Exploring Climate Risk, Risk Retention, and CMBS: Understanding their Interplay

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Abstract

In this study, we explore the effects of climate hazards on Commercial Mortgage-Backed Securities (CMBS). While Ouazad and Kahn (2019) discovered a significant increase in mortgage securitizations to agency RMBS following a billion-dollar natural disaster, our results indicate a more cautious approach in response to climate threats, incentivized by the risk retention rule. Following the risk retention rule, CMBS issuers shift their loans away from areas with high climate risks. Meanwhile, loan originators are not able to expedite the sale of loans affected by climate events before they are bundled into securities, and underwriters tend to lower their exposure to climate risks in their loan portfolios. This provides empirical evidence for the "lemon" problem in the securitization model concerning the hidden climate risk in the absence of interest alignment and symmetric information. Consequently, deals under risk retention tend to offer a pricing advantage, with a lower premium for climate hazard exposure. This is linked to a decrease in the default risk associated with climate hazards after the retention rule was put in place.

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1 Introduction

Climate-related risks, including rising sea levels and extreme weather events, have become significant concerns within the commercial real estate sector, particularly for Commercial Mortgage-Backed Securities (CMBS) investors[3]. These risks pose the potential to cause physical property damage and disrupt business operations, which can lead to a ripple effect on property values and tenant cash flows. Furthermore, they result in various financial implications, such as declining property values, heightened operational expenses, increased earnings volatility, elevated insurance premiums, reduced property demand, and regulatory pressures, all of which are well-documented in the literature (Mueller et al., 2009, Hamilton-Webb et al., 2017, Bernstein et al., 2019, Baldauf et al., 2020, Keys and Mulder, 2020, Murfin and Spiegel, 2020, Clayton et al., 2021, Holtermans et al., 2023). Consequently, there is a growing need to assess and address climate risk in CMBS investments. However, the complexity of these risks often makes them less observable and more challenging to quantify.

One of the primary challenges in assessing climate risk in CMBS securities is the localized nature of climate-related disasters. These events exhibit significant variability across different neighborhoods at the local level (Masozera et al., 2007, Vigdor, 2008, Holtermans et al., 2023), implying that the conventional screening of mortgages may not comprehensively capture the risk associated with natural disasters. Additionally, the 'originate-to-distribute' model, which involves lenders originating mortgages and subsequently selling them for securitization, raises moral hazard concerns. Local lenders possessing more precise information about local disaster risks may be inclined to securitize mortgages with higher but less observable risks (Ouazad and Kahn, 2019). Furthermore, the risk associated with natural disasters is intricately linked to specific properties

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[3] Climate change: the CMBS angle, Financial Times Oct 28, 2019.

and mortgages within the large, geographically diversified pools that constitute CMBS, further complicating the assessment of climate risk.

Thus, two key issues emerge in the context of climate risk and its impact on commercial mortgage debt: firstly, whether mortgage lenders and CMBS sponsors are inclined to transfer default risk due to climate shocks by securitizating and selling bundled mortgage loans, the so called "lemon" problem; secondly, whether the risk retention rule mandated by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, which requires sponsors to retain at least 5% of the credit risk of the assets they securitize, will help to solve the "lemon" problem by reducing the propensity for risk transfer.

There is still a lack of empirical evidence on some of these questions. In the context of residential mortgages, Ouazad and Kahn (2019) discovered a significant increase in mortgage securitizations for loan amounts just below this limit following a billion-dollar natural disaster. In our study, we shift the focus to commercial mortgage-backed securities, and use the 2017 risk retention rule as a treatment that reduces the information asymmetry and aligns the interest. If a "lemon" problem exists in the CMBS market concerning the "hidden" climate risk, we would expect that CMBS loans without risk retention requirements would be subjected to a higher exposure to climate risk. In other words, the risk retention rule would incentivize CMBS issuers to allocate their loans from high-risk areas to low-risk areas. Consequently, the default risk stemming from climate hazards significantly decreases in retention loans.

Figure 1 compares the geographic allocation of loans in CMBS with and without risk retention requirements. We compared the average number of CMBS loans per year located in zip codes with the highest and lowest climate risk before and after the enforcement of risk retention rules (December 24th, 2016). Zip codes with the highest (lowest) climate risk are defined as the

25% of zip codes with the highest (lowest) ex-post hurricane and tornado risks (Panel A); ex-ante future flood risk (Panel B); and ex-ante sea level rising risk (Panel C). The detailed definitions of the three types of climate risk are provided in Section 3.2. Given that agency CMBS, which are loans pooled by government-sponsored entities, are exempt from the requirement, we used the loans securitized in agency CMBS as a control group. Consequently, we illustrated the geographic location of four groups of loans: agency CMBS loans before and after 2017, and non-agency CMBS loans before and after 2017.

As illustrated in Figure 1, agency loans experienced a dramatic increase after 2017 and have already surpassed the volume of non-agency loans. Taking the ex-post hurricane and tornado risk (Panel A) as an example, the annual volume of agency loans in low-risk zip codes is nearly twice that of non-agency loans. In high-risk zip codes, the volume is 10% higher than that of non-agency loans. Before 2017, non-agency loans exhibited a higher volume than agency loans. In low-risk areas, after 2017, the volume of both agency and non-agency loans increased by 103% and 16%, respectively. In contrast, in high-risk areas, the volume of agency loans increased by 89%, but the volume of non-agency loans decreased by 15%. Similar findings are obtained when future flood risk and rising sea level risk are used as measurements. The risk retention loan volume in areas with the highest flood risk and rising sea level risk also declined by 7.7% and 0.1%, respectively. Meanwhile, for loans without risk retention requirements (agency CMBS loans), the loan volume in the high risk areas increased. It appears that risk-retention deals tend to avoid high-risk areas. However, the loan gap in high-risk areas resulting from the shrinkage of risk retention loans is filled by agency loans. This aligns with the observation of increased securitization volume in agency CMBS in the years following billion-dollar disasters (Ouazad and Kahn, 2019).

Figure 1 about here

Our analysis is based on historical data from 18 billion-dollar hurricane disasters and 105 billion-dollar tornadoes and severe storms, along with property location information from 40,175 loans securitized in 556 CMBS deals issued between 2011 and 2018, and distributed between 2011 and 2020. This comprehensive dataset enables us to quantify the climate hazard exposure of both the individual commercial real estate (CRE) loans and CMBS deals, allowing a comparative examination of the decisions made by CMBS loan originators and underwriters in regard to risk transfer.

Utilizing the enactment of the Dodd–Frank Act (DFA, 2010) as the treatment and employing several difference-in-differences methods, our empirical findings provide evidence of the sale of 'lemons' in the CMBS market due to a lack of interest alignment. Thus, this paper provides additional evidence for the 'Skin in the Game' theory in complex financial innovations such as asset-backed securities. A substantial body of empirical literature has documented that the relatively poorer performance of securitized loans can be attributed to asymmetric information between investors and loan originators. (Keys et al., 2010, An et al., 2011, Loutskina and Strahan, 2011, Purnanandam, 2011, Demiroglu and James, 2012). We observed significantly higher exposure to high climate risk areas in CMBS deals without risk retention requirements and a higher default risk associated with climate hazards. Additionally, in the absence of risk retention, CMBS loan originators are more likely to expedite the sale of loans impacted by climate shocks before the securitization process, and CMBS underwriters do not thoroughly assess climate risks. Conversely, for loans subject to risk retention, underwriters are less likely to originate loans affected by climate. Retention deals tend to have lower geographic exposure to climate hazards by shifting the loan allocation from high-risk areas to low-risk areas.

These findings also provide empirical evidence of the effectiveness of the risk retention rule in mitigating the climate hazard exposure of CMBS loans. Risk retention requirements serve as incentives for underwriters to actively assess and mitigate climate risk, thus reducing their exposure to climate-related hazards. This aligns with the argument that retention can mitigate the information asymmetry between investors and loan originators, albeit at the cost of underwriting fewer loans in areas with a higher risk of climate-related hazards.

Furthermore, our study also contributes to the literature on the pricing of climate risk in mortgages. Although substantial evidence indicates that natural disasters can lead to financial losses for mortgage lenders, it is still unclear whether the exposure to climate hazards has been factored into mortgage loans and, more importantly, into CMBS deals[4]. To assess the impact of climate related events, this study extends the climate hazard events to include 18 high-impact hurricanes and 105 severe storms and tornados, collectively accounting for 80.0% of the total damages caused by all billion-dollar weather and climate disaster events. This approach allows the study to assess the impact of climate hazards on loan performance more comprehensively. This is important because, as shown in previous literature (e.g.,Holtermans et al. (2023)), the impact of climate hazards on real estate value and mortgage performance varies across different events,

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[4] The risk factors and the pricing of these factors for CMBS have attracted a lot of attention from researchers. One strand of literature focuses on the incentives, experience, and financial performance of issuers, underwriters, and credit rating agencies (Titman and Tsyplakov, 2010, Guettler et al., 2011, Black et al., 2012, He et al., 2012, An et al., 2015, Flynn and Ghent, 2018, Eichholtz et al., 2023), and even the creditworthiness of borrowers (Longstaff, 2005). Other literature studies the risks associated with loan and deal characteristics, such as deal complexity (Childs et al., 1996, Furfine, 2014), tranche structures (Begley and Purnanandam, 2016), documentation requirements (Frame, 2018), current loan to value ratio (Kau et al., 2009), property characteristics (sustainability) (An and Pivo, 2015), and more. Additionally, macroeconomic conditions, such as interest rates (Boudoukh et al., 2015), macroeconomic-driven prepayment (Chernov et al., 2018), market efficiency (Christopoulos et al., 2008), and many other factors have also been documented in the literature. However, the impact of climate hazards has not been explored, especially at the CMBS deal level.

depending on the area and time. Thus, relying on one or two events as case studies may either underestimate or overestimate the impact due to the specific characteristics of those events.

We have found that climate hazard exposure has been factored into CMBS deals, as the deal yield spread shows a significant increase in response to climate shocks affecting underlying assets. Furthermore, we find a significant decrease in the climate hazard exposure premium for retention deals, which can be explained by the reduced geographic exposure to climate hazards. Consequently, risk retention rules can have a price advantage due to the reduced risk. This is different from previous literature, which has shown that risk retention increases the cost of debt (Furfine, 2020), but consistent with the findings by Agarwal et al. (2021), which confirms the price advantage of retention loans. However, our study focuses on the pricing of climate hazards.

The rest of the paper is organized as follows: In Section 2, we review the related literature and develop hypotheses. Section 3 describes the data. Section 4 presents the empirical results. Finally, Section 5 provides the conclusion.

2 Literature Review and Hypothesis Development

2.1 Overview of CMBS and Dodd-Frank Act

The intricate process of aggregating mortgages and issuing a CMBS involves several key participants. Firstly, the loan originator analyzes a borrower's commercial loan application and determines their suitability for financing. They initiate the underwriting process to evaluate the property's debt capacity. Following this, the borrower and lender agree on the loan terms, and the mortgage is originated. Then, the CMBS issuer gathers many such mortgages and places them into a trust. These loans are chosen to meet various criteria, including the total loan portfolio size, geographic distribution, and mortgage risk profiles. The CMBS issuer aims to build a portfolio of loans backed by properties with reliable cash flow and a minimum of additional protection for the top-rated AAA tranches. The third key participant is the rating agency, which assigns ratings and establishes the required levels of protection within the CMBS waterfall structure. Subsequently, the pool is securitized, and a CMBS deal is offered to investors.

With the various participates and complex structure, CMBS creates distance between loan's originator and the the party assuming the loan's default risk. The practice of passing loans through securitization markets reduced the originating lenders' incentives to screen and assess the quality of the loans rigorously (Petersen and Rajan, 2002, Eichholtz et al., 2023). This potential moral hazard issue can lead to concern over the "originate-to-distribute" model derives from theories of financial intermediation (Longstaff, 2005, Ashcraft and Schuermann, 2008, Purnanandam, 2011, Ghent et al., 2019). Therefore, reputation concerns, regulatory oversight, or sufficient balance sheet risk are necessary to prevent moral hazard on the part of lenders (Keys et al., 2010). On the other hand, the literature also argues that, unlike the portfolio lenders, the CMBS lenders lack the capacity and motivation to gather private information regarding loan quality. Consequently, conduit lenders have the potential to help resolve the problem of "lemons" in the selection of loans for sale in securitization markets by portfolio lenders (An et al., 2011).

To address the moral hazard issue in the "originate-to-distribute" model, Dodd-Frank Act introduced fresh regulations governing aspects of mortgage origination, securitization, and investment. A key feature of this legislation was the introduction of a "Risk Retention Rule" for those issuing CMBSs. The rationale behind this rule was to ensure that the creators of securitization deals had a vested interest aligned with investors (Demiroglu and James, 2015). This rule mandates that sponsors retain 5% of the credit risk in a securitization deal. In other words, the Dodd-Frank Act aims to put skin in the game to alleviate the moral hazard problem. Indeed, previous literature has documented the Dodd-Frank Act's effectiveness in imposing tighter underwriting standards and reducing the riskiness of the CMBS loans (Furfine, 2020, Agarwal et al., 2021). On the other hand, Ashcraft et al. (2019) also document that the complexity and opaqueness in structured finance can reduce the effectiveness, because they found evidence that informed parties in the CMBS pipeline reduce their skin-in-the-game in a manner not observable to other market participants.

