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Flood Risk Exposures and Mortgage-Backed Security Asset Performance and Risk Sharing[*]

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Abstract

The distribution of risks for residential real estate, including flood risk, depends largely on how these risks are allocated across individual mortgages and within mortgage-backed securities (MBS). This paper is the first to document how flood risks relate not only to individual mortgage performance and underwriting, but also how flood risks correlate to MBS performance and structure. Across residential mortgages we find that defaults are concentrated among the most flood-prone properties and this risk is somewhat offset by larger down payments and slightly higher mortgage rates. Even when mortgages are combined into MBS's, we show that average mortgage default within MBS's increases with average flood risk and that higher flood risk is primarily offset by increased credit protection or subordination; a one unit increase in flood risk is associated with a 2.6 percent increase in subordination. Ultimately, our analysis suggests that flood risk is reflected in mortgage-level performance and pricing and is partially, but not fully, accounted for in MBS deal-level performance and structure.

Keywords: Climate Risk, Flooding, Mortgage-Backed Securities, Structured Finance, Bond Markets
JEL Classification Codes: Q54, R3, D89, G12

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1 Introduction

The U.S. mortgage-backed securities (MBS) market is large – $9.4T in MBS securities were outstanding as of September 2023 – and critical to a well functioning domestic housing market. Thus, understanding how these markets respond to new information or embody old information is important for market participants (e.g., home owners, banks, investors, and governments) and the broader functioning of mortgage markets (Goodman et al., 2023). Credit rating agencies and investors account for many mortgage characteristics, such as credit scores, loan-to-value ratios, and interest rates when rating and pricing mortgage-backed securities. However, it is unclear whether or how agencies and investors account for salient climate-related risks, especially flooding – one of the most costly climate-linked natural disasters (Siegel, 2003; NOAA, 2023). Given the opacity of MBS markets, adequately accounting for climate risks is creating challenges for investors and government agencies alike (Craig, 2022; Carlson & Huang, 2021).[1] Although information regarding the potential risks of a changing climate are not new (Smith & Tirpak, 1989; USGCRP, 2018), the way financial markets and investors assess those risks may have changed. Given the evolving landscape of climate awareness and risk perceptions, this paper aims to document how MBS products have historically captured risks like flooding.

In this paper, we document patterns in MBS deal-level flood risk, deal-level performance, and structure, for private-label subprime and Alt-A MBS issuances from 1992 to 2009. In order to do this, we first investigate the relationship between flood risk and default probabilities as well as mortgage underwriting terms, for individual residential mortgages. We find that mortgages in areas with high flood risk are up to 1.8 percentage points more likely to default than similar mortgages in areas with low flood risk. This increased default risk is somewhat offset by slightly higher spreads and significantly higher down payments. Importantly, we also find that higher average MBS deal-level flood risk is associated with greater deal-level default and greater credit protection (subordination), especially for more highly-rated tranches (specifically, AAA tranches) – a one unit increase in measured flood risk is associated with an 1.6 percentage point increase in the share of mortgage defaults and 2.6 percentage point increase in credit protection for AAA tranches. As a result, increased credit protection helps offset some of the increased risk stemming from greater flood exposure. While our quantitative results provide important measures of how flood risk impacts private-label mortgages and MBSs, our qualitative results also provide important insights on how flood risks may impact other MBS and security markets more broadly. Most notably, this paper

[1]Our analysis focuses on residential mortgages and residential mortgage backed securities (RMBS). For the remainder of the text, we refer to these securities as mortgage-backed securities or MBS.

shows that lenders, investors, and other market participants have at least partially adjusted the terms of mortgages and MBS deals in ways that provide increased protection against the higher default risk posed by flooding.

Our paper provides a series of contributions to the discussion of how mortgage and MBS securities embody flood risks. First, we provide evidence that MBS security performance and structure reflect the natural disaster risk of the underlying mortgages.[2] Our work is consistent with recent research showing that sophisticated market players (i.e., banks) are behaving strategically in response to growing climate risk by securitizing a greater share of mortgages that are exposed to natural disasters (Ouazad & Kahn, 2021). Furthermore, our findings are consistent with Gete, Tsouderou, and Wachter (2023), who show that private investors adjust the pricing of credit risk transfers in response to hurricane risk. Overall, we provide evidence that investors are adjusting for natural disaster risks even before disaster strikes. Our work is one of the few papers (currently) to examine the impacts of climate risks on MBS products and the first (to our knowledge) to establish a historical pattern of MBSs adjusting to flood risk.[3]

Second, our paper estimates how flood risks interact with mortgage performance and consequently affect mortgage terms, especially down payments. We show that while mortgage rates only slightly adjust to increased flood risk, down payments significantly increase by up to 1.7 percentage points in the riskiest areas. Our results are consistent with previous research examining how mortgage performance and mortgage terms differ based on underlying climate risk (Sastry, 2022; Gete et al., 2023; Issler et al., 2021; Biswas et al., 2023; Gallagher & Hartley, 2017). Additionally, our mortgage default results highlight the important nonlinear relationships between risk exposures and asset performance (i.e., default risk is driven by the most flood-prone properties), contributing to a growing body of evidence on the importance of tail risks for climate-linked natural hazards (Quiggin, 2018; Y. Zhou et al., 2023).

Lastly, our paper makes a methodological contribution by linking local flood risk at the mortgage level to overall security-level risk for MBS's. Working with mortgage-level flood exposures and aggregating up to the MBS security level is a non-trivial undertaking that should be done with care. Due to the highly local nature of flood risk, granular spatial data for individual mortgages is a necessary precondition for assessing risk at the asset level and then aggregating that risk to the security level. With better spatial data at the mortgage

[2] See F. Zhou, Endendijk, and Botzen (2023) for a review.

[3] Kahn, Ouazad, and Yönder (2024) show how wildfire risk affects the entire securitization chain from mortgage-level to deal-level cash flows. However, they show that investors should be exposed to wildfire risk because it allows for important diversification and hedging against other risks.

level, our methods and risk analysis could be applied to the broader universe of MBS products (e.g., agency MBS).

Ultimately our work contributes to the broader conversation about how flood risk affects real estate markets and the growing body of research showing that flood risk has had a negative effect on real estate markets and house prices (Mcalpine & Porter, 2018; Bernstein et al., 2019). Furthermore, there is growing evidence that flooding risk has grown not only for low-lying coastal markets but is more geographically pervasive and affects in-land communities across the United States (Rodziewicz et al., 2022; Gourevitch et al., 2023). As climate-related risks mount, lenders are starting to price coastal inundation risk into mortgages (Nguyen et al., 2022) and lenders may be transferring more at-risk mortgages to Government Sponsored Enterprises (GSEs) such as Fannie Mae and Freddie Mac following natural disaster events (Ouazad & Kahn, 2021). We establish that lenders and investors have been adjusting loan terms and deal structures in ways that offset underlying flood risk going back to the early 2000s.[4] Our results suggest that adjusting to new data on climate risk is a matter of updating risk assessments and not necessarily one of suddenly and sharply reacting to unaccounted-for risk, which is an important insight for underwriters, investors, and financial regulators.

The rest of our paper is organized as follows: Section 2 provides an overview of MBS products, the securitization process, and important institutional details. Section 3 provides and overview of the data used and how we link flooding risk to properties. Section 4 describes the empirical model and results of our mortgage-level analysis and Section 5 describes the empirical model and results of our deal-level analysis. Finally, Sections 6 and 7 discuss our results and conclude.

2 Background

Mortgage-backed securities (MBS) are mortgage bonds with cash flows originating from the principal and interest payments of the underlying mortgages making up those securities. These MBS securities function as diversified portfolios of mortgages and MBSs embody the underlying risk characteristics of the loans they comprise of (e.g., average FICO scores, geographic concentration, borrower characteristics, and natural hazard risk). As a result,

[4]While subprime and Alt-A MBS are only about 3 percent of the current mortgage market, they made up over 50 percent of the mortgage market prior to the Global Financial Crisis and the underlying data has higher geographic resolution than is available in other MBS data (Rappaport, 2020).

the characteristics of return and risk at the mortgage level flow through to the performance, pricing, and ultimate structure of an MBS (Ashcraft et al., 2010).

MBS are an integral part of domestic mortgage markets and provide a series of functions, including portfolio diversification, market liquidity, and improved credit availability for mortgage lending. Roughly 65 percent of home mortgage debt within the United States is packaged into residential mortgage backed securities (RMBS), making MBS markets an important part of domestic mortgage markets (Fuster et al., 2022). RMBS markets are broadly broken into two categories: agency and nonagency. Agency MBS have an implied government guarantee; are issued by a government-sponsored enterprise (GSE) such as Fannie Mae, Freddie Mac, and the Federal Home Loan Bank; and comprise lower risk "conforming" mortgage loans. Nonagency, or private-label MBS – the focus of this paper – are issued by private institutions, do not carry a government guarantee and comprise higher risk (e.g., subprime or Alt-A) or non-conforming (e.g., jumbo) mortgage loans. As of August 2023, Agency MBS make up over 65 percent of RMBS markets, with nonagency MBS making up 3 percent (roughly split equally between sub-prime, Alt-A, and jumbo loans) (Goodman et al., 2023). While nonagency MBS are a smaller part of the current mortgage market, they made up over half of mortgage securitizations in the years leading up to the Great Recession (Goodman et al., 2023; Rappaport, 2020).

An RMBS may be made up of several varieties of underlying mortgages with differing borrower and risk characteristics. The common varieties of residential mortgages include prime, Alt-A, subprime, and jumbo loans. Prime mortgages are issued to lower-risk borrowers with higher credit scores who generally have higher income and lower debt-to-income ratios. Subprime mortgages are issued to higher-risk borrowers who have lower credit scores, lower incomes, and/or higher debt-to-income ratios. Alt-A mortgages fall somewhere between prime and subprime. These loans generally have less documentation and may be easier to obtain for borrowers, but can carry high interest rates. Lastly, jumbo loans are large loans issued for higher value properties (e.g., luxury homes). Due to the large loan size, these loans cannot be securitized by the GSEs. Because mortgages can have a wide range of characteristics, when mortgages are packaged into securities, they are typically bundled with like-kind mortgages, creating MBS deals that comprise the same type of mortgages (e.g., Subprime or Alt-A securities).

In order to understand how flood risk at the individual mortgage level flows through to MBS deal-level risk, it is important to understand how these securities are created. The process of packaging or securitizing mortgages begins with a lender (e.g., bank or mortgage lender) originating a loan and terminates in a sale of MBS to investors (e.g., pensions, insurance companies, banks, or individual investors), with four notable participants in the process (Figure 1 provides an overview).

