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Do Mortgage Lenders Respond to Flood Risk?

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Abstract

Using unique nationwide property-level mortgage, flood risk, and flood map data, we analyze whether lenders respond to flood risk that is not captured in FEMA flood maps. We find that lenders are less willing to originate mortgages and charge higher rates for lower LTV loans that face "un-mapped" flood risk. This effect is weaker for high income applicants, as well as non-banks and small local banks. However, we find evidence that non-banks and local banks are more likely to securitize/sell mortgages to borrowers prone to flood risk. Taken together, our results are indicative that mortgage lenders are aware of flood risk outside FEMA's identified flood zones.

JEL classification: G20, G23, Q54
Key words: flood risk, flood maps, bank lending, climate change, natural disasters, HMDA, FEMA, credit constraints

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1 Introduction

In 2021 over 200,000 mortgages for residential homes – worth over 66 billion USD – were originated in areas covered by a FEMA 100-year flood map. Properties located in these "flood zones" are considered sufficiently at risk of water-related disasters that flood insurance is required for originated mortgages. This ensures the risk of catastrophe is not borne by the mortgage borrower or their lender. The insurance scheme and the consequences thereof are discussed in detail in Blickle and Santos (2021). However, flood maps are discrete with stark boundaries while flood risk itself is continuous across certain geographies. Moreover, flood maps can be outdated or inaccurate in the face of rapidly changing climate and weather patterns. Indeed, 671,000 mortgages for residential properties – worth over 205 billion USD – were originated in regions not covered by a FEMA flood map while still facing relatively high levels of flood risk. Of the properties in the top 1% of the flood risk distribution, nearly two-thirds (64%) are in an official flood zone and the remaining third (36%) are not. Similarly, of the properties in the top 5% of the flood risk distribution, half (52%) are in an official flood zone and the other half (48%) of these high risk properties are not. If unnoticed by lenders or borrowers, such risk could pose a serious threat to not only the homeowners but also financial stability.

Researchers have paid a great deal of attention to mortgage markets' responses to flood risk within FEMA's flood insurance zones. In this paper, we focus instead on flood risk outside FEMA's flood zones. This gives us the opportunity to ascertain mortgage lenders' and markets' responses to flood risk that, while similar to that present in FEMA's flood zones, is neither subject to FEMA's mandated insurance nor does it benefit from the information contained in flood maps. We build on a restricted version of the HMDA dataset that contains addresses. This dataset enables us to match records of individual mortgage applications to property-level flood risk measures from CoreLogic as well as individually digitized flood maps for the years 2018-2021. We then analyze the degree to which lenders factor flood risk into their lending and securitization decisions for properties that are located entirely **outside** flood zones. We call properties that are not covered by either a 100-year or 500-year FEMA flood map, but which face similar flood risk to those that are covered, "un-mapped".

We find that lenders are less likely to originate mortgages that face un-mapped flood risk, when compared with similar borrower-property combinations that face no such risk. For mortgages that are originated despite the risk, lenders charge slightly higher interest rates – all else equal. Moreover, although we can use transaction data to show that house prices fall somewhat in response to un-mapped risk, lenders assign a lower value than the market to such properties. This leads to a divergence between sales price and lender-valuation (i.e. lower LTV loans). Finally, lenders are marginally more likely to securitize loans with un-mapped flood risk.

Together, these reactions to (unofficial) flood risk show that lenders are responsive to this risk and are mitigating it to some extent. This assertion is corroborated in our analyses on the cross section of lenders' responses. We find that large banks are perhaps the most conservative while non-bank entities and smaller local banks are still likely to lend despite the risk. However, the latter lenders are among the most aggressive in securitizing or selling loans for un-mapped properties, indicating that their propensity to keep lending is not a consequence of being unaware of risks, but rather a business model decision.

It is worth noting that we cannot – without the gift of perfect foresight – speak to the efficacy of lender risk mitigation. It could well be that their attempt to mitigate un-mapped flood risk is insufficient in the face of true future flooding. However, we **can** state that lenders have begun acknowledging flood risk beyond what FEMA maps dictate and are incorporating this risk into their lending decisions.

Methodologically, we are able to make use of property-level data. As such, we can account for property and borrower characteristics in all regressions. Perhaps more importantly, we are further able to make use of property-level flood risk information and place each property on a FEMA flood map. Properties with risk that are not covered by a FEMA 100-year, 500-year, or flood-way map can thus be identified.

Empirically, we can then relate loan-level outcomes to our measure of un-mapped flood risk and borrower characteristics. Unfortunately, we do not know what flood information a lender has access to. We make use of publicly available – but proprietary – risk data from CoreLogic and assume that lenders have access to similar data. We further cannot see how true flood risk has changed over the years. As such, we are analyzing ex-post equilibrium lending decisions for a narrow band of time during which information on flooding was **theoretically** widely available. Arguably, our results could be seen as lower bound estimates of lender's true responses to risk information.

Our paper is related to recent research on banks' responses to physical climate risks. For example, Ivanov et al. (2022) and Jung et al. (2022) look for evidence on U.S. banks' corporate lending responses to climate transition policies. A more closely related branch of this literature focuses on banks' ex ante responses to changes in physical risks. For example, Sastri (2021) looks at credit rationing following flood map changes in Florida. Similarly, Blickle and Santos (2021) use national map changes to show that banks are less likely to lend to certain customers and in certain areas following map changes. Ortega and Petkov (2024) look at the effects of NRI 2.0 on insurance uptake. Keenan and Bradt (2020) document that local lenders, in particular, 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 refinancing practices, rates loan denial, or rates securitization in the flood exposed areas of Florida between 2013 and 2018. Another branch of related literature looks at how banks change their ex post responses to climate disasters. Cortes (2015), Chavaz (2016) and Schüwer et al. (2018) show 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), 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.[1] Similar to us, Meisenzahl (2023) uses supervisory data and finds that banks reduce lending to areas exposed to climate disasters/risk. He finds that banks are less willing to hold flood risk on their balance sheets. Our approaches differ in that we are explicitly looking outside mandatory flood regions and focus on the overall mortgage market effects of being in un-mapped regions. Mulder (2022) analyzes the welfare implications of inaccurate flood mapping[2]. In a somewhat similar vein to our paper, Cohen et al. (2021) show the negative impact on real estate of flooding outside flood zones during hurricane sandy in New York. They highlight the issues that can arise when flooding breaks out of historical flood map boundaries.

There exists already a large literature that considers to what extent the flood risks within FEMA flood zones is capitalized into housing prices. For example, Hino and Burke (2021) find that even within FEMA flood zones, housing prices fail to fully price the underlying flood risk, and that, considering only the flood risk communicated in these maps, housing in FEMA flood zones is overvalued by 32.6-55.6 billion USD. In a more recent study of housing both inside and outside of FEMA flood zones, Gourevitch et al. (2023) estimate that U.S. housing is overvalued by 121-237 billion USD due to unpriced flood risk.

[1]This evidence, which has been questioned by Lacour-Little et al. (2021), also contrasts with Garbarino and Guin (2021) finding that UK banks do not adjust mortgage lending following a severe flood event in England notwithstanding the decline in local property prices.

[2]The NFIP program itself as well as the implications flood risk broadly are discussed in a number of prominent papers such as Kousky (2010), Dinan et al. (2019), Kousky (2018), Kousky et al. (2020), or Gourevitch et al. (2023)

Moreover, the authors highlight that overvalued properties are especially common in coastal areas just outside of official FEMA flood zones. Similarly, a number of studies have analyzed the pricing effects of risk revelations that are associated with the mandatory disclosure of existing flood maps (see for instance: Troy and Romm (2004), Pope (2008), Shr and Zipp (2019), or Gibson and Mullins (2020)). In this paper, we focus specifically on how mortgage lenders treat these properties with "un-mapped" flood risks, thereby connecting this body of literature focused on flood risk in the housing market to the mortgage market and role of financial intermediaries.

The remaining paper is structured as follows. Section 2 outlines our data and section 3 presents our methodology. Section 4 showcases our main findings regarding bank lending decisions in the face of flood risk. Section 5 looks at bank securitization. Section 6 compares lending decisions across different lenders and for different borrower types. Finally, section 7 concludes.

2 Data

Our primary dataset for this paper is a restricted version of the confidential Home Mortgage Disclosure Act (cHMDA) data set. We complement this dataset with CoreLogic flood risk data and FEMA flood maps. In a supplement to the primary analysis, we further incorporate data on real estate listings and sales, also from CoreLogic.

2.1 CoreLogic Flood Risk Data

We begin with a structure-level dataset of composite flood risk (including inland flooding and hurricane storm surge flooding) from CoreLogic for 2021. This dataset contains flood risk metrics for structures on over 107 million properties in the United States. CoreLogic measures flood risk by first using hydrological models that map storm events to water levels. This is then coupled this with hydraulic models that map these to streamflow characteristics (e.g., the velocity of flood streams). With the mapping between storm scenarios and physical flooding outcomes, CoreLogic then uses calibrated damage functions that map these flooding conditions along with structure characteristics (e.g., number of levels, structure age, occupancy status) to estimate flood damages under a given climate scenario and timeline.We filter for residential properties and exclude from our data unfinished structures or secondary structures within a single parcel of land. As such, we do not conflate residences with sheds or garages that may face different risks than the residential structure itself. For each structure, the dataset includes longitude and latitude information that we use to match to flood map and mortgage data.

Our primary flood risk measure is a property's average annual loss (AAL) from flooding. This is the expected value of a structure's annual flood damages as a proportion of the estimated cost to reconstruct the entire structure. We use property-level AALs that incorporate losses due to any available type of flooding (inland, hurricane storm surge, tsunami) under current climate conditions.

A major assumption in our approach is that the risk for a property did not change between 2018 and 2021. This assumption is partly defensible, as information about risks is not produced at a sufficiently rapid pace to be released annually. Nevertheless, our inability to use historically available risk data means we could be assuming a greater knowledge of risk on the part of the lender than was truly available. Therefore, any estimates on a lender's response to flood risk must be viewed as lower bound estimates.