2.2. Climate Risk and CMBS

The effect of climate hazards on commercial real estate investment has been extensively documented in the literature. These hazards, including hurricanes, floods, wildfires, and storms, can cause physical damage and depreciation of property values (Beltrán et al., 2018, McCoy and Walsh, 2018, Ortega and Taşpınar, 2018, Eichholtz et al., 2019, Gibson and Mullins, 2020, Cvijanovic and Van de Minne, 2021, Issler et al., 2021, Miller and Pinter, 2022, Addoum et al., 2023), increase operating costs and earning volatility (Zhu and Fuerst, 2022, Holtermans et al., 2023), higher insurance premiums (Gallagher and Hartley, 2017), and reduce property demand and regulatory pressures (Roberts et al., 2015, Clayton et al., 2021). Changes in collateral value and the ability of borrowers to meet their payment obligations can influence mortgage delinquency. Given the documented adverse impact of climate hazards on the property value and operating income and costs, we would expect that the climate risk should affect the CMBS performance. Indeed, focusing on the impact of Hurricanes Harvey and Sandy, Holtermans et al. (2023) find evidence that climate risks increase mortgage delinquency rates for commercial real estate mortgages. However, focusing on the residential buildings in California from 2001 to 2015, Issler et al. (2021) also find that most of the effects of wildfire on mortgage termination do not come from default. Rebuilding codes and the post-wildfire effects on rebuilt houses, essentially extinguish the default option for most borrowers. This indicates other options for mortgage termination after climate disasters.

On one hand, there is growing evidence indicating that natural disasters can lead to financial losses for mortgage lenders. On the other hand, since the impact of these disasters varies significantly among different neighborhoods at the local level, as demonstrated by studies such as (Masozera et al., 2007, Vigdor, 2008, Holtermans et al., 2023), the screening of mortgages may not fully take into account the risk of natural disasters. Because the risk of natural disasters is tied to specific properties and mortgages within large pools in CMBS, it's possible that local lenders, armed with more precise information about the local impact and occurrence of such disasters, may securitize mortgages with higher, but less observable, risk. Indeed, Ouazad and Kahn (2019) discovered a significant increase in mortgage securitizations for loan amounts just below this limit following a billion-dollar natural disaster. They also observed that this increase is more pronounced in neighborhoods where the disaster is considered 'new news', suggesting lenders may become more aware of local risks.

2.3. Hypothesis Development

In context of the 'originate-to-distribute' model, there is a potential risk for moral hazard, as loan originators may lack the incentive to thoroughly scrutinize the loans they issue. Adding to this challenge, climate risk, being less observable and often hidden, is more likely to be shifted onto other participants within the CMBS market. However, having skin in the game in place, such as regulatory oversight and sufficient balance sheet risk, can curtail this risk transfer. Specifically, in CMBS transactions involving risk retention, issuers are likely to perform more rigorous loan assessments and reduce their balance sheet exposure to climate risk. Given the uncertainties of the impact of climate related disasters, CMBS sponsors may reduce their exposure to climate hazards, often favoring loans associated with a lower level of climate risk for underwriting. This leads to our first hypothesis:

Hypothesis 1: The Implementation of risk retention rule incentivizes CMBS sponsors to assess loan risks more thoroughly, thereby reducing their exposure to climate related hazards.

Considering the negative impact of climate hazards on collateral value and operational performance of commercial real estate, it is expected that the default risk will increase with higher levels of climate risk. Therefore, CMBS deals with greater exposure to climate hazards are likely to demand a higher risk premium. The inclusion of climate hazard exposure in pricing further indicates that originators and issuers recognize the potential impact of climate hazard. This supports the moral hazard argument in Hypothesis One, leading to our next hypothesis:

Hypothesis 2: Climate hazard exposure is reflected in the pricing of CMBS deals.

3 Data

3.1 CMBS Loans

Our data on the CMBS loan database comes from the Trepp database, which is a major data provider for all CMBS issued in the US. Trepp provides detailed information on each CMBS transaction at the deal, loan, and property levels. Nationally, the loan dataset covers 106,969 loans, pooled into some 1,200 deals, since 1965 (Holtermans et al., 2023). Those loans represent about USD 1.14 trillion in commercial mortgages. At the deal level, we collect detailed information such as issuance date, the underwriter, the deal dollar balance, weighted average debt coverage ratio at securitization and distribution, weighted average loan-to-value ratio at securitization and distribution, weighted average maturity at securitization and distribution, weighted average coupon rate at securitization and distribution, and the deal type, among other details. At the loan level, we extract information on the origination year, the originator, debt coverage ratio, loan rate, loan term, and delinquency status, among other factors. At the property level, we obtain information on location, property type, built year, property value, net operating income, occupancy, and more.

We restrict our sample to CMBS issued from January 2011 to December 2018. To observe the loan performance, we collect the performance data during each distribution period of the CMBSs from January 2011 to April 2020[5]. To make sure the loan can be tied to a specific location for analytical purposes, we exclude loans with multiple assets and multiple originators. However, it should be noted that CMBS deals can include loans on multiple assets at multiple locations. After removing missing data, our sample includes 47,102 loans securitized in 556 deals. Table 1 reports the summary statistics. The mortgages in these deals were originated over the period from 2010 to 2018. Around 68% of the mortgages are collateralized by multifamily houses, followed by retail properties (11.3%) and office buildings (5.0%). The average time lag between loan origination and securitization is 5.108 months, with a standard deviation of 5.087 months. The time lag for some mortgages is several years. The average loan rate at securitization is 4.3%, ranging from 1.1% to 10.39%. The loans have an average debt-to-coverage ratio of 2.152, an average loan-to-value ratio of 66.2%, an average occupancy rate of 93%, and an average loan term of 118 months. In our loan sample, 10.6% of loans are interest-only loans. Moreover, the distribution of the built years is relatively equal. Nearly 20% of the properties were built between

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[5] We conclude our sample analysis in April 2020 because loan performance was significantly impacted by the Covid-19 pandemic. Policies like the CARES Act, which included a foreclosure moratorium and offered mortgage borrowers options to temporarily suspend payments during the pandemic, also played a role in the termination of the loans. Consequently, our investigation focuses exclusively on the period preceding the pandemic.

1980 and 1990, and 15% were built between 1970 and 1980. In our sample, the 556 CMBS are underwritten by 24 underwriters, and loans originated from 150 different institutes. 16.9% of them are originated and underwritten by the same institution from origination to securitization. 24.5% of the loans were originated by one of the 24 underwriters. In other words, 74.5% of the loans were originated by non-underwriters.

Over time, 0.4% of these loans were reported in a 90 or more days delinquency, foreclosure or ROE status. The average net operating income at the distribution is 2.61 million USD, the average debt service coverage ratio is 2.03, the average loan-to-value ratio is 72.7%, the average occupancy rate is 91.0%, and the average loan rate remains at 4.9%. The total number of establishments in the zip code where the property is located in the distribution year is 34,527 on average, and the average Herfindahl index for business concentration is 16.5%.

Table 1 here

At the deal level, on average, CMBS deals have an initial AAA subordination rate of 28.3%, indicating that if $1 billion USD in CMBS securities are issued in a deal, $717 million are senior securities that are rated AAA, and the remaining $283 million are junior in priority to the AAA securities and have lower ratings. Besides, the weighted average initial coupon rate at securitization is 4.5%, the weighted average initial loan-to-value ratio is 59.3% on average, and the weighted average initial debt service coverage ratio is 2.32. The weighted average occupancy rate is 93.3%, and the term to maturity is, on average, 108 months. These figures are very similar to the loan-level analysis. The slight difference is due to the weighting scheme used in the CMBS deals.

Table 2 here

To study the impact of the risk retention rule, we compare the underwriting standards and performance for loans that may be under the risk retention rule and loans that are not. For deals securitized after 24th December 2016, they are subject to the risk retention rule, which requires securitization sponsors to retain not less than a 5% share of the aggregate credit risk of the assets they securitize. On the other hand, some deals, especially securities issued with a guarantee of timely principal and interest by a Government-Sponsored Enterprise (GSE) such as Fannie Mae or Freddie Mac, are exempt from the rule. While the GSEs are primarily recognized for their involvement in residential mortgage securitization, they also support the securitization of commercial mortgages linked to properties like apartment complexes, mobile home parks, healthcare facilities, and assisted living communities loans, known as "qualified commercial real estate (QCRE) loans" can receive an exemption from the regulations. These loans, which adhere to specific underwriting criteria, are also not subject to any risk retention requirements. As documented by Furfine (2020), approximately 4% of non-agency backed securitized commercial mortgages would seem to satisfy the conditions necessary to be classified as QCRE loans. Thus, a majority of the exemption deals are agency CMBSs. In our sample, 23% of the deals are subjected to risk retention requirements, and 81% of deals are categorized as non-agency deals.

3.2 Geographic Exposure to Climate Hazards

Our assessment of geographic exposure to climate hazards is based on the FEMA national risk database. Since the Trepp database reports the zipcode of the property, we consider the zipcode level climate hazards, measured by the ex-post estimated annual loss ratio for buildings in the zipcode :

$$ED_m^{HT} = \phi_m^H f_m^H + \phi_m^T f_m^T, \tag{1}$$

where ED_i^{HT} is the ex-post estimated annual loss ratio for hurricane and tornado hazards in zipcode m. ϕ_m^H and ϕ_m^T are the estimated percentage of the exposed building value (for all types of buildings) that is expected to be lost due to climate hazard occurrence. We consider the total historical building loss ratio for hurricanes, riverine flooding, and sea level flooding as the potential damages for hurricane events (ϕ_m^H). And we use the historical building loss ratio for hazards, including lightning, strong winds, and tornados, as the measurement for the potential damage caused by storms and tornados (ϕ_m^T). f_m^H and f_m^T are the FEMA-estimated zip code-level ex-post projected annual frequency for hurricanes, riverine flooding, sea level flooding (f_m^H) as well as lightning, strong winds, and tornados (f_m^T). We use ED_m^{HT} to quantify the asset allocation decision made by the CMBS issuers because CMBS issuers or investors will make their decisions based on the FEMA-predicted ex-post climate risk likelihood.

Figure 1A presents the zip code-level ex-post estimated annual loss ratio. We classify these zip codes into four quantiles, ranging from the 25% of zip codes with the lowest annual loss ratio (Q1) to the 25% with the highest annual loss ratio (Q4). The colors red, orange, yellow, and green represent the 25% of zip codes with the highest risk (Q4) to the lowest risk (Q1). Areas such as the Gulf Coast of Florida, the Pacific Northwest, and the eastern coasts of New Jersey and Maryland face elevated risk levels, which are primarily attributed to hurricanes. Similarly, some areas in the Mideast exhibit heightened loss ratios, which could be largely attributed to tornadoes. The ex-post annual loss ratio is not solely influenced by the frequency of natural hazards but also by the capacity of building structures to withstand an adverse event.

One concern about the aforementioned climate hazard may be that it relies on the ex-post estimated risk rather than forward-looking risk. Due to data limitations, we are not able to quantify the future risk for all hurricanes and strong wind-related hazards. Thus, we provide additional results based on two specific future risk: flooding risk and sea level rising under the high emissions 'RCP8.5' global warming scenario in the late century. The data is obtained from Climate Mapping for Resilience and Adaptation (CMRA).[6] The flood risk is measured by the annual number of days with precipitation exceeding the 99th percentile, calculated relative to the 1976-2005 average. We classify zip codes into four groups based on the severity of this risk, ranging from the areas with the lowest number of days (Q1) to the highest number of days (Q4). Figure 1B illustrates the zipcodes under different levels of future flood risk. Regarding the rising sea level risk, it is quantified as the percent area impacted by a one-meter sea level rise by 2100. We divide the zip codes into two distinct categories: zip codes subjected and not subjected to sea level rise risk under the high emissions 'RCP8.5' global warming scenario in the late century. The areas at risk of rising sea levels are illustrated in red in Figure 1C.

Figure 2 here

Figure 3 displays the distribution of securitized loans at the zip code level. The colors on the map represent the number of the properties. White color indicates that there are no buildings within that zip code. Firstly, it is evident that our CMBS loans hold assets across the US, except for mountainous areas in the West. Moreover, the bulk of loan assets are concentrated in the New England, Middle Atlantic, and South Atlantic regions. Following closely are cities in the East South Central and East North Central regions. Thirdly, RE firms' assets exhibit significant concentration not only in traditional gateway cities such as San Francisco, Los Angeles, Chicago, Miami, New York, Boston, and Washington, DC, but also in emerging gateway cities like Seattle, Dallas, Houston, Atlanta, Denver, Phoenix, and others. As reported in Table 3, CMBS deals have

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[6] CMRA was developed as part of an interagency partnership working under the auspices of the U.S. Global Change Research Program (USGCRP) and with guidance from the U.S. Federal Geographic Data Committee (FGDC). The project was funded by the Department of the Interior (DOI) and National Oceanic and Atmospheric Administration (NOAA). The site was developed by Esri, working under contract to NOAA.

loan portfolios distributed relatively equally across climate zones. Approximately 22.06% of loans in a deal are collateralized by properties located in the bottom quantile of zip codes with the lowest ex-post climate risk, while around 19.87% are in the top quantile of zip codes with the highest risk. In terms of ex-ante flood risk, on average, 32.90% of loans in a deal are collateralized by properties located in zip codes with the lowest future flood risk, and around 35.16% of loans are in zip codes with the highest future flood risk. Additionally, an average of 39.95% of loans in a CMBS deal are located in zip codes subjected to sea level rise risk under the high emissions 'RCP8.5' global warming scenario.

