

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

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## Abstract

This paper investigates how climate risks influence the CMBS market and examines the role of the Dodd-Frank Act's risk retention rule in shaping the behavior of CMBS issuers and loan originators. Using a dataset of over 40,000 loans from 556 CMBS deals issued between 2011 and 2018, we identify significant moral hazard within the "originate-to-distribute" model, particularly related to climate risks. Our findings indicate that following the implementation of the risk retention rule, CMBS issuers reduce their exposure to high-risk geographic areas. In contrast, in the absence of this rule, loan originators expedite the securitization of climate-affected loans, while underwriters avoid including such loans in their portfolios. Although climate risk is reflected in loan pricing, we find evidence of mispricing at the deal level. These results highlight the need for strong regulations to align the interests of market participants and mitigate moral hazard, with important implications for investors, policymakers, and financial stability.

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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<sup>3</sup>. The increasing frequency and severity of these events pose a growing threat to the \$1.2 trillion CMBS market, yet little is known about how these risks are assessed, priced, and managed within the complex structure of securitization. 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).

Despite these risks, the complexity of the CMBS market securitization structure, which involves pooling geographically diverse loans, makes it difficult for investors and issuers to fully assess, price, and manage geographic climate hazards. One key challenge in assessing climate risk in CMBS securities is the localized nature of climate-related disasters. Events such as floods, hurricanes, and wildfires can vary significantly between even neighboring areas (Masozera et al., 2007, Vigdor, 2008, Holtermans et al., 2023), making it difficult for traditional risk assessment tools to capture specific climate risks across regions. Additionally, the 'originate-to-distribute' model, which involves lenders originating mortgages and subsequently selling them for securitization, raises moral hazard concerns. Local lenders, with better knowledge of local disaster risks, may securitize mortgages with higher but less

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<sup>3</sup> Climate change: the CMBS angle, Financial Times Oct 28, 2019.

observable risks (Ouazad and Kahn, 2019). This risk transfer, without fully disclosing the geographic vulnerabilities to investors, create a lemon problem, where loans from climate vulnerable areas are mispriced and sold without adequate risk transparency.

To fully understand how climate risks are transferred and sometimes mispriced, it is important to understand the role of CMBS originators, sponsors, issuers, and underwriters. Originators, typically also serving as sponsors, are responsible for originating the loans, providing initial financing to commercial property owners. These originators have detailed knowledge of the climate risks associated with the properties, such as flood or hurricane exposure. Once enough loans are originated, the sponsor (often the same as the originator) pools these loans together for securitization. The issuer—either the sponsor or another entity—then structures the CMBS securities from the pooled loans and issues them to the market.

Underwriters, who play a critical role in determining the pricing and distribution of the securities, often lack the geographic climate risk information known by the originators and sponsors. This information asymmetry creates a gap between those who price and market securities and those who are most familiar with the underlying climate vulnerabilities of the loans. As a result, climate risks can sometimes be undervalued, leading to mispricing as these risks are transferred to investors.

Recent research by Griffin and Priest (2023) highlights the persistence of moral hazard in CMBS, showing that nearly 30% of securitized loans overstated projected income by at least 5%. Their findings illustrate how sponsors manipulate loan characteristics to maximize loan size and transfer these risks through securitization. While they primarily critique the limited effectiveness of the Dodd-Frank risk retention rule in preventing income overstatement, the issue of climate related risks – which are also subject to information asymmetry – remains

underexplored. As the frequency and severity of climate events increase, understanding the role of mispricing in securitizing climate vulnerable loans is vital to ensuring market stability.

In this study, we aim to address two key gaps in the existing literature. First, we investigate whether CMBS issuers and loan originators engage in risk transfer behaviors that shift the burden of climate risks onto investors. Given that originators often have detailed knowledge of geographic climate risks, we explore whether they transfer loans with higher climate risks to investors without fully disclosing these risks. This behavior is of particular concern in the originate-to-distribute model, where loans are securitized and sold, allowing originators to offload risk. Second, we examine whether the Dodd-Frank risk retention rule can mitigate this moral hazard by aligning the interests of issuers and investors. We hypothesize that if a lemon problem exists due to unobserved climate risks, CMBS loans without risk retention requirements will exhibit greater climate risk exposure. In contrast, the risk retention rule should incentivize issuers to shift loans from high-risk areas to low-risk areas, reducing climate-related default risk.

In the context of residential mortgages, Ouazad and Kahn (2019) discovered a significant increase in securitization of loans with amounts just below the conforming loan limit—specifically, the maximum loan size eligible for securitization by government-sponsored enterprises like Fannie Mae and Freddie Mac—following a billion-dollar natural disaster. Their findings suggest that lenders were incentivized to keep loans under this limit to take advantage of securitization opportunities. Building on this work, our study shifts the focus to commercial mortgage-backed securities, extending the analysis to a different segment of the real estate market with its own unique characteristics and risk profiles. We use the 2017 risk retention rule as a treatment that reduces the information asymmetry and aligns the interest between issuers and investors. If a “lemon” problem exists in the CMBS market due to unobserved climate risks, we would expect that CMBS loans without risk retention

requirements would exhibit greater exposure to climate risk. In contrast, the risk retention rule would incentivize CMBS issuers to shift their loans from high-risk to low-risk areas, ultimately reducing the default risk from climate hazards in retention loans.

To investigate these issues, we employ a comprehensive dataset. Our analysis includes zipcode level data on hurricanes and tornado, expected annual frequency, historical building loss ratios, future flood risk under the high emissions 'RCP8.5' global warming scenario, and sea level rise risk the same 'RCP8.5' scenario. We also incorporate historical data from 18 billion-dollar hurricane disasters and 105 billion-dollar tornadoes and severe storms, collectively accounting for 80% of the total damages caused by all billion-dollar weather and climate disaster events. We combine this dataset 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 as well as CMBS deals, providing a basis for comparative analysis of the risk-transfer decisions made by CMBS loan originators and underwriters.

We utilize the enactment of the Dodd–Frank Act (DFA, 2010) as a quasi-experimental treatment to examine the impact of risk retention on climate risk exposure within the CMBS market. Our methodology includes several difference-in-differences (DiD) and triple difference methods (DDD), which allow for causal inference by controlling for time-invariant unobserved heterogeneity and differential trends between treated and control groups. To further strengthen the robustness of our results, we control for potential confounding variables such as local economic conditions, property characteristics, and deal-specific factors that may also influence CMBS issuance behaviors. Additional robustness checks were performed by varying the length of the pre- and post-Dodd-Frank periods and by using alternative measures of

climate risk (e.g., sea level rise and flood risks). These checks consistently confirm the presence of 'lemons' in non-risk-retention deals.

Our findings make a substantial contribution to the literature on moral hazard, particularly within the context of the 'Skin in the Game' theory as it applies to financial innovations like asset-backed securities. By linking the impact of the Dodd-Frank risk retention rule with climate risk exposure in the CMBS market, we provide new empirical evidence of how regulatory interventions can mitigate the inherent moral hazards of the 'originate-to-distribute' model. Our results highlight the importance of aligning incentives between issuers and investors to reduce mispricing and moral hazard in the context of climate-related risks. These findings not only extend existing theories of financial intermediation but also have practical implications for future regulatory frameworks designed to manage environmental risks in financial markets.

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). Our study contributes to this literature by focusing specifically on climate risk in CMBS. 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 hazards. Retention deals tend to have lower geographic exposure to climate hazards by shifting the loan allocation from high-risk areas to low-risk areas. Our empirical results indicate that approximately 7% (equivalent to 5.4 billion USD per year) of loans in risk

retention deals were shifted from zip codes with the highest ex-post climate risk to those with the lowest risk, compared to non-risk retention deals. Similarly, about 6.04% (or 4.65 billion USD per year) of loans were moved from zip codes with the highest ex-ante climate risk to those with the lowest ex-ante risk.

These findings 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, we contribute 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 remains unclear whether climate risk is fully reflected in CMBS loan pricing<sup>4</sup>. Our findings indicate that climate hazard exposure has been incorporated into CMBS loans, as evidenced by a significant increase in loan rates for properties situated in high-risk areas. However, there is no clear evidence that climate risk exposure is fully reflected at the deal level. This could be attributed to the complexity of the CMBS structure, which makes it challenging for investors to comprehensively evaluate the climate risk exposure of all the loans

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<sup>4</sup> 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.

within each tranche. Consequently, it is essential to have 'skin in the game' to motivate underwriters to carefully assess climate risks and reduce exposure to 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 participants and complex structure, CMBS creates distance between loan's originator and the party assuming the loan's default risk. This distance can potentially lead to moral hazard issues, particularly in the context of less visible risks such as climate hazards.



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 CMBS sponsor is required to retain 5% of the face value of each class of securities issued in the CMBS transaction or the most subordinate class or classes of securities issued in the CMBS transaction in an amount equal to 5% of the "fair value" of all of the CMBS issued. 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).