2.2 Flood Maps

To differentiate between mortgage borrowers that **are** and **are not required** to purchase flood insurance, we make use of the National Flood Hazard Layers from the Federal Emergency Management Agency (FEMA). The map layers demarcate regions at risk of experiencing a 100-year flood – that is, regions that FEMA estimates have at least a 1% probability of experiencing a severe flooding event in any given year. Importantly, borrowers for properties in these areas are required to purchase flood insurance through the National Flood Insurance Program (NFIP). We use an archived snapshot of the FEMA flood map layer but are missing 2021. We instead use the snapshot from early 2022, just after our sample period. FEMA map boundaries rarely change. It's highly unlikely then that we classify mortgages as being outside a 100-year flood zone when they were actually within a 100-year flood zone at the time of origination.

We place each property from the CoreLogic flood risk data onto the FEMA flood maps to determine which of these properties fall into a 100-year flood zone, a 500 year flood zone and which do not fall into any time of flood region. Borrowers in the 500-year flood zone areas are not required to purchase flood insurance but do still have a public signal of their homes' underlying flood risk. We do not which to conflate this effect with the effect of completely un-mapped flood risk on lending decisions. Given that our property-level flood risk data must be anonymized after merging with the property-level mortgage lending data (more on this below), we form flood risk buckets. Just over 48% of properties have no risk (i.e. AAL = 0). Conditional on having non-zero risk, we flag properties in the upper half of this distribution (the top 26% of the full distribution) as high risk. We classify a property as "un-mapped" if it is high risk and does not fall into a FEMA-designated 100-year flood zone, 500-year flood zone, or flood way. Similarly, we classify a property as "possibly un-mapped" if it has any non-zero flood risk and is not in a FEMA-designated 100-year flood zone, 500-year flood zone, or flood way.

Appendix Figure A.1 plots the AAL density distributions of properties that are un-mapped, in 100-year flood zones, and in either a 100-year or 500-year flood zone. While the mean un-mapped property has a lower AAL than the mean property in the 100-year flood zones, it is also true that all un-mapped properties have AALs that are comparable to a reasonable number of properties in FEMA designated flood zones. Over 93.7% of properties in 100-year FEMA flood zones fall into our high risk group and 91.8% of properties in either a 100-year or 500-year flood zone fall into our high risk group. The AAL score cutoff for the high risk group falls 0.5 standard deviations away from the mean of the properties in 100-year flood zones and 0.4 standard deviations away from the mean of the properties in either 100-year or 500-year flood zones. Ultimately, it is reasonable for borrowers and lenders in "un-mapped" regions to concern themselves with flood risk.

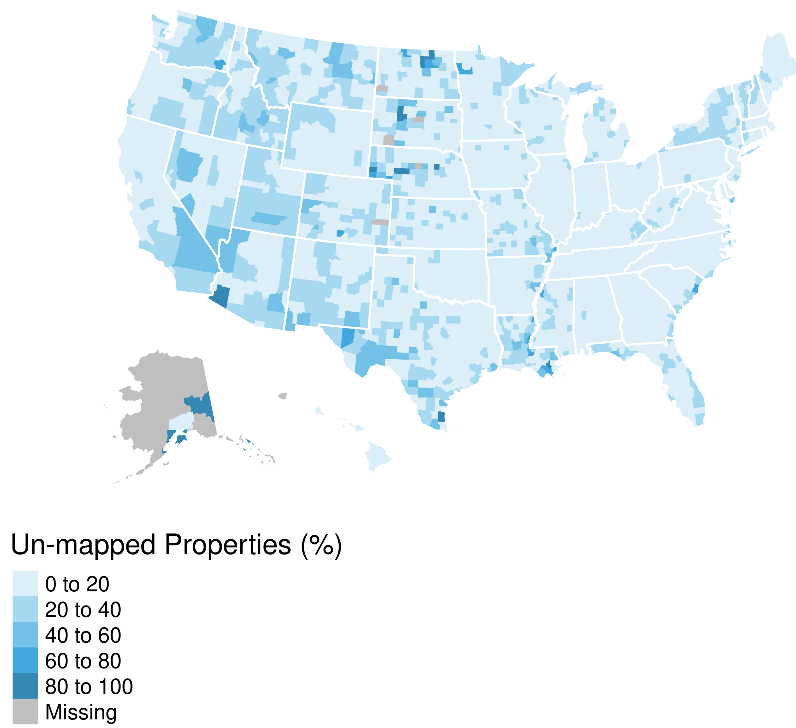
Figure 1 shows a county-level map of the United States on which we depict the share of properties from our data that are un-mapped in each county. We can see that affected properties can be found throughout the country along both inland waterways – such as the Mississippi – and along the coast. Importantly, no parts of the country are truly unaffected by un-mapped flood risk.

2.3 HMDA Data

Data on mortgage applications comes from a restricted version of the confidential Home Mortgage Disclosure Act (cHMDA) database available to the Federal Reserve for the years 2018 to 2021. Unlike the public HMDA dataset, the cHMDA dataset contains specific dates of application and origination, the credit scores of mortgage applicants, and more precise values for fields such as the loan amount, loan sale/securitization, and property value. Importantly, the restricted version we use contains the address of the property on the mortgage application, which allows us to geocode the mortgage records in HMDA and ultimately match these mortgage records to property-level measures of flood risk and FEMA flood map coverage. We restrict our sample to new primary home-purchase applications, excluding mortgage applications with the purpose of refinancing or home improvements.

Similar to the public version, confidential HMDA contains mortgage applicant characteristics like income, gender, and race. The addition of applicant credit scores in the confidential data helps us

Figure 1: *County-level % of Un-mapped Properties*



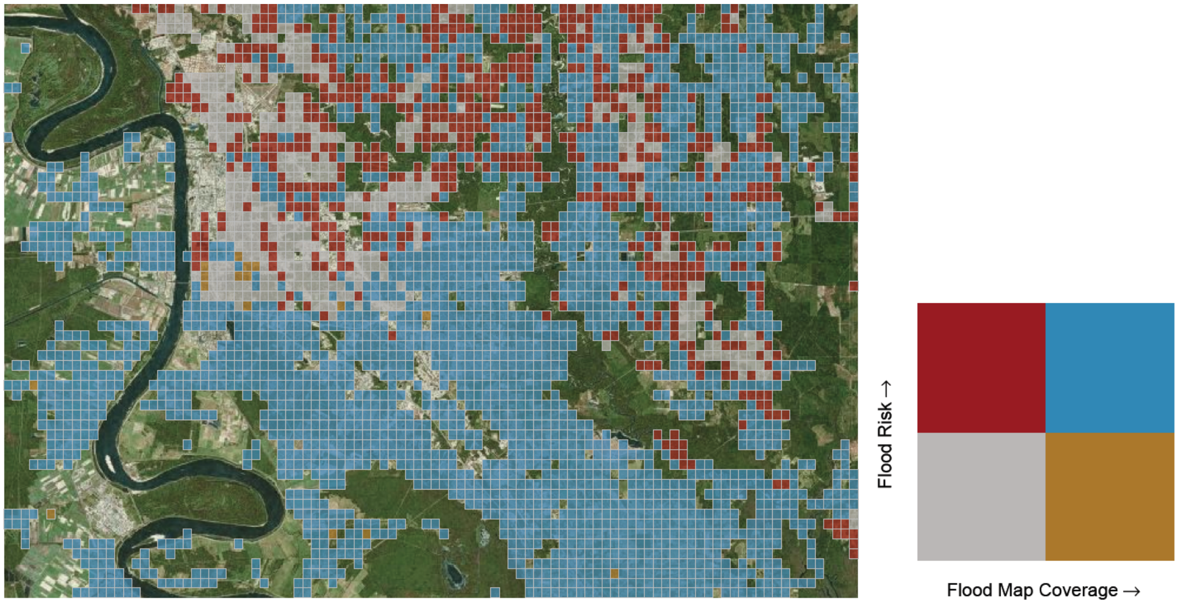
Note: Figure displays the percent of properties in the matched sample of mortgages either approved or denied that we classify as un-mapped in each county. Un-mapped properties compose the largest share of properties in counties along the coast, stretches of the Mississippi river, and across large portions of the western US.

account for borrower credit quality. HMDA data also includes details on the mortgage, such as the loan amount, whether it was originated, and whether it was sold to another financial institution or securitization agency. Additional fields with census tract-level income and demographics come from the 2015 American Community Survey.

Lastly, we are interested in the value assigned to the property by the lender. This value is important as it comes from the approval and inspection process (i.e. the inspection that goes into each mortgage origination decision). It will naturally include a bank's and an expert assessor's view of the property and inform the loan amount that a property would potentially be eligible for, no-matter the sale price. High price properties with low valuations imply the need for buyers to put in more equity (i.e. low LTV loans).

For each property, we use the address data available in the restricted version of cHMDA to identify the property's longitude and latitude to the sixth decimal place. We then match our cHMDA data to CoreLogic and FEMA flood map data using nearest property matches. Because parcel size varies with population density, we implement match-filters that vary with population density. For properties

Figure 2: *Parcels with Mapped and Un-Mapped Properties*



Note: This map plots flood risk measures derived from the CoreLogic data and FEMA flood map coverage along the Mississippi river by Baton Rouge, Louisiana. We overlay a $0.0025° \times 0.0025°$ ($\approx 250 \times 250$ meters) grid over the city. In each grid cell, we compute the (1) the proportion of properties in a 100-year FEMA flood zone, and (2) the mean composite flood risk AAL for CoreLogic properties located in the cell. We only display grid cells with at least five CoreLogic properties. The coloring for each grid cell is then determined by (1) whether the majority of the cell is covered by a FEMA flood map, and (2) whether the mean property in the cell has a high enough AAL that we would consider it to be "high risk." Gray cells have low flood map coverage and low flood risk; red cells have high flood risk and low flood map coverage; blue cells have high flood risk and high flood map coverage; and gold cells have low flood risk but high flood map coverage.

located in census tracts that overlap with a census-designated urbanized area or cluster (i.e., "urban tracts"), we keep only matches where the geolocated cHMDA property is within 250 meters of the CoreLogic property; for properties in all other census tracts ("rural tracts"), we keep only matches where the geolocated cHMDA property is within 1000 meters of the CoreLogic property. Our results are unaffected by our choice of cutoff values, but these differentiated cutoffs prevent us from systematically excluding rural properties from the sample. Of all the properties in cHMDA from 2018-2021 we match two thirds to a property in the CoreLogic flood risk data within 25 meters.