Figure 3 here

To study the underlying channel of the behavior shift in the geographic exposure to climate hazards, we investigate the impact of historically *realized* climate-related loss on the loan and CMBS performance. Although ED_m^{HT} reflects the zipcode level climate-related loss ratio, it may still suffer from the problem of unobserved confounding factors. For instance, many US coastal areas subjected to a higher historical building loss ratio, such as Miami, with a higher population concentration, more real estate investments, and a more restricted land supply, typically have higher systematic risk (Zhu and Lizieri, 2022). Thus, we use US historical hurricane and tornado tracking data to conduct a natural experiment analysis. One concern could be that hurricanes do not typically occur randomly but along relatively well-known routes (e.g., hurricane alleys). Crucially, however, for the set-up of a natural experiment, the exact locations and times of hurricane damage are not knowable in advance.

We consider 18 high-impact US hurricanes and 105 severe storms and tornados from 2011 to 2020 (with a cost of over 1 billion USD) as climate shocks. According to the billion-dollar weather and climate disaster events reported by NOAA, these events (18 hurricanes and 105 storms) accounted for 80.0% of the total damages caused by all billion-dollar weather and climate disaster events. For hurricane events, we define the hurricane-affected area as the circle within 100 miles of the hurricane eye. For tornados, we gather the data regarding the starting and ending dates as well as the influenced counties from the NOAA Storms Prediction Center. For each loan, we construct event histories from loan origination to CMBS securitization and distribution and to loan termination or the end date of data collection, whichever comes first. Figure 1 illustrates the paths of 18 hurricanes and the affected areas of 105 tornadoes and severe storms from 2011 to 2020. The yellow dots indicate areas within 100 miles of the eye of the hurricane. The depth of color in each county represents the frequency of tornadoes and severe storms in that county. A darker color indicates a higher occurrence.

Figure 1 here

The historically realized climate-related loss is defined as:

$$PD_{i,t}^{HT} = \phi_m^H Post_{i,t}^H + \phi_m^T Post_{i,t}^T, \tag{1}$$

where $PD_{i,t}^{HT}$ is the hurricane and tornado hazards for loan on asset i in period t. $Post_{i,t}^H$ and $Post_{i,t}^T$ represent the building was affected by one of the 18 hurricane events and one of the 105 tornado events. ϕ_m^H and ϕ_m^T represent the historical building loss ratio in the zipcode area of the asset, which are defined as in the previous section.

As reported in Table 3, on average, 13.3% of loans were affected by hurricanes at least once over the sample period, measured by the fact that the properties are located in the hurricane path. 7.05% of loans were affected by tornadoes and severe storms at least once, measured by the fact that the properties are located in the affected counties. In 2011, 2012, 2017, 2018, and 2020, nearly or over 20% of loans were affected by hurricane events in these years. In 2011 and 2020, 13.3 % and 14.8% of loans were affected by tornados. On average, the historical building loss ratio by hurricanes is 0.21% of buildings across all zipcodes, with the highest loss ratio of 3.4%. Tornados actually cause more substantial building damage, with an average historical building loss ratio of 9.28% and the highest loss ratio of 58.16%.

Table 3 here

4 Empirical Analysis

In our empirical analysis, we first investigate the change in the climate hazard exposure of CMBS deals and then focus on the risk-transferring behavior of CMBS loan originators and underwriters. To support these arguments, we also study the impact of climate shocks on mortgage performance, including default risk and operating income, as well as their impact on CMBS credit risk. Lastly, we investigate the pricing of climate hazard exposure in the CMBS loans.

4.1 Geographic Exposure to Climate Hazards

We first compare the climate hazard exposure of the deals with and without risk retention requirements:

$$ED_{j,t}^{Deal} = \alpha I_{j,t}^{Deal} + \delta X_{j,t}^{Deal} + \tau_t^{Deal} + \omega_j^{Deal} + \epsilon_{j,t}^{Deal}. \quad (3)$$

where $ED_{j,t}^{Deal}$ is the face value-weighted average climate exposure of deal *j* during securitization period t, with $ED_{j,t}^{Deal} = \sum_{l_j=1}^{L_j} w_{l,t} ED_l^{HT}$. $I_{j,t}^{Deal}$ is the risk retention dummy for deal *j*, equaling one if the deal is subject to the risk retention requirement. We use the risk retention flag in the Trepp database to identify loans in retention deals. Here, retention deals encompass non-agency CBMS but exclude QCRE loans. $X_{j,t}^{Deal}$ represents a set of control variables, incorporating dynamic and static mortgage attributes, property characteristics, and local economic conditions. To account for local economic conditions, we include the deal level face value-weighted total number of establishments at the zip code where the properties are located, and also the face value-weighted zip code business concentration measured by the Herfindahl index of establishments across three digital industry sectors where the properties are located. This is because previous literature has demonstrated that local economic conditions, such as population density and business concentration, can influence commercial real estate performance (Fisher et al., 2022, Liu et al., 2022). Additionally, we control for loan characteristics, encompassing the weighted average debt service coverage ratio, weighted average loan-to-value, occupancy, weighted average loan rate, loan term, and the share of interest-only loans. All these metrics are calculated over the securitization period. Following Eichholtz et al. (2019) we also include built-year vintage shares, as the vintage of buildings in certain cities, like New York, may be older than those in rapidly expanding cities. Built year categories are considered as: before 1960, between 1960 and 1970, between 1970 and 1980, between 1980 and 1990, between 1990 and 2000, and after 2000. Moreover, we consider other characteristics, such as the share of different property types, deal type dummies (including Agency CMBS, Agency Pools, Conduit, Miscellaneous, Single Assets, and others), and securitization year-month dummies.

The results are reported in Table 4, Column 1. As expected, deals under the risk retention framework show significantly lower geographic exposure to climate hazards. This supports our *Hypothesis One*: with risk retention, CMBS issuers or underwriters are motivated to reduce climate hazard exposure. Additionally, we find that the loan-to-value ratio and loan rate are positively correlated with climate hazard exposure. This confirms that deals with higher climate hazard exposure are related to higher risk and, therefore, a higher loan rate. Moreover, smaller deals tend to be subject to higher geographic exposure to climate hazards due to the lack of diversification.

We then investigate the distribution of loans across zip codes with different levels of ex-post estimated climate risk. We first sort the zip codes according to their annual loss ratio (ED_m^{HT}) and then categorize these zip codes into four quantiles, from the 25% of zip codes with the lowest loss ratio (Q1, green colored areas in Figure 1) to the 25% of zip codes with the highest loss ratio (Q4, red colored areas in Figure 1). We then replace the weighted average ex-post estimated climate hazard with the share of loans collateralized by properties located in each category of zip code areas (from Q1 to Q4). The results are also reported in Table 4, from Column Two (Q1) to Column Five (Q4). As shown in Columns One and Five, risk retention deals have a significantly higher share of loans (7.36%) in the bottom quantiles with the lowest climate risk (Q1) and a significantly lower share of loans (7.25%) in the top quantiles with the highest climate risk (Q2). Around 7% of loans in a risk retention deal were shifted from the highest-risk to the lowest-risk regions compared to non-risk retention deals. This further supports *Hypothesis One*.

Table 4 here

We also estimate the impact of risk retention requirements on the geographic exposure to ex-ante climate risk, specifically focusing on future flood risk and sea level rise risk. The results are reported in Table 5, with the first four columns addressing future flood risk (from Q1 lowest risk to Q4 highest risk), the fifth column addressing the risk of rising sea level rise, and the sixth column representing the proportion of the loans in the zip codes with the highest flood risk or sea level rise risk. As shown in Columns One and Four, the risk retention deals show a significantly higher geographic exposure (6.61%) to the zip codes with the lowest future flood risk and a significantly lower exposure (8.18%) to zip codes with the highest future flood risk. Additionally, we also find that risk retention deals show a 7.57% lower share of loans in zipcodes at the risk of rising sea levels. The exposure to the combination of flood risk and sea level rise risk is also significantly lower in risk retention deals. These findings further support our *Hypothesis One*: the presence of risk retention motivates CMBS issuers to reduce the geographic exposure to expected climate risk in their loan portfolio.

Table 5 here

We use staggered difference-in-difference methods to identify the causal impact of the risk retention rule, using agency CMBS deals as the control group. We investigate whether we can observe a significant change in geographic exposure in non-agency CMBS five quarters before and after the enforcement of the risk retention rule by running regressions:

$$ED_{j,t}^{Deal,H} - ED_{j,t}^{Deal,L} = \sum_{k=-5}^{5} \alpha_k D_k + \delta X_{j,t}^{Deal} + \tau_t^{Deal} + \omega_j^{Deal} + \epsilon_{j,t}^{Deal}. \quad (4)$$

where $ED_{j,t}^{Deal,H}$ is share of loans in deal j located in the 25% zip codes with the highest ex-post or ex-ante climate risk and $ED_{j,t}^{Deal,L}$ is the share of loans in the 25% zip codes with the lowest climate risk. For the ex-ante climate risk, $ED_{j,t}^{Deal,H}$ is based on the share of loans in zip codes with the highest future flood risk or sea level rise risk. , $ED_{j,t}^{Deal,L}$ is based on the share of loans in zip codes with the lowest future flood risk and without sea level rise risk. D_k is a dummy variable indicating whether the deal is securitized within six quarters before and after the risk retention requirement (December 24, 2016). The remaining variables are defined as in the previous section, except for τ_t^{Deal}. τ_t^{Deal} now represents the year-quarter dummies.

Figure 5 illustrates the dynamics of α_k for both ex-post climate risk (Panel A) and ex-ante climate risk (Panel B). The squares indicate the expected value of $\alpha_k$and the lines indicate a 90% confidence interval. As illustrated in Panel A, before the risk retention rule, there is no significant difference in the exposure to risky areas. However, after the risk retention rule, deals securitized in the fourth quarter exhibited a significantly lower share of loans allocated in areas with the highest ex-post climate risk (Panel A). Additionally, deals securitized in the same quarter, in the third and fourth quarters after the retention rule, show a significantly lower share of lows in areas with the highest ex-ante climate risk (Panel B). This confirms our argument that the risk retention rule incentivizes the CMBS issuers to avoid climate risk.

Figure 5 here

4.2 Warehouse Risk

To provide additional evidence, we investigate the transferring of 'warehouse risk'. If mortgages are subjected to a higher level of climate hazards, we would expect greater warehouse risk for the originators. Consequently, this should incentivize originators to expedite the mortgage packaging process for securitization. However, with risk retention rule, it is more difficult to expedite the issuing process. Hence, we study the time span between mortgage origination and CMBS issuance using a triple difference method:

$$TS_{i,t} = \alpha PD_{i,t}^{HT} + \alpha^* PD_{i,t}^{HT} I_{i,t} + \beta \phi_m^{HT} + \beta^* \phi_m^{HT} I_{i,t} + \theta I_{i,t} + \delta X_{i,t} + \tau_t + \omega_i + \epsilon_{i,t}. \quad (6)$$

where $TS_{i,t}$ is the number of months between mortgage origination and CMBS issuance. $PD_{i,t}^{HT}$ is historically realized climate-related loss of loan i within two year time up to the securitization. We follow Holtermans et al., (2022) and consider two year post event periods to reflect the fact that the economic effects of a climate shock may be persistent over a longer time period. The results based on one year or half year post-event period generate robust results. ϕ_m^{HT} is the historical building loss ratio in zipcode where the building is located, which is also defined in the previous section. $I_{i,t}$ is the dummy variable indicating whether the loan is included in the risk retention deal. $X_{i,t}$ is a set of control variables at the loan level. They are defined in the previous section, including zipcode level employment, business concentration, debt service coverage rate, loan to value ratio, occupancy rate, loan term, loan rate, and interest-only loan dummy. Property construct year dummies, property-type dummies, MSA dummies, year-month dummies, and loan originator dummies are also included.

As stated by Black et al. (2012), most CMBS originators secure warehouse financing internally or through lines of credit and repurchase agreements within their firms. However, conduit lenders, which are not affiliated with major financial categories (financial institutes, insurance companies, commercial banks, and investment banks), had limited capital and had to seek external warehouse financing. As a result, owing to the lack of warehouse risk and risk retention, conduits may have no incentive to shorten the warehouse period. Additionally, since the financing options of conduit lenders are only the subset of other major classic financial institutions, they were more restricted in financial options than other originator types, likely resulting in higher capital costs. This made it challenging for conduits to compete with other originators for low-risk borrowers, leading them to focus on riskier borrowers offering higher coupons. Consequently, conduit lenders may behave differently from classical CMBS loan lenders. Thus, we also exclude loans made by conduit lenders since they may not be subjected to warehousing risk.

The results are presented in Table 6. In Column One, we consider all loans. In Column Two, we exclude conduit lenders. As shown in Column One, climate hazard risk has a significant negative impact on the time lag between origination and securitization. If a building collateralizing the CMBS loan has been damaged by a climate disaster over the past two years, the originator will shorten the time lag by 16.50%. This confirms that if mortgages suffer from climate hazards, the originator tends to sell the mortgage quicker. Under risk retention requirements, originators are not able to shorten the warehouse period for loans that were subjected to climate shock. As shown in Column Two, the coefficient for the interaction term is significantly positive, indicating that it will take a longer time to securitize loans with a higher climate risk in the risk retention deal. This finding supports our *Hypothesis One*. With the risk retention rule, it can be more difficult to issue mortgages with higher potential risks. And since deal issues have to retain the risk, they will be more cautious on the loan selection. This is in line with previous findings that the risk retention rules have made securitized loans safer (Black et al., 2012).