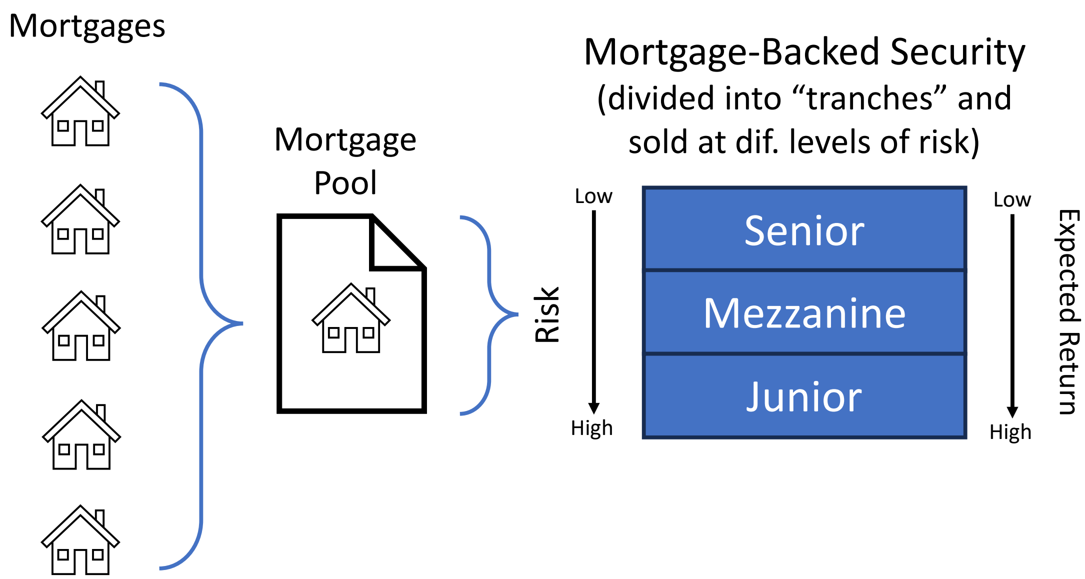
First, *lenders* originate mortgages for the purchase or refinance of properties. Second, an *issuer* (i.e., sponsor or originator) collects mortgages into large groups called "pools." Third, an *underwriter* (or lead bank) arranges one or more mortgage pools and securitizes them into MBS "deals" for sale to investors, usually via over-the-counter transactions. In the case of agency MBS, the underwriters are one of the GSEs. Underwriters structure the MBS deal into "tranches" (or slices) with varying degrees of risk and return, with prevailing market conditions and investor demand both contributing to how those tranches are structured and priced.[5] Deal tranches range from the least risky "senior" tranches, which have the greatest credit protection or "subordination", to higher risk "junior" tranches, which have little or no credit protection, with "mezzanine" tranches falling somewhere in between. Fourth, *rating agencies* work closely with underwriters to design the tranche structure of a deal and determine the credit protection level (i.e., the percent of an MBS deal that falls below a more senior tranche) for each tranche. This subordination of junior tranches to senior tranches protects more senior tranches from credit loss and reduces overall risk to the senior tranches (An et al., 2015). In addition to helping determine the final MBS deal structure, credit rating agencies provide a rating for each tranche (e.g., AAA, AA, A, BBB...etc) making tranche risk and returns profiles comparable across debt markets—and, in turn, making the securities more marketable to investors (Ashcraft et al., 2010; Cetorelli & Peristiani, 2012).

3 Data

To document the relationship between flood risk, mortgage performance, mortgage terms, and pricing, as well as MBS performance and structure, we need mortgage data, MBS deal-level data, local flood risk information, and local economic data. In this section, we outline the series of datasets we use to establish those relationships. Our sample includes 16.6 million individual mortgages and 3,499 MBS deals for non-agency subprime and Alt-A MBS markets from 1992 to 2009.

[5]Each tranche within an MBS deal is assigned a Committee on Uniform Securities Identification Procedures (CUSIP) number. Once an MBS deal is securitized and broken into tranches, there is no direct relationship between a tranche and the underlying mortgages. The MBS deal (as a whole) assumes the average characteristics of the underlying mortgages, but there is no way to attribute individual mortgages to a given tranche. This is an important feature of securitizations for our MBS deal-level analysis.

Figure 1: MBS Deal Securitization Process and Structure



3.1 Mortgage and MBS Data

We obtain mortgage-level data from CoreLogic Solutions Private Label Securities-ABS (Subprime and Alt-A). This data set covers about 90 percent of the subprime and Alt-A market and contains information on the individual mortgages that make up each MBS as well as the MBS' performance over time. We focus on a range of origination variables, including origination date, interest rate, loan-to-value ratio (LTV), debt-to-income ratio (DTI), level of documentation, FICO scores, default status, balloon payment indicator, prepayment penalty indicator, interest-only indicator, share of a mortgage that is privately insured, type of mortgage interest rate (fixed or adjustable), length of fixed period, lien position, and property location (state and zip code). To assess mortgage performance, we add information on whether a mortgage became 90 or more days past due, was foreclosed, became real estate owned (REO), or was paid off at a loss within 12 months of origination (i.e., mortgage default).

To combine mortgage-level data with other property-level measures such as flood risk, we restrict our sample to 15- or 30-year fixed rate mortgages or two-, three-, or five-year adjustable rate mortgages on properties within the 50 states, DC, and Puerto Rico. We drop any mortgages with negative amortization, prime categorization, invalid zip codes, invalid origination dates, LTV > 100 percent or negative LTV, or interest rates > 20 percent or exactly 0 percent. Overall, we drop about 28 percent of the sample, mostly driven by our restriction to common types of mortgages. See Table A.1 for details of how this affects our sample.

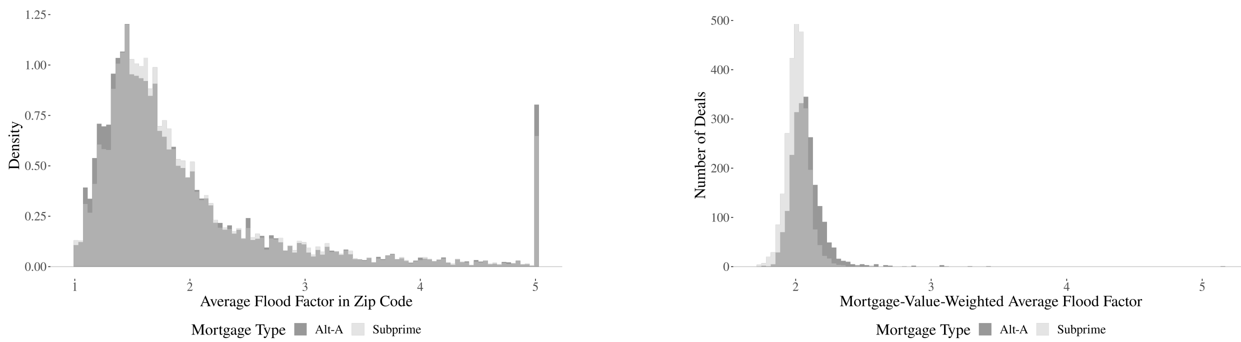
Mortgages in our sample are aggregated into MBS "deals." These deals are broken into tranches (portions of a deal) with corresponding Committee on Uniform Securities Identification Procedures (CUSIP) numbers and then sold to investors. Using a deal-CUSIP crosswalk provided by CoreLogic Solutions, we match each deal with its constituent CUSIPs. We then match each CUSIP with MBS data provided by Intex Solutions, a leading provider of information on a variety of structured finance products, including collateralized loan obligations (CLO). Intex Solutions data are sourced directly from trustees, third-party financial institutions responsible for enforcing the indenture that governs the structure. The data are used widely by market participants and include information on coupon rates, credit ratings, tranche seniority, and interest type (e.g. fixed or floating).

3.2 Flood Risk and Other Economic Data

We use zip-code level flood risk from the First Street Foundation, which we then match to each mortgage in our sample. First Street's Flood Factor Risk score is a relative measure of flood risk ranging from 1-10 and accounts for both the probability of a flood (within a 30 year period) and severity of flood (depth). This measure of flood risk reflects the flood risk of a property from all flooding sources (including heavy rainfall, which is excluded from FEMA's flood maps) A low Flood Factor score (e.g., 1 or 2) implies a property is relatively safe from flood (less than a 0.4 percent of flooding in a given year) whereas a high Flood Factor score (e.g., 9 or 10) implies some combination of a high probability for flooding (20 percent or more) or much more severe flooding (extreme flood depths) in a manner we cannot separate (First Street Foundation, 2023). See Appendix A.2 for an additional description of First Street Foundation's Flood Factor risk scores. We then aggregate individual mortgage exposures up to the MBS deal.

Figure 2a shows that the vast majority of mortgages are in zip codes with low Flood Factor Risk scores, with a tail of mortgages in zip codes with high flood risk scores. However, MBS products could have very different underlying flood risks depending on how mortgages are securitized and allocated across zip codes. Figure 2b illustrates noticeable variation in flood risk across securities and shows that Alt-A securities have higher flood risk compared with subprime securities. However, the distribution of flood risk is more symmetric and normally distributed at the deal level than at the individual mortgage level, suggesting securitizers package MBS deals to diversify risk. For context, moving from an average Flood Factor exposure of 1 to 5 would move a property's risk from low flood risk (low probability and severity) to major flood risk (much higher probability and or severity). Moving from a risk score of 1 to 2 would imply a relatively small change in risk profile for an individual property but could still be a meaningful change in risk for an diversified MBS deal comprised of thousands of individual mortgages.

Figure 2: Distribution of Flood Risk



(a) Mortgage-Level (b) MBS Deal-Level

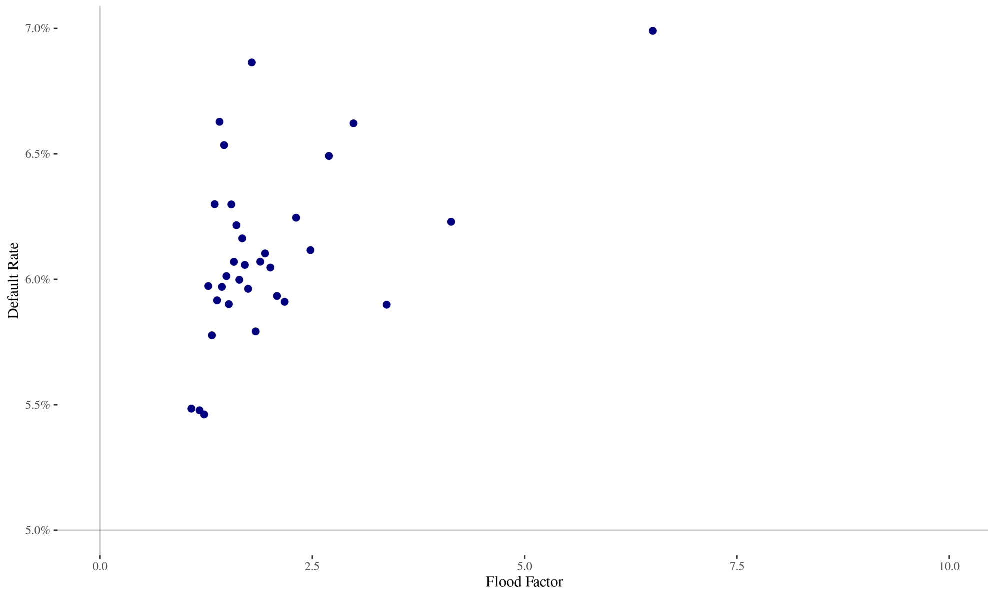
Note: This figure shows the distribution of flood risk for each mortgage (left panel) and deal (right panel) in our sample. The flood risk of a mortgage is equal to the average flood risk of the zip code where the property is located. The flood risk of a deal is equal to the weighted average flood risk of the mortgages that make up the deal (weights are equal to the origination value of the mortgage). Mortgage-level flood risk is topcoded at 5 (out of 10). Source: Author calculations based on data from CoreLogic Solutions and First Street Foundation.

After combining data on flood risk and mortgage default, we can see a strong, positive correlation in the raw data. To help visualize the positive correlation between flood risk and mortgage default, we use a binscatter and show the results in Figure 3 (Cattaneo, Crump, Farrell, & Feng, 2024). The figure shows that default is strongly increasing even at low levels of flood risk. This relationship will be more rigorously analyzed in Section 4.

In addition to flooding data, we include local economic data in order to account for series of additional factors that may contribute to mortgage and MBS performance that are not accounted for in borrower or MBS deal characteristics. Specifically, we use county-level monthly unemployment rates from the Bureau of Labor Statistics to capture local economic health. We also include information on median home values (census tract), 12-month housing price growth (county), household income (census tract), and racial composition (census tract), which capture other factors that may affect mortgage and MBS deal performance or pricing.[6]

[6]To match zip codes with census tracts, we use the zip-tract crosswalk developed by the Department of Housing and Urban Development, available at https://www.huduser.gov/portal/datasets/

Figure 3: Binscatter of Mortgage Defaults and Flood Risk



Note: This figure shows the correlational relationship between mortgage defaults and underlying flood risk. Source: Author calculations based on data from CoreLogic Solutions and First Street Foundation.

Average MBS deal-level characteristics (e.g., LTV, FICO, and flood risk) are calculated as taking the weighted of the mortgages that make up the deal (weights are equal to the origination value of the mortgage). This method of aggregating mortgage risk and return characteristics to the deal level is consistent with Ashcraft et al. (2010).