CMBS issued before the risk retention rule became effective on 24<sup>th</sup> December 2016 are not required to comply with the rule retroactively. Additionally, certain deals, especially those guaranteed by a Government-Sponsored Enterprise (GSE) such as Fannie Mae or Freddie Mac, are exempt. 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 multifamily, mobile home parks, healthcare facilities, and assisted living

communities loans, known as "qualified commercial real estate (QCRE) loans", which are not subject to retention requirement. Approximately 4% of non-agency securitized commercial mortgages meet QCRE criteria (by Furfine (2020)).

The Dodd-Frank Act aims to promote accountability by putting 'skin in the game' to mitigate moral hazard. Previous studies have documented the Dodd-Frank Act's effectiveness in imposing tighter underwriting standards and reducing the riskiness of CMBS loans (Furfine, 2020, Agarwal et al., 2021). Nevertheless, the impact of the Act on climate risk assessment and management in CMBS remains uncertain. On one hand, the risk retention rule could incentivize more thorough evaluation of all risks, including climate-related ones. On the other hand, Ashcraft et al. (2019) document that the complexity and opaqueness in structured finance can reduce the effectiveness of such regulations. They found evidence that informed parties reduce their skin-in-the-game in a manner not observable to other market participants, which could potentially apply to the handling of climate risks as well.

## **2.2. Climate Risk and CMBS**

The effect of climate hazards on commercial real estate investment has been extensively documented in the literature. This section reviews the key impacts and their implications for CMBS.

*Impacts on Property Value and Operations:* Climate 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). They also increase operating costs and earning volatility (Zhu and Fuerst, 2022, Holtermans et al., 2023), lead to higher insurance premiums

(Gallagher and Hartley, 2017), and reduce property demand and regulatory pressures (Roberts et al., 2015, Clayton et al., 2021).

*Implications for Mortgage Performance:* 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. Deng et al. (2023) also find that households treated to high-temperature show elevated rates of default and prepayment, particularly in high-amenity locations that are vulnerable to sea-level rise risk.

*Localized Nature of Climate Risk:* One key challenge in assessing climate risk in CMBS is the localized nature of climate-related disasters. 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). This localization implies that conventional screening of mortgages may not fully capture the risk of natural disasters.

*Implications for CMBS:* 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 the 'originate-to-distribute' model, there is an inherent risk of moral hazard because loan originators have little incentive to carefully assess loan quality if they plan to sell the loans quickly to investors. Climate risks, which are often more difficult to observe and quantify, can exacerbate this problem. Originators may securitize loans from high-risk areas without thoroughly evaluating the associated hazards, passing the risks to investors. The introduction of the risk retention rule under the Dodd-Frank Act aims to reduce this moral hazard by requiring issuers to retain a portion of the credit risk, incentivizing better risk assessment. Based on this, we develop the following hypotheses:

**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, we expect default risk to increase with higher levels of climate risk.

**Hypothesis 2:** Climate risk has a negative impact on loan performance, increasing default risk.

The rationale behind this hypothesis is that properties in high-risk areas are more likely to experience physical damage or decreased value due to climate events, potentially leading to higher rates of default or delinquency.

Given the increased risk associated with climate hazards, we would expect this risk to be reflected in loan pricing. Therefore, loan originators will likely demand a higher premium for loans with greater exposure to climate hazards. This leads to our third hypothesis:

**Hypothesis 3:** Climate risk is reflected in CMBS loan pricing but not fully accounted for at the deal levels.

However, while individual loan originators may price in climate risk, the complexity of CMBS structures and the potential for information asymmetry at the deal level leads us to consider pricing at the deal level separately. If the climate risk exposure is not easily observable to end investors of certain tranches, those tranches may not exhibit higher yields commensurate with their actual risk. This consideration forms the basis for our fourth hypothesis:

**Hypothesis 4:** CMBS deals with higher climate risk exposure will not offer higher yields or additional protection to compensate for the risk.

Hypothesis Four is consistent with moral hazard argument in Hypothesis One. Without risk retention requirements, CMBS sponsors may not carefully screen the loan quality, as the climate risk is not fully observable to investors. Thus, it is important to align the interests of CMBS sponsors and investors.

These hypotheses have important implications for various stakeholders in the CMBS market. For investors, they suggest the need for careful due diligence, particularly regarding climate risk exposure. For issuers, they highlight the potential benefits of thorough climate risk assessment. For regulators, they underscore the importance of measures like risk retention rules in mitigating moral hazard and improving market efficiency.

### **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. We chose this period to capture the post-financial crisis CMBS market and to include sufficient time before and after the implementation of the risk retention rule in December 2016. To observe the loan performance, we collect the performance data during each distribution period of the CMBSs from January 2011 to April 2020<sup>5</sup>. 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.

Tables 1 and 2 provide summary statistics for our sample at the loan and deal levels, respectively.<sup>6</sup> As shown in Panel A, Table 1, the average time lag between loan origination and

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<sup>5</sup> 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.

<sup>6</sup> As shown in Appendix 1, 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%).

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 10.4%. 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 20.3% of the properties were built between 1980 and 1990, and 17% were built between 2000 and 2010.

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.

**Table 1 here**

At the deal level, as shown in Panel A, Table 2, CMBS deals have an initial AAA (BBB) subordination rate of 28.3% (8.5%), indicating that if \$1 billion USD in CMBS securities are issued in a deal, \$717 million (\$91.5 million) are senior securities that are rated AAA (BBB), and the remaining \$283 million (\$ 8.5 million) are junior in priority to the AAA (BBB) 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**

In our sample, 23% of the deals are subjected to risk retention requirements, and 81% of deals are categorized as non-agency deals. To study this impact of risk retention requirement,

we compare the underwriting standards and loan performance for deals that are subject to the rule versus those that are exempt. As seen in Table 1, Panel B, retention loans are generally of higher quality at the time of securitization. For instance, retention loans have a lower loan-to-value (LTV) ratio (59.3% vs. 66.8% for non-retention loans), indicating that these loans are less leveraged and carry lower risk. Additionally, the debt service coverage ratio (DSCR) for retention loans is higher (2.312 vs. 2.104), meaning that the income generated from the properties securing these loans is sufficient to comfortably cover debt payments, enhancing their safety profile.

Moreover, the delinquency rate (the percentage of loans more than 90 days overdue) is significantly lower for retention loans (0.056%) compared to non-retention loans (0.371%). This lower delinquency rate suggests that loans, where the originator retains risk, are more likely to be well-underwritten and perform better, demonstrating the effectiveness of the risk retention policy in ensuring higher loan quality and minimizing default risk.

Additionally, retention loans also tend to be located in areas with stronger economic fundamentals with higher employment. Interest-only loans are more common among retention loans, indicating greater short-term flexibility. Furthermore, retention loans have higher loan rates, reflecting investors' demands for a premium when issuers retain part of the risk.

A key factor contributing to the higher quality of retention loans is the originator's role as the underwriter. In 45% of retention loans, the originator is also the underwriter, compared to only 15% in non-retention loans. This alignment of roles between the originator and underwriter ensures stricter underwriting standards and better risk assessment, as the originator has a direct stake in the loan's performance. This also helps to reduce information asymmetry, ensuring that the risks of the loan are more carefully evaluated. Consequently, retention loans benefit from both better loan terms and more rigorous underwriting, leading to overall stronger loan performance compared to non-retention loans.



At the deal level (Panel B, Table 2), we observe that retention deals have lower leverage, reflected in a lower weighted average loan to value (WALTV) ratio of 55.5% compared to 60.3% for non-retention deals. This lower LTV indicates a less risky and more conservative structure compared to non-retention ones. Retention deals are typically located in areas with higher employment levels, averaging 50,762 jobs compared to 44,241 in non-retention deals, aligning with the focus on economic stability and ensuring the loans are backed by properties in economically resilient regions. However, there is no significant difference in coupon rates between retention and non-retention deals, meaning investors receive similar returns on both types of deals.

### 3.2 Geographic Exposure to Climate Hazards

Our assessment of geographic exposure to climate hazards is based on the FEMA national risk database, which provides estimates of the risk associated with various climate events at the zip code level. Since the Trepp dataset reports the zipcode of each property, we integrate this information to quantify the climate risk exposure of each loan. Climate hazards are measured by the ex-post estimated annual loss ratio for buildings in each zipcode. This is calculated as:

$$ED_m^{HT} = \phi_m^H f_m^H + \phi_m^T f_m^T, \quad (1)$$

where  $ED_i^{HT}$  represents the ex-post estimated annual loss ratio for hurricane and tornado hazards in zipcode  $m$ .  $\phi_m^H$  and  $\phi_m^T$  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 ( $\phi_m^H$ ). 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 ( $\phi_m^T$ ).  $f_m^H$  and  $f_m^T$  are the FEMA-provided

zip code-level ex-post annual frequency for hurricanes, riverine flooding, sea level flooding ( $f_m^H$ ) as well as lightning, strong winds, and tornados ( $f_m^T$ ). This measure reflects past climate events and their impact on building structures in each zip code, providing insight into historical climate risk that CMBS issuers or investors consider when making asset allocation decision.