Moreover, mortgages located in zipcode area with a higher business concentration, with a higher debt service coverage ratio, lower loan to value ratio, shorter loan term, and not being interest-only are sold more slowly. These findings tend to support the idea that originators sell mortgages more quickly when the mortgages are viewed as riskier. Moreover, a loan with a lower mortgage rate will also be sold quickly.

Table 6 here

4.3 Exposure to Climate Risk of Originators and Underwriters

In this section, we explore whether underwriters tend to selectively exclude risky mortgages in their own deals, especially when these mortgages have been affected by climate shocks. Thus, we consider two situations: 1) underwriters choose their own deal to underwrite, and 2) the deal is originated by non-underwriters. First, we consider whether the underwriters are less likely to choose to underwrite their own deal if the deal was affected by the climate shock. To represent this choice, we create a binary dummy variable called 'Originates for Own Deal'. This dummy takes a value of one for mortgages where the originator is the underwriter for the CMBS deal to which the mortgages are placed, and it takes a value of zero otherwise. Thus, we perform a triple difference method:

$$Prob\left(D_{i,t}^{own}=1\right)=\alpha PD_{i,t}^{HT}+\alpha^{*}PD_{i,t}^{HT}I_{i,t}+\beta\phi_{m}^{HT}+\beta^{*}\phi_{m}^{HT}I_{i,t}+\theta I_{i,t}+\delta X_{i,t}+\tau_{t}+\omega_{i}+\epsilon_{i,t} \qquad (7)$$

where $D_{i,t}^{own}$ is the ‘originates for own deal’ dummy. Other variables are defined in the previous section.

The results are presented in Table 7, Columns One and Two. As shown in Column One of Table 7, the coefficient for the interaction variable becomes significantly negative. This indicates that when the underwriter or the issuer of the deal has to bear the risk, they are more inclined to sell this mortgage with a higher climate hazard to other issuers. In other words, underwriters or issuers scrutinize mortgages more rigorously when they are required to retain the risk.

Moreover, originators tend to sell the mortgage to other investors or issuers when the mortgage has a lower debt coverage ratio, a higher loan-to-value ratio, a shorter term and a lower mortgage rate. This consists of the argument that underwriters cherry-pick safer loans and loans with a higher rate and include them in their own deal. However, we also find that underwriters are more likely to underwrite self-originated loans if the loan is under risk retention requirement. This may be explained by the fact that underwriters prefer to include their own loans into the portfolio under risk retention because of the lower information asymmetry.

Table 7 here

Second, we study whether the loan is originated by institutions that exclusively serve as originators rather than those qualified to underwrite CMBS deals. To address this, we introduce another binary variable called the 'Never Underwrit' dummy. This variable takes a value of one for mortgages originated by institutions that have never been CMBS underwriters in Trepp database and zero otherwise. We then investigate whether the underwriters or sponsors of the CMBS deals tend to cherry-pick loans with lower climate hazard exposure. Thus, we have:

$$Prob\left(D_{i,t}^{nunder}=1\right)=\alpha PD_{i,t}^{HT}+\alpha^{*}PD_{i,t}^{HT}I_{i,t}+\beta\phi_{m}^{HT}+\beta^{*}\phi_{m}^{HT}I_{i,t}+\theta I_{i,t}+\delta X_{i,t}+\tau_{t}+\omega_{i}+\epsilon_{i,t}. \quad (8)$$

where $D_{i,t}^{nunder}$ is the 'Never Underwrit' dummy. Other variables are defined in the previous section.

Table 7, Column Two reports the results for the likelihood of CMBS loans originated by non-underwriters. The coefficient for the interaction variable of climate shock and the risk retention dummy is now statistically significantly positive. When underwriters are required to retain the risk, they tend to avoid originating loans with higher climate hazard exposure. If the negative relationship between climate shock and loans originated by experienced underwriters can be attributed to adverse selection or reduced motivation for thorough loan scrutiny, the risk retention rule appears to effectively mitigate this issue. After the risk retention rule, the task of loan origination and deal issuance became more separated.

Additionally, if a loan was affected by a climate shock in the past two years, it is less likely that it originated from non-underwriters. This can be explained by the fact that institutions that can serve as the underwriters or issuers of the CMBS tend to be more experienced, have more capital capacity, and are more likely to sell the loan, given their network. Therefore, they may originate risker loans. Besides, the underwriters are typically investment banks and financial institutions, who have the option to decide whether to hold the loan in their balance-sheet portfolio or securitize the loan. This may lead to adverse selection issues, and they can choose more risky loans and put them into the CMBS deals.

Furthermore, the coefficients for the control variables also support the idea that risky loans in CMBS deals are more likely to originate from financial institutions that have the capacity to underwrite or issue the deal. In CMBS pools, mortgages with higher debt service ratios and lower loan rates are more likely to originate from non-underwriters. Loans secured by zipcode properties with a higher historical building loss ratio are more likely to originate from non-underwriters. This may be explained by the fact that non-underwriters may have less experience. However, it should also be noted that the historical building loss ratio may also correlate with other local economic factors.

Overall, the above-mentioned findings provide further evidence for our *Hypothesis One*. To further support this hypothesis, we investigate the underwriters' exposure to climate hazard risk ($\sum_{k=1}^{K_i} w_k \sum_{t_1}^{t_i} PD_{t_1,k_i}^{HT}$). In our sample, we have 24 distinct underwriters and 556 distinct deals. In total, we have 846 deal-underwriter observations. We then focus on the deal-underwriter relationship and investigate whether the underwriter changes its underwriting strategy in terms of climate hazard exposure under the risk retention framework.

We calculate the face value-weighted average geographic exposure to climate shocks two years before their next CMBS underwriting. Suppose that before the next underwriting, underwriter A had underwritten two deals in the past two years, which included 500 loans in total (k=500). For each loan, we quantify the climate hazard exposure for each loan since securitization ($\sum_{t_1}^{t} PD_{t_1,k_i}^{HT,Deal} = \sum_{i=1}^{N} w_{i,t} \sum_{t_1=1}^{t} \phi_{m_i}^{H} Post_{k_i,t_1}^{H} + \sum_{i=1}^{N} w_{i,t} \sum_{t_1=1}^{t} \phi_{m_i}^{T} Post_{k_i,t_1}^{T}$), which is based on the number of shocks ($Post_{k_i,t_1}^{H}$ and $Post_{k_i,t_1}^{T}$) that affect the building since securitization and the historical building loss ratio of all real estate in the zip code where the building is located ($\phi_{m_i}^{H}$ and $\phi_{m_i}^{T}$). It should be noted that since securitization, a loan may be affected by more than one hazard. We count the total number of climate shocks for each loan since securitization. We can convert the loan level climate shocks to the deal level by weighing the face value of the loan.

$$ED_{k,t}^{Deal} = \alpha \sum_{l=1}^{K_t} w_{l,t}^{Deal} \sum_{t_1}^{t} PD_{t_1,k_i}^{HT,Deal} + \alpha^{*} \sum_{l=1}^{K_t} I_{l,t}^{Lead} w_{l,t}^{Deal} \sum_{t_1}^{t} PD_{t_1,k_i}^{HT,Deal} + \beta \sum_{l=1}^{K_t} w_{l,t}^{Deal} \phi_{m_i,t}^{HT,Deal} + \beta^{*} \sum_{l=1}^{K_t} I_{l,t}^{Lead} w_{l,t}^{Deal} \phi_{m_i,t}^{HT,Deal} + \partial I_{i,t}^{Lead} + \delta \sum_{l=1}^{K_t} w_{l,t}^{Deal} X_{l,t}^{Deal} + \tau_k + \omega_t + \epsilon_{k,t}. \quad (9)$$

where $ED_{k,t}^{Deal}$ is geographic exposure to ex-post estimated climate hazard for a loan underwrote by underwriter *k* in period *t*, which is defined as in the previous section. We also use the share of the properties located in high-risk areas as the dependent variable. $\sum_{l=1}^{K_t} w_{l,t}^{Deal} \sum_{t_1}^{t} PD_{t_1,k_i}^{HT,Deal}$ is the climate hazard exposure of all loans previous deals in the past two years before period t by the underwriter *k*, as defined before. $\sum_{l=1}^{K_t} w_{l,t}^{Deal} \phi_{m_i,t}^{HT,Deal}$ is the face value weighted FEMA historical building loss for the loans that are underwritten by the underwriter of loan i. We also control for the face value weighted loan characteristics ($\sum_{l=1}^{K_t} w_{l,t}^{Deal} X_{l,t}^{Deal}$), including weighted average zip code level total number of establishments, weighted average the zip code level business concentration, weighted average debt service coverage ratio, weighted average loan to value, weighted average occupancy, weighted average loan rate, weighted average loan term, the share of interest only loan, the share of buildings built in different year range and the share of different types of properties. Year-month dummies and underwriter dummies are also included.

The results are reported in Table 8. We find that the climate hazard exposure of underwritten retention loans significantly negatively relates to the weighted average ex-post estimated climate hazards in the next loan that the underwriter underwrites in the risk retention deals, as shown in Column One. This indicates that when underwriters have a higher level of climate hazard exposure in the loans that they have to retain the risk, they tend to avoid loans in high-risk areas in the next deal. However, if the loan is not under the risk retention rule, in the absence of risk retention, underwriters do not intentionally reduce the climate hazard exposure in the next deal, even if the loans they underwrite are affected by climate disasters. This can be reflected by the insignificant coefficient for $\sum_{l=1}^{K_t} w_{l,t}^{Deal} \sum_{t_1}^{t} PD_{t_1,k_i}^{HT,Deal}$. When and only when the issuers have to retain the loan risk (where the underwriter is the leading underwriter of a retention loan), issuers tend to reduce the climate hazard exposure in the next loan.

If we investigate the share of loans in zip codes with different levels of climate risk, we find similar findings. The retained climate risk in the previously sponsored CMBS leads to a significantly higher share of loans in 25% of zip codes at the lowest climate risk (Q1). Meanwhile, it also significantly decreases the loan proportion in the 25% of zip codes at the highest climate risk (Q4). This further supports Hypothesis One: the presence of risk retention causes underwriters to selectively choose loans in zip codes with lower climate risk during the underwriting process.

Table 8 here

Similarly, when examining the ex-ante estimates of climate risk, the results are slightly weaker but qualitatively robust. Because the future risk only includes flood risk and sea level rise risk, we only consider the realized loss caused by hurricane events. In other words, in stead of $\sum_{t_1}^{t} PD_{t_1,k_i}^{HT,Deal}$, we have $\sum_{t_1}^{t} PD_{t_1,k_i}^{H,Deal}$, and in stead of $\phi_{m_i,t}^{HT,Deal}$, we have $\phi_{m_i,t}^{H,Deal}$ in Equation 9. As indicated in Column Five of Table 9, the realized losses resulting from hurricanes in the previously sponsored CMBS influence the loan allocation in the subsequent CMBS deal, diverting it away from areas at risk of rising sea levels. This aligns with our expectations. However, we do not observe a significant impact on the exposure to ex-ante flood risk. This can be attributed to the absence of data on historical flash-flooding events; hence, we are unable to construct a measurement of the realized loss caused by flash-flooding events.

Table 9 here

4.4 Pricing of Climate Hazard Exposure in CMBS Loans

In this section, we further investigate the pricing of climate hazard exposure in CMBS deals, with a specific focus on the spread of the initial CMBS rate. The initial CMBS rate is defined as the weighted average loan rate minus the comparable maturity Treasury rate at the time of securitization. The results of our analysis are presented in Table 10.

As indicated in Table 10, Column One, CMBS deals with a higher proportion of assets in areas with the highest future flood risk and sea level rising risk exhibit a significantly higher spread. Specifically, a one percent increase in the portfolio in high-risk areas leads to a 0.77% increase in spread. Additionally, as shown in Column Two, we observe a significant increase in CMBS spread associated with a higher proportion of assets in areas with the highest ex-post climate risk. The premium for a one percentage point increase in assets in these high ex-post risk areas is 0.56%. As anticipated, our analysis reveals no significant increase in loan spread attributable to climate hazard shocks occurring before the securitization process (Columns Three and Four). Events preceding the securitization are not factored into the pricing of securities.

If we interact the climate shock variables with the retention loan dummy, the coefficient for the interaction variable between shares of assets in high ex-ante flood and sea level rising risk and the retention variable is statistically significantly negative, as shown in Column Five, Table 10. The risk retention rule reduces the borrowing cost of CMBS loans caused by ex-ante climate risk, leading to a price advantage. This can be explained by the findings in the previous section, indicating that the risk retention rule incentivizes issuers to reduce climate hazard exposure. Consequently, default risk becomes less sensitive to climate shock. Thus, CMBS investors charge a lower premium for bearing that risk. This confirms *Hypothesis Two*.

Additionally, we identified that deals with loans collateralized by properties located in zip codes with lower employment, shorter terms, principal amortization, and smaller deal sizes have a higher subordination rate and/or higher spread. This aligns with our previous analysis of the loan's riskiness.

