverage from the previous to the most recent year, β_2. As such, we are measuring any lending decision that follows in response to an exogenous increase in the need for insurance coverage. We include the degree to which the region was covered by a flood zone in the previous period as a control. Areas with high ex-ante coverage may have very different acceptance rates while high-ex ante coverage may relate mechanically to large changes in coverage. Moreover, we include the same exhaustive list of controls and fixed effects as in the regressions above. Further, we again interact our variable of interest with a variety of borrower, loan or bank interaction terms to identify the key drivers of our results.

Finally, in extensions to the paper, we perform a number of sample splits. This allows us to further pinpoint sensitivities within our results. Two key distinctions are (i) sample splits between regions that experience frequent flooding disasters and those that do not, as well as (ii) regions with high delinquency rates and those with lower delinquency rates. The first sample split allows us to test for the salience of the impact of disasters. Flood insurance may appear more necessary in regions that experience frequent events. As such, monitoring flood-insurance adherence may be more important as regulators may more actively enforce such adherence (consider hypothesis 3). Further, reactions to flood insurance requirements may be very different by state. The second sample split facilitates a deeper understanding of bank risk aversion. Banks may be particularly weary in states with ex-ante high delinquency rates. While evidence of a decline in lending in these states may be consistent with either Hypothesis 2 or 3, it will run counter Hypothesis 1 which posits that mandated flood insurance improves access to mortgage financing.

5 Baseline Results

In this section, we show that banks are less likely to accept mortgage applications in flood zones. Our results are more pronounced for low-income and low-fico borrowers. the We also show that the onus of monitoring adherence limits bank lending. These results are generally stronger when looking at the conditionally exogenous changes to flood zones.

5.1 Loan Acceptance Rates in Flood Zones

In Table 2 we first relate the degree to which a census tract is covered by a flood zone to loan acceptance rates. As discussed in the previous section, we include a number of borrower, bank, and region characteristics in the regression to ensure we are correctly identifying our effect of interest. Column (1) shows the results of our baseline specification. We find that being in a census tract with a higher risk of flooding is associated with a reduction in loan acceptances. Applying in an area fully covered by a flood zone would be associated with a 1.6% lower acceptance rate. While this is an economically meaningful effect, the result is not so large that requiring insurance drastically decreases the availability of loans to the *average* applicant. Overall, this finding helps us reject hypothesis 1. Despite theoretically reducing a lender's flood-risk exposure, flood insurance requirements do *not* induce greater lending. The negative coefficients seems to speak to the validity of hypothesis 2 – which postulates a reduction in lending due to the insurance costs faced by borrowers – or 3 – which postulates a reduction in mortgage acceptances by lenders due to the burden of ensuring adherence.

Our control variables follow an expected pattern. Applicant income is naturally associated with an increase in the likelihood that a loan is accepted, all else equal. Similarly, the median income in the census tract is positively associated with loan acceptance rates (though the coefficient is naturally small). Local banks are, on average, more likely to accept borrowers all else being equal. Minority as well as sole female applicants are somewhat less likely to be accepted.[17] Jumbo loans (i.e. loans above

[17] A large literature has explored the issue of discrimination especially against minority applicants, which we could – potentially – be measuring here. For recent examples and literature discussions, see for instance: Ladd (1999); Yinger (1997); Bartlett et al. (2022); Black et al. (1978); Barocas and Selbst (2016); Buchak et al. (2018); Black et al. (2003); Cheng et al. (2015); Wei and F. (2022). We abstain form exploring this phenomenon in our paper, though we control for primary applicant race and

the local conforming limit) are less likely to be accepted. After all, these are harder to securitize and represent greater relative risk to a bank. More populated tracts see a slightly elevated rate of acceptance. Surprisingly, loan amount is positively correlated with acceptance, though it should be noted that this coefficient reflects a residual measurement that remains after we control for the 'jumbo-loan' dummy as well as the loan to income ratio, which is negatively related to loan acceptances. Finally, cumulative past flood damages are negatively associated with loan acceptances. This may reflect bank risk management and – in part – a bank aversion to actual flood risk.

Finally, it is noteworthy that the 500-Year flood zone, which represents a flood risk, but does *not* require borrowers to hold flood insurance, is associated with an increased chance that a loan application is accepted. This is evidence against hypothesis 1. The risk of flooding as outlined by th eFEMA maps – all else being equal – does not deter lending. However, the introduction of mandatory insurance does appear to.

In column (2), we show the interaction between our variable of interest and applicant fico score. Our sample is reduced substantially due to the limited availability of the credit score variable. It should be noted that fico scores are bounded between 400 and 850 and we scale the variable by 100 for ease of interpretation. We find that the interaction term is strongly positive and significant. This implies that the negative effect of applying for a mortgage in a flood zone is attenuated by good credit – for each 100 points in applicant credit score, the chance of being rejected due to the insurance requirement in effect is reduced by 1% point. This implies a substantial and economically meaningful difference in the ability of low-score applicants and high score applicants to obtain credit in flood zones.

Similarly, in column (3), we show that the effect of flood mapping is greater for applicants with low income (relative to average applicant income in their region). In total, an applicant with low income may expect to experience a 4% lower acceptance rate in an area designated a flood zone – this is a sizeable effect that goes above and beyond any reduced acceptance rates low-income applicants may already expect, all else equal.

Our results in columns (2) and (3) indicate that banks may be curtailing lending to less affluent or less financially secure borrowers. This is in keeping with our hypothesis 2. It is evident that the added burden of insurance requirements may deter lenders from accepting borrowers for whom insurance payments pose a significant financial burden. However, we can also see that a baseline reduction in lending, which is not explained by income or credit score, remains.

sex in our regressions.

In Table 3 we again replicate the regressions discussed above. Here, we interact our variable of interest with bank and loan characteristics. Column (1) replicates column (1) from the table above. It shows the baseline effect of applications being in a flood zone. Columns (2) and (3) interact the degree to which a census tract is covered by a flood zone with bank-type dummy variables. This allows us to differentiate the reactions of various types of lenders to flood risk. However, one may expect some lender-types to change behaviour based on loan sized. The ability to move loans off of a balance sheet (through GSE securitization) may be especially important for certain types of lenders – first and foremost non-bank mortgage lenders. As such we split our sample into conforming and non-conforming (i.e. jumbo) loans. As expected, we see that independent mortgage brokers are averse to making jumbo-loans in flood zones. These loans, after all, remain on a bank's balance sheet. And although monitoring adherence to flood insurance falls to the lender despite securitization, we see from column (3) that non-bank lenders are willing to make conforming loans in flood zones. National banks, on the other hand, are always averse to lending when insurance requirements bind. This observation is in keeping with hypothesis 3. The burden of monitoring insurance adherence deters lending b y large national banks far removed from an area (equally across conforming and non-conforming loans). Conversely, we find that state banks and credit unions – usually much more local banks – are somewhat more comfortable in lending to borrowers facing insurance requirements. Given relatively few observations, the coefficients on non-conforming loans are somewhat imprecisely estimated for these banks.[18]