To visualize these risks geographically, Figure 1 represents a detailed breakdown of climate hazard exposure across US zip codes. Figure 1A presents the ex-post annual loss ratio for hurricane and tornadoes. We classify the 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). High risk areas include coastal regions like the Gulf Coast of Florida, the eastern coasts of New Jersey and Maryland, and part of the Pacific Northwest, all of which face elevated hurricane risks. Similarly, some areas in the Mideast exhibit heightened loss ratios, which could be largely attributed to tornadoes. This pattern suggests that the concentration and intensity of climate events significantly influence risk, requiring precise risk management tailored to regional characteristics.

We use "ex-post" risk to refer to historically observed risk, based on past occurrences and damages. "Ex-ante" risk, on the other hand, captures forward-looking projections based on potential future scenarios. The integration of both these measures into our analysis provides a comprehensive view of both historical and anticipated climate risks.

To address the limitations of using only ex-post risk, we also incorporate forward-looking projections under the high emissions 'RCP8.5' scenario, which assumes continued high greenhouse gas emissions through the late 21st century. This scenario is considered a "business as usual" pathway and represents a worst-case climate impact scenario. Due to data limitations, we are not able to quantify the future risk for all hurricanes and strong wind-related hazards, so we obtained the data from Climate Mapping for Resilience and Adaptation

(CMRA).<sup>7</sup> Figure 1B illustrates the projected future flood risk by showing the number of annual extreme precipitation days surpassing the 99th percentile (relative to the 1976-2005 average). We classify the 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). High risk areas include the Midwest, the Gulf Coast, and portion of the Northeast. Figure 1C shows the risk associated with sea level rise, identifying coastal regions that would be affected by a one meter rise by 2100. Coastal cities like Miami, parts of New Jersey, and the Gulf Coast are particularly vulnerable, highlighting the necessity of incorporating future risks into current CMBS valuations.

**Figure 1 here**

We integrate these risk measures into our CMBS loan dataset by matching each property to its zip code's risk profile. This process assigns each loan a climate risk score, which we use in subsequent analyses to investigate the relationship between climate risk and loan performance, and to assess the effectiveness of risk retention policies.

We further investigate the exposure of CMBS loans to climate hazards using NOAA's historical data on 18 high-impact hurricanes and 105 severe storms and tornadoes from 2011 to 2020. These events, which caused over \$1 billion in damages each, accounted for 80% of the total damages caused by all billion-dollar weather events during this period. Figure 2 illustrates the paths of these hurricanes, and the regions affected by severe storms and tornadoes. Yellow dots represent areas within a 100-mile radius of a hurricane's eye, while county shading indicates tornado frequency, with darker colors marking higher occurrences. These visual patterns align with known high-risk corridors, such as the Gulf Coast ("hurricane alley") and

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<sup>7</sup> 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.

the Midwest ("tornado alley"), emphasizing the importance of localized risk management strategies in the CMBS market.

**Figure 2 here**

Table 3 provides an in-depth analysis of loans affected by significant climate events. On average, 13.3% of loans were exposed to hurricane events, while 7.05% of loans were impacted by tornadoes. These figures illustrate the substantial impact that climate events have on the CMBS market. Notably, certain years saw higher levels of exposure, with 2020 standing out as a peak year when 42.0% of loans were affected by hurricanes. This year corresponds to a particularly active hurricane season, reflecting the cyclicity and intensity of these events. Tornadoes also caused significant damage with up to 14.3% of loans affected in 2020, emphasizing the need for detailed regional risk assessments. In specific years, such as 2012, 2017, 2018, and 2020, nearly or over 20% of loans were impacted by hurricanes, while tornadoes had a substantial effect in 2011 and 2020, with 13.3% and 14.8% of loans affected, respectively. The historical building loss ratio due to hurricanes averages around 0.19%, while tornadoes cause a much higher average loss ratio of 10.51%, underscoring the varying severity of different climate events. The data highlights that tornadoes, while less frequent, can cause more extensive damage compared to hurricanes.

Retention deals, according to Table 3, tend to allocate loans more conservatively, avoiding high-risk areas more effectively than non-retention deals. For instance, 28.03% of retention loans are located in areas classified as the lowest ex-post hazard zones compared to 20.60% for non-retention loans, leading to a statistically significant difference of 7.43%. This is economically intuitive, as the risk retention rule incentivizes issuers to retain safer loans to minimize default risk. Conversely, non-retention deals allocate a higher percentage of loans to riskier regions, suggesting a strategy that potentially seeks short-term profit despite increased exposure.

The trend continues when considering ex-ante flood risk measures. Retention deals allocate 32.15% of loans to areas with the lowest flood risk, while non-retention deals allocate 33.03%, showing minimal difference. However, for the second lowest risk category, retention deals allocate only 7.29%, compared to 10.33% in non-retention deals, resulting in a statistically significant difference of -3.04%. This indicates that retention deals remain highly selective even within low-risk categories.

Retention deals also show a higher share of loans in the highest flood risk areas (39.18% compared to 34.43% for non-retention deals). This somewhat counterintuitive finding suggests that while retention deals generally favor safer areas, they may still target higher-risk zones if they perceive these areas as economically viable due to potentially high returns. Retention deals likely implement stricter risk management practices, such as enhanced pricing or insurance requirements, to justify this allocation.

The pattern observed in retention versus non-retention deal allocation is further visualized in Figures 3A and 3B. Figure 3A illustrates that, after the risk retention rule was enforced, agency loans saw a marked increase in volume in both high- and low-risk areas, aligning with prior findings (Ouazad and Kahn, 2019). Conversely, non-agency loans expanded significantly only in low-risk regions post-2017. Figure 3B shows a notable decline in the share of non-agency loans allocated to high-risk regions post-2017, indicating that the rule effectively prompted issuers to shift their focus towards safer areas.

### **Figure 3 about here**

To validate these findings, we investigate the impact of 18 major hurricanes and 105 severe storms from 2011 to 2020 as natural experiments. This method allows us to precisely

estimate how historically realized hazards influence loan and CMBS performance. The historically realized climate-related loss for each loan is expressed as follows:

$$PD_{i,t}^{HT} = \phi_m^H Post_{i,t}^H + \phi_m^T Post_{i,t}^T, \quad (2)$$

where  $PD_{i,t}^{HT}$  measures the exposure of loan  $i$  in period  $t$  to hurricane and tornadoes.  $Post_{i,t}^H$  and  $Post_{i,t}^T$  are binary indicators that reflect whether the property was affected by one of the 18 hurricane events or one of the 105 tornado events.  $\phi_m^H$  and  $\phi_m^T$  represent the historical building loss ratio in each zip code.

Retention deals show higher exposure to hurricanes due to their concentration in coastal regions. For instance, Table 3 indicates that the variable  $PostH \times DamageH$  is higher for retention loans (0.041% mean value) compared to non-retention loans (0.026% mean value), suggesting a higher hurricane impact. Conversely, non-retention loans, which are more geographically dispersed, show greater exposure to tornadoes as indicated by a higher value in  $PostT \times DamageT$ . This suggests that non-retention deals are structured with a broader risk profile, potentially due to less stringent risk assessment practices.

Overall, Table 3 reveals that retention deals generally allocate loans to areas with lower ex-post and ex-ante risks, emphasizing the regulatory influence of the risk retention rule. The conservative geographic strategy of retention deals, combined with stricter underwriting and pricing, aligns with a risk-averse approach aimed at minimizing the likelihood of defaults and safeguarding market stability. This stands in contrast to non-retention deals, which adopt a more diversified risk approach, potentially reflecting a focus on short-term gains in exchange for higher risk exposure.

**Table 3 here**

## 4 Empirical Analysis

In this section, we conduct an in-depth empirical analysis to investigate the relationship between climate hazard exposure and CMBS loan allocation, focusing on the impact of the risk retention rule on geographic exposure to climate risks. We assess the extent to which CMBS issuers have adjusted their risk-taking behavior post-implementation of the rule. Additionally, we examine the impact of climate shocks on mortgage performance, including default risk and operating income, as well as the pricing of climate hazard exposure in CMBS loans.

### 4.1 Geographic Exposure to Climate Hazards

We begin by analyzing how CMBS deals' geographic exposure to climate risks has evolved before and after the implementation of the risk retention rule. This evaluation includes both ex-post risks (estimated climate risk based on historical events) and ex-ante risks (projected climate threats such as flooding and sea level rise).

To quantify the geographic exposure to climate hazards at the deal level, we define the average climate exposure of the deal during the securitization period  $t$  using the following equation:

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

where  $ED_{j,t}^{Deal}$  is the face value-weighted average climate exposure of deal  $j$  during securitization period  $t$ , with  $ED_{j,t}^{Deal} = \sum_{l=1}^{L_j} w_{l,t} ED_l^{HT}$ .  $I_{j,t}^{Deal}$  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, weighted average occupancy, weighted average coupon rate, log of the weighted average loan term, the share of loans with income overstatement over 5%<sup>8</sup>, the share of interest-only loans and log of deal size. 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, between 2000 and 2010, and after 2010. 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.