Table 10 here

4.5 Underlying Channel

4.5.1 Climate Hazard Exposure and Loan Performance

To support our argument, we further investigate whether climate hazards indeed lead to higher default risk and poorer performance of the underlying asset. To assess this impact, we collected data on loan performance in each distribution month. In total, we obtained 878,234 loan-month observations. We then conducted a regression as follows:

$$y_{i,t} = \alpha \sum_{t_1}^{t} PD_{t_1,i}^{HT} + \beta \phi_m^{HT} + \delta X_{i,t} + \tau_t + \omega_i + \epsilon_{i,t}. \quad (10)$$

where $y_{i,t}$ is the probability of over 90 day delinquency or more ($\Pr(default_{i,t})$). $\sum_{t_1}^{t} PD_{t_1,i}^{HT}$ represents the climate hazard exposure since securitization but before distribution. We also consider the Net Operating Income Ratio in distribution period t ($NOI_{i,t}$). To ease comparison, loans affected by climate hazards two years before securitization have been excluded from the sample in this analysis. After removing the loans affected by climate disasters before securitization, we are left with 837,248 loan-month observations. This is to ensure that $NOI_{i,t}$ is attributable to climate hazards occurring after securitization but before distribution. The other independent variables are defined as before, but at the time of distribution, rather than securitization.

The results are reported in Table 11. As expected, default risk increases significantly with the climate shock, as the coefficient is significantly positive. If a building is damaged by a climate hazard, the default probability increases by 3.51%. This finding is consistent with Eichholtz et al. (2019), who also found a significant increase in the default probability two years after Hurricane Harvey. Moreover, default risk decreases with a good local economy, as captured by higher employment and business diversification, and with less risky loans, as represented by a higher debt service coverage ratio, lower loan-to-value ratio, longer loan term, and principal amortizations. Moreover, default risk is positively related to the loan rate.

Additionally, we also find that the net operating income (NOI) ratio decreases significantly after the occurrence of climate hazards. The zipcode-level historical building loss ratio is positively related to changes in NOI. Good local economic conditions, such as higher employment and a more diversified business pattern, increase the NOI. A lower debt coverage ratio, higher loan-to-value ratio, and higher loan rate result in higher interest expenses and, therefore, reduce the NOI. Loans with longer terms and interest-only features tend to have a lower NOI rate. Overall, the loan level analysis confirms the transmission channel: climate shocks reduce the net operating income of the collateralized property and, therefore, increase the default risk.

Table 11 here

Again, we employ the staggered DiD method to investigate the causal effect. Figure 6 illustrates the dynamics of 90-day delinquency (Panel A) and net operating income (Panel B) six months before and nine months after the disaster event. Squares indicate the expected values, while lines represent a 90% confidence interval. We observe a significant increase in delinquency four months after the disaster events, with this rise persisting over time. Regarding property's cash flow, we also note a significant decline in net operating income during the fourth month after the event.

Figure 6 here

4.5.2 Climate Hazard Exposure and Credit Risk of CMBS

We further investigate the risk channel at the deal level by examining the credit risk of the CMBS securities. The credit risk is measured by the subordination levels of CMBS deals (An et al., 2015). We focus on the AAA subordination levels, represented as the percentage of the total

CMBS deal comprising securities rated below AAA. When rating agencies perceive mortgages in a pool as riskier, they require a higher AAA subordination level. By examining the impact of climate risk on the subordination level, we can further test our argument that issuers are aware of the climate risk. Therefore, we conduct the following analysis:

$$y_{j,t}^{Deal} = \alpha \sum_{i=1}^{N_j} w_{i,t} PD_i^{HT} + \beta \sum_{i=1}^{N_j} w_{i,t} \phi_{m_i}^{HT} + \alpha^* \sum_{i=1}^{N_j} w_{i,t} PD_i^{HT} I_{j,t}^{Deal} +$$

$$\beta^* \sum_{i=1}^{N_j} w_{i,t} \phi_{m_i}^{HT} I_{j,t}^{Deal} + \theta I_{j,t}^{Deal} + \delta X_{j,t}^{Deal} + \tau_t^{Deal} + \omega_j^{Deal} + \epsilon_{j,t}^{Deal}. \qquad (11)$$

$y_{j,t}$ represents the AAA subordination rate at the securitization period t. It should be noted that since only 437 deals report AAA subordination rate, the observation in this section is reduced to 437 deals, and all of them are non-agency deals. $\sum_{i=1}^{N_j} w_{i,t} PD_i^{HT}$ denotes the weighted average realized climate-related loss two years before the securitization, as measured by previous events multiplied by the historical building loss ratio given this type of hazard for loan j. N_j is the number of loans in deal j. $\sum_{i=1}^{N_j} w_{i,t} \phi_{m_i}^{HT}$ represents the face-value weighted deal-level historical building loss ratio for the zip code where the building is located. $I_{j,t}^{Deal}$ is the risk retention deal dummy. $X_{j,t}^{Deal}$ represents the face-value weighted deal-level loan characteristics, as defined in the previous section.

The results are presented in Table 12. As depicted in Table 12 Column Two, deals with more loans affected by climate disasters before the securitization show an increased AAA rate. However, in the risk retention deal, the increase in the credit risk due to the climate risk is reduced, as the coefficient for the interaction variable is significantly negative. Additionally, we also find that a higher subordination rate is associated with risker loans, as captured by a lower debt service coverage ratio and shorter loan terms, but it increases with principal amortization. Moreover, the AAA subordination rate also increases with deal size. Overall, the analysis confirms our assumptions that climate hazards increase loan risk and are reflected in the subordination levels of CMBS deals.

Table 12 here

5 Conclusions

Although the impact of climate risk on stock prices has been extensively studied, there remains a surprising lack of evidence regarding debt securities, such as mortgages and securitized mortgages. This paper focuses on climate risk and aims to provide new evidence on the moral hazard problem in the 'originate-to-distribute' model within CMBS securities. Using historical data from 18 billion-dollar hurricane disasters and 105 billion-dollar tornadoes and severe storms, in addition to property location information from 41,701 loans securitized in 556 CMBS deals issued between 2011 and 2018 and distributed between 2011 and 2020, we investigate the impact of climate shocks on the warehouse period, the climate hazard exposure of underwriters, loan performance, as well as the implications of the 2017 risk retention rule.

We find that the risk retention rule motivates the CMBS issuers to avoid loans collateralized by properties located in high-climate risk areas, as the risk retention deals show significantly lower geographical exposure to zipcodes with high ex-post estimated climate hazards. This finding can further be supported by the risk-transferring behaviors in the CMBS issuers and originators. Without the risk retention rule, CMBS loan originators tend to expedite the sale of loans impacted by climate shocks before securitization. However, in the case of retention deals, originators cannot accelerate the packaging and issuance of such loans. With risk retention, underwriters are less likely to originate loans affected by climate shocks compared to non-underwriters. They are also less inclined to include loans impacted by climate shocks in their retention deal portfolios. The exposure of underwriters to climate hazards, as measured by the share of loans in their sponsored retention deals, significantly reduces the geographic exposure to ex-post estimated climate hazard risk in future loans they underwrite.

The shift in loan originators' and underwriters' behavior indicates a more rigorous loan screening process due to the risk retention rule. Our empirical results indeed show that having 'skin in the game' incentivizes underwriters to carefully assess climate risk and avoid exposure to climate hazards. Consequently, the default risk associated with climate hazards significantly decreases in retention loans. These deals can also benefit from price advantages because the risk premium related to climate hazard shocks (0.0294% per 1% increase in climate hazard) is offset in the risk retention deals.

Our study supports the moral hazard concerns associated with CMBS deals, especially concerning less observable and hidden risks, such as climate hazards. Without risk retention, participants tend to shift this risk to others. Retention can help alleviate the information asymmetry between investors and CMBS issuers, effectively reducing CMBS loans' risk, such as climate hazard exposure, and improving loan performance. This finding underscores the importance of having a stake in the 'originate-to-distribute' finance structure to align the interest between investors and CMBS issuers.

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Figure 1: CMBS Loan Allocation across Zip Code Areas with High and Low Climate Risks

Figure 1A: Number of Loans Allocated in Zipcodes with High and Low Hurricane and Tornado Risk

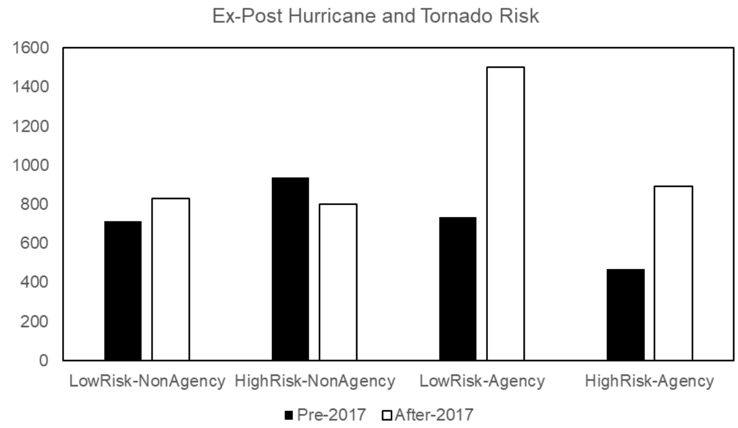


Figure 1B: Number of Loans Allocated in Zipcodes with High and Low Future Flood Risk

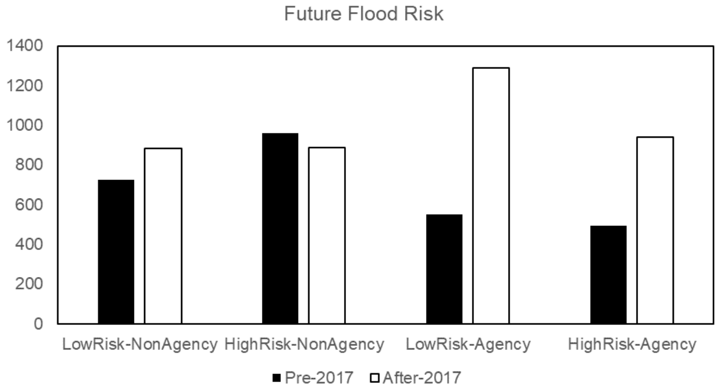
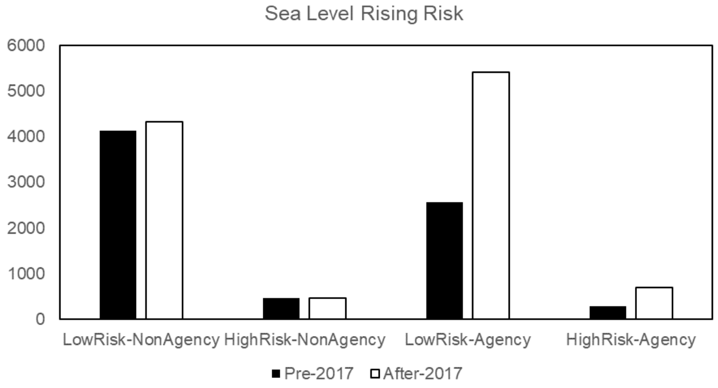


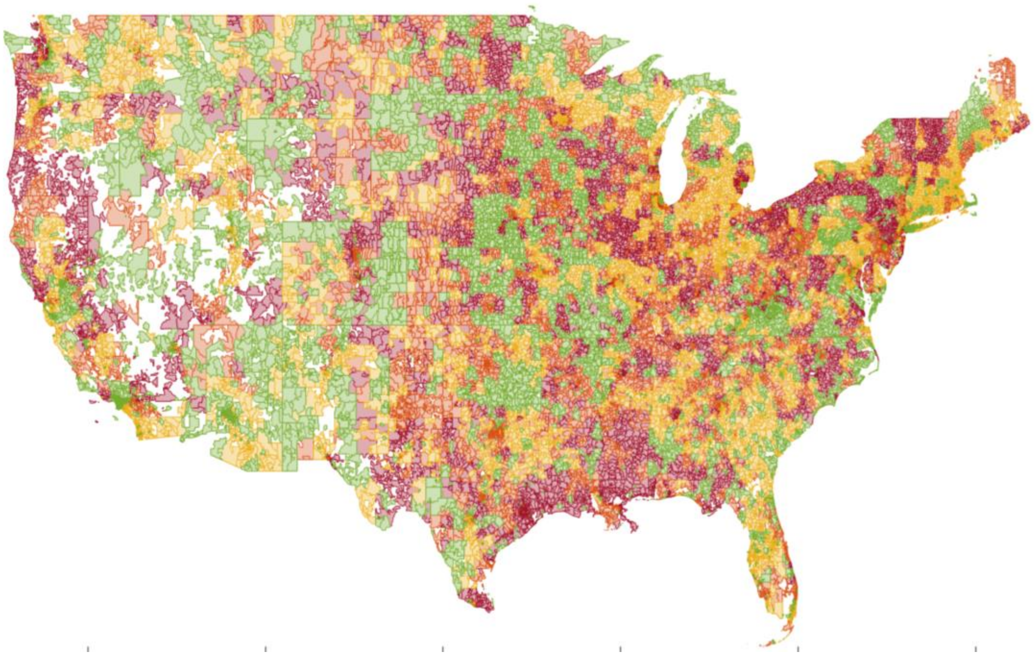
Figure 1C: Number of Loans Allocated in Zipcodes with High and Sea Level Rising Risk



Note: Figure 1A presents the FEMA National Risk zip code-level ex-post estimated annual loss ratio for hurricane and strong wind related hazards. Figure 1B is based on annual number of days with precipitation exceeding the 99th percentile, calculated with reference to the 1976-2005 average under 'RCP8.5' global warming scenario in the late century. Figure 1C is based on the percent area impacted by one meter sea level rise by year 2100 under 'RCP8.5' global warming scenario. We classify these zip codes into five quantiles, ranging from the 25% of zip codes with the lowest loss ratio (Q1) to the 25% with the highest loss ratio (Q4). The colors red, orange, yellow, blue, and green represent the 25% of zip codes with the highest risk (Q4) to the lowest risk (Q1).