Figure 2 shows an example of our approach. For anonymity, we take parcels of land that include five or more properties and then group these by their AAL risk exposure as well as their placement on a flood map. Parcels that are accurately mapped are blue. Parcels that bear flood risk but have no map are in red. Finally, property-parcels with no flood risk but no flood map are in grey. Our approach (discussed in detail below) ostensibly compares properties in red parcels with properties in grey parcels.

Our primary analysis makes two additional sample restrictions. First, we consider only properties that are outside of 100-year and 500-year FEMA flood zones. This sample restriction allows us to compare lending outcomes for properties that do not have any officially mapped flood risk, but still differ in their expected flood damages. Second, we limit our primary analysis to conforming loans. Lenders may respond differently to un-mapped flood risk for jumbo loans as they do not have the option to securitize these with one of the public securitization agencies. We consider jumbo loans in Appendix A.3.

In total, we have a sample of over 13.7 million applications over the four year period between 2018-2021. Table 1 shows summary statistics for this sample.[3] Based on their AAL estimates, we classify 17% of properties in the sample as un-mapped and 47% of properties as possibly un-mapped (i.e. an additional 30% of properties, as the categories are not mutually exclusive). Conditional on a lender approving a loan application, nearly all (96%) of borrowers accept the terms and the loan is originated.[4] Some variables are reported at a slightly lower frequency, which costs us observations in specific tests.

As can be seen from Table 1 the average age of the primary applicant is 41 years. The average applicant further has a credit score of 727 and total average annual income of 98,000 USD. The average value of (conforming) properties in our sample is 300,000 USD for which the applicant is seeking 242,000 USD. In our sample, 87% of loans are originated and 73% of all conforming loans are ultimately moved from the lender's balance sheet through either sale or securitization.[5]

2.4 House Price Data

To gain a more complete understanding of the impact of un-mapped flood risk throughout the mortgage lending process, we incorporate data on real estate listings. These data come from CoreLogic's Multiple Listing Services (MLS) database, which sources real estate listing and transaction records from local MLS across the country. These data allow us to observe the closing prices for individual properties for the majority of the country over the sample period. Due to confidentiality concerns we cannot match these data on house listings to the restricted cHMDA data at the property level. Instead, we form a supplementary panel dataset that combines the real estate data and cHMDA data after aggregating both to the census tract-quarter level. The resulting panel allows us to benchmark the pricing of flood risk in

[3]See Table A.7 in the Appendix section for supplemental Tables and Figures shows similar summary statistics for the sample that includes non-conforming (jumbo) loans and properties in 100-year or 500-year FEMA flood zones.

[4]It should be noted that we consider a loan accepted only if both parties agree to the terms.The relatively high acceptance rate in our data follows from the fact that many applicants are "soft rejected" by a bank before completing the official application process.

[5]Many non-bank entities first sell loans to organizations under the same umbrella before they are ultimately securitized, so we treat sold and securitized as similar outcomes for our purposes.

Table 1: *Primary Sample Descriptive Statistics*

Variable	Obs	Mean	SD	10%	Median	90%
Primary Applicant Characteristics						
Age	13,713,259	41	14	26	38	61
Credit Score	13,715,494	727	61	642	736	800
Income	13,715,494	98	75	38	78	175
Male	13,715,494	0.61	0.49	0	1	1
Hispanic	13,715,494	0.12	0.33	0	0	1
Black	13,715,494	0.09	0.28	0	0	0
White	13,715,494	0.72	0.45	0	1	1
Loan Characteristics & Outcomes						
Property Value (1000 USD)	13,585,842	300	189	116	258	532
Loan Amount (1000 USD)	13,715,494	242	137	86	220	428
Loan-to-Value Ratio	13,585,842	85	20	62	92	100
Loan Term (Months)	13,686,232	344	53	300	360	360
Interest Rate	12,281,365	3.8	1.1	2.8	3.8	5.1
Loan Approved	13,715,494	0.9	0.3	1	1	1
Loan Originated	13,715,494	0.87	0.33	0	1	1
Loan Sold or Securitized	13,715,494	0.73	0.44	0	1	1
Loan FHFA Securitized	13,715,494	0.43	0.5	0	0	1
Flood Risk						
Un-mapped	13,715,494	0.17	0.38	0	0	1
Possibly Un-mapped	13,715,494	0.47	0.5	0	0	1

Note: Descriptive statistics for our primary variables of interest and controls appear in the table above. In addition to restricting the dataset to mortgage applications for primary home purchases, the sample we use in the table keeps only mortgage applications that were either approved or denied (excluding applications that were withdrawn), are within the conforming loan limit, and lie outside of 100-year and 500-year FEMA flood zones. Applicant age, income, property value, loan amount, combined LTV, and interest rate are winsorized between the first and ninety-ninth percentiles. Our dummy for loan securitizations includes only those loans that were sold to one of the public securitization agencies within the same calendar year.

the mortgage market, as reflected by the appraisal values banks use in their lending decision, against the pricing of flood risk in the housing market. In particular, this dataset allows us to study a flood risk mitigation channel that works through the appraisal process.

Table A.8 displays summary statistics for this panel. The average number of properties purchased in each quarter is 16 in both the cHMDA and CoreLogic real estate data – a strong indication that we successfully capture the same properties within each tract-quarter. On average, the property values that lenders use when determining whether or not to lend is greater than the closing price of properties in our sample. It is possible that this is a purely contemporaneous feature of the sample period – a period that includes the first two years of the COVID-19 pandemic – but may just as well reflect some consistent feature of the housing and mortgage lending markets. Regardless, our identification focuses not on the difference between closing prices and appraised property values, but on the relative differences in appraised property values for un-mapped and other properties, conditional on their closing prices.

3 Methodology

Given the detail and granularity of our data, we can afford to employ richly saturated regressions. We focus on three outcome variables of interest. Firstly, we want to ascertain to what extent loans are originated by lenders if the property in question bears un-mapped flood risk. This outcome reveals whether lenders are even aware of the risk in question. Secondly, we are interested in understanding whether lenders change the rate charged for properties with un-mapped flood risk for originated loans or whether these loans are securitized more aggressively in a risk-mitigation attempt. Finally, we seek to analyze if lenders change the valuation for properties with un-mapped flood risk. These outcomes help us understand more about the lender's risk awareness as well as their ability/attempts to mitigate this risk.

Our primary approach relates these three outcome variables of interest to borrower and region characteristics and to our variables designating un-mapped risk. As we noted above, we explicitly focus on properties that are outside of flood zones. As such, we ignore flood mapping as this is discussed in detail in Blickle and Santos (2021).

Our specification of interest takes the following form:

$$Y_{i,p,b,c,t} = \beta InaccurateMap_p + \gamma X_{i,t} + \eta_c + \nu_b + \omega_t + \varepsilon_{i,p,b,c,t} \tag{1}$$

where we relate the outcome variable for a given loan to individual i, for property p, from lender/bank b in census tract c at quarter t to whether the property is inaccurately flood mapped.

As previously indicated, we consider several possible outcomes Y. First, we study loan origination decisions, where our dependent variable is a dummy variable indicating when a mortgage is originated. Second, we consider the interest rate on loans approved by the lender. Third, we consider the property value assigned by the home appraiser that the lender uses in the lending decision. Finally, we look to see whether the loan in question was securitized or otherwise sold/moved off of the bank's balance sheet.

We include the two variables of flood map inaccuracy previously discussed: (i) "un-mapped" is a binary variable equal to one if the property in question faces high flood risk but has no flood map coverage, and (ii) "possibly un-mapped" is a binary variable equal to one if the property faces some flood risk but has no flood map. Every property that is un-mapped is also possibly un-mapped, such that in all regression results reported, the estimated effect on un-mapped properties will be the sum of the coefficient estimates on the un-mapped and possibly un-mapped variables. X is a vector of borrower controls that include the primary applicant's sex, ethnicity, race, credit score, and income.

We consider several combinations of fixed effects, including census tract fixed effects η, lender fixed effects ν, and quarter fixed effects ω. Census tract fixed effects will absorb any variation at the tract-level, which could include how desirable the location itself is. In some cases, census tract fixed effects appear to be too granular, as there may be little meaningful variation in flood risk and lenders' perceptions of flood risk within census tracts. Alternatively, we present results using county $\times$ quarter fixed effects that are arguably more appropriate in these cases. Given that our variable of interest varies at the individual property-level, we are able to include very granular controls. In our most restrictive specification, we compare properties bought by similar borrowers, located in the same census tract, but differenced by the degree to which the property faces un-mapped flood risk.

Finally, in extensions, we interact our variable of interest with bank and region characteristics to determine whether different lenders or different regions are more sensitive to un-mapped flood risk. Specifically, we look at non-bank entities and applicants with higher than average income for their region. Non-bank entities have differing business models than banks. their high propensity to securitize or sell mortgages may make them less risk averse than banks, who may keep some mortgages on their balance sheets.

4 Lending Response

4.1 Loan Origination

We first analyze whether mortgages are less likely to be originated for properties that face "un-mapped" flood risk. Our sample is limited specifically to those properties that are not covered by a either a FEMA 100-year or 500-year flood zone. This sample restriction allows us to identify the effect of flood risk by comparing similar properties unaffected by the NFIP insurance mandate and unaffected by the public signal contained in FEMA flood maps.