In Column 1 of Table 4, the coefficient for the retention deal dummy is negative and statistically significant, indicating that deals subject to risk retention have a lower weighted average exposure to climate hazards. This supports our *first hypothesis* that the risk retention

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<sup>8</sup> Griffin and Priest (2023) demonstrate that the property income reported for CMBS loans tends to be overstated relative to actual property income. Their analysis, as shown in Appendix 1, indicates that properties with higher climate risk are more likely to overstated income at issuance. To address this, we control for the income statements of the loans and deals, with income overstatement measured as the discrepancy between the underwritten NOI (Net Operating Income) and the realized NOI in the year of CMBS issuance. Furthermore, we exclude loans with more than a 5% income overstatement from our sample due to the significant impact of such overstatements on loan performance, as documented by Griffin and Priest (2023). Despite these adjustments, our results remain robust.



rule motivates issuers to reduce risk by avoiding areas with high climate exposure. Additionally, the positive coefficients for loan-to-value (LTV) ratios and loan rates suggest that deals with higher exposure to climate hazards are associated with higher LTV ratios and loan rates, reflecting the elevated risk premium required by investors for taking on such risks. Smaller deals tend to show higher geographic exposure to climate hazards, suggesting a lack of diversification.

We first examine the impact of risk retention on the geographic exposure to ex-post climate hazards, defined by historical events like hurricanes and tornadoes. Table 4, Column 1 shows that retention deals exhibit a statistically significant reduction in average ex-post estimated annual loss ratio by (2.36%), supporting our *hypothesis one* that the risk retention rule effectively reduces geographic exposure to climate hazards. In Columns 2 and 5 of Table 4, the results indicate that retention deals have a significantly higher share (7.47%) of loans in zip codes with the lowest risk (Q1) and a significantly lower share (6.67%) in the highest-risk zip codes (Q4). Given that non-agency CMBS provides approximately 77 billion USD in loans per year, the estimated percentage shift indicates an increase of around 5.75 billion USD per year in loan supply to low-risk areas, and a decline of 5.14 billion USD in loan supply to high-risk areas.

**Table 4 here**

To further validate these results, we shift our focus to ex-ante climate risks, including flood risk and sea level rise under a high-emissions global warming scenario (RCP8.5). As shown in Columns 1 and 4 of Table 5, the risk retention deals show a significantly higher geographic exposure (7.46%) to the zip codes with the lowest future flood risk and a significantly lower exposure (6.04%) to zip codes with the highest future flood risk. The results are even more pronounced when examining sea level rise risk, where retention deals have 10.08%

fewer loans in high-risk zip codes, suggesting a shift equivalent to approximately 4.65 billion USD annually. The exposure to the combination of flood risk and sea level rise risk is also significantly lower in risk retention deals. These findings provide strong support for our first hypothesis, demonstrating that the presence of risk retention motivates CMBS issuers to reduce geographic exposure to expected climate risk in their loan portfolios.

**Table 5 here**

We use staggered difference-in-difference methods to identify the causal impact of the risk retention rule by 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:

$$ED_{j,t}^{Deal,H} - ED_{j,t}^{Deal,L} = \sum_{k=-5, k \neq -1}^5 \alpha_k D_k + \delta X_{j,t}^{Deal} + \tau_t^{Deal} + \omega_j^{Deal} + \epsilon_{j,t}^{Deal}. \quad (4)$$

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 five quarters before and after the risk retention requirement (December 24, 2016). The remaining variables are defined as in the previous section, except for  $\tau_t^{Deal}$ .  $\tau_t^{Deal}$  now represents the year-quarter dummies.

Figure 4 illustrates the dynamics of  $\alpha_k$  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. The key observation here is the change in behavior after the risk retention rule was implemented. Before the rule, there was no significant difference in exposure to risky areas. However, after implementation, deals securitized in the fourth quarter exhibited

a significantly lower share of loans allocated in areas with the highest ex-post climate risk. Similarly, for ex-ante risk, deals securitized in the same quarter and in the third and fourth quarters after the retention rule show a significantly lower share of loans in high-risk areas. This visual representation clearly supports our hypothesis that the risk retention rule incentivizes CMBS issuers to avoid climate risk.

**Figure 4 here**

## 4.2 Warehouse Risk

To further understand the dynamics of risk transfer in the CMBS market, we investigate the warehouse risk, which refers to the risk originators face when holding onto mortgages before securitizing them. If mortgages are subject to higher levels of climate hazard, we expect that this risk would increase for originators, providing a strong incentive for them to expedite the mortgage packaging and securitization process. However, the implementation of the risk retention rule makes this more difficult, as it requires originators to hold a portion of the risk, thereby influencing their ability to quickly securitize high-risk loans. We analyze the time span between mortgage origination and CMBS issuance using a triple difference method:

$$y_{i,t} = \alpha PD_{i,t}^{HT} + \alpha^* PD_{i,t}^{HT} I_{i,t} + \beta \phi_m^{HT} + \beta^* \phi_m^{HT} I_{i,t} + \theta I_{i,t} + \delta X_{i,t} + \tau_t + \omega_i + \epsilon_{i,t}. \quad (5)$$

where  $y_{i,t}$  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. Following Holtermans et al., (2022), we consider two-year as it captures the persistent economic effects of a climate shock over a longer time period. The results based on one year or half year post-event period generate robust results.  $\phi_m^{HT}$  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, income overstatement at securitization, and interest-only loan dummy. We also include dummy variables for property construction year, property type, MSA, year-month, and loan originator.

Black et al. (2012) indicates that most CMBS originators secure warehouse financing through internal lines of credit, repurchase agreements, or directly from their firms. However, conduit lenders—who are not affiliated with large financial institutions—often rely on external financing sources. Due to limited capital and higher capital costs, conduits face greater challenges compared to other originators and thus behave differently. Their restricted financial options and higher costs mean that conduit lenders cannot effectively compete for low-risk borrowers and often target riskier loans offering higher returns. For this reason, we also exclude loans made by conduit lenders to isolate the behavior of traditional CMBS lenders who face true warehouse risk.

The results are presented in Table 6. In Column 1, we consider all loans, while Column 2 excludes conduit lenders. In Column 1, we find that climate hazard risk significantly reduces the time lag between origination and securitization. The coefficient for the interaction term ( $\text{PostHT} \times \text{DamageHT}$ ) is -0.1284, significant at the 5% level. This indicates that when a property securing a CMBS loan is damaged by a climate disaster within the past two years, the originator expedites the securitization process, reducing the warehouse period by 12.84%. This behavior suggests that originators aim to quickly offload the risk associated with these loans, which supports the notion that climate hazards lead to a faster securitization timeline

However, when risk retention requirements are in place, the dynamics change. As shown in Column 2, which excludes conduit lenders, the coefficient for the interaction term ( $\text{PostHT} \times \text{DamageHT} \times \text{Retention}$ ) is 0.4669 and is significant at the 5% level. This positive coefficient suggests that, under the retention rule, originators take longer to securitize

loans exposed to climate risk. The retention requirement constraints originators to hold onto these loans longer as they need to conduct thorough risk assessments and ensure quality control before securitization. This finding confirms our hypothesis that the risk retention rule constrains the ability of originators to expedite the issuance of high-risk mortgages, leading to a more cautious and slower securitization process.

Moreover, Table 6 also reveals that other loan and zip code characteristics influence the warehouse period. Mortgages located in areas with higher business concentration, higher DSCR, lower LTV ratios, and shorter loan terms are sold more slowly. For example, DSCR shows a positive relationship with the time lag, with coefficients of 0.0301 and 0.0231 in Columns One and Two, respectively, both significant at the 1% level. This indicates that loans with strong debt coverage are held longer before securitization, reflecting confidence in these loans' performance.

Interest-only loans, which are typically seen as riskier due to their structure, are sold faster. The negative coefficient of -0.0568 in Column 1 (significant at the 1% level) indicates that these loans are securitized more quickly, as originators aim to minimize their exposure to higher-risk assets. By reducing the time these riskier loans are held in the warehouse, originators effectively manage their risk exposure. In contrast, loans with higher mortgage rates are securitized more slowly, as evidenced by the significant positive coefficients for the loan rate variable (13.0722 in Column 1 and 12.0940 in Column 2, both significant at the 1% level). This indicates that higher-rate loans, which often correlate with higher risk, may require more time for originators to package and sell. Originators may delay securitizing these loans until they find favorable market conditions or investors willing to accept the higher risk associated with these loans

The OverStatement variable, reflecting inflated income projections at securitization, shows a significant negative coefficient (-0.2328 in Column 2). This indicates that loans with

overstated income are securitized more quickly. Originators, aware of the potential risk if these inflated figures are later disproven, expedite the sale of such loans. This strategy aligns with the "originate-to-distribute" model, where originators aim to transfer risk quickly to minimize their own exposure. By securitizing these loans rapidly, they capitalize on favorable market perception before any discrepancies in income performance can be detected.