Figure 2: Climate Hazards across Zip Code Areas

Figure 2A: Ex-post Estimated Annual Loss Ratio related to Hurricane and Strong Wind



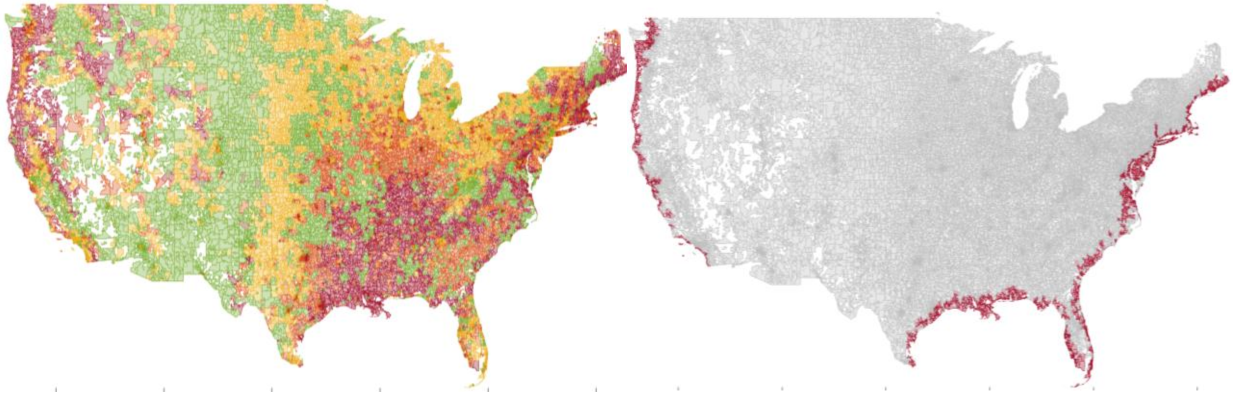
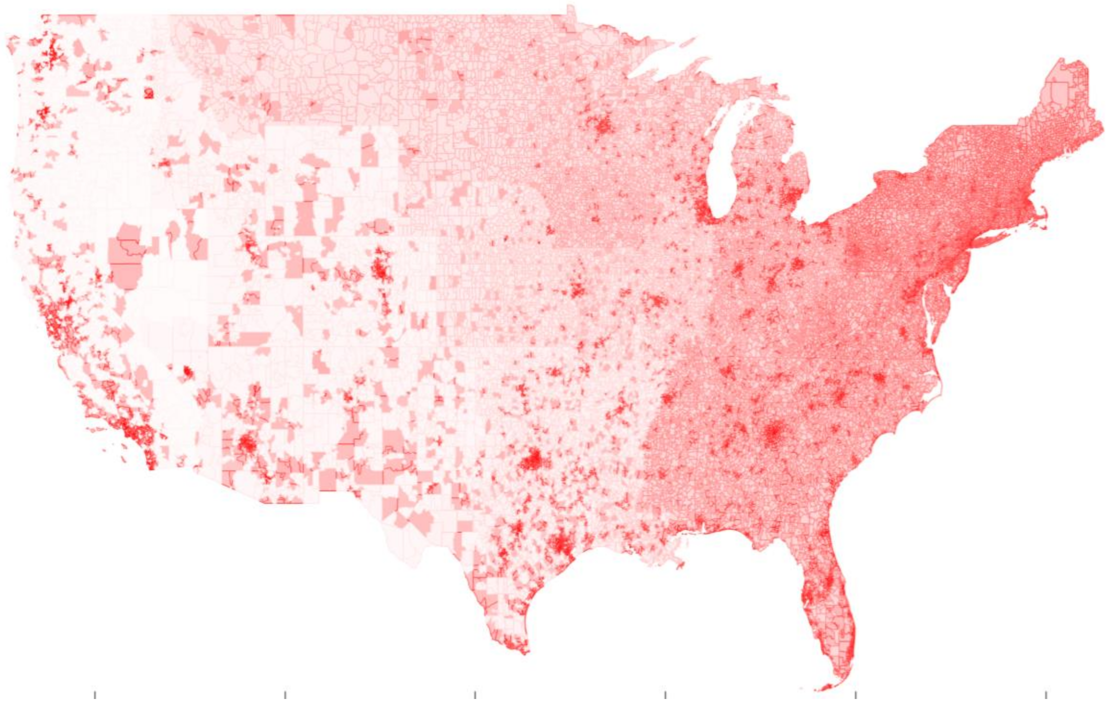


Figure 2B: Flood Risk under the High-Emissions Global Warming Scenario in the Late Century

Figure 2C: Sea Level Rise Risk under the High-Emissions Global Warming Scenario in the Late Century

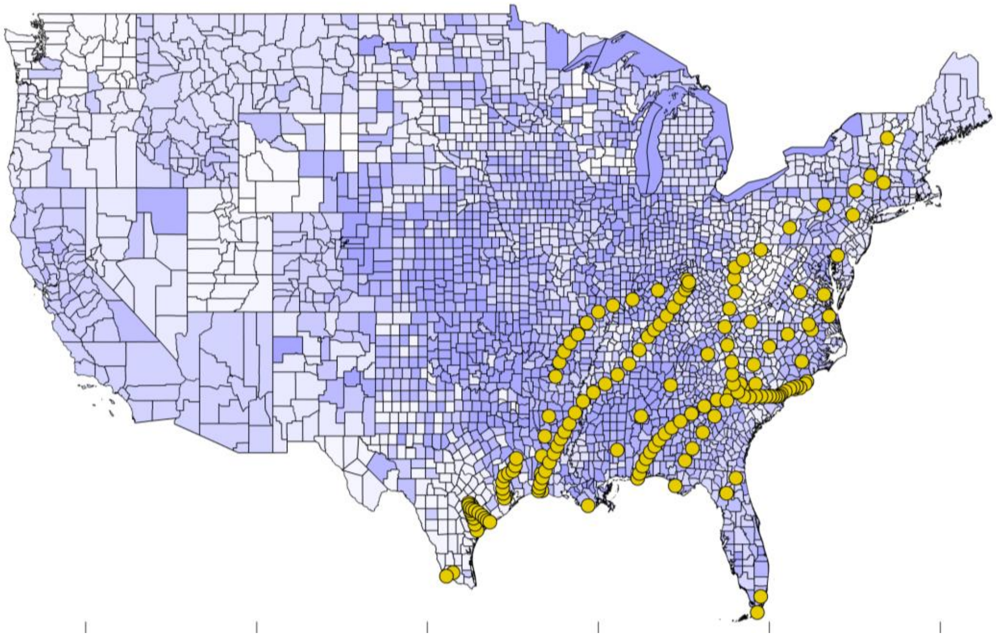
Note: Figure 2A presents the FEMA National Risk zip code-level ex-post estimated annual loss ratio for hurricane and strong wind related hazards. Figure 2B is based on annual number of days with precipitation exceeding the 99th percentile, calculated with reference to the 1976-2005 average under 'RCP8.5' global warming scenario in the late century. Figure 2C is based on the percent area impacted by one meter sea level rise by year 2100 under 'RCP8.5' global warming scenario. We classify these zip codes into five quantiles, ranging from the 25% of zip codes with the lowest loss ratio (Q1) to the 25% with the highest loss ratio (Q4). The colors red, orange, yellow, blue, and green represent the 25% of zip codes with the highest risk (Q4) to the lowest risk (Q1).

Figure 3: Number of Properties as the Collaterals of CMBS Loans across Zip Code Areas



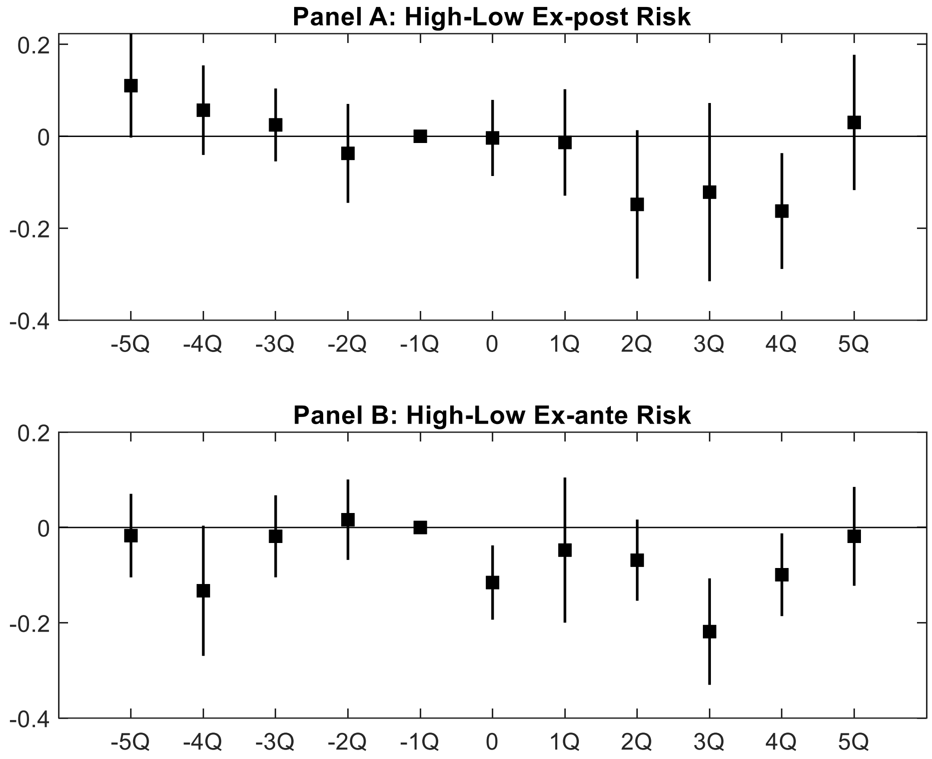
Note: this figure shows the distribution of properties as the collateral of mortgages in the CMBS issued between 2013 and 2018. A darker color signifies a higher number of properties in t

Figure 4: Paths of 18 Hurricanes and Affected Counties by 105 Tornadoes



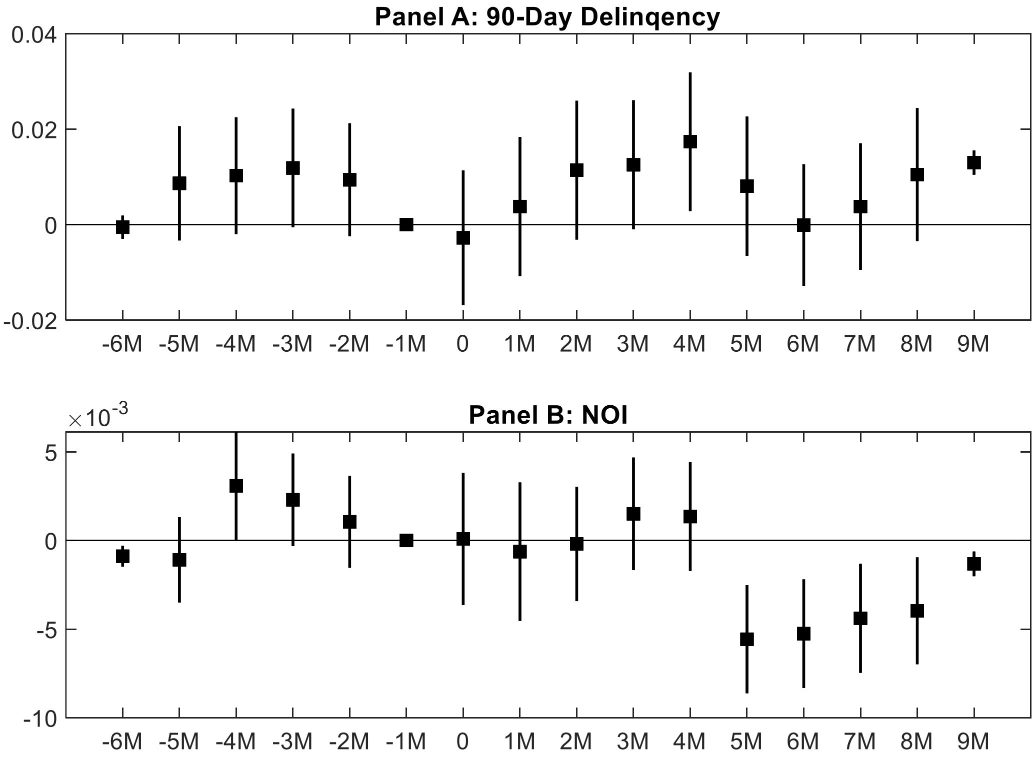
Note: This figure illustrates the paths of 18 hurricanes (yellow dots) and the starting points of 105 tornadoes (blue dots) with costs exceeding 1 billion USD from 2011 to 2020. The yellow dots represent the affected area within 100 miles from the hurricane's eye. The affected area by tornadoes is determined based on the counties reported by the FEMA database.