Furthermore, we include state information for our mortgage analysis and geographic concentration (by state) for our MBS deal-level analysis to control for other unobserved factors that may be associated with location. Geographic concentration at the MBS deal level is measured by the Herfindal-Hirschman index by state. This is computed as the sum of the squared share of a deal's value in each state.

Lastly, we use the average mortgage rates and Treasury rates to calculate loan spreads. To calculate mortgage spreads, we use the Federal Home Loan Mortgage Corporation (FHLMC) 15-year and 30-year mortgage rates, as well as the 5/1 ARM rates from FHLMC and the Mortgage Bankers Association. To calculate MBS deal-level spreads, we use the 10-year Treasury rate.

`usps_crosswalk.html`. Home price growth is calculated using the housing price index (HPI) from CoreLogic. We calculate the 12-month percent change and merge the index in at the county level

4 Mortgage-Level Analysis: Flood Risk, Mortgage Default, and Mortgage Terms

Before examining the relationships between flood risk and MBS deal-level performance, we must first establish that there is a strong relationship between flood risk and individual mortgage performance that could pose risks to MBS deals. We then examine whether banks adjust their lending terms to offset some of these higher risks. At the mortgage level, we investigate the relationship between flood risk and mortgage default (or mortgage interest rates) using the following regression:

$$Y_{ist} = \beta_0 + \beta_1 \text{Flood}_i + \beta X_i + \lambda_t + \lambda_s + \epsilon_{ist} \tag{1}$$

where Y_{ist} is a series of dependent variables associated with mortgage i issued in state s in time t. Our three dependent variables are: (1) an indicator of whether a mortgage defaults within 12 months of origination, (2) the interest rate spread of the mortgage, and (3) the loan-to-value ratio (LTV) of the mortgage at origination. For our analysis of mortgage default, we define default as a mortgage that is 90 or more days past due, in foreclosure, real estate owned (REO), or paid off at a loss within 12 months of origination. This regression uses a linear probability model to predict defaults.[7] For our analysis of interest rate spreads, we calculate a mortgage-specific spread matched to the type of mortgage (e.g. 30-year mortgages, 15-year mortgages, or adjustable rate mortgages).[8]

Flood_i denotes the flood risk of mortgage i as measured by the average flood risk score from First Street. To allow for potentially non-linear effects of flood risk, we discretize the flood risk measure in bins ranging from low to high levels of flood risk. X_i is a vector of mortgage-specific controls, which includes LTV, FICO score at origination, a balloon

[7]Some readers may prefer nonlinear models such as logit or probit. When estimating a logit model, the average marginal effects are similar to the results of the linear probability model (0.0195 and 0.0139 for the 6-8 and 8-10 risk buckets, respectively) but we prefer the linear model because coefficients are easier to interpret and compare (Breen et al., 2018). Furthermore, while there may be concern about estimation errors in linear probability models, our results are very similar (and some results are stronger) even after re-estimating the model on a trimmed sample that drops observations initially predicted to be outside of the unit interval (Horrace & Oaxaca, 2006). See Table A.5.

[8]The rates used to calculate mortgages spreads are: 30-year mortgages (average FHLMC 30-year mortgage rate), 15-year mortgages (average FHLMC 15-year mortgage rate), and adjustable rate mortgages (average 5/1 year ARM from FHLMC and Mortgage Bankers Association). Due to data availability and 5/1 ARM data only extending back to 2005, we lose roughly 6.1 M observations (30 percent of the sample) matching mortgage types to mortgage-specific base rates. We conduct an additional robustness check by calculating mortgage spreads on the FHLMC 30-year fixed mortgage rate (See Table A.7)

payment indicator, documentation dummies, an investment property dummy, debt-to-income (DTI) ratio, a cash-out indicator, log origination amount, prepayment penalty flag, county unemployment rate, interest rate at origination, interest type (fixed or floating), mortgage type (i.e., Alt-A or subprime), mortgage duration, and lien type. Also included in this vector are census tract-level variables such as log median household income, log median home value, 12-month change in housing prices, and minority share of households in a tract.[9] λ denotes quarterly fixed effects and state fixed effects. Time fixed effects control for factors that may influence the entire mortgage market over time (e.g., financial conditions, interest rates, housing demand, or investor preferences).

4.1 Flood Risk and Mortgage Default Results

Table 1 reports the regression results from estimating Equation 1. We find that flood risk is positively associated with mortgage default for only the highest flood risk properties (those with a score of six or higher).[10] This finding holds even after controlling for a range of borrower characteristics, loan characteristics, local economic and demographic factors, and fixed effects (e.g., time, location, and mortgage terms).

Our results show that higher flood risk is correlated with higher probabilities of mortgage level default (90+ days past due) within 12 months of origination. Specifications 2 and 3 add in time and state fixed effects. In each specification, the flood risk exposure coefficient has a positive sign, is statistically significant, and has a consistent magnitude across specifications.[11] Compared with mortgages with the lowest flood risk, properties in areas with a flood score of six or higher have a 1.2 to 1.8 percentage point higher default rate. Given the average default rate of 5.9 percent, these effects correspond to a 21 to 30 percent increase in the default rate even after controlling for a rich set of mortgage, economic, and neighborhood-level variables. Furthermore, these results are robust (and stronger) when examining 24- or 36-month default windows or alternate definitions of mortgage spreads (See Appendix Tables A.4 and A.6). Overall, these results indicate that flood risk is positively associated with higher mortgage defaults and that this effect is driven almost entirely by properties with the highest flood

[9] When LTV is the dependent variable, we change the right-hand side variables to have interest rate spread instead of LTV.

[10] For high flood risk properties, some homeowners may be required to hold flood insurance. In this case, we would expect insurance to have a protective effect against default. As a result, our estimates will include that potentially protective effect of insurance, meaning our estimates are a conservative lower bound on the strength of the relationship between flood risk and mortgage default.

[11] Adding in state fixed effects slightly decreases the flood risk coefficients, but this is to be expected because flood risk is tied to geography (e.g., Florida has higher flood risk than Iowa).

Table 1: Flood Risk and Mortgage Default (with Mortgage-Specific Spread)

Dependent Variable:	Mortgage Default		
Model:	(1)	(2)	(3)
Variables			
Flood Risk (2, 4]	0.0001	-0.0004	0.0009
	(0.0019)	(0.0019)	(0.0010)
Flood Risk (4, 6]	0.0041	0.0030	0.0016
	(0.0029)	(0.0030)	(0.0013)
Flood Risk (6, 8]	0.0240***	0.0233***	0.0176***
	(0.0069)	(0.0075)	(0.0064)
Flood Risk (8, 10]	0.0175***	0.0173***	0.0122***
	(0.0028)	(0.0028)	(0.0024)
LTV	-0.0086***	0.0022	0.0036
	(0.0026)	(0.0044)	(0.0047)
FICO	-0.0003***	-0.0003***	-0.0003***
	(1.06×10^{-5})	(1.14×10^{-5})	(1.13×10^{-5})
DTI	0.0574***	0.0532***	0.0534***
	(0.0042)	(0.0041)	(0.0039)
Log Orig. Amt	0.0372***	0.0305***	0.0298***
	(0.0032)	(0.0023)	(0.0025)
Spread at Origination	0.0195***	0.0200***	0.0201***
	(0.0009)	(0.0010)	(0.0010)
Fixed-effects			
Time FEs		Yes	Yes
State FEs			Yes
Dummies for missing values	Yes	Yes	Yes
Other Loan Controls	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes
Fit statistics			
Observations	10,692,150	10,692,150	10,692,150
R^2	0.06250	0.06643	0.06763
Within R^2		0.04693	0.04533
Dep. Var. Mean	0.0592	0.0592	0.0592

Clustered (State FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of estimating a linear probability model of mortgage default (within 12 months of origination) on flood risk scores, loan characteristics (LTV, credit score, DTI, origination amount, and mortgage spread), other loan characteristics (interest only flag, balloon payment flag, documentation level, investor flag, cashout flag, prepayment penalty flag, and dummies for missing values of these variables), local economic conditions (county unemployment, home price changes, median home values, median income, minority shares), quarterly fixed effects, and state fixed effects. Default is defined as a mortgage that is 90 or more days past due, in foreclosure, real estate owned (REO), or paid off at a loss. Flood risk is from the First Street Foundation and is the average Flood Factor risk for the zip code in which the property is located.

exposures. The direction and magnitude of these mortgage default results are consistent with our findings in MBS deals, which we address in section 5.1.

4.2 Flood Risk and Mortgage Pricing Results

Table 2 reports the regression results from estimating Equation 1. We find that across all specifications, average flood risk is positively associated with mortgage spreads at origination, but this coefficient is only significant for mortgages at high risk of flooding. These results are consistent with our finding in section 4.1 and hold even after controlling for borrower characteristics, loan characteristics, local economic and demographic factors, and fixed effects (e.g., time, location, and mortgage terms).

Our results show that greater flood risk is associated with higher loan pricing spreads at origination. Compared with the lowest flood risk properties, mortgages in areas with a flood factor score of six or higher have mortgage spreads that are 4 to 13 basis points higher. While these results are statistically significant, they are not economically meaningful given that moving from the lowest to highest risk areas imply the interest rate increases by 13 basis points and the smallest notch increase for mortgages is typically one-eighth of a percentage point (12.5 basis points). While flood risk is associated with higher default rates, this greater risk doesn't appear to be fully captured by these small increases in mortgage rates.

4.3 Flood Risk and Mortgage LTV Ratio Results

Table 3 reports the regression results from estimating Equation 1. We find that across all specifications, average flood risk is negatively associated LTVs at origination, and this effect is stronger as flood risk becomes more severe. Put differently, these results suggest that banks are requiring higher down payments, or greater credit protection against losses, at origination for mortgages on homes in riskier areas. These results are consistent with our finding in section 4.1 and suggest that banks are even getting credit protect at lower levels of flood risk with mortgages in areas scoring 6 or less having down payments that are 28 to 74 basis points higher than mortgages in the lowest risk areas. Mortgages in the highest risk areas have down payments that are 80 to 165 basis points higher. This pattern holds true and, in some cases, becomes stronger, after controlling for borrower characteristics, loan characteristics, local economic and demographic factors, and fixed effects (e.g., time, location, and mortgage terms). These findings are consistent with Sastry (2022), which uses a different dataset of mortgages on single-family homes in Florida from 2010-2016, and finds that mortgages in flood-prone areas have LTVs that are about 83 basis points lower.

Table 2: Flood Risk and Mortgage Spread at Origination

Dependent Variable:	Spread at Origination		
Model:	(1)	(2)	(3)
Variables			
Flood Risk (2, 4]	0.0279*	0.0265*	0.0148**
	(0.0156)	(0.0152)	(0.0069)
Flood Risk (4, 6]	0.0012	-0.0057	0.0065
	(0.0219)	(0.0259)	(0.0130)
Flood Risk (6, 8]	0.1094***	0.1222***	0.0435**
	(0.0341)	(0.0324)	(0.0166)
Flood Risk (8, 10]	0.1861***	0.1959***	0.1292***
	(0.0425)	(0.0399)	(0.0238)
LTV	2.108***	2.018***	1.968***
	(0.0505)	(0.0558)	(0.0651)
FICO	-0.0100***	-0.0097***	-0.0097***
	(0.0003)	(0.0003)	(0.0003)
DTI	0.0689**	0.0590*	0.0710*
	(0.0337)	(0.0329)	(0.0370)
Log Orig. Amt	-0.3963***	-0.3136***	-0.2974***
	(0.0180)	(0.0211)	(0.0282)
Fixed-effects			
Time FEs		Yes	Yes
State FEs			Yes
Dummies for missing values	Yes	Yes	Yes
Other Loan Controls	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes
Fit statistics			
Observations	10,239,981	10,239,981	10,239,981
R^2	0.64932	0.66242	0.66521
Within R^2		0.65105	0.64562
Dep. Var. Mean	2.223	2.223	2.223

Clustered (State FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of regressing mortgage rate spread at origination on flood risk scores, loan characteristics (LTV, credit score, DTI, and origination amount), other loan characteristics (interest only flag, balloon payment flag, documentation level, investor flag, cashout flag, prepayment penalty flag, and dummies for missing values of these variables), local economic conditions (county unemployment, home price changes, median home values, median income, minority shares), quarterly fixed effects, and state fixed effects. Flood risk is from the First Street Foundation and is the average Flood Factor risk for the zip code in which the property is located. We calculate a mortgage-specific spread matched to the type of mortgage (e.g. 30-year mortgages, 15-year mortgages, and adjustable rate mortgages).