Column (4) interacts our variable of interest with measures of loan size. Small loans are loans that fall wholly under the insurance limit of 250,000 USD. We use this cutoff because it is the cleanest and simplest measure of "fully insured" properties. We recognize that we are introducing a slight downward bias into our estimation with this restrictive measure. As discussed, loans above the threshold of 250,000 USD are likely to be defacto fully insured too. After all, even a catastrophic flood might not reduce the value of a property to 0. In any case, our results indicate that lenders appear unwilling to make fully insured loans in an area of high flood zone coverage. This is arguably the opposite of what one would expect in terms of pure risk minimization. Larger loans (i.e. those that surpass the jumbo limit), on the

[18] In the Appendix we analyze the willingness of banks to securitize loans in flood zones in Table A.1. We find that the likelihood a loan is securitized – conditional on being both accepted and within the conforming limit– is lower in a flood zone. This may be a byproduct of the residual responsibility the originator bears when it comes to ensuring adherence of the borrower to flood insurance. Independent mortgage brokers and national banks reverse this trend somewhat (being happier to securitize in flood zones). However, they do not reverse the aggregate effect. In Table A.2 we show that changes to flood zones have no effect on whether lenders securitize loans. Finally, it is worth noting that the propensity to securitize with a government backed agency rises (relative to securitization with private agencies) after flood zone growth (see: Appendix Table A.3). This may reflect a relative aversion of private securitization firms to engage with the burden of insurance.

other hand, seem less affected. Taken together, this is strong evidence for hypothesis 3. We see that the cost of monitoring insurance adherence detracts bank lending. Even if a property can be insured – the burden of ensuring compliance with insurance requirements may be large, relative to a small loan's profitability – the bank may forego lending.

In column (5) we can see that local banks[19] are – relatively speaking – more likely to make loans in flood zones. The baseline negative effect is not attenuated by the positive interaction coefficient, however. Together with the results from columns (2) and (3), these results lend further credence to hypothesis 3, i.e. to the notion that local knowledge is a factor in banks' ability/desire to monitor insurance compliance. This is explored further in our Extensions below.

It is important to highlight, again, that we do not speak to the overall welfare costs of flood insurance mandates. Some evidence does point to the fact that delinquency rates, which can follow a flood, are somewhat reduced if flood insurance mandates are in effect (see Appendix A.4). However, the reduction in lending deserves some attention. Especially given that default rates following a flood do not rise substantially and do not, as was discussed in Blickle and Morgan (2022), affect bank stability.

5.2 Loan Acceptance Rates after Flood Zone Changes

The above results showed that banks are generally less willing to lend in flood zones where borrowers face insurance requirements. However, our results may be the product of varying differences at the census tract level. In this section, we instead focus on changes in flood maps. Given the age of the average map and variability in when map changes occur, such changes can be made conditionally exogenous of individual mortgage applications or pre-existing underlying flood risk (see discussion above). Our tables take the same form as those in the previous sub-section. We first interact our variable of interest – the year on year change in flood maps – with borrower characteristics.

In column (1) of Table 4, we can see that the change in flood zone from the previous year is associated with a significant reduction in the chance of an application being accepted. The effect is substantial, with a region that is suddenly fully covered by a flood zone experiencing a 2.3% decline in acceptance rates. Of course, the changes to flood zones in our data are typically much smaller, making aggregate reductions in lending somewhat less pronounced. Our estimates here can perhaps best be viewed as an approximation of what the average applicant, who suddenly finds themselves in a flood zone, may experience in terms of a reduction in lending. After all, the average applicant is either fully covered by

[19] As discussed, local banks are those with at least 40% of their mortgages in a given county.

or not covered by a flood map and therefore subject to the mandatory insurance requirement. Column (1) adds further evidence against Hypothesis 1, which supposed that the benefits of risk mitigation, brought about by insurance requirements, may increase bank lending.

From column (2) of Table 4, we can see that the sensitivity of our result to applicant credit scores is enormous. The baseline reduction in lending to applicants with extremely poor fico scores in regions that are suddenly subject to mandatory insurance requirements due to flood-map changes is 22%. Similarly, in column (3), we find that applicants with low income experience a drastic reduction in loan acceptance rates following a revision of FEMA's flood maps. The effect of suddenly being subject to mandatory insurance is a full order of magnitude greater for low-income applicants than for average applicants.

As a preliminary conclusion we can say we find substantial evidence for our hypothesis 2. The costs of insurance for marginal borrowers in newly zoned regions – where insurance must be purchased at *market rates* – significantly limits borrowing.

In Table 5 we replicate our analysis from above and interact our coefficient of interest– changes in census tract-level flood maps – with loan and bank characteristics. As such, we can offer more evidence on the role of asymmetric information in compounding the effects of flood insurance mandates (i.e. our hypothesis 3). In column 1, we once again show the baseline coefficient. In columns (2) and (3) we again split our sample into conforming and non-conforming (i.e. jumbo) loans and interact our variable of interest with bank-type fixed effects. We can see that our results above are largely confirmed. Independent mortgage brokers are averse to making loans they have to keep on their balance sheet. National banks are generally averse to lending in flood zones where they will have to ensure insurance adherence. The coefficients in column (2) are all large in magnitude, though imprecisely estimated.

Table 2: ***Loan Acceptance in a Flood Zone by Borrower Type***

	Loan Accepted		
	(1)	(2)	(3)
Flood Zone Coverage	-0.016***	-0.086***	-0.014***
	[0.000]	[0.006]	[0.000]
FZ Coverage x App. FICO Score		0.010***	
		[0.000]	
FZ Coverage x Low App. Income			-0.026***
			[0.002]
500 Year FZ	0.008***	0.005***	0.008***
	[0.001]	[0.001]	[0.001]
Log Applicant Income	0.071***	0.043***	0.076***
	[0.000]	[0.000]	[0.000]
Tract Median Family Income	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]
Local Bank	0.013***	0.003***	0.013***
	[0.000]	[0.001]	[0.000]
Minority Applicant	-0.057***	-0.028***	-0.058***
	[0.000]	[0.000]	[0.000]
Female Applicant	-0.008***	-0.006**	-0.008***
	[0.000]	[0.000]	[0.000]
Jumbo Loan	-0.078***	-0.055***	-0.078***
	[0.000]	[0.000]	[0.000]
Tract Population	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]
Loan Amount (thousands USD)	0.001***	0.002***	0.001***
	[0.000]	[0.000]	[0.000]
Log Loan to Income	-0.003***	-0.016***	-0.003***
	[0.000]	[0.000]	[0.000]
Long Term Flood Damage	-0.006*	-0.004	-0.006*
	[0.003]	[0.002]	[0.003]
Applicant Credit Score		0.092***	
		[0.000]	
Low App. Income			-0.115***
			[0.000]
Observations	45,781,878	13,816,817	45,781,878
R^2	0.096	0.178	0.096
Bank, County-Year, Quarter-Year FE	Yes	Yes	Yes