Overall, Table 6 provides strong evidence that originators adjust their securitization timelines based on climate risk and regulatory requirements. The implementation of the risk retention rule compels originators to exercise greater caution, extending the securitization timeline when higher climate risks are present.

**Table 6 here**

#### **4.3 Exposure to Climate Risk of Originators and Underwriters**

In this section, we examine whether underwriters selectively exclude risky mortgages from their own deals, especially when these mortgages have been affected by climate shocks. We consider two scenarios: 1) when underwriters choose their own deal to underwrite, and 2) when deals are originated by institutions that do not underwrite CMBS. We first consider whether the underwriters are less likely to underwrite their own deal if the deal are impacted by the climate shocks. To represent this choice, we create a binary variable called ‘Originates for Own Deal’, which takes the value of one if the originator underwrites the CMBS deal containing their own mortgages and zero otherwise.. We apply Equation (5), substituting the dependent variable with the ‘Originates for Own Deal’ dummy variable.

Table 7 provides insight into how climate shocks influence the relationship between loan originators and underwriters. Column 1 indicates that, in retention deals, underwriters are less inclined to include mortgages with higher climate hazards in their own deals, with a coefficient of -0.5414 (significant at the 5% level). This suggests that when underwriters face

the risk of retaining loans, they demonstrate more caution in selecting loans, preferring to avoid those with higher climate risks. This behavior aligns with the idea that the risk retention rule prompts stricter scrutiny and more conservative loan selection.

Additionally, the results show that originators are likely to sell mortgages to other issuers when loans have lower debt service coverage ratios (DSCR), higher loan-to-value (LTV) ratios, shorter terms, and lower mortgage rates. This pattern indicates that underwriters tend to cherry-pick safer and higher-rate loans for their own deals. However, the study also finds that underwriters are more likely to include their own originated loans when these are subject to the risk retention requirement. The reasoning here is that when underwriters have more complete information about the risks of their own loans, they prefer to retain these loans in retention deals, as this reduces information asymmetry and improves their ability to manage the risk effectively.

**Table 7 here**

Next, 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, which equals one for mortgages originated by institutions that have never underwritten CMBS deals (as recorded in the Trepp database) and zero otherwise. We apply Equation (5) again with this variable as the dependent measure to determine whether underwriters or CMBS sponsors tend to cherry-pick loans with lower climate hazard exposure.

Table 7, Column 2 reveals that after implementing the risk retention rule, underwriters tend to avoid originating loans with higher climate hazard exposure. The coefficient for the interaction term of climate shock and the risk retention dummy is now statistically significantly positive, indicating that underwriters, when required to retain the risk, tend to avoid originating loans exposed to high climate risk. 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, leading to a more separated task of loan origination and deal issuance.

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 riskier 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.



To quantify exposure to climate shocks, we calculate the face value-weighted average of past climate-related events impacting loans underwritten in previous deals. This approach incorporates the historical building loss ratios and the frequency of climate events (e.g., hurricanes, floods, tornadoes) for each loan's location, effectively capturing the cumulative risk that underwriters have faced. By weighting each loan's exposure by its face value, our methodology ensures that larger loans with greater financial stakes have a proportionately larger influence on the overall risk profile. This allows us to accurately reflect the geographic exposure to climate hazards in future underwriting decisions, especially under the risk retention framework. The approach highlights how underwriters, when compelled to retain portions of the risk, are likely to adjust their strategies to minimize future losses by prioritizing safer regions. This response underscores the economic intuition that risk retention rules can mitigate moral hazard by incentivizing underwriters to select loans with lower climate risks.

The results in Table 8 offer detailed insights into how underwriters adapt their strategies in response to climate hazards, particularly under the influence of the risk retention rule. Column 1, which evaluates the average ex-post estimated annual loss ratio, reveals a significant negative coefficient of -0.9521 (at the 5% level) for the interaction term ( $\text{PostHT} \times \text{DamageHT} \times \text{PreRetention}$ ). This suggests that when underwriters were exposed to significant climate risks in deals conducted before the enforcement of the risk retention rule, they subsequently adjusted their strategies to reduce geographic exposure to high-risk areas once the rule was in effect. This shift implies that underwriters who experienced past climate-related losses proactively altered their behavior to minimize future risk when required to retain part of the loan risk. In Column 6, which measures the share of loans in zip codes with the highest climate hazard (top 25%), the interaction term ( $\text{PostHT} \times \text{DamageHT} \times \text{PreRetention}$ ) also shows a significant negative coefficient of -1.4848 (at the 5% level). This finding further corroborates that underwriter, when facing the obligation to retain risk, deliberately move away

from lending in high-risk areas. By reducing their allocation of loans in the most climate risky zip codes, underwriters demonstrate a cautious approach aimed at minimizing exposure to potential climate-related losses, aligning with the intended purpose of the retention rule.

Interestingly, the standalone effect of climate hazards, represented by (PostHT × DamageHT), does not show significant results in either Column 1 or Column 6. This suggests that without the risk retention rule, underwriters did not consistently adjust their exposure based solely on climate hazards. The rule, therefore, acts as a catalyst, motivating underwriters to make more conservative and strategic decisions to avoid high-risk areas.

Column 3, which reflects the share of loans in the 25% of zip codes with the second-lowest hazard, shows a positive and significant coefficient of 0.1751 (at the 5% level) for the Retention variable. This finding indicates that underwriters are more likely to focus on areas with moderately low risk when the retention rule applies. By concentrating on areas that are safe but not necessarily the safest, underwriters aim to balance risk and return, demonstrating a measured and strategic response under the regulatory framework.

Another notable finding is related to the OverStatement variable, which is significant in Column 4 (representing the share of loans in the second-highest hazard zip codes) with a coefficient of -0.1665 (significant at the 1% level). This negative relationship implies that loans with higher levels of income overstatement are less likely to be located in these moderately risky areas. Underwriters, when faced with overstated income information, may perceive these loans as riskier, thus avoiding these zip codes. This is consistent with the behavior of cautious underwriting practices, where underwriters seek to avoid additional layers of risk, such as exaggerated income figures, when already dealing with higher climate hazard exposures.

Overall, the results in Table 8 highlight the impact of the risk retention rule in transforming underwriting behavior. Underwriters, once required to retain a portion of the loan risk, show a clear tendency to minimize geographic exposure to high-risk areas, supporting a

more conservative and strategically cautious approach. They also demonstrate a preference for areas with lower or moderately low risk, and they are particularly wary of loans with overstated income levels, aligning their strategies to minimize exposure to both financial and climate-related risks

**Table 8 here**

Similarly, when examining the ex-ante estimates of climate risk, specifically flood (FLD) and sea level rise (SLR) risks, and how past hurricane impacts influence these allocations, the results show a consistent pattern of risk-averse behavior under the influence of the risk retention rule as in Table 8. Specifically, the coefficient for (PostHT  $\times$  DamageH  $\times$  PreRetention) in Column 5 is -1.4995 (significant at the 5% level), indicating that underwriters who have faced significant hurricane-related damages in previous deals under the pre-retention framework are likely to decrease loan allocations in areas with high SLR risk. This behavior reflects a proactive approach by underwriters to limit future exposure based on past climate risk experiences.

Additionally, the coefficient for PostHT  $\times$  DamageHT in Column 1 is 3.7256 (significant at the 5% level), suggesting that underwriters facing hurricane impacts tend to increase allocations in areas with the lowest flood risk. This further demonstrates an adjustment in underwriting strategy where underwriters shift loan allocations away from high-risk areas, focusing instead on lower-risk zones based on past events.

Together, the results from Tables 8 and 9 demonstrate that the risk retention rule not only affects immediate underwriting decisions but also leads to a systematic shift in strategy. Underwriters increasingly avoid geographic areas with higher climate risks in both future and retention deals, underscoring the rule's effectiveness in shaping underwriting behavior to mitigate climate-related exposure.

**Table 9 here**

#### 4.4 Climate Hazard Exposure and Loan Performance

In this section, we investigate whether climate hazards actually increase default risk and negatively impact the performance of underlying assets. We analyzed loan performance data on a monthly basis, consisting of 878,234 loan-month observations, to explore the relationship between climate events and loan outcomes. The following regression model was applied:

$$y_{i,t} = \alpha \sum_{t_1}^t PD_{t_1,i}^{HT} + \beta \phi_m^{HT} + \delta X_{i,t} + \tau_t + \omega_i + \epsilon_{i,t}. \quad (6)$$

where  $y_{i,t}$  is the probability of over 90 days delinquency ( $\Pr(\text{default}_{i,t})$ ). The term  $\sum_{t_1}^t PD_{t_1,i}^{HT}$  captures the cumulative exposure to climate hazards from the time the loan is securitized to the month when the loan's performance is being assessed (i.e., the distribution month). We also consider the Net Operating Income Ratio in distribution period  $t$  ( $NOI_{i,t}$ ). To isolate the impact of climate hazards occurring post-securitization, we excluded loans affected by such events within the two years preceding securitization, resulting in a sample of 826,703 loan-month observations. This is to ensure that  $NOI_{i,t}$  is attributable to climate hazards occurring after securitization but before distribution. Except for debt service coverage ratio and loan rate, other independent variables, including loan characteristics and local economic conditions, are measured at the time of distribution.