Table 3: Flood Risk and Loan-to-Value Ratio at Origination

Dependent Variable:		LTV	
Model:	(1)	(2)	(3)
Variables			
Flood Risk (2, 4]	-0.0026**	-0.0022*	-0.0028***
	(0.0013)	(0.0013)	(0.0008)
Flood Risk (4, 6]	-0.0098***	-0.0093***	-0.0074***
	(0.0017)	(0.0014)	(0.0021)
Flood Risk (6, 8]	-0.0018	-0.0021	-0.0080**
	(0.0040)	(0.0040)	(0.0031)
Flood Risk (8, 10]	-0.0106**	-0.0114***	-0.0165***
	(0.0046)	(0.0042)	(0.0021)
Mort. Spread	0.0208***	0.0204***	0.0198***
	(0.0016)	(0.0011)	(0.0010)
FICO	0.0003***	0.0003***	0.0003***
	(1.7×10^{-5})	(1.87×10^{-5})	(1.94×10^{-5})
DTI	0.0603***	0.0651***	0.0668***
	(0.0042)	(0.0044)	(0.0044)
Log Orig. Amt	0.0672***	0.0747***	0.0777***
	(0.0065)	(0.0092)	(0.0100)
Fixed-effects			
Time FEs		Yes	Yes
State FEs			Yes
Dummies for missing values	Yes	Yes	Yes
Other Loan Controls	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes
Fit statistics			
Observations	10,239,981	10,239,981	10,239,981
R^2	0.44746	0.45602	0.46210
Within R^2		0.44732	0.43914
Dep. Var. Mean	0.8068	0.8068	0.8068

Clustered (State FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of regressing mortgage loan-to-value ratio at origination on flood risk scores, loan characteristics (interest rate spread, credit score, DTI, origination amount, and mortgage spread), other loan characteristics (interest only flag, balloon payment flag, documentation level, investor flag, cashout flag, prepayment penalty flag, and dummies for missing values of these variables), local economic conditions (county unemployment, home price changes, median home values, median income, minority shares), quarterly fixed effects, and state fixed effects. Flood risk is from the First Street Foundation and is the average Flood Factor risk for the zip code in which the property is located. We calculate a mortgage specific spread matched to the type of mortgage (e.g. 30-year mortgages, 15-year mortgages, and adjustable rate mortgages).

5 MBS Deal-Level Analysis: Flood Risk, Deal Default, and Credit Protection

While understanding the how flood affects individual mortgages is important, our purpose with this paper is to investigate how MBS deals respond to flood risk. For our MBS deal-level analysis, we investigate the relationship between MBS deal-level flood risk and deal-level default and credit protection (subordination) using the following regression:

$$Y_{it} = \beta_0 + \beta_1 \text{Flood}_i + \beta X_i + \lambda_t + \epsilon_{it} \tag{2}$$

where Y_{it} denotes a series of dependent variables associated with an MBS deal i in quarter t. Our two dependent variables are: (1) MBS deal default measured as the share of a deal that defaulted within 12 months of origination and (2) Credit risk protection or subordination measured as the share of a deal below a specific rating category (e.g., below AAA or below BBB-).[12]

Flood_i denotes the average flood risk of MBS i.[13] X_i is a vector MBS deal characteristics and aggregated deal-level mortgage controls including: deal type (Subprime or Alt-A), average mortgage interest rate, share of low/no-documentation shares, average FICO score at origination, share of interest-only mortgages, share of non-owner-occupied properties, average 12-month HPI change, average LTV, and weighted average mortgage interest rate, and the weighted average coupon rate for the deal. The last control is a geographic concentration measure using the Herfindahl-Hirschman Index (HHI) for state level share of a deal. λ_t denotes quarterly fixed effects.

[12]In the case of split ratings, we take the median rating and "round down" if necessary. For example, if a tranche is rated AAA and AA+, the median would be AA+.

[13]While our analysis in section 4 broke flood risk into categories (low to high risk), this regression uses average deal-level flood risk because MBS deals are intended to reduce risk by creating diversified portfolios of assets. Rating agencies and underwriters work to offset the risk of individual mortgages through carefully constructing deals that provide extensive diversification. As a result, investors are likely to evaluate MBS deal quality primarily through the average deal characteristics and only secondarily will examine the distribution of risk across hundreds or thousands of constituent mortgages (after all, rating agencies give ratings as a way to allow for simple comparisons of such complex products). As a result, MBS deals have a tighter and more normal distribution across deal characteristics compared to individual mortgages. See Appendix A.8 demonstrating those characteristic of MBS deal-level diversification. Thus, average flood risk is a more appropriate measure for this component of our analysis.

5.1 Flood Risk and MBS Deal Default Results

Table 4 reports the regression results from estimation Equation 2 looking at flood risk and MBS deal-level default. We find that across all specifications, average flood risk is positively associated with greater MBS deal-level default. This holds even after controlling for a range of MBS deal-characteristics and underlying mortgage characteristics.

Table 4: Flood Risk and MBS Default

Dependent Variable:	Defaulted Share of Deal	
Model:	(1)	(2)
Variables		
Avg. Flood Factor	0.0321***	0.0155***
	(0.0073)	(0.0055)
LTV	0.0232	0.0239
	(0.0199)	(0.0210)
FICO	-0.0005***	-0.0005***
	(0.0001)	(0.0001)
Interest Rate	0.0010	0.0025***
	(0.0007)	(0.0007)
Coupon Rate	0.0058***	0.0035***
	(0.0008)	(0.0007)
Geographic Conc.	-0.0130*	0.0057
	(0.0071)	(0.0062)
Fixed-effects		
Time FEs		Yes
Other Deal Controls	Yes	Yes
Fit statistics		
Observations	3,499	3,499
R^2	0.65378	0.69132
Within R^2		0.58027
Dep. Var. Mean	0.0488	0.0488

Clustered (Time FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of regressing shares of an MBS deal that have defaulted on deal characteristics, geographic concentration of the deal, and flood risk. The flood risk of a deal is equal to the weighted average flood risk of the mortgages that make up the deal (weights are equal to the origination value of the mortgage). Other deal controls include average loan-to-value ratio, average credit score, average interest rate, balloon flag shares, low/no documentation shares, non-owner-occupied shares, 12-month home price changes, deal type, coupon rate, and geographic concentration.

Our results show that higher flood risk is correlated with higher MBS deal-level default, in line with the mortgage-level results in Section 4.1. Specifically, a one-unit increase in First Street Flood Factor is associated with a 1.6 percentage point increase in the share of an MBS deal that defaults within 12 months of origination. In terms of standard deviations, a one standard deviation increase in flood risk (0.10 unit increase) generates a 16 basis point increase in deal-level default—a 3.2 percent increase on the average deal-level default rate. Even at a deal level, flood risk is meaningfully correlated with default.

5.2 Flood Risk and MBS Deal Credit Protection Results

Table 5 reports the regression results from estimation Equation 2 looking at flood risk and MBS deal-level credit protection (subordination). We find that credit protection (subordination) increases with flood risk and that credit protection is higher for deal tranches with better credit ratings (e.g., AAA rated tranches). This relationship holds true even after controlling for a range of MBS deal-characteristics and underlying mortgage characteristics (see Section 5 for a detailed description of controls).

Our results show that higher flood risk is correlated with greater tranche-level subordination, (i.e., the share of the deal value beneath a given rating category that provides credit protection). Not surprisingly, with greater risks like flood, investors for more senior tranches demand improved protection against credit losses. Specifications 1 and 2 give results for subordination levels to AAA MBS tranches (highest rated tranches). A one-unit increase in First Street Flood Factor is associated with a roughly 2.6 percentage point increase in the share of an MBS deal providing credit protection to the AAA tranches. Specifications 3 and 4 give results for subordination levels to BBB- MBS tranches (lowest investment grade tranche). A one-unit increase in First Street Flood Factor is associated with a 0.4 percentage point change in the share of an MBS deal providing credit protection to the BBB tranches. Mapping into standard deviations, a one standard deviation increase in the flood risk of a deal (0.10 units) would increase the AAA-subordination of a deal by about 26 basis points—a 2.6 percent increase on the average subordination of 10.1 percent. Additionally, these results are consistent with how investors are protected from risk. The flood risk coefficient is substantially larger for subordination to AAA tranches compared with the subordination to BBB- tranches. For each unit of flood risk at the deal level, investors in more highly rated tranches (AAA) demand greater levels of protection than investors in the riskier (BBB-) tranches. Furthermore, subordination levels are generally higher for more

Table 5: Flood Risk and Deal Subordination Regression

Dependent Variables:	Below AAA		Below BBB-	
Model:	(1)	(2)	(3)	(4)
Variables				
Avg. Flood Factor	0.0425***	0.0259**	0.0056***	0.0038***
	(0.0131)	(0.0124)	(0.0011)	(0.0014)
LTV	0.2017***	0.1875***	0.0133***	0.0123***
	(0.0282)	(0.0269)	(0.0026)	(0.0027)
FICO	-0.0006***	-0.0006***	4.89×10^{-6}	2.19×10^{-6}
	(0.0001)	(0.0001)	(5.45×10^{-6})	(5.21×10^{-6})
Coupon Rate	0.0062***	0.0073***	0.0007***	0.0007***
	(0.0017)	(0.0012)	(0.0001)	(0.0001)
Interest Rate	-0.0025*	0.0029***	-0.0001	0.0002**
	(0.0013)	(0.0010)	(0.0001)	(0.0001)
Geographic Conc.	0.0102	0.0617***	-0.0045***	-0.0010
	(0.0135)	(0.0101)	(0.0015)	(0.0016)
Fixed-effects				
Time FEs		Yes		Yes
Other Deal Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,499	3,499	3,499	3,499
R^2	0.50346	0.57551	0.06931	0.12799
Within R^2		0.55226		0.07313
Dep. Var. Mean	0.1010	0.1010	0.0034	0.0034

Clustered (Time FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of regressing deal-level credit protection on deal characteristics, geographic concentration of the deal, and flood risk. Credit protection is measured as the share of a deal below a specific rating category (i.e., below AAA or below BBB-). The flood risk of a deal is equal to the weighted average flood risk of the mortgages that make up the deal (weights are equal to the origination value of the mortgage). Other deal controls include average loan-to-value ratio, average credit score, average interest rate, balloon flag shares, low/no documentation shares, non-owner-occupied shares, 12-month home price changes, deal type, coupon rate, and geographic concentration.

highly rated debt tranches and lower for lower rated tranches, making these results consistent with the credit protection investors experience.[14]

6 Discussion

Our regression results establish a relationship between flood risk and the default probabilities, pricing, and terms (i.e., LTVs) across individual mortgages, as well as between average flood risk and the performance and structure of MBS deals. Overall, we find that higher flood risk at the mortgage level is associated with a higher probability of default, slightly higher mortgage spreads, and meaningfully lower LTV ratios at origination. Additionally, our mortgage results are driven almost entirely by mortgages with high levels of flood exposure, suggesting tail risks are important for mortgage performance and underwriting. For MBS deals, higher average flood risk is also associated with higher average default rates and enhanced credit protection, especially for higher rated, less risky tranches (i.e., AAA). Ultimately, we find that flood risk across individual mortgages is important for predicting defaults and mortgage terms, a relationship that holds for MBS deals as well.