From Table 2 we can see that lenders are less likely to originate loans – all else equal – for properties that have un-mapped flood risk. Specifically, a mortgage application for a property that has no flood

Table 2: ***Loan Origination for Conforming Loans***

Dependent Variable:	Loan Originated			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-Mapped	-0.0044***	-0.0035***	-0.0024***	-0.0008***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Possibly Un-Mapped	-0.0051***	-0.0063***	-0.0014***	-0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log Loan Amount		0.0278***	0.0329***	0.0099***
		(0.0002)	(0.0002)	(0.0002)
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	13,715,494	13,715,330	13,715,330	13,715,330
R^2	0.06050	0.06350	0.08063	0.16805
Within R^2	0.05913	0.06214	0.05496	0.03396

Note: We estimate equation 1, above. Our outcome variable is binary and tracks whether a mortgage is originated (i.e. accepted by both borrower and lender) and our variables of interest are also binary and denote whether a property is un-mapped or possibly un-mapped. Each specification contains controls for an applicant's sex, ethnicity, race, credit score, and income. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by tract and the year-quarter of origination; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

map despite facing any amount of flood risk (i.e. a possibly un-mapped property) has a 0.5 percentage point lower chance of being originated. The effect of being un-mapped is cumulative to the baseline effect of being possibly un-mapped, so that a property that has high flood risk without flood map is just under 1 percentage point less likely to receive a mortgage loan – all else equal.[6] This is a large effect, given that the sample overall has a rejection rate of just 13%.

As we add controls for loan size in column (2) or additional fixed effects in columns (3) and (4), the magnitude of our coefficient of interest diminishes, though remains statistically significant. Ultimately, if we include census tract fixed effects and lender fixed effects, the coefficients reflects an only 0.2 percentage point additional rejection rate in areas with un-mapped risk. While still statistically significant, the effect is much less pronounced.

It is possible that the inclusion of census tract fixed effects reduces the magnitude of our estimates

[6]The effect is cumulative and calculated as $0.0044 + 0.0051$.

Table 3: *Interest Rates for Conforming Loans*

Dependent Variable:	Interest Rate			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-Mapped	0.0197***	0.0119***	0.0014**	0.0006
	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Possibly Un-Mapped	0.0004	0.0143***	-0.0017***	0.0014***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Log Loan Amount		-0.3066***	-0.3560***	-0.2601***
		(0.0008)	(0.0010)	(0.0009)
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	12,084,309	12,084,294	12,084,294	12,084,294
R^2	0.58861	0.62054	0.63759	0.73073
Within R^2	0.05217	0.12573	0.12703	0.08723

Note: We estimate equation 1, above. The interest rate is continuous and bounded between 2 and 8. We remove properties with extreme interest rates (above the 99th percentile or below the 1st percentile). Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. Each specification contains controls for an applicant's sex, ethnicity, race, credit score, and income. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

because banks take a region-level approach to flood risk management. Any area with un-mapped flood risk is treated somewhat similarly, with borrowers less likely to obtain a loan in these communities. Overall, however, we can say that lenders are aware of some of the risks posed by possible flooding.

4.2 Interest Rate Charged

We next focus on interest rates, employing the same approach as above to determine whether banks charge higher rates for mortgages on properties with un-mapped flood risk. If loans are originated **but** at higher prices, this may still compensate the lender or loan owner for un-mapped flood risk and reveal that the lender is managing risk through pricing.

We can see from Table 3 that mortgages which are accepted pay higher rates if they are at risk of flooding but have no flood map. Specifically, facing un-mapped flood risk is associated with an up to 2 basis points higher interest rate, depending on specification. This increase is small, representing only a minor jump over the 3% average rate.

If we include more detailed controls, such as census tract fixed effects, we can see that the effect becomes smaller and insignificant. Again, this seems to be a result of banks applying risk management practices to the tract at large. Ultimately, the baseline results on interest rates charged in un-mapped flood zones are somewhat inconclusive, given the small increase over baseline rates.

4.3 House Prices and Property Valuation

Banks' decisions are not limited to accepting/denying a mortgage application and the interest rates charged for originated loans. They also play a critical role on properties' valuations they consider in the loan application. However, the bank's decision on value has to be seen in connection with the market price of houses.

4.3.1 House Price Reactions

We begin by looking at the overall market reaction to flood risk in general and un-mapped flood risk in particular. We first relate closing prices of transacted properties to the risk faced by these properties as well as a series of other controls to account for property location and quality. We are able to make use of property-level risk data for this specification, as we do not need to merge in mortgage data and are therefore not concerned with applicant privacy. We again exclude all properties that are covered by a FEMA 100 year or 500 year flood map and focus instead on properties that have un-mapped flood risk.

In Table 4, we find that flood risk is negatively associated with closing house prices. The AAL risk score, which measure the expected annual loss from flooding disasters (see above), is bounded between 1 and 100. We find that properties with risk sell for up to 183 USD less per point of risk exposure. The effect is more pronounced if we account for property-type characteristics an location controls. THen a point of risk exposure reduces a sale price by over 380 USD.

In column (4), we can make use of the same variables as above, assigning properties to being un-mapped or possibly un-mapped based on their risk exposure. Moreover, we can include not only property-level characteristics but also census tract fixed effects. We find that the final sale price of a property that is exposed to un-mapped flood risk is over 29,000 USD lower[7] than a comparable property in the same tract that faces no such risk. This represents an almost 7% drop in value.

[7] Total value reduction can be read as: 28697 + 1542.

Table 4: ***Property Prices***

Dependent Variable:	Closing price			
Model:	(1)	(2)	(3)	(4)
Variables				
Risk Score	-183.1***	-366.1***	-385.2***	
	(-49.36)	(-94.82)	(-100.17)	
Time on Market		6.612***	6.440***	6.608***
		(66.77)	(65.36)	(66.89)
Tract Income		4.367***	4.337***	4.330***
		(1478.43)	(1466.60)	(1475.14)
Number Rooms		22874.1***	23035.2***	23438.3***
		(695.91)	(702.34)	(714.82)
Year Built		47.85***	34.76***	42.56***
		(15.00)	(10.94)	(13.54)
Waterfront Property		131216.8***	146191.1***	142590.5***
		(388.39)	(414.39)	(413.42)
Foreclosure		-35539.1***	-46403.4***	-46278.6***
		(-39.58)	(-50.92)	(-51.00)
Un-Mapped				-28697.3***
				(-127.32)
Possibly Un-Mapped				-1542.4***
				(7.8)
Fixed-effects				
Quarter-Year	Yes	Yes		
County		Yes		
County-Quarter-Year			Yes	Yes
Tract				Yes
Fit statistics				
Observations	28,191,498	28,191,498	28,191,498	28,191,498
Adjusted R^2	0.023	0.282	0.290	0.290

Note: We relate closing prices of house-purchases to flood risk, measured as expected annual loss from flooding (in columns (1)-(3)), or whether a property is un-mapped (columns (4)) and a series of house characteristics. We exclude all observations covered by a FEMA flood map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

It should be noted that we are unable to determine whether the price change is a response to consumers fearing flood dangers or due to the fact that banks are more hesitant to lend in these areas. All else equal, credit constraints and reduced lending to affected properties/in affected areas should reduce prices to some extent. We therefore look specifically at the value lenders assign to properties.

4.3.2 Property Valuation

We next investigate the valuation of properties that face flood risk. These valuations are computed by assessors that inspect the property during the final phase of the mortgage approval process. As such,

Table 5: ***Property Valuations***

Dependent Variable:	Log Assessed Value		
Model:	(1)	(2)	(3)
Variables			
Un-Mapped	-0.0233***	-0.0245***	-0.0200***
	(0.0006)	(0.0004)	(0.0003)
Possibly Un-Mapped	0.0541***	-0.0169***	-0.0119***
	(0.0005)	(0.0003)	(0.0002)
Fixed-effects			
Quarter-Year	Yes		Yes
County-Quarter-Year		Yes	
Tract			Yes
Lender			Yes
Fit statistics			
Observations	13,403,882	13,403,882	13,403,882
R^2	0.40854	0.62647	0.73750
Within R^2	0.39677	0.32120	0.20251

Note: We estimate equation 1, above. Our outcome variable is the natural logarithm of the property value the lender uses when making the lending decision. Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. Each specification contains controls for an applicant's sex, ethnicity, race, credit score, and income. We add additional controls and fixed effects in columns (2)–(3). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

the valuation is liable to include all available information on a property, especially information on flood risk.

We find in Table 5 that properties, which face un-mapped flood risk, experience an up to 3.2% reduction in value. Importantly, unlike the effects of flood risk on interest rates, discussed above, the effect on house valuation persists even if we include census tract fixed effects (column (3)). We argue that this is the result of valuations being conducted on a case-by case basis during the assessment and reflect a property's specific flood risk – rather than risk for an entire area. The assessor is able to make use of the property's true location and risk in a way that risk-management at the bank might not. We next combine bank valuation and property prices to see which effect dominates the other. If banks are dropping their valuations by more than the market price reaction, then they are demanding more equity from borrowers and thereby reducing their risk exposure.

Table 6: ***Property Value and Loan to Value***

Dependent Variables:	Log Mean Property Value		Closing Price to Loan Amount ×100
Model:	(1)	(2)	(3)
Variables			
Log Mean Closing Price	0.6301***	0.6378***	
	(0.0025)	(0.0023)	
Log Mean Closing Price × Un-mapped Dummy		-0.0703***	
		(0.0069)	
Log Mean Closing Price × Possibly Un-mapped Dummy		-0.0067**	
		(0.0031)	
Un-mapped Dummy		0.3891***	1.599***
		(0.0407)	(0.3061)
Possibly Un-mapped Dummy		0.0372**	-0.6267***
		(0.0179)	(0.2425)
Fixed-effects			
County	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Fit statistics			
Observations	790,681	783,942	784,367
R^2	0.84002	0.83979	0.01252
Within R^2	0.54599	0.54688	5.59×10^{-6}

Note: We construct tract-quarter dummies such that the un-mapped dummy is 1 if more than 50% of the HMDA properties in the given tract-quarter are un-mapped, and the analogous dummy variable for the possibly un-mapped group. Heteroskedasticity-robust standard-errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

4.3.3 LTV Ratios

We find that the decrease in valuation is larger than the decrease in prices. We calculate a ratio of property sales prices to loan amounts at the tract level. As such, we are able to gauge the true extent to which households have to post equity when buying a home. A large deviation between price and loan amount implies that households must make use of more equity in the house purchase.[8]

From Table 6 we can first see that the average value assigned to properties is strongly linked to the closing price (column (1)). However, the closing price of properties is negatively related to the share with un-mapped risk (column (2)). In fact, the higher the price of a property, the larger the deviation between value and price becomes in areas with un-mapped risk. This likely reflects a bank's aversion to being overly exposed to risky properties at high values. Finally, in column (3), we see the ratio of closing

[8]As described above, we are unable to match property sales prices to mortgage data at the household level, given data concerns. Instead, we must make use of data at the tract*quarter level.

prices to loan amount grows by 1.6 percentage points in areas with low coverage.[9] This implies that – all else equal – the amount of equity households have to post for these types of buildings is higher than in comparable areas with no flood risk. Despite the fact that these regressions are at the census tract level, they provide indicative evidence that, even with a drop in property prices, loan amounts are responding more strongly.