Table 10 provides detailed insights into how various factors influence both default risk (Column 1) and net operating income (NOI) (Column 2) of loans, emphasizing the significant impact of climate hazards, local economic conditions, and loan characteristics. The results show that properties affected by climate events ( $\text{PostHT} \times \text{DamageHT}$ ) exhibit significantly higher default risk (0.1006) and reduced NOI (-0.0202) after these events. This indicates that the financial impact of climate hazards is substantial, with properties facing higher likelihoods of default and decreased cash flows due to operational disruptions, repairs, or tenant loss. The

results highlight that disaster-prone regions are inherently riskier, underscoring the importance of incorporating climate risk assessments into underwriting practices to ensure lenders adequately price these risks. This finding is consistent with Eichholtz et al. (2019), who also observed a significant increase in default probability two years after Hurricane Harvey.

In contrast, DamageHT, which isolates the direct effect of disaster damage, shows a coefficient for default risk (-0.0004) that is not statistically significant, indicating no measurable effect on defaults. However, it has a significant negative impact on NOI (-0.0051), reflecting that properties in areas with a history of climate-related damage tend to generate lower net income. This suggests that climate events impair property cash flows directly, even if they do not immediately trigger loan defaults.

Higher employment levels in a zip code (Emp) significantly reduce default risk (-0.0008), indicating that stronger local economies and job availability enhance tenant stability and support consistent loan repayments. However, these same areas are associated with a decrease in NOI (-0.0013), potentially due to higher operational expenses such as wages, taxes, or maintenance costs, which offset the benefits of higher occupancy. In contrast, employment concentration (BusiConcen) shows no significant impact on default risk (-0.0016), suggesting that the concentration of jobs in fewer industries does not strongly influence loan repayment ability. However, it significantly reduces NOI (-0.0020), indicating that economic specialization may expose properties to sector-specific risks that diminish property income, supporting the notion that economic diversification is more favorable for long-term property performance and financial stability.

The Overstatement variable, which reflects the tendency to overestimate income during underwriting, is not significant in the default risk model but shows a negative impact on NOI (-0.0173). This indicates that properties with overestimated income at origination tend to

underperform financially, as they likely do not generate the expected revenue, leading to cash flow shortfalls.

The significant influence of property-specific metrics like DSCR, LTV, and Loan Rate shows that traditional financial indicators remain critical determinants of loan performance. Properties with higher DSCRs are more likely to generate sufficient income to cover debt obligations, reducing default risk. Conversely, higher LTV ratios, which indicate greater leverage, are associated with increased default risk. However, there is also a positive relationship between NOI and LTV, suggesting that properties with higher income levels often attract more aggressive financing. This could be due to overstatement during underwriting, where inflated income projections justify higher loan amounts, potentially leading to a mismatch between income expectations and debt levels. These findings emphasize the need for prudent loan-to-value and debt service coverage ratio management, ensuring that income estimates are accurate and conservative to mitigate risk, especially as climate hazards become a growing concern.

The positive relationship between loan rate and both default risk and NOI highlights the complexity of pricing risk in CMBS deals. Higher loan rates might indicate a premium for riskier properties or areas, which, while initially boosting NOI, can also lead to increased default risk if cash flows become insufficient to cover these higher costs.

Overall, Table 10 reveals that climate hazards significantly influence loan performance by reducing NOI and increasing default risk, thus confirming Hypothesis Two. This underscores the necessity for lenders and investors to integrate climate, economic, and property-specific factors into their risk assessment frameworks to enhance the resilience and stability of their portfolios.

**Table 10 here**

To investigate the timing and persistence of climate impacts, we employ a staggered difference-in-differences (DiD) method. Figure 5 presents the dynamics of 90-day delinquencies (Panel A) and net operating income (Panel B) six months before and nine months after the climate event. Squares indicate the expected values, while lines represent a 95% confidence interval<sup>9</sup>. We observe a significant increase in delinquency in the third month following a climate event, with this rise persisting thereafter. Regarding property's cash flow, we note a significant decline in net operating income beginning in the fourth month after the event, with this negative trend continuing into the ninth month. This pattern documents the prolonged adverse effects of climate events on property income, emphasizing that such shocks have lasting economic impacts. The staggered DiD analysis further supports *Hypothesis Two*, highlighting that climate events not only disrupt property income but also increase default risk over an extended period.

**Figure 5 here**

#### **4.5 Pricing of Climate Hazard Exposure in CMBS Loans**

In this section, we analyze whether and how climate hazard exposure is priced in CMBS loans. Table 11 explores how climate hazard exposures, economic conditions, and property-specific factors influence the loan rate at securitization for CMBS loans. The results show that loans located in zip codes that fall within the bottom 25% for historical risk (low ex-post risk) receive significantly lower rates (-0.0326), suggesting that lenders view these properties as safer investments. Similarly, loans in zip codes that fall within the bottom 25% for either historical (ex-post) or future (ex-ante) climate risks (low risk OR) also benefit from significantly reduced rates (-0.0294), reflecting the perceived safety when a property meets at

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<sup>9</sup> We acknowledge that some properties may be affected by more than one hazard within the fifteen-month event window (six months before and nine months after the event). As a robustness test, we exclude properties that were affected by more than one hazard during a two-year time span and run the staggered DiD. The results remain robust.

least one low-risk criterion. In contrast, loans in areas that fall within the top 25% for both ex-post and ex-ante climate risks simultaneously (high risk AND), indicating compounded risk, are charged higher rates (0.0467). This indicates that lenders actively price in the increased risk associated with multiple overlapping climate hazards while offering more favorable terms to loans in zones perceived as safer.

Other factors also significantly influence loan rates. Higher employment levels in the zip code (Emp) are associated with lower loan rates (-0.0324), indicating that economically strong areas reduce perceived risk. Additionally, properties with higher Debt Service Coverage Ratios (DSCR) receive better pricing (-0.0487) due to their strong cash flow coverage. The positive and significant relationship between the Overstatement variable and loan rates (0.0758) shows that lenders increase rates when they detect inflated income projections, compensating for the risk of potential revenue shortfalls. These results collectively highlight how originators integrate climate, economic, and property-specific factors into their loan pricing strategies, confirming that risk is actively accounted for, thus validating *Hypothesis Three*.

#### **Table 11 here**

Table 12 analyzes how climate hazard exposures and the risk retention behavior of loan originators affect the loan rates at securitization for CMBS loans. The results highlight that lenders differentiate loan pricing based on whether the originator retains part of the risk and the type of climate exposure associated with the loan. Specifically, loans in areas exposed to high risk in both historical and projected (ex-post and ex-ante) scenarios (high risk AND) are priced significantly higher (0.0541) compared to those meeting only one risk criterion (high risk OR). This demonstrates that lenders are particularly cautious when risks are compounded over time, charging a premium when originators do not retain any part of the risk. Conversely,



when loans are located in areas that are low risk based on historical or projected data (low risk OR), loan rates are significantly lower (-0.0306), showing that lenders reward perceived safety. Table 12 confirms the findings of Table 11 by demonstrating that lenders consistently price climate risks into loan rates, offering lower rates for properties in low-risk areas and charging premiums for properties exposed to compounded risks, while also revealing the additional influence of risk retention on these pricing strategies.

The retention of risk by originators plays a crucial role in mitigating lender concerns, as evidenced by the interaction terms. For instance, when originators retain risk for loans exposed to sea level rise, loan rates are significantly reduced (-0.0616), suggesting that retention signals confidence and effective risk management, thereby lowering perceived risk. Similarly, for loans classified as high risk under either historical or projected data (high risk OR), retention results in significantly lower loan rates (-0.0547), indicating that originators' willingness to retain risk can reassure lenders even in higher-risk scenarios. However, retention does not significantly influence pricing for loans with compounded high risks (high risk AND), implying that when risks are severe and consistent, the act of retention alone may not be sufficient to offset the elevated risk perception. These findings suggest that while retention can be an effective tool to reduce loan rates under certain conditions, its effectiveness depends on the specific climate risk profile of the property.

**Table 12 here**

#### **4.6 Pricing of Climate Hazard Exposure in CMBS Deals**

At the deal level, climate risk is not fully reflected in the pricing of CMBS deals. In Table 13 explores how climate hazard exposure, economic conditions, and loan-specific characteristics influence the pricing and structuring of CMBS deals, with a focus on

the Weighted Average Coupon (WAC) and subordination levels for below-AAA and below-BBB tranches. It provides insight into how issuers and underwriters manage risks, especially climate-related ones, and protect various tranches.

The analysis in Columns 1 and 2 shows that climate risk exposure—whether High Risk OR or High Risk AND—does not significantly influence coupon rates. Both High Risk OR (0.1199) and High Risk AND (0.1781) have positive but insignificant coefficients, suggesting that issuers do not increase interest rates based solely on climate risks. This indicates that climate risks are not fully priced into WAC, meaning other mechanisms, such as structural protections like subordination, might be used to mitigate these risks.