Our findings for MBS deals are useful for several reasons. First, because of the nuances of securitization, it is not obvious that mortgage-level effects would also be reflected at the deal level. Our MBS deal-level default results suggest that flood risk is correlated to poorer deal performance (i.e., higher mortgage default shares). While we cannot say whether deal underwriters and rating agencies are choosing mortgage pools with flood exposures as an input for their selections, we do know characteristics like geographic diversity and borrower characteristics are important inputs for choosing diversified mortgage pools (Ashcraft et al., 2010; Siegel, 2003).[15] We surmise that the diversification we see for flood risk at the

[14]Generally, our results are economically meaningful and also coincide with the level of subordination applied to protect investors in both AAA and BBB MBS tranches. See Appendix Section A.7 for further details on the distribution of subordination for these debt categories across our sample. We run additional robustness checks for tranche-level pricing using tranche level credit spreads. For that analysis, tranche coupon spread is measured as the spread above the London Inter-bank Offering Rate (LIBOR) for floating rate tranches and the spread to the 10-year Treasury rate for fixed rate tranches. We do not find significant evidence that tranche-level pricing responds to flood risk (see Section A.6 for details). While we do not find that flood risk is statistically significant as a predictor for tranche level spreads, there could be a few reasons for this. Subordination levels and credit spreads are both methods for providing credit enhancement in securitizations and may be co-determined (Mason, 2008). Investors may be buffered from risk with higher subordination levels, compensated for risk with higher spreads, or some combination of the two. If subordination levels are improved to compensate for risk, investors may not be provided additional credit protection in the form of higher spreads. Either way, our analysis shows evidence for higher credit protection through subordination decisions but is inconclusive with respect to tranche level pricing.

[15]These diversification strategies are evident across characteristics like LTVs, FICO scores, and flood risk, when comparing distributions of individual mortgage characteristics and MBS deals (section A.8).

MBS-level is likely driven by geographic selection, which would have securitizers choosing properties from a wide array of markets across the country. Different geographies will have varying degrees of flood risk and by choosing a diverse set of mortgages across different geographies (e.g., mortgages selected across states and counties, some with high flood risk and some with low flood risk), those mortgage pools and MBS deals will implicitly have more diverse and less concentrated flood risk overall[16]. Regardless of whether mortgage selection and diversification for flood risks is done implicitly (by geographic selection), our results indicate that flood risk is a factor *explicitly* worth considering when originating mortgages and securitizing MBS deals. The findings of this study may inform market participants about the relationship between flood risk, mortgage origination, and securitization processes, potentially influencing how they assess and manage risk exposures.

Secondly, our MBS results are also useful in base-lining the discussion around credit protection associated with flood risk. From our analysis, we can say there is a relationship between flood risk and higher subordination, indicating dealmakers may consider flood risks when choosing the final deal structure. However, similar to the discussion on geography, dealmakers are more likely providing protections based on overall expected losses or mortgage defaults in a deal, and not necessarily flood risk explicitly. While our analysis does show that some of these risks are being adjusted for, we cannot say whether the credit protection is sufficient to offset these higher risks. Further, if flooding hazards were to worsen in the future, constructing these securities may become more expensive as investors demand greater credit protection against that higher flooding risk.

Finally, while our analysis focuses on private-label MBS deals, our approach generalizes to other MBS and structured finance products, as well as asset portfolios writ-large. The spatial matching methods and risk aggregation used is this paper could be applied to agency MBS products. However, public information regarding the precise location of mortgages in agency MBS tends to be aggregated and only available at the regional (MSA) level, which is too high-level for a hyperlocal risk like flood risk. As climate risk grows in importance, our research helps highlight the value of improving matching across datasets and improving the geographic resolution of underlying assets so that they can be more tightly linked with future

[16] Furthermore, the mortgages and MBS deals in our sample were all originated and securitized from 1992 to 2009, which is well before climate risk was front of mind for most investors, underwriters, and homeowners (GALLUP, 2023; Tyson et al., 2023; Capstick et al., 2015). Additionally, the flood risk data sets used in our analysis have only been widely available in the last half decade and progression of spatial matching methods for linking flood risk to mortgages rapidly improved during that period, making this risk matching more approachable in recent years. All of these factors support the idea that historically, mortgage originators and securitizers were implicitly controlling for flood risk in their decision making, rather than explicitly considering flood risk for those decisions.

climate risks. This is fruitful ground for other research projects, including improving spatial data for GSE mortgages and running a similar analysis in those securities. Additionally, a similar risk matching and risk aggregation approach could be applied to flood risk and its association with wider ranging asset markets (e.g., CRE, banking exposures, or critical infrastructure) or utilized for other natural hazards (e.g., extreme temperature, fire, hurricanes, or drought).

7 Conclusion

Our paper documents a few important patterns for how MBS products account for flood risk and how those risks influence asset performance. First, mortgages that face higher flood risk are more likely to default. This risk is most important for mortgages exposed to the highest levels of flood risk, suggesting tail risks continue to play an important role in mortgage performance. Additionally, mortgage originators demand greater protection for at risk properties, by underwriting loans with lower LTVs in areas more highly exposed to flood. Our results indicate that mortgage interest rates do not entirely reflect flood risk. Second, MBS deals with higher average flood risk also have higher default shares but do not have higher spreads. Instead, the increased risk appears to be offset by significantly increased subordination, particularly for the highest rated (i.e., AAA) tranches. Therefore, we find evidence that MBS deals are offering investors more credit protection to offset the higher risk of flooding instead of offering them higher returns.

In addition to documenting these facts for private-label mortgages and MBSs, this paper also provides an externally valid easy-to-replicate framework for estimating the flood risk for a range of structured finance products, given detailed geographic information on the underlying assets. This flexible framework will be useful to other researchers and market participants so they can estimate the distribution of risks across a range of structured finance products and other asset portfolios. Methodologically, our risk matching approach underscores the importance of using asset specific location data and risks, rather than regional or more generalized risk exposures. Risk practitioners should be wary in using flood risk exposures that are regional in scope.

Our analysis, provides valuable evidence on how flood risk has historically resulted in poorer performance for mortgages and MBS securities and our work is one of the first to document this relationship. Furthermore, our mortgage analysis points to the importance of tail risks when conducting this type of risk work. Lastly, our risk matching methods expose the importance of improving geo-location data for mortgages (and other at risk asset classes), in order to properly assess climate risk in those markets. Research should continue to examine how natural disasters affect key aspects of financial markets, so that we can better understand the extent to which markets are already capturing this risk and how prices reflect relevant risks.

References

An, X., Deng, Y., Nichols, J., & Sanders, A. (2015, August). What is Subordination About? Credit Risk and Subordination Levels in Commercial Mortgage-backed Securities (CMBS). *The Journal of Real Estate Finance and Economics*, *51*(2), 231-253. Retrieved from https://ideas.repec.org/a/kap/jrefec/v51y2015i2p231-253.html doi: doi:10.1007/s11146-014-9480-1

Arnold, J. B. (2023). ggthemes: Extra themes, scales and geoms for 'ggplot2' [Computer software manual]. Retrieved from https://CRAN.R-project.org/package=ggthemes (R package version 5.0.0)

Ashcraft, A. B., Goldsmith-Pinkham, P., & Vickery, J. (2010, May). *MBS ratings and the mortgage credit boom* (Staff Reports No. 449). Federal Reserve Bank of New York. Retrieved from https://www.newyorkfed.org/research/staff_reports/sr449.html

Barrett, T., Dowle, M., & Srinivasan, A. (2023). data.table: Extension of 'data.frame' [Computer software manual]. Retrieved from https://CRAN.R-project.org/package=data.table (R package version 1.14.10)

Bergé, L. (2018). Efficient estimation of maximum likelihood models with multiple fixed-effects: the R package FENmlm. *CREA Discussion Papers*(13).

Bernstein, A., Gustafson, M., & Lewis, R. (2019, 11 1). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, *134*(2), 253–272. doi: doi:10.1016/j.jfineco.2019.03.013

Biswas, S., Hossain, M., & Zink, D. (2023). California wildfires, property damage, and mortgage repayment. *Federal Reserve Bank of Philadelphia Working Papers*.

Breen, R., Karlson, K. B., & Holm, A. (2018). Interpreting and understanding logits, probits, and other nonlinear probability models. *annual review of sociology*, *44*, 39–54.

Capstick, S., Whitmarsh, L., Poortinga, W., Pidgeon, N., & Upham, P. (2015). International trends in public perceptions of climate change over the past quarter century. *WIREs Climate Change*, *6*(1), 35-61. Retrieved from https://wires.onlinelibrary.wiley.com/doi/abs/10.1002/wcc.321 doi: doi:https://doi.org/10.1002/wcc.321

Carlson, M., & Huang, J. (2021, Sept). *Hidden dangers: Navigating climate risks in cmbs.* Retrieved 2024-01-15, from https://www.alliancebernstein.com/corporate/en/

insights/investment-insights/hidden-dangers-navigating-climate-risks-in-cmbs.html

Cattaneo, M. D., Crump, R. K., Farrell, M. H., & Feng, Y. (2024). On binscatter. *American Economic Review (Forthcoming)*.

Cetorelli, N., & Peristiani, S. (2012, July). The Dominant Role of Banks in Asset Securitization. *Liberty Street Economics*(20120719). Retrieved from https://ideas.repec.org/p/fip/fednls/86818.html

Congressional Research Service. (2022, November). *Introduction to the national flood insurance program.* Retrieved 2023-12-11, from https://sgp.fas.org/crs/homesec/R44593.pdf (CRS Report R44593)

Craig, M. (2022). An overview of flood risk to the housing finance ecosystem. *Cityscape*, *24*(1), 345–368. Retrieved 2024-01-17, from https://www.jstor.org/stable/48657956

Federal Emergency Management Association (FEMA). (2021, June). *Fema national hazard layer.* Retrieved 2023-05-30, from https://www.fema.gov/flood-maps/national-flood-hazard-layer (https://www.fema.gov/flood-maps/national-flood-hazard-layer)

First Street Foundation. (2023, July). *First street foundation flood model (fsf-fm) technical methodology documentation version 3.0.* Retrieved 2023-08-08, from https://assets.firststreet.org/uploads/2023/07/FSF_Flood_Methodology_2023July.pdf

Fuster, A., Lucca, D. O., & Vickery, J. (2022, February). *Mortgage-Backed Securities* (Staff Reports No. 449). Federal Reserve Bank of New York. Retrieved from https://www.newyorkfed.org/research/staff_reports/sr1001.html

Gallagher, J., & Hartley, D. (2017). Household finance after a natural disaster: The case of hurricane katrina. *American Economic Journal: Economic Policy*, *9*(3), 199–228.

GALLUP. (2023). *Environment survey.* Retrieved 2024-3-5, from https://news.gallup.com/poll/1615/environment.aspx

Gete, P., Tsouderou, A., & Wachter, S. M. (2023). Climate risk in mortgage markets: Evidence from hurricanes harvey and irma. *Available at SSRN 3961832*.

Gillies, S., & team. (2013–). *Rasterio: geospatial raster i/o for Python programmers.* Retrieved from https://github.com/mapbox/rasterio

Goodman, L., Ratcliffe, J., Neal, M., Choi, J. H., Zhu, L., Walsh, J., ... others (2023). Housing finance: At a glance monthly chartbook, september 2023. *Urban Institute Housing Finance Policy Center*.

Gourevitch, J. D., Kousky, C., Liao, Y. P., Nolte, C., Pollack, A. B., Porter, J. R., & Weill, J. A. (2023, 03 1). Unpriced climate risk and the potential consequences of overvaluation in us housing markets. *Nature Climate Change*, *13*, 250-257. doi:

doi:10.1038/s41558-023-01594-8

Grolemund, G., & Wickham, H. (2011). Dates and times made easy with lubridate. *Journal of Statistical Software*, *40*(3), 1–25. Retrieved from https://www.jstatsoft.org/v40/i03/

Hlavac, M. (2022). stargazer: Well-formatted regression and summary statistics tables [Computer software manual]. Bratislava, Slovakia. Retrieved from https://CRAN.R-project.org/package=stargazer (R package version 5.2.3)

Horrace, W. C., & Oaxaca, R. L. (2006). Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Economics letters*, *90*(3), 321–327.