Note: We estimate equation 1, above. Our variable of interest is the degree to which a census tract is covered by a flood zone (bounded between 0 and 1). Column (2) interacts our variable of interest with applicant fico score, column (3) with whether the applicant has below average income for the county. All regressions include the share of the census tract covered by a 500-year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression on column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3: ***Loan Acceptance in a Flood Zone by Loan and Lender Type***

	Loan Accepted				
	(1)	(2)	(3)	(4)	(5)
Flood Zone Coverage	-0.016***	-0.008***	-0.021***	-0.014***	-0.017***
	[0.000]	[0.003]	[0.001]	[0.001]	[0.000]
FZ x Indep. Mortg. Broker		-0.031***	0.012***		
		[0.004]	[0.001]		
FZ x Nat. Bank		-0.011***	-0.011***		
		[0.003]	[0.001]		
FZ x Credit Union		0.005	0.004*		
		[0.009]	[0.002]		
FZ x State Bank		0.012	0.021***		
		[0.012]	[0.004]		
FZ x Small Mortg.				-0.006***	
				[0.001]	
FZ x Large Mortg.				0.002	
				[0.001]	
FZ *Local Bank					0.008***
					[0.002]
Observations	45,781,878	2,525,085	43,255,662	45,781,878	45,781,878
R^2	0.096	0.096	0.096	0.536	0.096
Sample	All	Non-Conforming	Conforming	All	All

Note: We estimate equation 1, above. Our variable of interest is the degree to which a census tract is covered by a flood zone (bounded between 0 and 1). Columns (2) and (3) interact our variable of interest with bank type. We have split our sample into conforming and non-conforming (i.e. jumbo) loans. Column (4) uses loan size with small loans falling fully within the 250,000 USD NFIP insurance limit and large loans exceeding the jumbo cutoff for the county in question. Column (5) interacts the variable of interest with a dummy denoting whether the lender in question is local to the county – a bank is considered local if more than 40% of its loans go to one county. We show only coefficients of interest for convenience. All regressions include the share of the census tract covered by a 500-year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, census tract population, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, and county-time fixed effects. Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4: ***Loan Acceptance after Flood Zone Change by Borrower Type***

	Loan Accepted		
	(1)	(2)	(3)
Change in FZ Cov.	-0.023***	-0.219**	-0.021***
	[0.007]	[0.102]	[0.003]
Flood Zone Coverage$_{t-1}$	-0.016***	-0.011***	-0.016***
	[0.001]	[0.001]	[0.001]
ΔFZ Cov. x App. FICO Score		0.026*	
		[0.014]	
ΔFZ Cov. x Low App. Income			-0.199**
			[0.042]
Observations	40,801,868	4,003,209	40,801,868
R^2	0.100	0.203	0.100

Note: We estimate equation 2, above. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). Column (2) interacts our variable of interest with applicant fico score, column (3) with whether the applicant has below average income for the county. We show only coefficients of interest for convenience. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5: *Loan Acceptance after Flood Zone Changes by Lender Type*

	Loan Accepted				
	(1)	(2)	(3)	(4)	(5)
Change in Flood Zone Coverage	-0.097***	0.151**	-0.041***	-0.069***	-0.026***
	[0.009]	[0.065]	[0.013]	[0.013]	[0.007]
Flood Zone Coverage$_{t-1}$	-0.016***	-0.022***	-0.017***	-0.016***	-0.016***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
ΔFZ Cov. x Indep. Mortg. Broker		-0.251**	0.080***		
		[0.113]	[0.021]		
ΔFZ Cov. x Nat. Bank		-0.142	-0.161***		
		[0.095]	[0.028]		
ΔFZ Cov. x Credit Union		0.245	0.046		
		[0.249]	[0.052]		
ΔFZ Cov. x State Bank		0.088	0.182***		
		[0.239]	[0.070]		
ΔFZ Cov. x Small Mortgage				0.039	
				[0.029]	
ΔFZ Cov. x Large Mortgage				0.053*	
				[0.030]	
ΔFZ Cov. x Local Bank					0.081*
					[0.044]
Observations	40,801,868	2,324,604	38,476,120	40,801,868	40,801,868
R^2	0.100	0.102	0.071	0.105	0.100
Sample	All	Non-Conforming	Conforming	All	All

Note: We estimate equation 2, above. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). Columns (2) and (3) interact our variable of interest with bank type. We have split our sample into conforming and non-conforming (i.e. jumbo) loans. Column (4) uses loan size with small loans falling fully within the 250,000 USD NFIP insurance limit and large loans exceeding the jumbo cutoff for the county in question. Column (5) interacts the variable of interest with a dummy denoting whether the lender in question is local to the county – a bank is considered local if more than 40% of its loans go to one county. We show only coefficients of interest for convenience. All regressions include the share of the census tract covered by a 500-year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, census tract population, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, and county-time fixed effects. Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

In column (4) of Table 5 we can see that loans, which are larger, are somewhat preferred in areas that experience a flood zone increase. This may follow from the fact that wealthier borrowers, who purchase larger houses, are more able to afford insurance. It may also relate to the fact that the monitoring of insurance adherence is a smaller burden, relatively speaking, for larger loans (as discussed above). Finally, in column (5) we again find support that the negative baseline effect is attenuated by local knowledge. Local banks, that understand the regional customer base best, are less affected by the flood insurance requirements. Overall, this table again presents strong evidence that hypothesis 3 likely holds true to some extent – i.e. the costs of monitoring borrower adherence to insurance prevents lending by unfamiliar banks or to borrowers taking out small loans.

5.3 Loan-to-Value Ratios after Flood Zone Changes

We have thus far focused on the extensive margin – i.e. whether a bank forgoes lending to a borrower entirely. It behoves us to also analyze the intensive margin effects of flood maps. Analysing the intensive margin allows us to further analyze both hypotheses 2 and 3. Banks concerned about the ability of borrowers to make both mortgage and insurance payments may lend less – relative to the value of the property – in order to reduce mortgage payments for the borrower and ensure better protection for themselves in the event of a default. However, we may expect a bank which finds the burden of monitoring insurance adherence too onerous to simply forego lending. In accordance with hypothesis 3, we should find no difference in the intensive margin. Giving smaller loans in the face of high fixed monitoring costs would be extremely counterproductive. Instead, we would expect a reduction in acceptance rates only.

In Table 7 we again replicate the analyses above, interacting our coefficient of interest with borrower characteristics. In column (1), we depict the baseline coefficient of an increase in regional flood zone coverage on LTVs. We abstain from showing the level effects as these can be seen in the lagged FZ-coverage coefficient. We can observe that the average loan made after an increase in a census tract's flood zone is relatively smaller. The loan-to-value ratio is reduced by 1.2%, implying that borrowers are forced to make larger down-payments relative to similar borrowers in different regions – when borrowing similarly sized loans from the same bank. The magnitude of the coefficient on flood zone coverage is similar – at 1.2%. This is further evidence against hypothesis 1. Insurance does not increase bank lending.