5 Securitization and Loan Sales

The evidence reported in the previous section suggests lenders are aware of flood risk and attempt to mitigate that risk in their mortgage lending decisions. Given that our evidence derives from conforming mortgages, a natural question to ask is whether lenders further mitigate the risk they face from lending in un-mapped regions by securitizing or selling properties that bear such risk. We investigate this question next.

HMDA data includes information on whether properties are securitized or sold[10]. For convenience, we have grouped loan sales and loan securitization together under the same umbrella. This is useful partly because some non-bank entities first "sell" a loan to a sister organization that prepares the loan for securitization and partly because we can be agnostic about the difference between sales and securitization, as either could be a risk mitigant from the perspective of a lender.

As can be seen from Table 7, we find that lenders are slightly – up to 1.2 percentage points – more likely to sell or securitize mortgages to properties in regions with un-mapped risk. The economic magnitude of the effect is smallest when we include tract fixed effects, implying that risk management may be conducted at the level of communities (as seen above). Moreover, only the effect of being un-mapped remains, with the coefficient on "possibly un-mapped" losing significance.

We find the same patterns if we look only at securitization (see Appendix A.4). Overall, our results suggest that lenders move flood risk from their balance sheet. Given the high propensity for securitizing conforming loans – i.e. 73% –, even a small increase in our measure of sold or securitized loans indicates that lenders are indeed cautious about holding such risks and are aggressive about moving the risk from their balance sheets.

The coefficients for all key regressions discussed above are summarized in figure 3. Here we plot

[9] Given that we have collapsed data to the tract level, "un-mapped" is no longer subsumed by "possibly un-mapped" and the effects are not cumulative.

[10] Banks use securitization to diversify risk and – often –increase their lending (Cebenoyan and Strahan (2004); Franke et al. (2022); Carbo-Valverde et al. (2015)

Table 7: ***Loan Sales***

Dependent Variable:	Loan Sold or Securitized			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-Mapped	0.0032***	0.0053***	0.0012***	0.0009***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Possibly Un-Mapped	0.0087***	0.0055***	0.0013***	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Interest Rate	-0.0941***	-0.0910***	-0.0881***	-0.0513***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Log Loan Amount		0.0754***	0.0727***	0.0424***
		(0.0002)	(0.0003)	(0.0002)
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	11,922,096	11,922,081	11,922,081	11,922,081
R^2	0.06294	0.07817	0.11164	0.41972
Within R^2	0.04144	0.05702	0.05236	0.01798

Note: We estimate equation 1, above. The outcome variable is binary and indicates when a loan is sold, including when sold a securitization agency. Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. Each specification contains controls for an applicant's sex, ethnicity, race, credit score, and income. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

the total effect of a property being un-mapped or possibly un-mapped along with confidence bands at the 95% level. The figure allows for an easy interpretation of the most important coefficients as well as a sense of the change in effect magnitude as we move to regressions that include a greater degree of saturation and – most importantly – tract fixed effects. Moving from specification (1) to (3) reveals the difference between an area-level and a property-level approach to risk management. As discussed, most lenders appear to take a region-level approach to mitigating many of these risks.

6 Lender and Borrower Types

In our analyses thus far, we have been agnostic about the type of lender making the loan. We have simply controlled for lenders themselves with lender fixed effects in our most saturated specifications. However, different types of lenders may have different approaches to flood risk. After all, local banks may have local knowledge and large banks may be too far removed to know about local flood risks. We therefore separate large banks, local banks, and non-banks from all other lenders, interacting our variables of interest with a lender-type dummy to identify whether these lenders respond differently.

For our purposes, we define the set of large banks as the bank holding companies included in the Large Institution Supervision Coordinating Committee (LISCC) program and their subsidiaries.[11] We classify lenders as "local" on a county-by-county basis. Specifically, we define a lender-county pair to be local if during the sample period 40% or more of the lender's originated mortgage volume was in the given county. Lastly, we define non-banks as any institution not classified as a large lender or local lender, and is not a bank or credit union.[12] This group will include internet mortgage brokers and their affiliated non-bank financial institutions.

We find in Table 8 that non-banks are slightly more willing to lend in areas with flood risk. In our most saturated specification, in column (4), the increase roughly compensates for the baseline aversion all lenders show in originating loans to un-mapped properties. This implies that non-banks are seemingly indifferent to lending in areas with un-mapped flood risk.

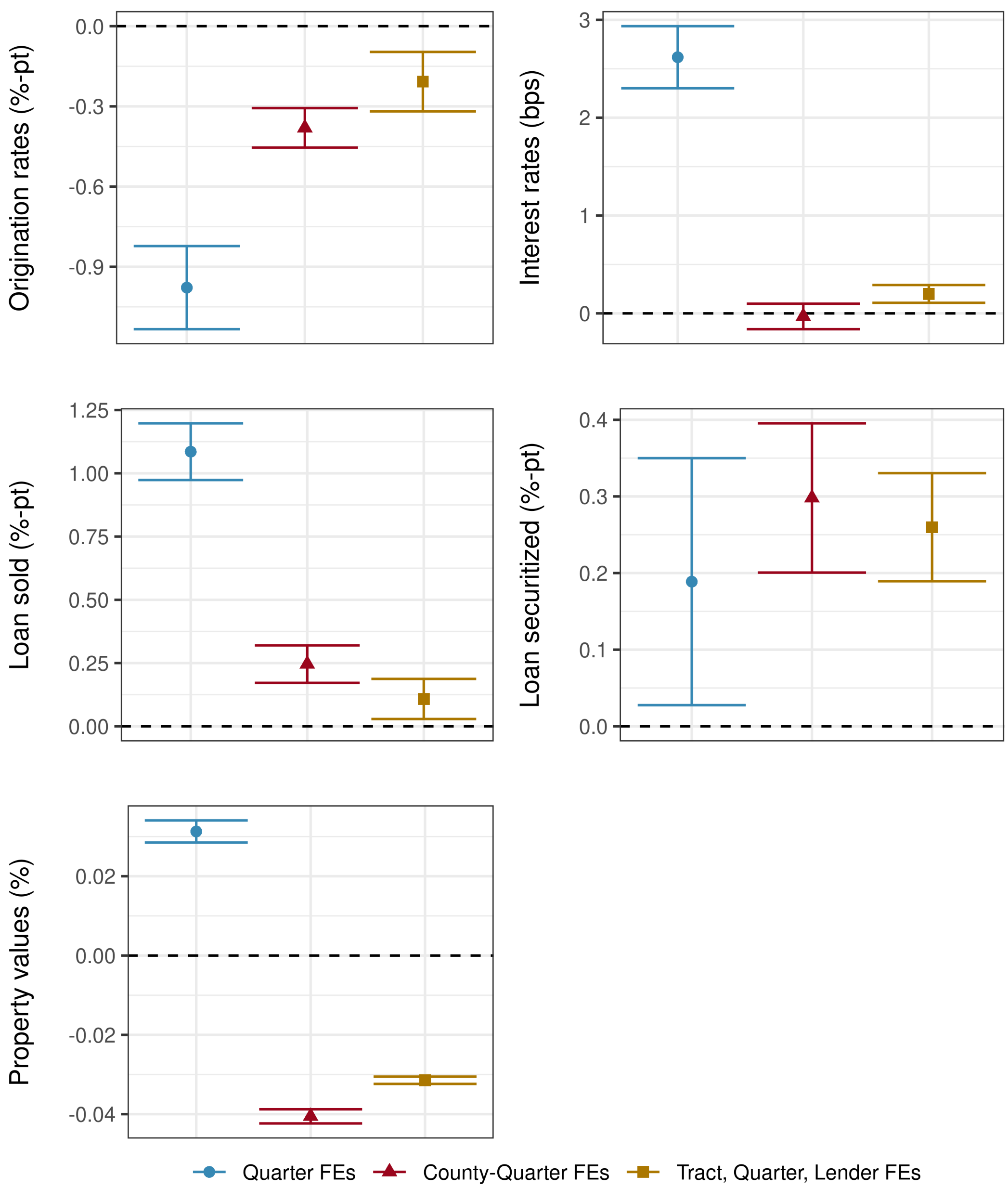
Similarly, local banks are significantly more likely to lend in areas with un-mapped flood risk. The coefficients are even statistically larger in magnitude than those for the non-bank interactions. It is therefore possible that local banks compensate the fact that other banks reducing their exposure in un-mapped regions. Local banks are ostensibly assuming flood risk to obtain market share. Large banks, on the other hand seem particularly averse to un-mapped regions (see column (4)). However, the coefficient on the large-bank interaction is not always stable.

In the Appendix (Tables A.1 and A.2) we further show that both non-banks and local banks are less likely to charge higher rates for loans to borrowers facing un-mapped risk. Furthermore, non-banks

[11]Currently, this list of bank holding companies includes Bank of America Corporation, The Bank of New York Mellon Corporation, Citigroup Inc., The Goldman Sachs Group, Inc., JP Morgan Chase & Co., Morgan Stanley, State Street Corporation, and Wells Fargo & Company.

[12]We identify banks and credit unions based on the entity types corresponding with their RSSD in cHMDA. Specifically, we consider national banks, state member banks, cooperative banks, domestic branches of domestic banks, non-member banks, savings and loans, federal savings banks, state savings banks, uninsured branches of foreign bank offices, federal credit unions, and state credit unions.

Figure 3: *Primary Coefficient Estimates on Un-mapped Properties*



Note: This figure plots the coefficient estimates on both the un-mapped dummies combined for our primary outcomes of interest along with their 95% confidence intervals. These coefficient estimates for the effects on origination rates, interest rates, loan sales, loan sercuritizations, and property values appear in tables 2, 3, 7, A.9, and 5 respectively.