Hunter, J. D. (2007). Matplotlib: A 2d graphics environment. *Computing in Science & Engineering*, *9*(3), 90–95. doi: doi:10.1109/MCSE.2007.55

Issler, P., Stanton, R., Vergara, C., & Wallace, N. (2021). Housing and mortgage markets with climate risk: Evidence from california wildfires.

Jordahl, K., den Bossche, J. V., Wasserman, J., McBride, J., Fleischmann, M., Gerard, J., ... maxalbert (2020, February). *geopandas/geopandas: v0.7.0.* Zenodo. Retrieved from https://doi.org/10.5281/zenodo.3669853 doi: doi:10.5281/zenodo.3669853

Kahn, M. E., Ouazad, A., & Yönder, E. (2024). *Adaptation using financial markets: Climate risk diversification through securitization* (Tech. Rep.). National Bureau of Economic Research.

Klik, M. (2022). fst: Lightning fast serialization of data frames [Computer software manual]. Retrieved from https://CRAN.R-project.org/package=fst (R package version 0.9.8)

Mason, S. (2008). *The basics of credit enhancement in securitizations.* Retrieved 2023-11-27, from https://elischolar.library.yale.edu/ypfs-documents/5166/ (Standard and Poor's Ratings Direct)

Mcalpine, S., & Porter, J. (2018, 06). Estimating recent local impacts of sea-level rise on current real-estate losses: A housing market case study in Miami-Dade, Florida. *Population Research and Policy Review*, *37*. doi: doi:10.1007/s11113-018-9473-5

Nguyen, D. D., Ongena, S., Qi, S., & Sila, V. (2022, 03). Climate Change Risk and the Cost of Mortgage Credit*. *Review of Finance*, *26*(6), 1509-1549. Retrieved from https://doi.org/10.1093/rof/rfac013 doi: doi:10.1093/rof/rfac013

NOAA. (2023). *United states billion-dollar weather and climate disasters.* Retrieved 2023-12-31, from https://www.ncdc.noaa.gov/billions/ (NOAA National Centers for Environmental Information (NCEI). https://www.ncdc.noaa.gov/billions/)

Oehlschlägel, J., & Silvestri, L. (2020). bit64: A s3 class for vectors of 64bit integers [Computer software manual]. Retrieved from https://CRAN.R-project.org/package=bit64 (R package version 4.0.5)

Ouazad, A., & Kahn, M. E. (2021, 11). Mortgage Finance and Climate Change: Securitization Dynamics in the Aftermath of Natural Disasters. *The Review of Financial Studies*, *35*(8), 3617-3665. Retrieved from https://doi.org/10.1093/rfs/hhab124 doi: doi:10.1093/rfs/hhab124

Quiggin, J. (2018). The importance of 'extremely unlikely' events: tail risk and the costs of climate change. *Australian Journal of Agricultural and Resource Economics*, *62*(1), 4-20. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-8489.12238 doi: doi:https://doi.org/10.1111/1467-8489.12238

R Core Team. (2023). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from https://www.R-project.org/

Rappaport, J. (2020, July). What to Do about Fannie and Freddie: A Primer on Housing Finance Reform. *Economic Review*, *105*(no.2), 5-29. Retrieved from https://ideas.repec.org/a/fip/fedker/88369.html doi: doi:10.18651/ER/v105n2Rappapo

Rodziewicz, D., Amante, C. J., Dice, J., & Wahl, E. (2022, December). Housing market impairment from future sea-level rise inundation. *Environment Systems and Decisions*, *42*(4), 637-656. Retrieved from https://ideas.repec.org/a/spr/envsyd/v42y2022i4d10.1007_s10669-022-09842-6.html doi: doi:10.1007/s10669-022-09842-

Sastry, P. (2022). Who bears flood risk? evidence from mortgage markets in florida. *Evidence from Mortgage Markets in Florida (December 18, 2022)*.

Siegel, J. (2003). *Moody's mortgage metrics: A model analysis of residential mortgage pools.* (https://elischolar.library.yale.edu/ypfs-documents/5058/)

Smith, J. B., & Tirpak, D. (1989, December). *The potential effects of global climate change on the united states* (Tech. Rep.). Environmental Protection Agency. Retrieved from http://hero.epa.gov/index.cfm/reference/download/reference_id/758876

The pandas development team. (2020, February). *pandas-dev/pandas: Pandas.* Zenodo. Retrieved from https://doi.org/10.5281/zenodo.3509134 doi: doi:10.5281/zenodo.3509134

Tyson, A., Funk, C., & Kennedy, B. (2023, Sept). *What the data says about americans' views of climate change.* Retrieved 2024-02-10, from https://www.pewresearch.org/short-reads/2023/08/09/what-the-data-says-about-americans-views-of-climate-change/

USGCRP. (2018). *Impacts, risks, and adaptation in the united states: Fourth national climate assessment.* Retrieved 2019-12-31, from https://nca2018.globalchange.gov/ (U.S. Global Change Research Program) doi: doi:10.7930/NCA4.2018

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. Retrieved from https://ggplot2.tidyverse.org

Wickham, H. (2023). stringr: Simple, consistent wrappers for common string operations [Computer software manual]. Retrieved from https://CRAN.R-project.org/package=stringr (R package version 1.5.1)

Wickham, H., & Bryan, J. (2023). readxl: Read excel files [Computer software manual]. Retrieved from https://CRAN.R-project.org/package=readxl (R package version 1.4.3)

Xie, Y. (2014). knitr: A comprehensive tool for reproducible research in R. In V. Stodden, F. Leisch, & R. D. Peng (Eds.), *Implementing reproducible computational research*. Chapman and Hall/CRC. (ISBN 978-1466561595)

Zeileis, A., & Grothendieck, G. (2005). zoo: S3 infrastructure for regular and irregular time series. *Journal of Statistical Software*, *14*(6), 1–27. doi: doi:10.18637/jss.v014.i06

Zhou, F., Endendijk, T., & Botzen, W. W. (2023). A review of the financial sector impacts of risks associated with climate change. *Annual Review of Resource Economics*, *15*, 233–256.

Zhou, Y., Wu, S., Liu, Z., & Rognone, L. (2023, 11). The asymmetric effects of climate risk on higher-moment connectedness among carbon, energy and metals markets. *Nature Communications*, *14*. doi: doi:10.1038/s41467-023-42925-9

A Appendix

A.1 Data Construction

To construct our data for analysis, we do the following. First, we obtain raw ABS data from CoreLogic's Private Label Securities database. For each loan that makes up a security, we obtain a range of origination variables including, but not limited to, credit score, debt-to-income ratio, loan-to-value ratio, origination amount, and mortgage term. We apply a range of restrictions on the data, which are summarized in Table A.1. After cleaning, we are left with 16.6 million mortgages with most of the sample dropping out due to restricting our analysis to more standard mortgage types (15 and 30-year mortgages and 2, 3, or 5-year ARMs) and dropping mortgages that had invalid zip codes.

Table A.1: Sample Restrictions

Filter	Mortgage Count
Starting Count	23,174,940
Only 15 or 30-year FRMs and 2, 3, or 5-year ARMs	18,601,778
Restricting Originations to Jan 1992 - Jun 2009	18,059,638
Dropping Negative Amortizing Mortgages	18,059,638
Dropping Invalid Zip Codes	17,796,383
Dropping Invalid Orig. Dates	17,766,772
Dropping LTV $>$ 100% or Negative LTVs	17,494,721
Dropping interest $=$ 0% or interest $>$ 20%	17,248,629
Restricting to 50 States, DC, and Puerto Rico	17,248,280
Dropping Missing Flood Scores	17,125,217
Dropping Missing HPI Changes	16,602,833

We also identify the set of loans which defaulted (90+ days past due), foreclosed, real estate owned, or involuntarily liquidated (MBA status = 9, F, R, or L) as well as those that were prepaid at a loss (MBA status = 0 and loss amount $>$ 0)

We apply a similar cleaning procedure for MBS deals, which are detailed in Table A.2.

A.2 First Street Flood Factor

First Street Foundation (FSF) Flood Factor Risk Score provides a comprehensive and forward looking estimate of relative flood risk for specific locations (e.g., property level or zip code) (First Street Foundation, 2023). FSF Flood Factor combines both the likelihood of a flooding event occurring and the severity of occurrence (i.e., water depth) over a 30 year return period.

Table A.2: Sample Restrictions

Filter	Deal Count
Starting Count	6,167
Dropping Deals Closed After June 2009	5,147
Dropping Deals With >10% Missing Ratings	4,037
Dropping Deals Missing FICO	3,888
Dropping Deals >10% Missing Flood Risk	3,553
Dropping Deals Missing LTV	3,549
Dropping Deals Missing Default Data	3,534
Dropping Deals With >10% Missing HPI	3,499

Figure A.1 shows a basic outline of the combination of flood probability and severity into a single score ranging from 1-10 (i.e., low to high risk). Furthermore, the FSF flood risk score includes a series of major flooding sources (i.e., rain, riverine, tidal, and storm surge), while also accounting for higher flood risk over time from a changing climate – risk scores are based on the most likely median climate risk scenario (i.e., SSP2-4.5). These forward looking flood risk estimates from FSF are a meaningful departure from other flood exposure measures like FEMA Special Flood Hazard Areas (SFHA), which are static, backward-looking risk measures, based on historical flooding events (e.g., probability of a 100 year flood event) that are also binary in nature (e.g., in a flood zone or not) (Federal Emergency Management Association (FEMA), 2021; Congressional Research Service, 2022).

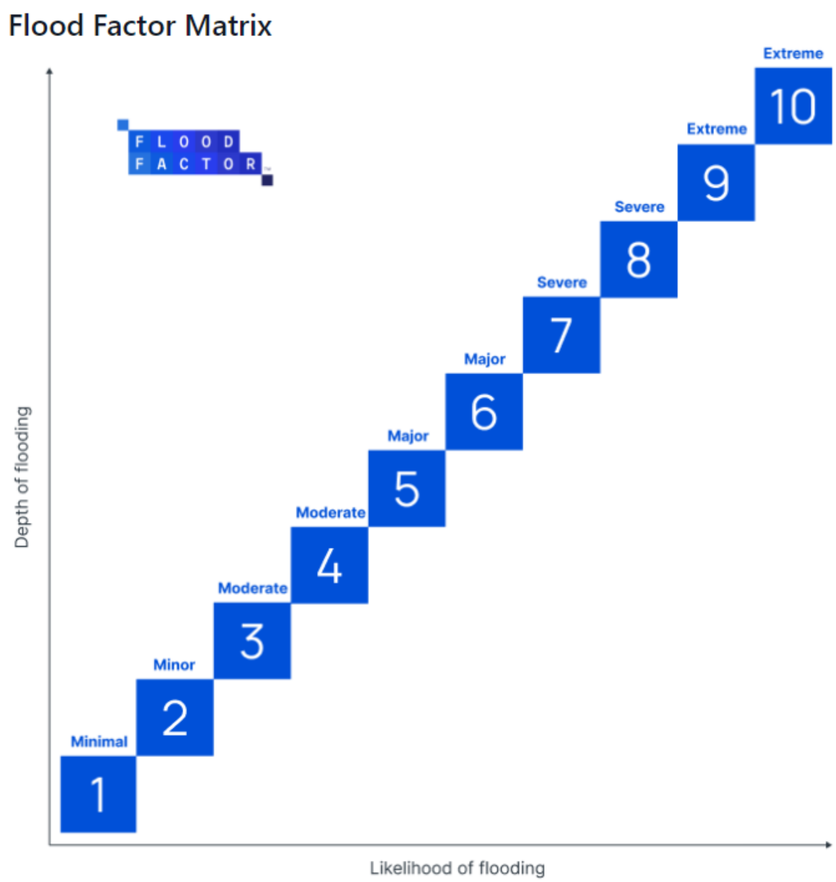
The Flood Factor score is the piecewise integration of flood depths and their associated probabilities. Because of this, a simple mapping between flood depths and probabilities and the Flood Factor score is not possible. However, there are some general bounds that can help conceptualize the meanings of each flood factor level and how they related to flood probabilities:[17]

- Areas with low flood risk (250-year or 500-year return periods) will have a score of 2
- Areas with 100-year return periods (1 percent annual risk) will have a score of at least 4
- Areas with 20-year return periods (5 percent annual risk) will have a score of at least 5
- Areas with 5-year return periods (20 percent annual risk) will have a score of at least 6
- Areas with 2-year return periods (50 percent annual risk) will have a score of at least 6, but likely a 7 or higher

[17] Correspondence with Mike Amodeo on January 15, 2024. Available on request.