The result in column (2) is somewhat puzzling, as it implies smaller loans for borrowers with

Table 6: ***LTV of Accepted Loans after Flood Zone Changes by Borrower Type***

	LTV		
	(1)	(2)	(3)
Change in FZ Cov.	-0.012**	0.433***	-0.015***
	[0.005]	[0.067]	[0.005]
Flood Zone Coverage$_{t-1}$	-0.012***	-0.010***	-0.012***
	[0.000]	[0.000]	[0.000]
ΔFZ Cov. x App. FICO Score		-0.060***	
		[0.009]	
ΔFZ Cov. x Low App. Income			-0.011***
			[0.000]
ΔFZ Cov. x Female App.			0.007
			[0.006]
Observations	14,045,646	11,441,077	14,045,646
R^2	0.240	0.311	0.240

Note: We estimate equation 2, above. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Unlike above, our dependent variable is the relative loan to value ratio of a mortgage (i.e. loan amount/house value). The variable is bounded between 0.1 and 1.2 due to our cleaning exercises. Our sample size is reduced relative to the tables above, as the data is not available in every year. Column (2) interacts our variable of interest with applicant fico score, column (3) with whether the applicant has below average income for the county. We show only coefficients of interest for convenience. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

higher fico scores. We see this as a mechanical sample issue. Better fico borrowers may wish to make larger down-payments, thus distorting our measurements. In column (3) we can again see that lower income borrowers receive relatively smaller loans/have to make larger down-payments in areas that see flood zone growth. This is in keeping with our assumption that banks may wish to lend less and protect themselves in cases where poorer/marginal borrowers must make large scale payments for flood insurance. As such, column (3), at least, is evidence of hypothesis 2.

Finally, in Table 7, we again interact our coefficient of interest with bank-type and loan characteristics. We find very few interaction terms are significant. This supports our hypothesis that the monitoring efforts involved in overseeing flood insurance adherence are preventing banks from lending. In such a situation, we would not expect a difference along the intensive margin. The costs of monitoring are prohibitive and a bank foregoes lending. Making smaller loans – which we would associate with risk management – would be counterproductive as it would result in even less profit relative to the costs of monitoring adherence. Only local banks, whose local knowledge reduces information asymmetries, continue to lend– offering relatively more generous LTV terms.

Taken together, our results paint a clear picture. Mandatory insurance requirements generally deter lending. On the one hand, this is due to the cost of insurance, which prevents lower income households from borrowing (hypothesis 2). On the other hand, this is also due to the costs of monitoring adherence, which falls to banks (hypothesis 3). This cost makes certain banks – such as less informed national banks without much local knowledge – less likely to lend. It also makes it more difficult for borrowers without pre-existing relationships or who may have fewer linkages to lenders to borrow.

It is worth highlighting again at this juncture that our results are not driven by flood risk per se. Much of the actual risk a census tract faces is absorbed by other variables, including past flood damage, past count of disasters, and local fixed effects. To a certain extent, the presence of existing flood maps also reflects the existence of some degree of flood risk. The random – at least in a timing-sense – changes to flood maps, are not a reflection of that risk but rather a binary requirement for more households to purchase insurance.

Table 7: ***LTV of Accepted Loans after Flood Zone Changes by Lender Type***

	LTV				
	(1)	(2)	(3)	(4)	(5)
Change in Flood Zone Coverage	-0.012**	-0.131***	-0.023*	-0.039***	-0.015***
	[0.005]	[0.043]	[0.012]	[0.009]	[0.005]
Flood Zone Coverage$_{t-1}$	-0.012***	-0.018***	-0.010***	-0.013***	-0.012***
	[0.000]	[0.001]	[0.000]	[0.001]	[0.001]
ΔFZ Cov. x Indep. Mortg. Broker		0.075	0.029**		
		[0.054]	[0.013]		
ΔFZ Cov. x Nat. Bank		0.046	0.007		
		[0.050]	[0.017]		
ΔFZ Cov. x Credit Union		0.144	0.018		
		[0.108]	[0.033]		
ΔFZ Cov. x State Bank		0.267	-0.091		
		[0.247]	[0.056]		
ΔFZ Cov. x Small Mortg.				0.009	
				[0.011]	
ΔFZ Cov. x Large Mortg.				0.073***	
				[0.014]	
ΔFZ Cov. x Local Bank					0.113***
					[0.031]
Observations	14,045,646	775,729	13,269,258	14,045,646	14,045,646
R^2	0.148	0.182	0.148	0.148	0.148
Sample	Accepted	Non-Conf. Acc.	Conf. Acc.	Accepted	Accepted

Note: We estimate equation 2, above. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Unlike above, our dependent variable is the relative loan to value ratio of a mortgage (i.e. loan amount/house value). The variable is bounded between 0.1 and 1.2 due to our cleaning exercises. Our sample size is reduced relative to the tables above, as the data is not available in every year. Columns (2) and (3) interact our variable of interest with bank type. We have split our sample into conforming and non-conforming (i.e. jumbo) loans. Column (4) uses loan size with small loans falling fully within the 250,000 USD NFIP insurance limit and large loans exceeding the jumbo cutoff for the county in question. Column (5) interacts the variable of interest with a dummy denoting whether the lender in question is local to the county – a bank is considered local if more than 40% of its loans go to one county. We show only coefficients of interest for convenience. All regressions include the share of the census tract covered by a 500-year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, census tract population, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, and county-time fixed effects. Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

6 Extensions and Robustness Tests

In this section, we first cement our evidence of local knowledge and distance between banks and lenders playing a key role in our results. Subsequently, we show that our results depend in part on pre-existing state or county-level factors. Towards that end, We split our sample by regions where floods are common/uncommon as well as by regions where the pre-existing mortgage delinquency rate – and therefore the risks to banks – was high and regions where the delinquency rate was low.

6.1 Extension – Distant Lender

In Table 8 we analyze whether distance between lenders and borrowers (or simply the familiarity of lenders with an area) may have an impact on the decision to lend after the imposition of mandatory insurance. This is important because lenders may find monitoring adherence easier if they are familiar with an area.