Table 8: ***Loan Originated with Bank Type Interactions***

Dependent Variable:	Loan Originated			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-mapped × Non-Bank	0.0078***	0.0077***	0.0072***	0.0020***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Un-mapped × Local Bank	0.0138***	0.0125***	0.0163***	0.0027**
	(0.0013)	(0.0013)	(0.0013)	(0.0012)
Un-mapped × Large Bank	-0.0002	-0.0005	0.0035***	-0.0025*
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Un-mapped	-0.0103***	-0.0092***	-0.0078***	-0.0021***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Possibly Un-mapped	-0.0059***	-0.0069***	-0.0013***	-0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Non-Bank	0.0426***	0.0384***	0.0446***	0.0021*
	(0.0002)	(0.0002)	(0.0002)	(0.0012)
Local Bank	0.0424***	0.0429***	0.0318***	0.0063***
	(0.0006)	(0.0006)	(0.0006)	(0.0009)
Large Bank	-0.0589***	-0.0621***	-0.0507***	-0.6149
	(0.0006)	(0.0006)	(0.0006)	(12,750.6)
Log Loan Amount		0.0253***	0.0308***	0.0099***
		(0.0002)	(0.0002)	(0.0002)
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	13,715,494	13,715,330	13,715,330	13,715,330
R^2	0.06687	0.06932	0.08636	0.16805
Within R^2	0.06551	0.06796	0.06085	0.03397

Note: We estimate equation 1, above. Our outcome variable is binary and tracks whether a mortgage is originated (i.e. accepted by both borrower and lender) and our variables of interest are also binary and denote whether a property is un-mapped or possibly un-mapped. Non-bank is a dummy variable indicating that, based on its entity type code, the lender is not a bank nor credit union. Local bank is a dummy variable indicating that at least 40% of the lender's mortgage origination occurs in the county the property is located in. Large bank is a dummy variable indicating that the lender is an entity or a subsidiary of an entity regulated under the Large Institution Supervision Coordinating Committee (LISCC) program. Each specification contains controls for an applicant's sex, ethnicity, race, credit score, and income. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by tract and the year-quarter or origination; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

are additionally somewhat less likely to reduce a property's value in relation to it facing un-mapped flood risk. Local banks, on the other hand, do seem to respond to this risk at least by reducing property valuations, though not by as much as large banks do.

The above results beg the question of whether entities such as non-banks or even local banks are truly aware of the potential issues posed by un-mapped flood risk. To test this proposition we can look at whether these lenders are more likely to move loans to un-mapped properties off of their balance sheets. In Table 9 we see that non-banks and local banks are indeed more aggressive in removing this risk from their books. Non-banks in particular seem aware of property-level risks. From column (4) we can see that these lenders are aggressively securitizing/selling individual properties within a census tract that bear risk. Local banks, on the other hand, are very aggressive in securitizing properties risky regions as a whole, making fewer property-level distinctions (column (1) vs column (4)). Once we include a census tract fixed effect, we can see that the coefficient on the interaction term becomes insignificant. Ultimately, non-banks and local banks are so aggressive in their attempts to move un-mapped risk from their balance sheets, that the baseline coefficient changes sign, implying that these lenders are the drivers of the baseline-effect discussed above. Large banks are the least aggressive in securitizing loans with un-mapped risk.

Overall, we can see that all manner of lenders are aware of the risks posed by un-mapped flood zones. Small local banks and non-bank entities are more prone to lend and securitize while larger banks are more likely to restrict lending (i.e. originate fewer loans) and charge higher rates to borrowers. The former's risk management approach may be of concern to supervisors as it ultimately may end up distributing the risk to other entities.

Finally, we look at whether tract or borrower characteristics can impact the effect un-mapped flood risk has on a lender's decision. In Appendix Table A.4 we show that loans are more likely to be originated if a given census tract falls into the top tercile of average incomes across the country. We find that lenders are slightly less risk averse in high income areas, possibly due to the fact that high income borrowers can more easily weather the negative impact of a flooding disaster. These results are corroborated if we look at high credit score borrowers or borrowers that have higher incomes than the average of their county (not reported for brevity). In the Appendix we also discuss the lending responses in for jumbo loans A.3. We find that the lending aversion is much smaller for these larger loans. This may similarly be a side-effect of lenders being more comfortable with wealthier borrowers, whose loan to income ratios are, on average, much higher.

Table 9: ***Loan Sales with Bank-Typer Interactions***

Dependent Variable:	Loan Sold or Securitized			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-mapped × Non-Bank	0.0062***	0.0059***	0.0045***	0.0031***
	(0.0008)	(0.0008)	(0.0008)	(0.0007)
Un-mapped × Local Bank	0.0218***	0.0193***	0.0248***	-0.0004
	(0.0022)	(0.0022)	(0.0021)	(0.0016)
Un-mapped × Large Bank	-0.0161***	-0.0166***	-0.0111***	-0.0020
	(0.0019)	(0.0019)	(0.0019)	(0.0016)
Un-mapped	-0.0016**	0.0003	-0.0020***	-0.0011*
	(0.0008)	(0.0008)	(0.0007)	(0.0006)
Possibly Un-mapped	0.0025***	0.0006**	0.0012***	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Non-Bank	0.2581***	0.2490***	0.2530***	0.0081***
	(0.0004)	(0.0004)	(0.0004)	(0.0014)
Local Bank	8.33×10^{-5}	0.0014	-0.0204***	0.0036***
	(0.0014)	(0.0014)	(0.0012)	(0.0013)
Large Bank	-0.0007	-0.0083***	0.0028***	1.021
	(0.0009)	(0.0009)	(0.0008)	(2,593.2)
Interest Rate	-0.0948***	-0.0926***	-0.0896***	-0.0513***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log Loan Amount		0.0529***	0.0600***	0.0424***
		(0.0002)	(0.0002)	(0.0002)
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	11,922,096	11,922,081	11,922,081	11,922,081
R^2	0.16711	0.17448	0.20311	0.41972
Within R^2	0.14800	0.15554	0.14994	0.01799

Note: We estimate equation 1, above. The outcome variable is binary and indicates when a loan is sold, including when sales to securitization agencies. Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. Non-bank is a dummy variable indicating that, based on its entity type code, the lender is not a bank nor credit union. Local bank is a dummy variable indicating that at least 40% of the lender's mortgage origination occurs in the county the property is located in. Large bank is a dummy variable indicating that the lender is an entity or a subsidiary of an entity regulated under the Large Institution Supervision Coordinating Committee (LISCC) program. Each specification contains controls for an applicant's sex, ethnicity, race, credit score, and income. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

7 Conclusion

We make use of property-level mortgage data, property-level risk data, and country-wide FEMA flood maps to identify the effects of flood risk on mortgage lending. We focus specifically on those properties that face flood risk but are not zoned as being in a FEMA flood zone. As such, we are abstracting from the effects of mandatory flood insurance and any other information coming from flood maps.

We find that lenders are less likely to originate loans to un-mapped properties subject to flood risk. The effect is still present, even in the face of very restrictive controls that account for lender and census tract. We further find that lenders charge slightly higher rates for originated loans and assessors assign lower values, leading to lower LTV loans. Finally, we find that lenders are more likely to securitize or sell their loans to affected properties. This effect is more pronounced among smaller local banks and non-bank lenders whose risk management approach seems focused on moving risk from their balance sheet post lending, while not reducing actual lending as much as larger banks.

Taken together, our results are indicative that mortgage lenders are aware of flood risk outside FEMA's identified flood zones. They manage that risk not only through the extensive margins and the interest rates they charge but also through their securitization/sale of mortgages to flood-prone borrowers.

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Appendix

A.1 Bank Type Interactions

Table A.1: ***Interest Rates with Lender Types***

Dependent Variable:	Interest Rate			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-mapped × Non-Bank	-0.0124***	-0.0084***	-0.0147***	0.0003
	(0.0014)	(0.0013)	(0.0013)	(0.0010)
Un-mapped × Local Bank	-0.0039	0.0102***	-0.0098***	0.0002
	(0.0029)	(0.0028)	(0.0027)	(0.0024)
Un-mapped × Large Bank	-0.0179***	-0.0149***	-0.0295***	-0.0033*
	(0.0021)	(0.0020)	(0.0020)	(0.0019)
Un-mapped	0.0295***	0.0180***	0.0131***	0.0005
	(0.0013)	(0.0012)	(0.0012)	(0.0009)
Possibly Un-mapped	0.0019***	0.0144***	-0.0018***	0.0014***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Non-Bank	-0.0204***	0.0386***	0.0172***	0.0109***
	(0.0006)	(0.0006)	(0.0005)	(0.0025)
Local Bank	-0.0522***	-0.0580***	-0.0336***	0.0045**
	(0.0014)	(0.0014)	(0.0013)	(0.0018)
Large Bank	-0.1844***	-0.1357***	-0.1651***	-1.124
	(0.0009)	(0.0009)	(0.0009)	(8,660.6)
Log Loan Amount		-0.3114***	-0.3579***	-0.2601***
		(0.0008)	(0.0010)	(0.0009)
Loan Sample	Conforming	Conforming	Conforming	Conforming
In Flood Zone	No	No	No	No
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	12,084,309	12,084,294	12,084,294	12,084,294
R^2	0.59009	0.62222	0.63910	0.73073
Within R^2	0.05557	0.12960	0.13067	0.08723

Note: We estimate equation 1, above. The interest rate is continuous and bounded between 2 and 8. We remove properties with extreme interest rates (above the 99th percentile or below the 1st percentile). Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. Non-bank is a dummy variable indicating that, based on its entity type code, the lender is not a bank nor credit union. Local bank is a dummy variable indicating that at least 40% of the lender's mortgage origination occurs in the county the property is located in. Large bank is a dummy variable indicating that the lender is an entity or a subsidiary of an entity regulated under the Large Institution Supervision Coordinating Committee (LISCC) program. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.2: ***Property Values with Lender Types***