Conversely, economic conditions and loan-specific factors play a significant role in WAC pricing. Employment levels in the property's zip code (WA Emp) have a negative and significant effect (-0.1700), indicating that properties in economically stable areas are charged lower coupon rates due to perceived lower risk. Higher Loan-to-Value (LTV) ratios are associated with higher WAC (0.8640), reflecting the increased default risk of more leveraged deals.

An important explanation for the insignificant climate risk exposure in WAC is asymmetric information between the loan originator and the CMBS issuer. Loan originators, who have better knowledge of property-specific risks, may not fully disclose or understate climate-related vulnerabilities. As a result, issuers might be hesitant to broadly raise coupon rates across the board and instead rely on more precise structural protections, such as subordination, to manage hidden risks. This helps issuers maintain competitive pricing on the overall deal without scaring off investors with higher borrowing costs.

Subordination levels—structural protections to shield senior tranches from potential losses—differ based on climate risk exposure. In Column 3, Low Risk OR (0.0792) is positive and significant, showing that subordination levels increase for below-AAA tranches even when

properties are located in low-climate-risk areas based on either historical or future risk. This may seem counterintuitive but reflects investor caution in lower-rated tranches, where non-climate-related risks (e.g., economic volatility) may still be a concern.

In Column 4, Low Risk AND is not significant, indicating that additional subordination is unnecessary for below-AAA tranches when properties are in areas with low climate risk across both historical and projected dimensions. Here, investors appear satisfied with the existing protections in the CMBS structure, as these properties are considered double-safe. The lack of significance here indicates that investors are more comfortable with their risk exposure when climate risks are mitigated across both dimensions, reducing the need for further structural adjustments.

Additionally, higher LTV ratios lead to increased subordination levels (0.5759 in Column 3 and 0.5898 in Column 4), highlighting the need for greater protections in more leveraged properties. Conversely, properties with higher Debt Service Coverage Ratios (DSCR) show lower subordination levels (-0.0297 in Column 3), reflecting lower perceived risk due to stronger income relative to debt obligations.

For below-BBB tranches in Column 5 and 6, the effects of climate risks and loan characteristics are less pronounced. Neither High Risk OR nor High Risk AND is significant, suggesting that investors in lower-rated tranches expect higher risk and are willing to absorb it without demanding additional protection. However, higher LTV ratios (0.3813 and 0.3772 in Columns 5 and 6) still lead to increased subordination, reflecting the need for stronger protections in high-leverage deals.

The findings in Table 13 suggest that CMBS issuers do not fully price climate risks into WAC, instead managing these risks through subordination levels, particularly for below-AAA tranches, providing confirmation of *Hypothesis Four*. Asymmetric information may also play

a role, with issuers opting for structural adjustments like subordination instead of raising interest rates, to mitigate the risks that may not be fully visible or disclosed by loan originators.

### **Table 13 here**

Table 14 further examines how climate hazard exposure and risk retention strategies affect the Weighted Average Coupon (WAC) and subordination levels for below-AAA and below-BBB tranches in CMBS deals. The analysis reveals how retention changes the relationship between climate risk and deal structuring, showing the strategies issuers use to manage risk. In Column 2, properties in areas with compounded historical and projected climate risks (High Risk AND) show a positive and significant increase in WAC (0.2144). This indicates that issuers charge higher coupon rates for these properties to reflect the greater perceived risk. However, when retention is applied, WAC decreases significantly (-0.3216), suggesting that retention effectively mitigates perceived risk, allowing issuers to lower yields. Retention provides confidence to investors by ensuring that issuers have "skin in the game," which helps reduce information asymmetry between originators and investors.

In Column 1, Low Risk OR  $\times$  Retention (0.3637) also leads to an increase in WAC, even in low-climate-risk areas. This may reflect concerns about non-climate-related risks, such as economic uncertainty, prompting investors to demand higher yields when retention is in play. This suggests that while retention mitigates risk, it may not eliminate investor caution in low-risk areas, where other factors come into play.

The subordination levels for below-AAA tranches, in Column 3 and 4, provide further insight into how issuers structure deals to protect senior tranches from potential losses. In Column 3, Low Risk OR (0.1831) shows that even in low-climate-risk areas, issuers increase subordination levels for below-AAA tranches. This likely reflects investor caution in

these tranches, where non-climate-related risks may still require protection. Investors demand extra protection to buffer against potential losses, even when climate risks are perceived as low. Investors in below-AAA tranches are likely to demand additional structural protection as a buffer against unexpected risks, even when climate risks are perceived to be low.

By contrast, Low Risk AND in Column 4 is not significant, indicating that when properties are safe from both historical and projected climate risks, investors and issuers perceive existing protections as sufficient. The lack of significance for Low Risk AND implies that when properties are "double safe," there is no need for further adjustments in the deal's structure, as investors and issuers alike perceive the built-in protections as adequate. High Risk AND  $\times$  Retention (0.1525) leads to increased subordination for below-AAA tranches, even though retention lowers WAC. This suggests that retention alone does not fully address the risk of compounded climate hazards, so additional protection is required to safeguard senior tranches.

In Column 5, Low Risk OR  $\times$  Retention (0.1059) indicates that for below-BBB tranches, retention leads to an increase in subordination levels in low-risk areas. This suggests that investors in below-BBB tranches demand greater protection when retention is applied, even in low-risk scenarios. Given that these lower-rated tranches are more vulnerable to losses, investors may be particularly cautious, demanding additional subordination to guard against potential risks that retention alone may not fully address. This is consistent with the idea that lower-rated tranches are seen as inherently riskier, requiring more structural protection regardless of the climate risk profile. Neither High Risk OR nor High Risk AND is significant for below-BBB tranches, implying that investors in these tranches may already anticipate high risks and are willing to absorb them without demanding additional protection based on climate risks. Instead, their concerns may be more focused on other factors, such as economic conditions or property-specific risks, rather than climate-related exposures.

In summary, Table 14 shows that both climate hazard exposures and risk retention significantly influence the pricing and structuring of CMBS deals. In high-risk areas, retention helps lower WAC, but issuers still increase subordination levels to protect senior tranches, indicating that retention alone is not enough to fully mitigate risk. In low-risk areas, retention leads to higher subordination for below-BBB tranches, reflecting investor caution, possibly due to non-climate risks or asymmetric information. These findings partially support *Hypothesis Four*, as climate risks do not always lead to higher yields, but retention plays a key role in adjusting both pricing and structural protections.

**Table 14 here**

## **5 Conclusions**

Although the impact of climate risk on stock prices has been extensively studied, there remains a surprising lack of evidence regarding its effects on debt securities, such as mortgages and securitized mortgages. This paper contributes to the understanding of climate risk in the Commercial Mortgage-Backed Securities market and examines the effectiveness of the Dodd-Frank Act's risk retention rule in mitigating associated moral hazard issues. Leveraging a dataset consisting of loans from over 41,701 properties in 556 CMBS deals issued between 2011 and 2018, alongside historical data on significant climate events such as hurricanes and tornadoes, we assess how climate shocks affect loan allocation, performance, and pricing.

Our findings reveal that the risk retention rule significantly influences CMBS issuers' behavior, leading to notably lower geographic exposure to high-climate risk areas compared to non-retention deals. This indicates that issuers prioritize safer assets when required to retain a portion of the risk, reducing their exposure to high-risk areas. In contrast, without retention requirements, loan originators expedite the sale of loans impacted by climate hazards, transferring these risks to investors without fully accounting for their potential impact. This

behavior highlights the moral hazard inherent in the "originate-to-distribute" model, where loan originators may securitize high-risk loans while shifting the risk to investors.

The adverse impact of climate risk on loan performance is also evident, as loans backed by properties in high-risk areas show higher default rates and lower net operating income (NOI). While some climate risks are partially factored into CMBS loan pricing, there is insufficient evidence that they are consistently accounted for at the deal level. This inconsistency may stem from the CMBS structure's complexity, which complicates the comprehensive assessment of climate risk exposure across all tranches.

Retention rule is essential for addressing these challenges. The results indicate that retention not only reduces geographic exposure to high-risk areas but also encourages more thorough loan screening and improves loan quality. When issuers retain risk, they become more selective in their underwriting, reducing climate hazard exposure in their loan portfolios.

However, while climate risk influences loan pricing, it is not consistently reflected in overall deal structuring without retention. This shows that retention mechanisms are critical for aligning the interests of issuers and investors, reducing information asymmetry, and ensuring transparent evaluation and management of climate risks. Additionally, retention allows issuers to adjust loan structuring and pricing strategies effectively, mitigating the impact of climate risks and emphasizing the need for ongoing regulatory measures and transparency in the CMBS market.

In summary, this study emphasizes the necessity of regulatory oversight and transparency to promote adequate risk management. The risk retention rule proves to be an effective measure for aligning issuers' and investors' interests, ultimately enhancing the stability and efficiency of the CMBS market.