We interact our variable of interest – i.e. the degree to which flood maps changed – with measures aimed at capturing the bank's presence in the area. Specifically, in column (1) we make use of the number of branches a bank operates in a given zip code, in column (2), we interact flood zone changes with the market power of local banks. This variable is bounded between 0 and 1, where 1 implies local banks control all lending in the census tract in the past decade. The greater the share of local bank lending, the harder distant national banks may find it to accurately evaluate borrowers. Similarly, in column (3) we interact our variable of interest with a simple measure of market power of the bank in question. Here too the variable is bounded between 0 and 1. More market power implies better information and lower relative information asymmetries. In column (4), conversely, we make use of a dummy denoting whether a flood map has been removed because a region failed to meet FEMA requirements for participation in the NFIP. This measure is important, as the flood map itself (as well as the underlying flood risk) remains. However, the removal of NFIP participation effectively removes the mandatory flood insurance requirement but implies that the community will not receive aid in the case of flooding. The test effectively determines whether the cost of insurance or the flood risk are more relevant impacts.

Overall, these tests speak to the effect of 'distance' between lenders and borrowers. 'Distance' may include physical and economic distance. A number of papers have established that the physical distance between lenders and borrowers is important, particularly when soft information plays a critical role .

Similarly, researchers have documented that a pre-existing relationship or the breath of the borrower relationship with a bank is valuable at overcoming the problems emanating from the asymmetry of information between the borrower and the bank.[20] Therefore, smaller relative 'distances' may increase banks' ability and willingness to monitor borrowers' compliance with the flood insurance mandate.

We can see from column 1 that a larger footprint - as measured by the number of branches in the area – limits the impact of flood zone changes on lending. Physical branches in a zip code likely reduce the information asymetries that arise when trying to assess and monitor adherence to complex flood insurance agreements. Further, as we can see from Table 8, column (2), a strong local bank footprint is a deterrent to other banks accepting mortgage applications after flood zone changes. Local banks are better able to assess local borrowers, especially after the added complexity of flood maps and associated insurance requirements are introduced. The greater the presence of local banks, the greater their ability to pick suitable borrowers and the greater the issue becomes form national banks, who may be faced with the classical lemons dilemma (Akerlof, 1970).

Conversely, a bank with greater local market share (column (3)), independent of whether it is a local bank or not, is comfortable with making loans that carry the burden of insurance requirements. This confirms our observations from column (1). In fact, local market knowledge may attenuate the effect of insurance requirements almost entirely. A bank with a 10% or more market share (which is a large share in many regions) would see no change in lending due to the insurance requirements.

Finally, in column (4), we can see that the removal of flood insurance increases the likelihood that loans are accepted. It is worth highlighting, again, that neither the risk nor the flood map has changed in these cases. The difference lies solely in the fact that the insurance requirement has been removed. Column (5) replicates column (4) but makes use of flood map levels, as opposed to changes (see Table 2, above). Using levels is perhaps more suited to this exercise, as changes are unlikely to occur in regions for whom the NFIP participation has been suspended. Our results here are a strong rejection of hypothesis 1 and a confirmation of hypothesis 3.

Taken together, this table presents clear evidence for the fact that bank experience and presence in an area can play a large role in how strong the impact of an insurance mandate is. Costs associated with monitoring borrowers' adherence to the flood insurance requirement deter lending. This effect is

[20] See for instance Klemperer (1995) who establishes that switching costs for borrowers can depend on distance or see also Petersen and Rajan (1994); Degreyse and Ongena (2005); Petersen and Rajan (2002); DeYoung et al. (2008). Other studies have focused on the importance of relationships or specialization in lending and its role in generating soft information, which can help overcome information asymmetries. See for instance: Bernanke (1983); James (1987); Petersen and Rajan (1995); Stein (2002); Harhoff and Koerting (1998); Berger and Udell (1995); Berger and Udell (2003); Blickle and Parlatore (2020).

Table 8: *Loan Acceptance – Market Power Interactions*

	Loan Accepted				
	(1)	(2)	(3)	(4)	(5)
Change in Flood Zone Coverage	-0.126***	-0.016***	-0.013***	-0.054***	
	[0.011]	[0.003]	[0.003]	[0.004]	
Flood Zone Coverage$_{t-1}$	-0.016***	-0.016***	-0.017***	-0.016***	-0.019***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]
ΔFZ Cov. x Log Numb. Branches in Zip	0.024**				
	[0.012]				
ΔFZ Cov. x Market Share of Local Banks		-0.262***			
		[0.002]			
ΔFZ Cov. x Market Share of Bank			0.455***		
			[0.034]		
ΔFZ Cov. x Map Suspended				2.41	
				[1.142]	
FZ Cov. x Map Suspended					0.098*
					[0.055]
Observations	40,801,868	40,801,868	40,801,868	40,801,868	45,781,878
R^2	0.099	0.114	0.096	0.100	0.099

Note: We estimate equation 2, above. Our dependent variable is loan acceptance, which takes the value of 1 if a mortgage application was accepted. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). Column (1) interacts our variable of interest with (1+the log of the number of branches it maintains in a zip code (for convenience, we average branches in a zip code to the census tract); column (2) intracts our variable with whether the market share of local banks in the census tract in question (based on the previous decade); column (3) interacts our variable of interest with the market share of the lending institution itself; columns (4) and (5) interact our variable with a dummy that takes the value of 1 if the community in question has been removed from the flood insurance program by the NFIP. We show only coefficients of interest for convenience. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

more pronounced for regions where costs are greater, banks are less present/with which banks are less familiar, and for borrowers who are more "distant" to loan officers.

6.2 Sample Split- Recent Flood

We first split our sample by whether floods have occurred within the last five years or not. Some regions, which are mapped as flood zones, flood regularly while others do not flood at all during the period covered by our data – or before. In part, this is a feature of the binary nature of flood maps. The map indicates a greater than 1% chance of flooding, where the upper bound could be *considerably* greater than 1%. Areas that flood repeatedly may be viewed by banks differently from those that do not. This distinction is important. Different states, with different flood risks, may see different lender reactions to changes in maps. The residual risks to banks, from borrowers who are less likely to maintain adequate insurance, is greater in areas that actually flood regularly. Moreover, regulators are more likely to examine and enforce adherence to insurance requirements in areas that flood regularly, given attention paid to such issues following a disaster.

Table 9: *Loan Accepted after Flood Zone Change – Floods are Common*

	Loan Accepted		
	(1)	(2)	(3)
Change in FZ Cov.	-0.147***	0.361	-0.129***
	[0.014]	[0.279]	[0.015]
Flood Zone Coverage$_{t-1}$	-0.019***	-0.020***	-0.018***
	[0.001]	[0.001]	[0.001]
ΔFZ Cov. x App. FICO Score		-0.062	
		[0.038]	
ΔFZ Cov. x Low App. Income			-0.389***
			[0.060]
Observations	19,195,613	5,844,200	19,195,613
R^2	0.089	0.153	0.089

Note: We estimate equation 2, above. We focus on counties that experienced floods in the past 5 years. Our dependent variable is loan acceptance, which takes the value of 1 if a mortgage application was accepted. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). Column (2) interacts our variable of interest with applicant fico score, column (3) with whether the applicant has below average income for the county. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

As we can see from Tables 9 – which showcases our results for regions that experienced flooding in the past 5 years – and 10 – which shows results for regions that did not experience flooding in the past 5 years, recent flooding matters for the impact of flood insurance requirements. The baseline impact of flood maps, and especially changes to these flood maps, significantly deter lending in regions that flood recently (see columns (1)). The single largest effect is seen for low income applicants. Low income applicants in areas with repeated floods experience a significant reduction in the chance of mortgage acceptances. Our interactions with applicant fico score are somewhat surprising in the high-flood sample. Here, the relationship is inverted. This may be a feature of our small sample.