Dependent Variable:	Log Property Value		
Model:	(1)	(2)	(3)
Variables			
Un-mapped × Non-Bank	0.0161***	0.0064***	0.0047***
	(0.0009)	(0.0007)	(0.0006)
Un-mapped × Local Bank	0.0354***	-0.0029*	-0.0010
	(0.0021)	(0.0017)	(0.0014)
Un-mapped × Large Bank	0.0109***	-0.0191***	-0.0100***
	(0.0019)	(0.0016)	(0.0013)
Un-mapped	-0.0362***	-0.0277***	-0.0227***
	(0.0008)	(0.0007)	(0.0006)
Possibly Un-mapped	0.0513***	-0.0169***	-0.0119***
	(0.0005)	(0.0003)	(0.0002)
Non-Bank	0.0954***	0.0046***	-0.0114***
	(0.0004)	(0.0003)	(0.0016)
Local Bank	-0.0261***	-0.0072***	-0.0059***
	(0.0011)	(0.0008)	(0.0011)
Large Bank	0.1402***	0.0184***	-0.4310
	(0.0008)	(0.0006)	(8,197.5)
Loan Sample	Conforming	Conforming	Conforming
In Flood Zone	No	No	No
Fixed-effects			
Quarter-Year	Yes		Yes
County-Quarter-Year		Yes	
Tract			Yes
Lender			Yes
Fit statistics			
Observations	13,403,882	13,403,882	13,403,882
R^2	0.41535	0.62653	0.73750
Within R^2	0.40372	0.32131	0.20253

Note: We estimate equation 1, above. Our outcome variable is the natural logarithm of the property value the lender uses when making the lending decision. Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. Non-bank is a dummy variable indicating that, based on its entity type code, the lender is not a bank nor credit union. Local bank is a dummy variable indicating that at least 40% of the lender's mortgage origination occurs in the county the property is located in. Large bank is a dummy variable indicating that the lender is an entity or a subsidiary of an entity regulated under the Large Institution Supervision Coordinating Committee (LISCC) program. We add additional controls and fixed effects in columns (2)–(3). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.3: ***Origination with Local Banks***

Dependent Variable:	Loan Originated			
Model:	(1)	(2)	(3)	(4)
Variables				
Very Low Coverage	-0.0050***	-0.0039***	-0.0031***	-0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Low Coverage	-0.0053***	-0.0065***	-0.0014***	-0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Very Low Coverage × Local Bank (≥ 20%)	0.0072***	0.0066***	0.0086***	0.0018**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Local Bank (≥ 20%)	0.0194***	0.0224***	0.0111***	0.0091***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Log Loan Amount		0.0282***	0.0330***	0.0099***
		(0.0002)	(0.0002)	(0.0002)
Loan Sample	Conforming	Conforming	Conforming	Conforming
In Flood Zone	No	No	No	No
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	13,715,494	13,715,330	13,715,330	13,715,330
R^2	0.06076	0.06385	0.08072	0.16807
Within R^2	0.05940	0.06248	0.05505	0.03399

Note: We estimate equation 1, above. Our outcome variable is binary and tracks whether a mortgage is originated (i.e. accepted by both borrower and lender) and our variables of interest are also binary and denote whether a property is un-mapped or possibly un-mapped. Local bank (≥ 20%) is a dummy variable indicating that at least 20% of the lender's mortgage origination occurs in the county the property is located in. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by tract and the year-quarter or origination; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

A.2 Neighborhood Income Interactions

Table A.4: ***Origination with Tract Income***

Dependent Variable:	Loan Originated			
Model:	(1)	(2)	(3)	(4)
Variables				
Very Low Coverage	-0.0046***	-0.0041***	-0.0037***	-0.0014***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Low Coverage	-0.0049***	-0.0060***	-0.0013***	-0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Very Low Coverage × Low Income Tract	0.0056***	0.0050***	-0.0001	0.0010
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Very Low Coverage × High Income Tract	-0.0011*	-0.0004	0.0040***	0.0012**
	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Low Income Tract	-0.0321***	-0.0267***	-0.0134***	-0.7683
	(0.0004)	(0.0004)	(0.0004)	(11,323.1)
High Income Tract	0.0006**	-0.0062***	-0.0086***	0.6873
	(0.0002)	(0.0003)	(0.0003)	(11,727.3)
Log Loan Amount		0.0269***	0.0328***	0.0099***
		(0.0002)	(0.0002)	(0.0002)
Loan Sample	Conforming	Conforming	Conforming	Conforming
In Flood Zone	No	No	No	No
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	13,714,718	13,714,554	13,714,554	13,714,554
R^2	0.06144	0.06412	0.08083	0.16802
Within R^2	0.06007	0.06276	0.05516	0.03396

Note: We estimate equation 1, above. Our outcome variable is binary and tracks whether a mortgage is originated (i.e. accepted by both borrower and lender) and our variables of interest are also binary and denote whether a property is un-mapped or possibly un-mapped. Low income tract and high income tract are dummy variables that denote . We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by tract and the year-quarter or origination; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

A.3 Regressions with Jumbo Loans

In this section, we showcase key regressions from the paper, making use of non-conforming (aka jumbo) loans instead of conforming loans. Jumbo loans are larger and – most importantly – not eligible for standard securitization with an FHFA. As we can see, the effects discussed above hold broadly true. Jumbo loans are less likely to be originated – because banks are aware of the un-mapped flood risk – and more likely to be charged a higher rate, as banks manage this risk. However, the effects are significantly less pronounced than for conforming loans. In fact, if we include census tract and bank-type fixed effects, we can see that both key results are insignificant. If we interact or variables of interest with bank-type fixed effects, we can see that none of the various lender types respond very differently (not reported for brevity). Similarly, while we find a reduction in the value of jumbo properties, we find that this reduction in value is below 1% if we include all controls and fixed effects (results not reported for brevity). Among conforming loans on the other hand, the reduction is much larger (over 3%).

At first, this may seem somewhat surprising. After all, jumbo loans are more likely to remain on a bank's balance sheet than conforming loans. A bank has greater incentives to manage its risk exposure. However, the average income as well as the average loan-to-income ratio is significantly higher among jumbo loan borrowers than conforming borrowers. In fact, average income is 3.5 as high and LTI is over 10% higher. As such, the bank may perceive the borrowers as being more likely to whether a negative financial shock from a flood, even without insurance. Similar phenomena – with wealthier households less affected – could be observed in Blickle and Santos (2021).

Table A.5: ***Interest Rates for Jumbo Loans***

Dependent Variable:	Interest Rate			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-mapped	0.0216***	0.0175***	0.0026	0.0018
	(0.0020)	(0.0019)	(0.0020)	(0.0018)
Possibly Un-mapped	-0.0130***	-0.0037**	-0.0030**	0.0019
	(0.0015)	(0.0014)	(0.0015)	(0.0014)
Log Loan Amount		-0.1972***	-0.0965***	0.0350***
		(0.0028)	(0.0035)	(0.0033)
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	797,477	797,477	797,477	797,477
R^2	0.57633	0.58001	0.60550	0.71186
Within R^2	0.07360	0.08163	0.06073	0.03949

Note: We estimate equation 1, above. The interest rate is continuous and bounded between 2 and 8. We remove properties with extreme interest rates (above the 99th percentile or below the 1st percentile). Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to non-conforming (jumbo) loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by tract and the year-quarter or origination; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.6: ***Origination for Jumbo Loans***

Dependent Variable:	Loan Originated			
Model:	(1)	(2)	(3)	(4)
Variables				
Un-mapped	-0.0070***	-0.0098***	-0.0007	-0.0007
	(0.0011)	(0.0010)	(0.0011)	(0.0011)
Possibly Un-mapped	-0.0098***	-0.0031***	-0.0016*	-0.0017*
	(0.0008)	(0.0008)	(0.0009)	(0.0009)
Log Loan Amount		-0.1389***	-0.1914***	-0.1808***
		(0.0015)	(0.0019)	(0.0020)
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	879,145	879,145	879,145	879,145
R^2	0.02476	0.03727	0.07249	0.14183
Within R^2	0.02053	0.03309	0.03365	0.03092

Note: We estimate equation 1, above. Our outcome variable is binary and tracks whether a mortgage is originated (i.e. accepted by both borrower and lender) and our variables of interest are also binary and denote whether a property is un-mapped or possibly un-mapped. Low income tract and high income tract are dummy variables that denote . We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to non-conforming (jumbo) loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by tract and the year-quarter or origination; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

A.4 Supplemental Tables and Figures

Table A.7: *Unrestricted Sample Descriptive Statistics*

Variable	Obs	Mean	SD	10%	Median	90%
Applicant Characteristics						
Applicant Age	18505309	42	14	26	39	62
Applicant Credit Score	16976449	729	61	644	740	800
Applicant Income	18290710	113	100	39	84	214
Applicant Male	18807654	0.61	0.49	0	1	1
Applicant Hispanic	18807654	0.12	0.33	0	0	1
Applicant Black	18807654	0.08	0.27	0	0	0
Applicant White	18807654	0.7	0.46	0	1	1
Loan Characteristics & Outcomes						
Property Value (1000 USD)	18471705	366	318	120	279	680
Loan Amount (1000 USD)	18807654	284	209	89	235	515
Loan-to-Value Ratio	18471705	84	20	60	90	100
Loan Term (Months)	18705647	340	61	276	360	360
Interest Rate	16694380	3.9	1.1	2.8	3.8	5.1
Conforming Loan	18807653	0.93	0.25	1	1	1
Loan Approved	18807654	0.9	0.31	0	1	1
Loan Originated	18807654	0.87	0.34	0	1	1
Loan Sold	18807654	0.69	0.46	0	1	1
Loan Securitized	18807654	0.4	0.49	0	0	1
Flood Risk						
100-yr Flood Zone	18187332	0.047	0.21	0	0	0
Un-mapped	18187332	0.16	0.36	0	0	1
Possibly Un-mapped	18187332	0.43	0.49	0	0	1