All of these scores will then be adjusted based on the severity of the corresponding floods.

Figure A.1: Flood Factor Risk Matrix



Source: First Street Foundation.

A.3 Summary Statistics

Table A.3: Mortgage Summary Statistics

Statistic	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)	Max
Default	0.06	0.23	0	0	0	1
Loan Balance ('000)	175.97	150.51	75.98	134.90	230.00	25,450.41
LTV	0.81	0.15	0.75	0.80	0.90	1.00
FICO	646.89	70.68	597	646	697	944
Balloon Payment	0.12	0.33	0	0	0	1
DTI	0.23	0.21	0.00	0.30	0.43	9.52
Interest Rate	8.17	1.92	6.75	7.88	9.35	20.00
Low Doc	0.45	0.50	0	0	1	1
Investor Flag	0.12	0.32	0	0	0	1
Avg. Flood Factor	2.01	1.07	1.44	1.68	2.13	10.00
N				16,602,833		

A.4 Flood Risk and Mortgage Default

Table A.4: Flood Risk and Mortgage Default (Different Default Horizons)

Dependent Variables:	12-Month Default	24-Month Default	36-Month Default
Model:	(1)	(2)	(3)
Variables			
Flood Risk (2, 4]	0.0009	0.0028	0.0040
	(0.0010)	(0.0023)	(0.0028)
Flood Risk (4, 6]	0.0016	0.0063	0.0120
	(0.0013)	(0.0044)	(0.0086)
Flood Risk (6, 8]	0.0176***	0.0350***	0.0453***
	(0.0064)	(0.0103)	(0.0138)
Flood Risk (8, 10]	0.0122***	0.0223***	0.0267***
	(0.0024)	(0.0058)	(0.0085)
LTV	0.0036	0.0858***	0.1844***
	(0.0047)	(0.0161)	(0.0279)
FICO	-0.0003***	-0.0006***	-0.0007***
	(1.13×10^{-5})	(2.4×10^{-5})	(4.93×10^{-5})
DTI	0.0534***	0.1161***	0.1511***
	(0.0039)	(0.0061)	(0.0081)
Log Orig. Amt	0.0298***	0.0620***	0.0782***
	(0.0025)	(0.0049)	(0.0047)
Spread at Origination	0.0201***	0.0333***	0.0315***
	(0.0010)	(0.0011)	(0.0015)
Missing FICO	-0.1671***	-0.3713***	-0.4669***
	(0.0072)	(0.0145)	(0.0296)
Fixed-effects			
Time FEs	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Dummies for missing values	Yes	Yes	Yes
Other Loan Controls	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes
Fit statistics			
Observations	10,692,150	10,692,150	10,692,150
R^2	0.06763	0.15875	0.22463
Within R^2	0.04533	0.08674	0.10333
Dep. Var. Mean	0.0578	0.1468	0.2257

Clustered (State FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of estimating a linear probability model of mortgage default (within 12, 24, or 36 months of origination) on flood risk scores, loan characteristics (LTV, credit score, DTI, origination amount, and mortgage spread), other loan characteristics (interest rate flag, balloon payment flag, documentation level, investor flag, cashout flag, prepayment penalty flag, and dummies for missing values of these variables), local economic conditions (county unemployment, home price changes, median home values, median income, minority shares), quarterly fixed effects, and state fixed effects. Default is defined as 90 or more days past due, foreclosure, real estate owned (REO), or paid off at a loss. Flood risk is from the First Street Foundation and is the average Flood Factor risk for the zip code in which the property is located.

Table A.5: Flood Risk and Mortgage Default (Trimmed Estimator)

Dependent Variable:	Mortgage Default	
Model:	(1)	(2)
Variables		
Flood Risk (2, 4]	0.0009	0.0012
	(0.0010)	(0.0011)
Flood Risk (4, 6]	0.0016	0.0019
	(0.0013)	(0.0016)
Flood Risk (6, 8]	0.0176***	0.0243***
	(0.0064)	(0.0068)
Flood Risk (8, 10]	0.0122***	0.0168***
	(0.0024)	(0.0028)
LTV	0.0036	0.0301***
	(0.0047)	(0.0100)
FICO	-0.0003***	-0.0004***
	(1.13×10^{-5})	(9.92×10^{-6})
DTI	0.0534***	0.0692***
	(0.0039)	(0.0044)
Log Orig. Amt	0.0298***	0.0449***
	(0.0025)	(0.0032)
Spread at Origination	0.0201***	0.0257***
	(0.0010)	(0.0010)
Fixed-effects		
Time FEs	Yes	Yes
State FEs	Yes	Yes
Dummies for missing values	Yes	Yes
Other Loan Controls	Yes	Yes
Local Economic Conditions	Yes	Yes
Trimmed Estimator	No	Yes
Fit statistics		
Observations	10,692,150	8,807,072
R^2	0.06763	0.06627
Within R^2	0.04533	0.04991
Dep. Var. Mean	0.0592	0.0711

Clustered (State FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of estimating a linear probability model of mortgage default (within 12 months of origination) on flood risk scores, loan characteristics (LTV, credit score, DTI, origination amount, and mortgage spread), other loan characteristics (interest rate flag, balloon payment flag, documentation level, investor flag, cashout flag, prepayment penalty flag, and dummies for missing values of these variables), local economic conditions (county unemployment, home price changes, median home values, median income, minority shares), quarterly fixed effects, and state fixed effects. Column 2 reports the results after dropping observations that had predicted default probabilities outside the unit interval. Default is defined as 90 or more days past due, foreclosure, real estate owned (REO), or paid off at a loss. Flood risk is from the First Street Foundation and is the average Flood Factor risk for the zip code in which the property is located.

Table A.6: Flood Risk and Mortgage Default (with 30 Year Fixed Rate Mortgage Spread)

Dependent Variable:	Mortgage Default	
Model:	(1)	(2)
Variables		
Flood Risk (2, 4]	0.0009	0.0005
	(0.0010)	(0.0009)
Flood Risk (4, 6]	0.0016	0.0005
	(0.0013)	(0.0013)
Flood Risk (6, 8]	0.0176***	0.0149**
	(0.0064)	(0.0056)
Flood Risk (8, 10]	0.0122***	0.0107***
	(0.0024)	(0.0021)
LTV	0.0036	-0.0111***
	(0.0047)	(0.0040)
FICO	-0.0003***	-0.0003***
	(1.13×10^{-5})	(1.53×10^{-5})
DTI	0.0534***	0.0512***
	(0.0039)	(0.0039)
Log Orig. Amt	0.0298***	0.0285***
	(0.0025)	(0.0022)
Spread at Origination	0.0201***	
	(0.0010)	
Missing FICO	-0.1671***	-0.1603***
	(0.0072)	(0.0093)
Spread at Origination (30-year FRM)		0.0212***
		(0.0009)
Fixed-effects		
Time FEs	Yes	Yes
State FEs	Yes	Yes
Dummies for missing values	Yes	Yes
Other Loan Controls	Yes	Yes
Local Economic Conditions	Yes	Yes
Fit statistics		
Observations	10,692,150	14,426,687
R^2	0.06763	0.05878
Within R^2	0.04533	0.04244
Dep. Var. Mean	0.0578	0.0578

Clustered (State FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of estimating a linear probability model of mortgage default (within 12 months of origination) on flood risk scores, loan characteristics (LTV, credit score, DTI, origination amount, and mortgage spread), other loan characteristics (interest rate flag, balloon payment flag, documentation level, investor flag, cashout flag, prepayment penalty flag, and dummies for missing values of these variables), local economic conditions (county unemployment, home price changes, median home values, median income, minority shares), quarterly fixed effects, and state fixed effects. Default is defined as 90 or more days past due, foreclosure, real estate owned (REO), or paid off at a loss. Flood risk is from the First Street Foundation and is the average Flood Factor risk for the zip code in which the property is located.

A.5 Flood Risk and Mortgage Pricing

Table A.7: Flood Risk and Mortgage Pricing with 30 Year FRM Spread

Dependent Variable:	Spread at Origination (30yr base)		
Model:	(1)	(2)	(3)
Variables			
Flood Risk (2, 4]	0.0391***	0.0344***	0.0138**
	(0.0129)	(0.0128)	(0.0059)
Flood Risk (4, 6]	0.0152	0.0020	0.0039
	(0.0157)	(0.0247)	(0.0129)
Flood Risk (6, 8]	0.1030***	0.1270***	0.0346**
	(0.0334)	(0.0309)	(0.0160)
Flood Risk (8, 10]	0.1817***	0.2038***	0.1135***
	(0.0474)	(0.0391)	(0.0212)
LTV	1.913***	1.933***	1.891***
	(0.0497)	(0.0664)	(0.0762)
FICO	-0.0102***	-0.0098***	-0.0097***
	(0.0003)	(0.0003)	(0.0003)
DTI	0.1103***	0.0716***	0.0870***
	(0.0254)	(0.0251)	(0.0269)
Log Orig. Amt	-0.4252***	-0.3460***	-0.3280***
	(0.0181)	(0.0204)	(0.0284)
Fixed-effects			
Time FEs		Yes	Yes
State FEs			Yes
Dummies for missing values	Yes	Yes	Yes
Other Loan Controls	Yes	Yes	Yes
Local Economic Conditions	Yes	Yes	Yes
Fit statistics			
Observations	13,878,759	13,878,759	13,878,759
R^2	0.60890	0.63740	0.64066
Within R^2		0.61190	0.60027
Dep. Var. Mean	1.897	1.897	1.897

Clustered (State FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of regressing mortgage rate spread at origination on loan characteristics, flood risk, local economic conditions, and local market conditions. We calculate a mortgage spread relative to the average 30-year FRM rate. Flood risk is from the First Street Foundation and is the average Flood Factor risk for the zip code in which the property is located.

A.6 Flood Risk and MBS Deal Tranche Pricing

Table A.8: Flood Risk and MBS Tranche Pricing (Tranche Specific Spread)

Dependent Variable:	CUSIP Spread	
Model:	(1)	(2)
Variables		
Avg. Flood Factor	-0.0760	-0.0057
	(0.1235)	(0.1087)
Tranche Rating	-0.2018***	-0.2016***
	(0.0065)	(0.0061)
LTV	0.0764	-0.0271
	(0.2577)	(0.2197)
FICO	-0.0013***	-0.0008**
	(0.0005)	(0.0004)
Coupon Rate	-0.0595***	-0.0055
	(0.0163)	(0.0163)
Interest Rate	0.0280	-0.0050
	(0.0175)	(0.0163)
Geographic Conc.	0.1879	-0.3245
	(0.2652)	(0.2605)
Share of Deal Below AAA	-0.2606	0.4921**
	(0.2063)	(0.2212)
Fixed-effects		
Time FEs		Yes
Other Deal Controls	Yes	Yes
Fit statistics		
Observations	26,685	26,685
R^2	0.18457	0.19801
Within R^2		0.17580
Dep. Var. Mean	0.9524	0.9524

Clustered (Time FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of regressing tranche rates on deal characteristics, flood risk, and deal geographic concentration. We calculate a spread relative to the respective reference rate of the security. The flood risk of a deal is equal to the average flood risk of the mortgages that make up the deal (weights are equal to the origination value of the mortgage).