Table 10: ***Loan Accepted after Flood Zone Change – Floods are Rare***

	Loan Accepted		
	(1)	(2)	(3)
Change in FZ Cov.	-0.046***	0.114	-0.042***
	[0.014]	[0.227]	[0.015]
Flood Zone Coverage$_{t-1}$	-0.015***	-0.012***	-0.014***
	[0.001]	[0.001]	[0.001]
ΔFZ Cov. x App. FICO Score		0.019	
		[0.031]	
ΔFZ Cov. x Low App. Income			-0.048
			[0.060]
Observations	19,673,355	6,777,336	19,673,355
R^2	0.103	0.188	0.103

Note: We estimate equation 2, above. We focus on counties that experienced no floods in the past 5 years. Our dependent variable is loan acceptance, which takes the value of 1 if a mortgage application was accepted. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). Column (2) interacts our variable of interest with applicant fico score, column (3) with whether the applicant has below average income for the county. We show only coefficients of interest for convenience. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

6.3 Sample Split- Delinquency

We expect banks to be more concerned about lending in regions where pre-existing delinquency rates are high. In such regions, the added burden of insurance payments may be too much for the average borrower to maintain. Similarly, the banks may be averse to investing in costly information acquisition in areas where the ex-ante costs of lending are high. We would expect the bank to be most sensitive to lending to low income borrowers in particular. This, ultimately, is what we find in Tables 11 – which shows our results for areas with high delinquency rates – and **??** – which shows our results for areas where delinquency rates are below average.

We find that areas with high ex-ante mortgage delinquency rates are more strongly affected by changes in flood zones. However, the differences are relatively small, as can be seen in the two table's respective column (1). As expected, however, the difficulties of low income applicants in obtaining mortgages is substantially larger in areas with high ex-ante delinquencies. This is support in favor of our hypothesis, that banks may mitigate risk.

Table 11: ***Loan Acceptance after Flood Zone Change – Delinquency Rate is High***

	Loan Accepted		
	(1)	(2)	(3)
Change in FZ Cov.	-0.088***	0.432**	-0.067***
	[0.013]	[0.191]	[0.013]
Flood Zone Coverage$_{t-1}$	-0.016***	-0.015***	-0.015***
	[0.001]	[0.001]	[0.001]
ΔFZ Cov. x App. FICO Score		-0.067**	
		[0.026]	
ΔFZ Cov. x Low App. Income			-0.255***
			[0.055]
Observations	21,613,635	10,097,771	21,613,635
R^2	0.116	0.189	0.116

Note: We estimate equation 2, above. We focus on counties that experienced above mean mortgage delinquency rates in the previous period. Our dependent variable is loan acceptance, which takes the value of 1 if a mortgage application was accepted. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). Column (2) interacts our variable of interest with applicant fico score, column (3) with whether the applicant self-identifies as a member of a minority race, column (4) with whether the applicant has below average income for the county; and column (5) with whether the primary applicant is female. We show only coefficients of interest for convenience. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

7 Aggregated Results

So far, we have shown results at the level of the individual applicant. In this section we show that flood insurance mandates, which follow as a result of flood maps and changes to flood maps, have consequences at the aggregate regional level. We collapse our data to the census tract-year level and regress a variety of outcomes on the share of the census tract that is covered by a flood zone and the year-on-year change in the flood zone. Our outcome variables of interest are the following. We look at the share of applications that are accepted, as a measure of the aggregate difficulty in receiving a mortgage; the log size of accepted loans; the average income of accepted borrowers; the differential in income between accepted borrowers and applicants (avg. applicant income - avg. accepted income per

Table 12: ***Loan Acceptance after Flood Zone Change – Delinquency Rate is Low***

	Loan Accepted		
	(1)	(2)	(3)
Change in FZ Cov.	-0.082***	0.107	-0.076***
	[0.014]	[0.326]	[0.014]
Flood Zone Coverage$_{t-1}$	-0.018***	-0.019***	-0.018***
	[0.001]	[0.001]	[0.001]
ΔFZ Cov. x App. FICO Score		0.014	
		[0.044]	
ΔFZ Cov. x Low App. Income			-0.116*
			[0.065]
Observations	19,187,850	3,705,687	19,187,850
R^2	0.077	0.140	0.077

Note: We estimate equation 2, above. We focus on counties that experienced below mean mortgage delinquency rates in the previous period. Our dependent variable is loan acceptance, which takes the value of 1 if a mortgage application was accepted. Our variable of interest is the degree to which a census tract flood zone coverage is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). Column (2) interacts our variable of interest with applicant fico score, column (3) with whether the applicant self-identifies as a member of a minority race, column (4) with whether the applicant has below average income for the county; and column (5) with whether the primary applicant is female. We show only coefficients of interest for convenience. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

census tract); and the difference between the average applied loan amount and accepted loan amount. We include a host of census tract controls such as tract population, tract size, tract income as well as share of applicants identifying as minorities and share primary female applicants. We include year – but not region – fixed effects. Naturally, we are unable to control for a host of applicant specific measures and these results should be viewed as suggestive evidence in support of the analyses above.

Our results show that flood zones, and especially changes in flood zones, are associated with fewer acceptances and smaller loans. In column (1) of Table 13 we see that the acceptance rate is 3% lower in areas with high-flood zone coverage and up to 6% lower if an area is suddenly fully covered by a flood zone. In column (2) one can see that accepted loans are substantially smaller, implying an across the board reduction in lending in these areas.

Similarly, in column (3) one can see that the average income of accepted applicants is higher. More importantly, perhaps, is the finding in column (4), which indicates that the difference between borrower and applicant income rises in flood zones and after flood zone changes. This implies a confirmation of our conjecture from above: lower income households are crowded out of areas that require mandatory insurance. Only applicants with high income are ultimately accepted by banks and become borrowers. The outcome variables are scaled to $10,000. This means that applicants need – all else equal almost $10,000 more in income in an area fully covered by a flood zone and almost $20,000 more in income if an area sees a 100% increase in flood zone coverage. This is likely due to the burden of having to buy flood insurance at almost actuarial rates. In the same vein, we can see from column (5) that the difference between the amount the average applicant requests and the amount the average borrower receives also shrinks in flood zones. This likely follows from our earlier analyses. Banks are unwilling to commit as much capital to areas where borrowers must also make insurance payments. Our aggregated results are in line with our results from the loan-level analysis, adding further support to our finding that mandated flood insurance had an unintended effect of reducing access to mortgage finance, particularly for low-income borrowers.