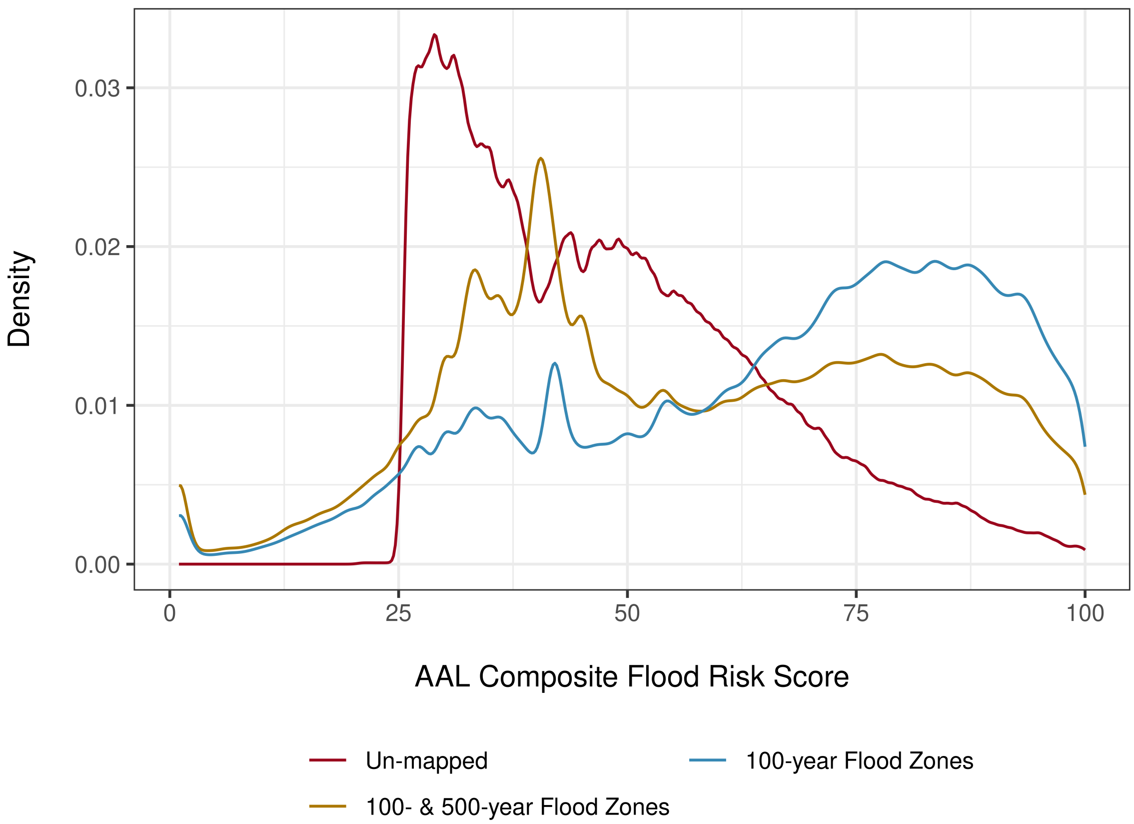
Note: Descriptive statistics for our primary variables of interest and controls appear in the table above. This sample keeps only mortgage applications that were either approved or denied (excluding applications that were withdrawn), but includes non-conforming (jumbo) loans and loans that lie outside of 100-year and 500-year FEMA flood zones. Applicant age, income, property value, loan amount, combined LTV, and interest rate all contain values we consider to be implausibly small and implausibly large. These variables as displayed in this table and used throughout the analysis are winsorized between the first and ninety-ninth percentiles. Our dummy for loan securitizations includes only those loans that were sold to one of the public securitization agencies within the same calendar year.

Table A.8: *Summary Statistics for Listings & HMDA Tract-Quarter Panel*

Variable	Obs	Mean	SD	10%	Median	90%
Pricing & Value						
Mean Closing Price	791113	373	308	115	284	723
Median Closing Price	791113	358	313	107	270	695
Mean Property Value	790681	394	319	134	296	764
Median Property Value	790681	374	320	125	276	718
Flood Risk						
Mean AAL $\times 100$	786197	0.11	0.13	0.0054	0.085	0.22
Mean AAL Risk Score	786197	29	25	3.1	22	69
% in 100-year FZ	784367	0.052	0.18	0	0	0.11
% in 500-year FZ	784367	0.056	0.19	0	0	0.11
% Un-mapped	784367	0.16	0.21	0	0.1	0.43
% Possibly Un-mapped	784367	0.44	0.32	0	0.38	1
Local Characteristics						
% in Foreclosure	791113	0.0071	0.052	0	0	0
Tract Median Family Income	791100	72757	34787	36500	65455	117500
Tract % Minority	791108	37	29	5.4	28	87
Tract Population	791108	4547	2097	2279	4258	7044
MSA Median Family Income	791108	69895	15178	52733	67322	92317
CL Obs. in Tract-Quarter	791113	16	17	2	12	33
HMDA Obs. in Tract-Quarter	791113	16	18	3	11	31
Tract Dummies						
Coast Within 1 mi	791113	0.045	0.21	0	0	0
Coast Within 5 mi	791113	0.085	0.28	0	0	0
Coast Within 10 mi	791113	0.13	0.34	0	0	1
100yr FZ Dummy	784367	0.038	0.19	0	0	0
Un-mapped Dummy	784367	0.061	0.24	0	0	0
Possibly Un-mapped Dummy	784367	0.34	0.47	0	0	1

Note: The table displays summary statistics for our census tract-quarter panel of housing market and lending outcomes. We restrict the sample of real estate listings in the CoreLogic MLS data to just residential properties that were sold and not rented. Similarly, we restrict the HMDA data to just those mortgages for residential properties that were successfully originated. For both closing prices and property values, we observed implausibly small and large values, so we winsorized these values between the first and ninety-ninth percentiles. Tract-quarter means and medians are taken after winsorization. The panel represents 60,621 2010 census tracts over sixteen quarters (an unbalanced panel).

Figure A.1: *AAL Risk Score Distributions by Risk Zones*



Note: The figure plots the AAL composite flood risk score empirical density distributions for properties classified as un-mapped, inside a 100- or 500-year flood zone, and inside a 100-year flood zone. All densities are conditional on the property having non-zero composite flood risk (AAL $\neq$ 0). The AAL composite flood risk score describes the quantile of the AAL composite flood risk distribution of a given property such that higher AAL risk scores correspond with higher AALs and vice versa. The quantiles described by the risk scores are not simply the percentiles of the AAL distribution (i.e., a risk score of 25 corresponds to the 50th percentile of the AAL distribution for properties with non-zero risk, not the 25th percentile). The exact mapping between AALs and risk scores is proprietary.

Table A.9: ***Loan Securitization***

Dependent Variable:	Loan Securitized			
Model:	(1)	(2)	(3)	(4)
Variables				
Very Low Coverage	0.0061***	0.0087***	0.0026***	0.0023***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Low Coverage	-0.0029***	-0.0069***	0.0004	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Interest Rate	-0.0605***	-0.0565***	-0.0587***	-0.0223***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log Loan Amount		0.0944***	0.1020***	0.0721***
		(0.0003)	(0.0003)	(0.0002)
Loan Sample	Conforming	Conforming	Conforming	Conforming
In Flood Zone	No	No	No	No
Fixed-effects				
Quarter-Year	Yes	Yes		Yes
County-Quarter-Year			Yes	
Tract				Yes
Lender				Yes
Fit statistics				
Observations	11,922,096	11,922,081	11,922,081	11,922,081
R^2	0.03101	0.04429	0.07488	0.43779
Within R^2	0.01397	0.02748	0.02681	0.01357

Note: We estimate equation 1, above. The outcome variable is binary and indicates when a loan is sold to a public securitization agency. Our variables of interest are binary and denote whether a property is un-mapped or possibly un-mapped. Each specification contains controls for an applicant's sex, ethnicity, race, credit score, and income. We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by census tract and year-quarter and shown in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.10: *Transaction Flows*

Dependent Variables:	Publicly Securitized	Privately Securitized	Sold to Bank	Sold to Financial Company	Sold to Life Insurance Company	Sold to Affiliate	Sold to Other Company
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Un-mapped	0.0019***	-0.0002**	-2.96×10^{-5}	-0.0008**	1.82×10^{-5}	0.0005***	-0.0014***
	(0.0004)	(8.73×10^{-5})	(0.0003)	(0.0003)	(7.06×10^{-5})	(0.0001)	(0.0003)
Possibly Un-mapped	0.0005	-3.62×10^{-6}	-0.0004*	0.0005**	-9.43×10^{-5}*	-0.0002**	-0.0003
	(0.0003)	(6.56×10^{-5})	(0.0002)	(0.0003)	(5.63×10^{-5})	(9.06×10^{-5})	(0.0002)
Interest Rate	0.0072***	0.0103***	-0.0019***	-0.0038***	-3.29×10^{-5}	0.0009***	-0.0126***
	(0.0002)	(9.92×10^{-5})	(0.0002)	(0.0002)	(4.38×10^{-5})	(7.1×10^{-5})	(0.0002)
Log Loan Amount	0.0616***	-0.0036***	0.0081***	0.0358***	0.0009***	0.0016***	-0.1044***
	(0.0003)	(5.99×10^{-5})	(0.0002)	(0.0002)	(4.61×10^{-5})	(6.27×10^{-5})	(0.0003)
Loan Sample	Conforming	Conforming	Conforming	Conforming	Conforming	Conforming	Conforming
In Flood Zone	No	No	No	No	No	No	No
Dependent Variable Mean	0.5949	0.0091	0.1183	0.1763	0.0061	0.0135	0.0819
Fixed-effects							
Action Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender RSSD	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	9,937,282	9,937,282	9,937,282	9,937,282	9,937,282	9,937,282	9,937,282
R^2	0.54383	0.33986	0.29735	0.37682	0.32131	0.51104	0.36476
Within R^2	0.01549	0.00555	0.00596	0.01019	0.00011	0.00046	0.06730

Note: We consider seven mutually exclusive outcomes that appear at the top of the columns of the table. Variables of interest are also binary and denote whether a property is un-mapped or possibly un-mapped. Low income tract and high income tract are dummy variables that denote . We add additional controls and fixed effects in columns (2)–(4). We restrict our sample to conforming loans and exclude all properties that are covered by a flood zone map. Standard errors are clustered by tract and the year-quarter or origination; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.