Table A.9: Flood Risk and MBS Tranche Pricing (Spread to 10-Year Treasury Rate)

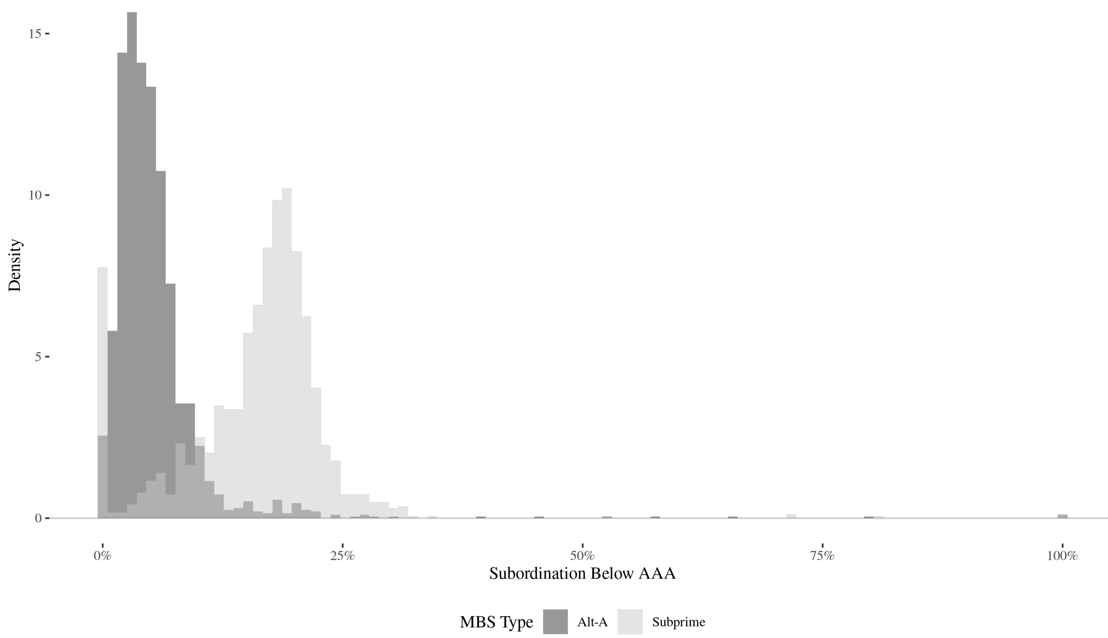
Dependent Variable:	CUSIP Spread (10yr base)	
Model:	(1)	(2)
Variables		
Avg. Flood Factor	0.2836*	-0.2168*
	(0.1591)	(0.1178)
Tranche Rating	-0.1888***	-0.1946***
	(0.0060)	(0.0060)
LTV	-0.2903	-0.1509
	(0.3155)	(0.2844)
FICO	0.0006	-0.0002
	(0.0007)	(0.0006)
Coupon Rate	0.6080***	0.3687***
	(0.0340)	(0.0160)
Interest Rate	-0.0124	0.0038
	(0.0153)	(0.0090)
Geographic Conc.	-0.6282**	0.0800
	(0.2807)	(0.2253)
Share of Deal Below AAA	0.6567	0.3353
	(0.4041)	(0.2854)
Fixed-effects		
Time FEs		Yes
Other Deal Controls	Yes	Yes
Fit statistics		
Observations	26,685	26,685
R^2	0.71594	0.79294
Within R^2		0.65094
Dep. Var. Mean	0.4260	0.4260

Clustered (Time FEs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Table reports the results of regressing tranche rates on deal characteristics, flood risk, and deal geographic concentration. We calculate a spread relative to the 10-year Treasury rate. The flood risk of a deal is equal to the average flood risk of the mortgages that make up the deal (weights are equal to the origination value of the mortgage).

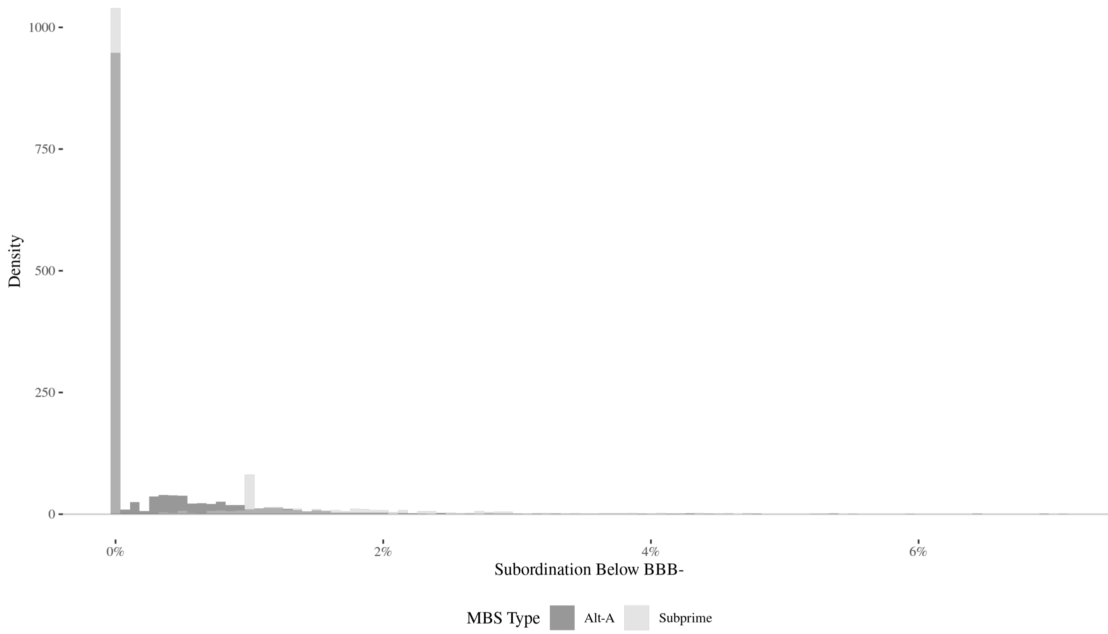
A.7 Deal Types and Subordination

Figure A.2: Distribution of AAA Subordination



Note: This figure shows the distribution of AAA credit protection for each MBS deal in our data. Credit protection is measured as the share of a deal rated below AAA.

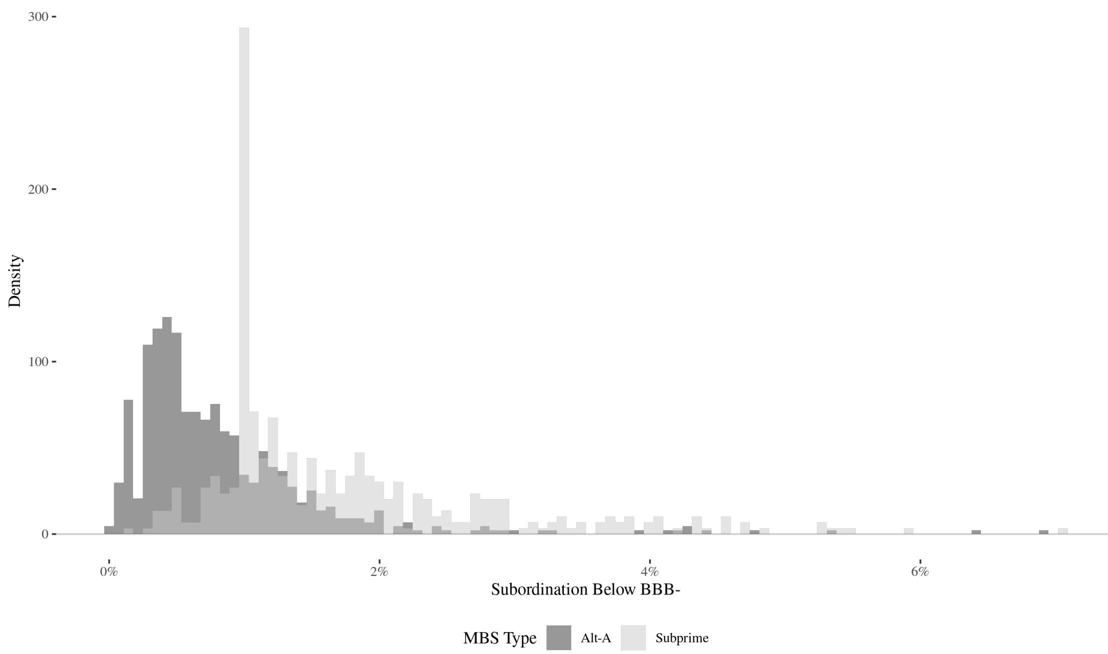
Figure A.3: Distribution of BBB- Subordination



Note: This figure shows the distribution of BBB- credit protection for each MBS deal in our data. Credit protection is measured as the share of a deal rated below BBB-.

A.8 Mortgage-Level and Deal-Level Risk Aggregation

Figure A.4: Distribution of BBB Subordination (Only Subordinated Deals)



Note: This figure shows the distribution of BBB- credit protection for each MBS deal in our data with positive BBB- subordination. Credit protection is measured as the share of a deal rated below BBB-.

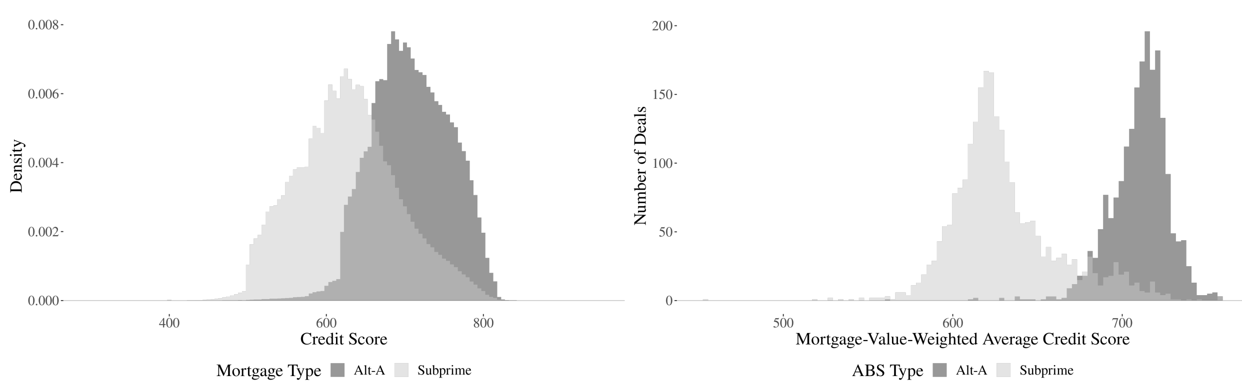


Figure A.5: Distribution of Mortgage- and Deal-Level Credit Scores

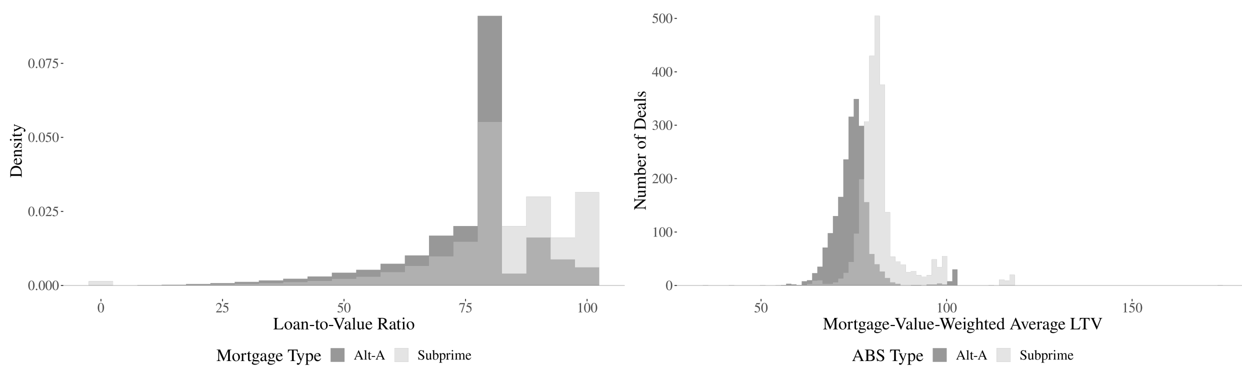


Figure A.6: Distribution of Mortgage- and Deal-Level Loan-to-Value Ratios