Table 13: ***Aggregate Results***

	Share Accepted	Avg. Amount Accepted	Avg. Income Acc. Loans	Income Diff.	Amount Diff.
	(1)	(2)	(3)	(4)	(5)
$\Delta FloodZone$	-0.057***	-0.271***	4.712*	-1.885***	-29.289***
	[0.010]	[0.025]	[2.421]	[0.540]	[8.231]
Flood Zone Coverage$_{t-1}$	-0.030***	-0.038***	10.450***	-0.995***	-4.404***
	[0.001]	[0.004]	[0.340]	[0.076]	[1.158]
Observations	357,614	355,125	355,125	355,125	355,125
R-squared	0.212	0.750	0.689	0.027	0.704

Note: We collapse our data to the census tract * year level. We regress the impact of changes in flood maps as well as lagged levels of the degree to which the tract is covered by a flood map on various outcome measures. Share Accepted is the share of applications that are accepted. Avg. Amount Accepted is the log size of accepted loans, Avg. Income is the average income of accepted borrowers, avg. income diff. is the differential in income between accepted borrowers and applicants (avg. applicant income - avg. accepted income per census tract), amount diff. is the difference between the average applied loan amount and accepted loan amount. Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

8 Conclusion

It is ex-ante unclear how mandatory flood insurance requirements should affect access to mortgage credit. On the one hand, insurance reduces the residual risks to borrowers and lenders by preventing flood-damage related defaults. On the other hand, the necessity for (i) borrowers to make expensive insurance payments and (ii) banks to monitor borrower adherence to the insurance requirements may reduce access to mortgage credit. This may hold in particular for lower income borrowers or for borrowers without pre-existing bank relationships and a greater distance – which can be measured in a number of ways – to the lender.

In this paper, we show that the latter cases hold. We first present evidence that flood insurance requirements may have the unintended consequence of reducing access to mortgage credit especially for low income applicants or applicants with a bad credit score. Low income applicants may be unable to make the required insurance and mortgage payments – or the bank may suspect them of being unable to do so – and are refused credit. Secondly, we find that banks, which are unfamiliar with an area, seem unwilling to engage in the complicated task of monitoring borrower adherence to mandatory NFIP insurance. Insurance can be complicated and based on dwelling and location specificities. This leaves large national banks, without local branches from which to pull knowledge, averse to lending in regions with mandatory insurance requirements.

To measure insurance requirements, we make use of NFIP/FEMA flood maps. Areas covered by flood zones must purchase NFIP flood insurance to be eligible for disaster aid and mortgage underwriting by federal mortgage underwriters. We make use of a unique nation-wide data set, constructed for this paper, which tracks changes in flood maps. Changes in flood maps occur quasi-randomly and follow a complicated multi-year procedure. As such, these changes can be made exogenous to the actual underlying flood risks of a region as well as individual mortgage applications.

Ultimately, our research links climate finance, financial intermediation, and access to credit. Our findings speak to the unintended consequences of well-intentioned regulation. Mandatory insurance, designed to share risk and facilitate lending, actually limits access to credit for particular borrowers. They also speak to the importance of factoring in affordability and feasibility when introducing mandatory standards.[21] Given that it seems socially undesirable to limit water-front neighbourhoods to the wealthy

[21] When Congress passed the Affordability Act of 2014 it asked FEMA to develop a Draft Affordability Framework. FEMA published its Affordability Framework in 2018 but it has not implemented it because it lacks authority and does not have the necessary funding.

our findings should be of particular interest to policymakers and academics alike.

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Appendix

A.1 Supplemental Tables

Table A.1: ***Securitization in Flood Zones***

	Securitized					
	(1)	(2)	(3)	(4)	(5)	(6)
FZ Coverage	-0.006*** [0.000]	0.026*** [0.007]	-0.006*** [0.000]	-0.024*** [0.001]	-0.006*** [0.001]	-0.005*** [0.000]
500-year FZ	0.007*** [0.001]	0.005*** [0.001]	0.007*** [0.001]	0.007*** [0.001]	0.007*** [0.001]	0.007*** [0.001]
FZ Coverage * FICO		-0.004*** [0.001]				
FZ Coverage * low income			0.002 [0.002]			
FZ Coverage * Indep. Mortgage Broker				0.025*** [0.001]		
FZ Coverage * Nat. Bank				0.023*** [0.001]		
FZ Coverage * Credit Union				0.026*** [0.002]		
FZ Coverage * SSB				0.024*** [0.003]		
FZ Coverage * Small Loan					-0.001 [0.001]	
FZ Coverage * Large Loan					0.001 [0.001]	
FZ Coverage * local Bank						-0.031*** [0.002]
Observations	32,885,050	11,634,499	32,885,050	32,885,050	32,885,050	32,885,050
R^2	0.441	0.395	0.441	0.442	0.441	0.441

Note: We estimate equation 1, above, on a sample of all accepted and conforming loans that are eligible for securitization. Our variable of interest is the degree to which a census tract is covered by a flood zone. All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.2: ***Securitization after Flood Zone Change***

	Securitized						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔFZ Cov.	-0.006	0.053	-0.004	-0.008	-0.026	0.001	-0.019*
	[0.009]	[0.209]	[0.009]	[0.015]	[0.016]	[0.009]	[0.010]
Δ 500 year zone	-0.002	-0.006	-0.002	-0.002	-0.006**	-0.002	-0.002
	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Flood Zone Coverage$_{t-1}$	-0.006***	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
500 year Zone Coverage$_{t-1}$	0.007***	0.005***	0.007***	0.007***	0.007***	0.007***	0.007***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
ΔFZ Cov. * Credit Score		-0.001					
		[0.028]					
ΔFZ Cov. * Low Income			-0.029				
			[0.043]				
ΔFZ Cov.* Indep. Mortgage broker				0.042**			
				[0.019]			
ΔFZ Cov. * Nat. Bank				-0.038			
				[0.025]			
ΔFZ Cov. * Credit Union				-0.325***			
				[0.048]			
ΔFZ Cov. * SSB				-0.164***			
				[0.061]			
ΔFZ Cov. * Small Loan					0.051***		
					[0.019]		
ΔFZ Cov. * Large Loan					-0.121***		
					[0.031]		
ΔFZ Cov. * Local Bank						-0.151***	
						[0.039]	
Observations	29196632	11633081	29196632	29196632	29196632	29196632	29196632
R^2	0.411	0.395	0.412	0.413	0.412	0.411	0.411

Note: We estimate equation 2, above, on a sample of all accepted and conforming loans that are eligible for securitization. Our variable of interest is the degree to which a census tract is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.3: ***Securitization with Gov. Backed Agency after Flood Zone Change***