Figure 5: Shifts in Geographic Exposure to Climate Hazard



Note: This figure illustrates the disparity in loan shares between high and low climate risk areas. In Panel A, high climate risk areas are defined as the top quantile (25%) zip codes with the highest ex-post climate risk, while low-risk areas consist of the bottom quantile (25%) zip codes with the lowest ex-post climate risk. In Panel B, high climate risk areas are identified as the top quantile (25%) zip codes with the highest ex-ante flood risk or sea level rise risk under a high-emissions global warming scenario in the late century. Conversely, low-risk areas comprise the bottom quantile (25%) zip codes with the lowest future flood risk and no sea level rise risk. The squares indicate the expected value of α_k and the lines indicate a 90% confidence interval.

Figure 6: Impact of Hurricanes and Tornados on Mortgage Delinquency and NOI



Note: This figure illustrates the coefficient from six month before the natural disaster to nine month after the disaster in staggered DID. The squares indicate the expected value of α_k and the lines indicate a 90% confidence interval.

Table 1: Summary Statistics of Loans

Loan Characteristics				
Year			# Mortgage Origination	# Mortgage Securitization
2010			911	-
2011			2709	2323
2012			3744	3348
2013			4918	4826
2014			6199	5345
2015			8595	7182
2016			7168	7908
2017			8787	8814
2018			4071	7356
Porperty Type			# Mortgage	% Mortgage
CH			725	1.5%
IN			769	1.6%
LO			2360	5.0%
MF			31912	67.8%
MH			1102	2.3%
MU			893	1.9%
OF			2773	5.9%
OT			66	0.1%
RT			5346	11.3%
SS			1156	2.5%
Mortgage Characteristics				
At Distribution (2011 to 2020)	Mean	Std	Max	Min
Delinquency (more than 90 days)	0.004	0.065	1	0
Employment	34527	37977	292915	4
Business Concentration	0.165	0.067	1	0.075
Debt Service Coverage Ratio	2.034	1.531	88.0	-2.340
NOI (USD)	2615362	7250650	396407925	-2084470
LTV	0.727	0.201	1.0	0.0096
Occupancy	0.910	0.106	1	0.0101
Loan Rate	0.049	0.007	0.12	0.009
Remaining Loan Term (month)	90	45	443	0
At Securitization (2011 to 2018)	Mean	Std	Max	Min
Time Lag (month)	5.108	5.087	35	0
Originator is the underwriter	0.169	0.375	1	0
Loan originated by non-underwriters	0.245	0.430	1	0
Spread	0.043	0.008	0.1039	0.011
Debt service coverage ratio	2.152	2.653	88.02	0.59
LTV	0.662	0.120	0.95	0.01
Occupancy	0.930	0.078	1.041	0.2
Loan Term (month)	118	51	411	2
Interest Only Loan	0.106	0.308	1	0
Built before 1960	0.153	0.360	1	0
Built between 1960 and 1970	0.124	0.329	1	0
Built between 1970 and 1980	0.155	0.362	1	0
Built between 1980 and 1990	0.203	0.402	1	0
Built between 1990 and 2000	0.122	0.328	1	0

Table 2: Summary Statistics of Deals

Distribution of Deals and Deal Characteristics				
Year of Securitization				# Deals
2011				15
2012				36
2013				59
2014				68
2015				73
2016				68
2017				69
2018				49
Securitization (2011 to 2018)				
AAA subordination (437 Deals)	0.283	0.133	0.87312	0
Risk Retention Deal	23%	42%	1	0
Non Agency Deal	81%	39%	1	0
Coupon	0.045	0.008	0.083	0.011
WADSCR	0.593	0.260	1	0
WAOCC	2.324	2.890	65.33	1
WALTV	0.933	0.043	1	0.61
Term to Maturity	0.592	0.098	0.89	0.0139
WA Employment	108	34	345	15
WA Business Concentration	45731	51881	285071	2411

Table 3: Share of Mortgages Affected by Over 18 Hurricanes and 105 Severe Storms, and Tornados from 2011 to 2020

Year			Hurricanes	Tornados
2011			17.6%	13.3%
2012			19.1%	7.5%
2013			0.0%	2.8%
2014			0.0%	2.7%
2015			0.0%	5.1%
2016			5.9%	7.7%
2017			19.4%	3.8%
2018			22.9%	5.9%
2019			6.4%	7.6%
2020			42.0%	14.3%
All			13.3%	7.05%
Loan	Mean	Std	Max	Min
PostH*DamageH	0.03%	0.17%	3.40%	0
PostT*DamageT	1.09%	4.34%	58.16%	0
DamageH	0.21%	0.39%	3.40%	0
DamageT	9.28%	7.31%	58.16%	0
Deal: Share of Loans in Zipcodes				
Lowest Hazard (Ex-Post)	22.06%	24.20%	1	0
Second Lowest Hazard (Ex-Post)	30.17%	24.28%	1	0
Second Highest Hazards (Ex-Post)	27.90%	25.08%	1	0
Highest Hazards (Ex-Post)	19.87%	20.16%	1	0
Lowest Flood Risk (Ex-Ante)	32.90%	25.09%	1	0
Second Lowest Flood Risk (Ex-Ante)	9.52%	16.31%	1	0
Second Highest Flood Risk (Ex-Ante)	18.98%	17.19%	1	0
Highest Flood Risk (Ex-Ante)	35.16%	29.77%	1	0
Sea Level Rise Risk (Ex-Ante)	35.95%	28.47%	1	0

Table 4: Risk Retention and Geographic Exposure to Climate Hazards (Ex-Post Risk)

	(1)	(2)	(3)	(5)	(6)
Dependent Variable:	Average Ex-post Estimated Annual Loss Ratio	Share of Loans in 25% Zipcodes with Lowest Hazard	Share of Loans in 25% Zipcodes with Second Lowest Hazard	Share of Loans in 25% Zipcodes with Second Highest Hazard	Share of Loans in 25% Zipcodes with Highest Hazard
Retention Deal	-0.0251*	0.0758**	0.0289	-0.0378	-0.0669**
	(0.0130)	(0.0359)	(0.0318)	(0.0388)	(0.0306)
Zipcode Emp	-0.0084	-0.0943***	0.0181	0.0790**	-0.0028
	(0.0119)	(0.0318)	(0.0265)	(0.0392)	(0.0257)
Zipcode BusiConcen	-0.1004	0.8399**	-0.8428***	-0.2673	0.2702
	(0.1153)	(0.3442)	(0.2575)	(0.3148)	(0.2277)
DSCR	0.1926**	-0.4539**	-0.0630	0.0478	0.0163
	(0.0950)	(0.1844)	(0.3511)	(0.3659)	(0.2729)
LTV	0.0020	-0.0087**	0.1684	-0.0469	0.3324
	(0.0017)	(0.0035)	(0.1834)	(0.1995)	(0.2657)
OCC	-0.0983	-0.0011	0.0010	0.0025	0.0052
	(0.1734)	(0.3465)	(0.0027)	(0.0028)	(0.0046)
Loan Rate	3.9869***	-1.3666	-2.7972*	-1.2785	5.4423***
	(1.4072)	(1.5957)	(1.6443)	(2.3811)	(1.7809)
Term	0.0572	0.0079	-0.0631	0.1695***	-0.1143**
	(0.0411)	(0.0414)	(0.0645)	(0.0556)	(0.0497)
Interest Only Loan	0.0881**	-0.0587	-0.0218	0.0310	0.0495
	(0.0401)	(0.0424)	(0.0352)	(0.0563)	(0.0439)
Deal Size	-0.0050	0.0385**	-0.0073	0.0109	-0.0422
	(0.0123)	(0.0173)	(0.0276)	(0.0276)	(0.0267)
Share Construct	Yes	Yes	Yes	Yes	Yes
Share PropType	Yes	Yes	Yes	Yes	Yes
Deal Type FE	Yes	Yes	Yes	Yes	Yes
Year_month FE	Yes	Yes	Yes	Yes	Yes
No. of obs	556	556	556	556	556
R^2	0.2444	0.3136	0.2275	0.2054	0.2051

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the weighted average climate hazard exposure (Column One) and share of properties in zipocodes with the lowest to the highest climate risk (Columns Two to Six). The climate risk is measured by the ex-post estimated annual loss ratio related to climate events. Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio at securitization and occupancy rate at securitization and loan term. We also include the dummy variables for construction year group, property type, MSA, deal type, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 5: Risk Retention and Geographic Exposure to Climate Hazards (Ex-Ante Risk)

Dependent Variable:	(1) Share of Loans in 25% Zipcodes with Lowest FLD Risk	(2) Share of Loans in 25% Zipcodes with Second Lowest FLD Risk	(3) Share of Loans in 25% Zipcodes with Second Highest FLD Risk	(4) Share of Loans in 25% Zipcodes with Highest FLD Risk	(5) Share of Loans in Zipcodes with SLR Risk	(6) Share of Loans in Zipcodes with FLD or SLR Risk
Retention Deal	0.0531*	-0.0199	-0.0034	-0.0561*	-0.0543*	-0.0264***
	(0.0293)	(0.0232)	(0.0205)	(0.0325)	(0.0329)	(0.0088)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Share Construct	Yes	Yes	Yes	Yes	Yes	Yes
Share PropType	Yes	Yes	Yes	Yes	Yes	Yes
Deal Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_month FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	556	556	556	556	556	556
R^2	0.2463	0.3294	0.3539	0.4314	0.4046	0.2609

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the share of loans in zipcode with future flood risk, from lowest to highest (Column One to Column Four), the share of properties in zipocodes with sea level rise risk (Column Five), and the share of loans in zipcodes with flood and/or sea level rise risk (Column Six). Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio at securitization and occupancy rate at securitization and loan term. We also include the dummy variables for construction year group, property type, MSA, deal type, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 6: Climate Shock and Warehouse Period

Dependent Variable: **Time Lag between Securitization and Origination**	(1) All Originators	(2) Excluding Conduit Lenders
PostHT* DamageHT	-0.1655***	-0.2775***
	(0.0630)	(0.0853)
PostHT* DamageHT* Retention	0.2868	0.6119**
	(0.2629)	(0.3088)
DamageHT	0.0388	0.0443
	(0.0513)	(0.0665)
DamageHT* Retention	-0.0569	-0.1521
	(0.1568)	(0.1772)
Retention	0.0779**	-0.0325
	(0.0378)	(0.0451)
Zipcode Emp	0.0024	0.0040
	(0.0034)	(0.0043)
Zipcode BusiConcen	0.0626	0.1224**
	(0.0430)	(0.0574)
DSCR	0.0345***	0.0266***
	(0.0051)	(0.0057)
LTV	-0.1609***	-0.2074***
	(0.0607)	(0.0713)
OCC	-0.0813**	-0.0017***
	(0.0386)	(0.0003)
Term	-0.0024***	12.8838***
	(0.0002)	(2.1813)
Loan Rate	14.3999***	-0.0380*
	(1.6669)	(0.0205)
Interest Only	-0.0611***	-0.0946***
	(0.0165)	(0.0261)
Construction Year FE	Yes	Yes
Property Type FE	Yes	Yes
MSA FE	Yes	Yes
Year_month FE	Yes	Yes
Originator FE	Yes	Yes
No. of obs	47102	27995
R^2	0.5446	0.5723

Note: This table reports the results of cross-sectional regressions. The dependent variable is the log of time span (in months) between securitization and the origination of the mortgage. PostHT is a dummy variable with a value of one when the property was affected by the disasters. Damage is the zip code level historical building loss rate for sea and river flood risk and hurricanes (Hurricane risk) and for tornado, hail and lightning (Tornado) from the FEMA database. Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio, occupancy at securitization and occupancy rate at securitization, loan spread, loan term, and a dummy variable for interest only loan. We also include the dummy variables for construction year group, property type, state, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Loan underwriter = originators have been removed.

Table 7: Climate Shock and Originator – Underwriter Relationship

Dependent Variable:	(1) Originates for its own deal	(2) never underwrit
PostHT*DamageHT	0.0506*	-0.1016***
	(0.0280)	(0.0389)
PostHT*DamageHT *Retention	-0.5492**	0.5682***
	(0.2191)	(0.2133)
DamageHT	0.0090	0.0412
	(0.0236)	(0.0311)
DamageHT* Retention	-0.1799	0.1204
	(0.1154)	(0.1127)
Retention	0.1026*	-0.1468**
	(0.0553)	(0.0595)
Zipcode Emp	0.0002	0.0012
	(0.0017)	(0.0019)
Zipcode BusiConcen	0.0062	0.0180
	(0.0218)	(0.0249)
DSCR	-0.0016	0.0038**
	(0.0010)	(0.0019)
LTV	0.0396	0.0828***
	(0.0322)	(0.0308)
OCC	-0.0158	0.0422
	(0.0255)	(0.0318)
Term	-0.0001	0.0000
	(0.0001)	(0.0001)
Loan Rate	0.0939	-1.8714
	(0.8796)	(1.2081)
Interest Only	0.0005	0.0014
	(0.0083)	(0.0104)
Construction Year FE	Yes	Yes
Property Type FE	Yes	Yes
MSA FE	Yes	Yes
Year_month FE	Yes	Yes
Originator FE	Yes	Yes
No. of obs	47102	47102
R^2	0.4742	0.4212

Note: This table reports the results of cross-sectional regressions. The dependent variable is the log of time span (in months) between securitization and the origination of the mortgage. PostHT is a dummy variable with a value of one when the property was affected by the disasters. Damage is the zip code level historical building loss rate for sea and river flood risk and hurricanes (Hurricane risk) and for tornado, hail and lightning (Tornado) from the FEMA database. Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio, occupancy at securitization and occupancy rate at securitization, loan spread, loan term, and a dummy variable for interest only loan. We also include the dummy variables for construction year group, property type, state, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Loan underwriter = originators have been removed.