	Securitized FHA						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔFZ Cov.	0.043*** [0.010]	-0.362 [0.246]	0.043*** [0.010]	0.157*** [0.018]	0.014 [0.018]	0.036*** [0.010]	0.040*** [0.012]
Δ 500 year Zone	-0.009*** [0.003]	-0.018*** [0.005]	-0.009*** [0.003]	-0.008*** [0.003]	-0.007** [0.003]	-0.008*** [0.003]	-0.009*** [0.003]
Flood Zone Coverage$_{t-1}$	0.005*** [0.001]	0.006*** [0.001]	0.004*** [0.001]	0.005*** [0.001]	0.005*** [0.001]	0.005*** [0.001]	0.005*** [0.001]
ΔFZ Cov. * Credit Score		0.060* [0.034]					
ΔFZ Cov. * Low Income			-0.034 [0.050]				
ΔFZ Cov. * Indep. Mortgage Broker				-0.193*** [0.021]			
ΔFZ Cov. * National Bank				-0.068** [0.030]			
ΔFZ Cov. * Credit Union				0.326*** [0.073]			
ΔFZ Cov. * SSB				0.148* [0.081]			
ΔFZ Cov. * Small Loan					0.038* [0.021]		
ΔFZ Cov. * Large Loan					0.037 [0.035]		
ΔFZ Cov. * Local Bank						0.193*** [0.052]	
Observations	22,837,240	9,336,802	22,837,240	22,837,240	22,837,240	22,837,240	22,837,240
R^2	0.598	0.567	0.598	0.598	0.598	0.598	0.598

Note: We estimate equation 2, above, on a sample of all accepted, conforming and securitized loans. Our dependent variable takes the value of 1 if the loan is securitized with Fannie, Freddie, or Ginny. Our variable of interest is the degree to which a census tract is changed from one year to the next. Our variable of interest is positively skewed and (bounded between -1 and 1). All regressions include the lagged share of the census tract covered by a 500-year flood zone, the change in the 500 year flood zone, borrower income, loan amount, log loan-to-income, applicant race, applicant gender, median census tract income, bank type, lagged total flood damage since 1970, whether the bank is local to a given county (>40% of lending in county), bank fixed effects, county-time fixed effects and applicant fico score in the regression in column (2). Standard errors are heteroscedasticity robust and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.4: ***Delinquency after Flood***

	Delinquency		
	(1)	(2)	(3)
Int: FZ Coverage x Flood Damage$_{t-1}$	-0.632*	-0.896*	-0.185
	[0.358]	[0.471]	[0.301]
Int: FZ Coverage x Flood Damage$_{t-2}$	-0.694**	-0.965**	-0.247
	[0.345]	[0.462]	[0.278]
Int: FZ Coverage x Flood Damage$_{t-3}$	-0.648*	-0.895*	-0.203
	[0.334]	[0.462]	[0.288]
Int: FZ Coverage x Flood Damage$_{t-4}$	-0.483	-0.752**	-0.037
	[0.300]	[0.343]	[0.232]
Int: FZ Coverage x Flood Damage$_{t-5}$	-0.037	-0.345	0.743
	[0.772]	[0.672]	[0.540]
Flood Damage$_{t-1}$	0.312***	0.141	0.126*
	[0.115]	[0.115]	[0.073]
Flood Damage$_{t-2}$	0.325**	0.143	0.138*
	[0.122]	[0.122]	[0.075]
Flood Damage$_{t-3}$	0.347***	0.136	0.161**
	[0.114]	[0.116]	[0.076]
Flood Damage$_{t-4}$	0.276***	0.178*	0.090*
	[0.102]	[0.100]	[0.047]
Flood Damage$_{t-5}$	0.342	0.173	-0.059
	[0.254]	[0.243]	[0.143]
FZ Coverage	0.071	0.494***	-0.159
	[0.096]	[0.159]	[0.242]
Observations	54552	54552	54552
R^2	0.609	0.458	0.822

Note: We estimate a regression relating the share of households in delinquency in a county to flood damages 1,2,3,4, and 5 months ago as well as interactions of the share of the county covered by flood maps and flood damages.

A.2 Historical Context

As the costs of flooding continued to increase and in 2012 Congress passed the Biggert-Waters Act to reform the NFIP. Many of the changes were designed to make the NFIP more financially stable, and ensure that flood insurance rates more accurately reflect the real risk of flooding.[1] Specifically, the 2012 Act immediately eliminated subsidies for a range of residential properties, including any property not insured by NFIP as of the date the act was enacted (July 6, 2012); any property purchased after the date of enactment of the act (property sales would trigger elimination of subsidies); any NFIP policy that had lapsed in coverage, as a result of the deliberate choice of the policyholder; and any prospective insured who refused to accept any offer for mitigation assistance (including an offer to relocate) following a major disaster.

Residential properties that experienced repeated losses, properties with substantial cumulative damages; as well as non-primary residential properties would see insurance premium rates go up 25% each year until the average risk premium rate for such properties was equal to the average of the risk premium rates for new properties with the same risk classification. For all the remaining residential properties there would be a five-year phaseout. The Biggert-Waters Act made several other relevant changes, including allowing insurance premiums to increase by 20 percent annually (previously capped at 10 percent), requiring FEMA to include the losses from catastrophic years in determining premiums that are based upon "average historical loss year", and requiring FEMA to establish a reserve fund.[2]

As implementation of the 2012 Biggert-Waters began, the resulting premium increases became a focus of intense political and public attention. Congress received testimony and letters arguing that the proposed rate changes for the pre-FIRM subsidized structures and grandfathered policies would result in premiums that were unaffordable for many persons who had mandatory purchase requirements. In response, in March of 2014 Congress passed the Homeowner Flood Insurance Affordability Act, reinstating certain subsidies removed by the Biggert-Waters Act and generally limiting yearly premium rate increases. Specifically, it eliminated the triggers that would have led to the immediate and full loss of pre-FIRM subsidized rates when a property was sold or a new policy purchased. For primary residences, the 2014 Act replaced the premium increases that would occur at the time of sale or when a policy lapsed with an increase that would begin immediately and was to be 5-15% annually within a single risk class, but no more than 18% annually. This increase would be imposed annually until the premium reached its NFIP risk-based rate. Non-primary residence increases were not affected by the 2014 Act; as required by Biggert-Waters 2012, annual premium increases of up to 25% would take place until premiums reached their full-risk rate. If a property was sold, the increase took place at the time of sale. The result was still that pre-FIRM subsidized premiums eventually will be gone, as was the case with Biggert-Waters 2012.

[1] Prior to the Biggert-Waters Act, subsidized policies accounted for about 21 percent of all NFIP policies, while those with full-risk premiums accounted for the remaining 79 percent. In its actuarial rate review for 2011, FEMA estimated that subsidized policy rates were between 40 and 45 percent of full-risk premium rates. See FEMA, National Flood Insurance Program: Actuarial Rate Review (Washington, D.C.: October 2011).

[2] See "Flood Insurance: More Information Needed on Subsidized Properties," GAO 2013.