Table 8: Geographic Exposure to Climate Hazards (Ex-Post Risk) and Underwriter's Exposure to Climate Shocks

Dependent Variable:	(1) Average Ex-post Estimated Annual Loss Ratio	(2) Share of Loans in 25% Zipcodes with Lowest Hazard	(3) Share of Loans in 25% Zipcodes with Second Lowest Hazard	(4) Share of Loans in 25% Zipcodes with Median Hazard	(5) Share of Loans in 25% Zipcodes with Second Highest Hazard
PostHT*DamageHT	0.5807	-1.1782	0.4833	0.1348	0.5601
	(0.3922)	(0.9724)	(0.9016)	(0.7849)	(0.6753)
PostHT*DamageHT* PreRetention	-0.9472**	1.0848*	0.3958	0.0024	-1.4831**
	(0.4182)	(0.6527)	(0.7985)	(0.7924)	(0.7480)
DamageHT	0.0005	0.0031	-0.0002	-0.0017	-0.0012
	(0.0007)	(0.0023)	(0.0017)	(0.0022)	(0.0019)
DamageHT* PreRetention	0.0028***	-0.0019	-0.0016	0.0002	0.0033
	(0.0009)	(0.0029)	(0.0029)	(0.0036)	(0.0027)
Retention	-0.0101	-0.0260	0.1746**	-0.1419	-0.0066
	(0.0304)	(0.0779)	(0.0772)	(0.1302)	(0.0379)
Zipcode Emp	0.0090	-0.1220***	0.0242	0.0637**	0.0341**
	(0.0061)	(0.0343)	(0.0362)	(0.0290)	(0.0138)
Zipcode BusiConcen	0.0319	0.2251	-0.1946	-0.1983	0.1679
	(0.0550)	(0.2119)	(0.1821)	(0.1674)	(0.1389)
DSCR	0.0222	-0.0461	-0.0299	0.0719	0.0041
	(0.0192)	(0.0548)	(0.0465)	(0.0711)	(0.0469)
LTV	0.4051***	-1.0870***	-0.1260	0.0393	1.1737***
	(0.0655)	(0.3792)	(0.3876)	(0.2358)	(0.2013)
OCC	-0.1317	0.1016	0.2350	-0.2605	-0.0760
	(0.1023)	(0.4952)	(0.6462)	(0.4406)	(0.3198)
Term	-0.0092	0.1026*	-0.0860	0.0160	-0.0327
	(0.0122)	(0.0528)	(0.0568)	(0.0347)	(0.0336)
Loan Rate	1.8907**	-4.6322	3.5704	1.2651	-0.2033
	(0.8277)	(3.5216)	(3.0271)	(3.6053)	(2.5476)
Interest Only	-0.0131	0.0517	-0.1242**	0.0345	0.0380
	(0.0284)	(0.0876)	(0.0521)	(0.0738)	(0.0635)
Share of Construct.	Yes	Yes	Yes	Yes	Yes
Deal Type FE	Yes	Yes	Yes	Yes	Yes
Share of PropType	Yes	Yes	Yes	Yes	Yes
Year_month FE	Yes	Yes	Yes	Yes	Yes
Underwriter FE	Yes	Yes	Yes	Yes	Yes
No. of obs	846	846	846	846	846
R^2	0.3808	0.3485	0.2593	0.2431	0.3336

Note: This table reports the results of cross-sectional regressions. The dependent variable is weighted average climate hazard exposure (Column One) and share of properties in zipocodes with the lowest to the highest climate risk (Columns Two to Six). The climate risk is measured by the ex-post estimated annual loss ratio related to climate events. PostHT is a dummy variable with a value of one when the property was affected by the disasters. Damage is the zip code level historical building loss rate for sea and river flood risk and hurricanes (Hurricane risk) and for tornado, hail and lightning (Tornado) from the FEMA database. Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio, occupancy at securitization and occupancy rate at securitization, loan spread, loan term, and a dummy variable for interest only loan. We also include the dummy variables for construction year group, property type, state, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Loan underwriter = originators have been removed.

Table 9: Geographic Exposure to Climate Hazards (Ex-Ante Risk) and Underwriter's Exposure to Climate Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Share of Loans in 25% Zipcodes with Lowest FLD Risk	Share of Loans in 25% Zipcodes with Second Lowest FLD Risk	Share of Loans in 25% Zipcodes with Second Highest FLD Risk	Share of Loans in 25% Zipcodes with Highest FLD Risk	Share of Loans in Zipcodes with SLR Risk	Share of Loans in Zipcodes with FLD or SLR Risk
PostHT*DamageH	3.5537*	0.5713	-0.6595	-3.4290	2.8405	0.0365
	(2.0270)	(1.1053)	(2.3143)	(2.8264)	(2.4423)	(0.6811)
PostHT*DamageH*	0.2507	0.1476	-0.1011	-0.1197	-1.4781**	0.1774
PreRetention	(0.8929)	(0.2572)	(0.6748)	(0.7989)	(0.7136)	(0.1788)
DamageH	-0.0044	-0.0121	0.0517	-0.0363	-0.0817	-0.0011
	(0.0633)	(0.0281)	(0.0475)	(0.0832)	(0.0504)	(0.0140)
DamageH*	0.0123	-0.0501	-0.1353*	0.1791	0.2445*	0.0059
PreRetention	(0.1119)	(0.0508)	(0.0817)	(0.1304)	(0.1482)	(0.0318)
Retention	0.0247	-0.0172	0.0706**	-0.1098	0.0395	-0.0317**
	(0.0719)	(0.0326)	(0.0334)	(0.0702)	(0.0819)	(0.0123)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Share of Construct.	Yes	Yes	Yes	Yes	Yes	Yes
Deal Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Share of PropType	Yes	Yes	Yes	Yes	Yes	Yes
Year_month FE	Yes	Yes	Yes	Yes	Yes	Yes
Underwriter FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	846	846	846	846	846	846
R^2	0.2048	0.3374	0.3739	0.3905	0.5079	0.3196

Note: This table reports the results of cross-sectional regressions. The dependent variable is share of loans in zipcode with four quantiles of future flood risk (Column One to Four), share of properties in zipocodes with sea level rise risk (Column Five) and share of loans in zipcodes with flood or sea level rise risk (Column Six). PostH is a dummy variable with a value of one when the property was affected by hurricanes. Damage is the zip code level historical building loss rate for sea and river flood risk and hurricanes (Hurricane risk) from the FEMA database. Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio, occupancy at securitization and occupancy rate at securitization, loan spread, loan term, and a dummy variable for interest only loan. We also include the dummy variables for construction year group, property type, state, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Loan underwriter = originators have been removed.

Table 10: The Pricing of Climate Hazard Exposure in CMBS Deals

Dependent Variable: Initial Spread	(1)	(2)	(3)	(4)	(5)
Exposure to High Ex-ante Risk	0.0077***			0.0073**	0.0076***
	(0.0030)			(0.0029)	(0.0029)
Exposure to High Ex-post Risk		0.0056***		0.0053***	0.0050***
		(0.0014)		(0.0015)	(0.0017)
PostHT*DamageH			0.0068	0.0047	0.0013
			(0.0094)	(0.0092)	(0.0104)
DamageHT			0.0090**	0.0055	0.0057
			(0.0041)	(0.0047)	(0.0048)
Exposure to High Ex-ante Risk * Retention					-0.0095**
					(0.0045)
Exposure to High Ex-post Risk * Retention					0.0004
					(0.0024)
PostHT*DamageH * Retention					0.0247
					(0.0246)
DamageHT * Retention					0.0061
					(0.0104)
Retention					0.0055
					(0.0047)
Zipcode Emp	-0.0013***	-0.0012**	-0.0012***	-0.0012**	-0.0013***
	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Zipcode BusiConcen	0.0001	-0.0017	-0.0003	-0.0011	-0.0003
	(0.0050)	(0.0058)	(0.0052)	(0.0055)	(0.0054)
DSCR	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
LTV	0.6279	0.4491	0.5842	0.3837	0.3131
	(0.5059)	(0.5112)	(0.4911)	(0.4928)	(0.4648)
OCC	0.0081	0.0071	0.0064	0.0073	0.0082
	(0.0062)	(0.0058)	(0.0065)	(0.0060)	(0.0061)
Term	-0.0060***	-0.0057***	-0.0060***	-0.0056***	-0.0055***
	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Interest Only	-0.0071***	-0.0072***	-0.0073***	-0.0072***	-0.0065***
	(0.0017)	(0.0016)	(0.0017)	(0.0016)	(0.0013)
Deal Size	-0.0020***	-0.0019***	-0.0021***	-0.0018***	-0.0019***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Share Construction Year	Yes	Yes	Yes	Yes	Yes
Share Property Type	Yes	Yes	Yes	Yes	Yes
Lead Underwriter FE	Yes	Yes	Yes	Yes	Yes
Deal Type FE	Yes	Yes	Yes	Yes	Yes
Year_month FE	Yes	Yes	Yes	Yes	Yes
No. of obs	556	556	556	556	556
R^2	0.6026	0.6157	0.6030	0.6185	0.6235

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the spread of the initial weighted average rate. Exposure to High Ex-ante Risk is the share of properties located in the zip code areas with the highest future flood risk and/or with sea level rising risk. Exposure to High Ex-post Risk is the share of properties located in the zip code areas with the highest ex-post climate risk. PostHT is a dummy variable with a value of one when the property was affected by the disasters. Damage is the zip code level historical building loss rate for sea and river flood risk and hurricanes (Hurricane risk) and for tornado, hail, and lightning (Tornado) from the FEMA database. Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio at securitization and occupancy rate at securitization and loan term. We also include the dummy variables for construction year group, property type, MSA, deal type, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 11: The Risk Channel: Loan Default Risk

Dependent Variable:	(1) Default Risk	(3) NOI
PostHT*DamageHT	0.0309**	-0.0209***
	(0.0152)	(0.0066)
DamageHT	0.0008	-0.0045***
	(0.0015)	(0.0006)
Zipcode Emp	-0.0006***	-0.0012***
	(0.0001)	(0.0000)
Zipcode EmpConcen	-0.0004	-0.0012***
	(0.0009)	(0.0003)
DSCR	-0.0004***	0.0046***
	(0.0000)	(0.0001)
LTV	0.0476***	0.0419***
	(0.0014)	(0.0006)
Loan Rate	0.1538***	0.3263***
	(0.0123)	(0.0044)
Term	0.0000***	0.0000***
	(0.0000)	(0.0000)
Interest Only	0.0021***	-0.0104***
	(0.0002)	(0.0001)
Construction Year FE	Yes	Yes
Property Type FE	Yes	Yes
Originator FE	Yes	Yes
MSA FE	Yes	Yes
Year_month FE	Yes	Yes
No. of obs	822702	822702
R^2	0.0931	0.3618

Note: This table reports the results of linear probit model. The dependent variable is the annual NOI change rate (column 1) and NOI to value ratio (column 2). Post HT is dummy variable with value of one when the property was affected by the disasters. Damage is the zip code level historical building loss rate for sea and river flood risk and hurricanes (Hurricane risk) and for tornado, hail and lightning (Tornado) from the FEMA database. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), debt service coverage ratio at securitization, loan to value ratio and occupancy rate, loan rate, loan term, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, MSA, and year month. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 12: The Risk Channel: Credit Risks of CMBS Securities

Dependent Variable:	(1) Initial AAA	(2) Initial AAA
PostHT*DamageHT	0.2289	0.3945**
	(0.1824)	(0.1785)
PostHT*DamageHT*		-1.1843***
Retention		(0.4536)
DamageHT	0.0965	0.0046
	(0.2149)	(0.2366)
DamageHT*Rention		0.2011
		(0.5023)
Retention		-0.0066
		(0.0496)
Zipcode Emp	0.0157	0.0145
	(0.0110)	(0.0119)
Zipcode BusiConcen	0.0590	0.0415
	(0.0872)	(0.0914)
DSCR	-0.0266***	-0.0276***
	(0.0045)	(0.0050)
LTV	57.7414***	56.8645***
	(9.1073)	(9.4278)
OCC	0.1752	0.1776
	(0.1295)	(0.1307)
Term	-0.0450**	-0.0447*
	(0.0227)	(0.0230)
Interest Only Loan	0.0630***	0.0637***
	(0.0179)	(0.0173)
Deal Size	-0.0477***	-0.0483***
	(0.0140)	(0.0145)
Share Constr. Year	Yes	Yes
Share Property Type	Yes	Yes
Underwriter FE	Yes	Yes
Deal Type FE	Yes	Yes
Year_month FE	Yes	Yes
No. of obs	437	437
R^2	0.7732	0.7761

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is AAA subordination (column 1) and spread (column 2). PostHT is a dummy variable with a value of one when the property was affected by the disasters. Damage is the zip code level historical building loss rate for sea and river flood risk and hurricanes (Hurricane risk) and for tornado, hail, and lightning (Tornado) from the FEMA database. Retention is a dummy variable for whether the deal is subjected to the risk retention requirement. It equals one when the deal is issued after 2016.12 and is a non-agency and non-qualified loan. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), Debt service coverage ratio, loan to value ratio at securitization and occupancy rate at securitization and loan term. We also include the dummy variables for construction year group, property type, MSA, deal type, year month, and originator. Heteroskedastic robust standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.