## References

- Addoum, J. M., Eichholtz P., Steiner E. and Yönder E. 2023. Climate change and commercial real estate: Evidence from Hurricane Sandy. *Real Estate Economics*, n/a.
- Agarwal, S., Ambrose B. W., Yildirim Y. and Zhang J. 2021. Risk Retention Rules and the Issuance of Commercial Mortgage Backed Securities. *The Journal of Real Estate Finance and Economics*, 1-31.
- An, X., Deng Y. and Gabriel S. A. 2011. Asymmetric information, adverse selection, and the pricing of CMBS. *Journal of Financial Economics*, 100, 304-325.
- An, X., Deng Y., Nichols J. B. and Sanders A. B. 2015. What is Subordination About? Credit Risk and Subordination Levels in Commercial Mortgage-backed Securities (CMBS). *The Journal of Real Estate Finance and Economics*, 51, 231-253.
- An, X. and Pivo G. 2015. Default Risk of Securitized Commercial Mortgages: Do Sustainability Property Features Matter? *RERI Working paper*, 1-35.
- Ashcraft, A. B., Goriah K. and Kermani A. 2019. Does skin-in-the-game affect security performance? *Journal of Financial Economics*, 134, 333-354.
- Ashcraft, A. B. and Schuermann T. 2008. Understanding the securitization of subprime mortgage credit. *Foundations and Trends® in Finance*, 2, 191-309.
- Baldauf, M., Garlappi L. and Yannelis C. 2020. Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33, 1256-1295.
- Begley, T. A. and Purnanandam A. 2016. Design of Financial Securities: Empirical Evidence from Private-Label RMBS Deals. *The Review of Financial Studies*, 30, 120-161.
- Beltrán, A., Maddison D. and Elliott R. J. 2018. Is flood risk capitalised into property values? *Ecological Economics*, 146, 668-685.
- Bernstein, A., Gustafson M. T. and Lewis R. 2019. Disaster on the horizon: The price effect of sea level rise. *Journal of financial economics*, 134, 253-272.
- Black, L. K., Chu C. S., Cohen A. and Nichols J. B. 2012. Differences across originators in CMBS loan underwriting. *Journal of Financial Services Research*, 42, 115-134.
- Boudoukh, J., Whitelaw R. F., Richardson M. and Stanton R. 2015. Pricing Mortgage-Backed Securities in a Multifactor Interest Rate Environment: A Multivariate Density Estimation Approach. *The Review of Financial Studies*, 10, 405-446.
- Chernov, M., Dunn B. R. and Longstaff F. A. 2018. Macroeconomic-driven prepayment risk and the valuation of mortgage-backed securities. *The Review of Financial Studies*, 31, 1132-1183.
- Childs, P. D., Ott S. H. and Riddiough T. J. 1996. The Pricing of Multiclass Commercial Mortgage-Backed Securities. *Journal of Financial and Quantitative Analysis*, 31, 581-603.
- Christopoulos, A. D., Jarrow R. A. and Yildirim Y. 2008. Commercial Mortgage - Backed Securities (CMBS) and Market Efficiency with Respect to Costly Information. *Real Estate Economics*, 36, 441-498.
- Clayton, J., Devaney S., Sayce S. and Van de Wetering J. 2021. Climate risk and real estate prices: what do we know? *The Journal of Portfolio Management*, 47, 75-90.
- Cvijanovic, D. and Van de Minne A. 2021. Does Climate Change Affect Investment Performance? Evidence From Commercial Real Estate. *MIT Center for Real Estate Research Paper*.
- Demiroglu, C. and James C. 2012. How important is having skin in the game? Originator-sponsor affiliation and losses on mortgage-backed securities. *The Review of Financial Studies*, 25, 3217-3258.



- Demiroglu, C. and James C. 2015. Bank loans and troubled debt restructurings. *Journal of Financial Economics*, 118, 192-210.
- Deng, Y., Han C., Li T. and Riddiough T. J. 2023. Adaptation to Climate Change Through Mortgage Default and Prepayment. *Available at SSRN 4550947*.
- Eichholtz, P., Ongena S., Simeth N. and Yönder E. 2023. Banks, Non-Banks, and the Incorporation of Local Information in CMBS Loan Pricing. *Journal of Banking & Finance*, 106918.
- Eichholtz, P., Steiner E. and Yönder E. 2019. Where, When and How Do Sophisticated Investor Respond to Flood Risk?
- Fisher, G., Steiner E., Titman S. and Viswanathan A. 2022. Location density, systematic risk, and cap rates: Evidence from REITs. *Real Estate Economics*, 50, 366-400.
- Flynn, S. and Ghent A. 2018. Competition and credit ratings after the fall. *Management Science*, 64, 1672-1692.
- Frame, W. S. 2018. Agency Conflicts In Residential Mortgage Securitization: What Does The Empirical Literature Tell Us? *Journal of Financial Research*, 41, 237-251.
- Furfine, C. 2020. The impact of risk retention regulation on the underwriting of securitized mortgages. *Journal of Financial Services Research*, 58, 91-114.
- Furfine, C. H. 2014. Complexity and loan performance: Evidence from the securitization of commercial mortgages. *The Review of Corporate Finance Studies*, 2, 154-187.
- Gallagher, J. and Hartley D. 2017. Household finance after a natural disaster: The case of hurricane Katrina. *American Economic Journal: Economic Policy*, 9, 199-228.
- Ghent, A. C., Torous W. N. and Valkanov R. I. 2019. Complexity in structured finance. *The Review of Economic Studies*, 86, 694-722.
- Gibson, M. and Mullins J. T. 2020. Climate risk and beliefs in new york floodplains. *Journal of the Association of Environmental and Resource Economists*, 7, 1069-1111.
- Griffin, J. M. and Priest A. 2023. Is COVID Revealing a Virus in CMBS 2.0? *The Journal of Finance*, 78, 2233-2276.
- Guettler, A., Hommel U. and Reichert J. 2011. The influence of sponsor, servicer, and underwriter characteristics on RMBS performance. *Financial Markets and Portfolio Management*, 25, 281-311.
- Hamilton-Webb, A., Manning L., Naylor R. and Conway J. 2017. The relationship between risk experience and risk response: a study of farmers and climate change. *Journal of Risk Research*, 20, 1379-1393.
- He, J., Qian J. and Strahan P. E. 2012. Are All Ratings Created Equal? The Impact of Issuer Size on the Pricing of Mortgage-Backed Securities. *The Journal of Finance*, 67, 2097-2137.
- Holtermans, R., Kahn M. E. and Kok N. 2023. Climate risk and commercial mortgage delinquency. *MIT Center for Real Estate Research Paper*.
- Issler, P., Stanton R., Vergara C. and Wallace N. 2021. Housing and mortgage markets with climate risk: Evidence from California wildfires.
- Kau, J. B., Keenan D. C. and Yildirim Y. 2009. Estimating Default Probabilities Implicit in Commercial Mortgage Backed Securities (CMBS). *The Journal of Real Estate Finance and Economics*, 39, 107-117.
- Keys, B. J., Mukherjee T., Seru A. and Vig V. 2010. Did securitization lead to lax screening? Evidence from subprime loans. *The Quarterly journal of economics*, 125, 307-362.
- Keys, B. J. and Mulder P. 2020. Neglected no more: Housing markets, mortgage lending, and sea level rise. National Bureau of Economic Research.
- Liu, C. H., Zheng C. and Zhu B. 2022. Does Putting All Your Eggs in One Basket Add Value? The Case of a Spatial Concentration of Same Industry Firms. Working Paper.

- Longstaff, F. A. 2005. Borrower Credit and the Valuation of Mortgage-Backed Securities. *Real Estate Economics*, 33, 619-661.
- Loutschina, E. and Strahan P. E. 2011. Informed and uninformed investment in housing: The downside of diversification. *The Review of Financial Studies*, 24, 1447-1480.
- Masozera, M., Bailey M. and Kerchner C. 2007. Distribution of impacts of natural disasters across income groups: A case study of New Orleans. *Ecological economics*, 63, 299-306.
- McCoy, S. J. and Walsh R. P. 2018. Wildfire risk, salience & housing demand. *Journal of Environmental Economics and Management*, 91, 203-228.
- Miller, R. G. and Pinter N. 2022. Flood risk and residential real - estate prices: Evidence from three US counties. *Journal of Flood Risk Management*, 15, e12774.
- Mueller, J., Loomis J. and González-Cabán A. 2009. Do repeated wildfires change homebuyers' demand for homes in high-risk areas? A hedonic analysis of the short and long-term effects of repeated wildfires on house prices in Southern California. *The Journal of Real Estate Finance and Economics*, 38, 155-172.
- Murfin, J. and Spiegel M. 2020. Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies*, 33, 1217-1255.
- Ortega, F. and Taşpınar S. 2018. Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market. *Journal of Urban Economics*, 106, 81-100.
- Ouazad, A. and Kahn M. E. 2019. *Mortgage finance in the face of rising climate risk*, National Bureau of Economic Research.
- Petersen, M. A. and Rajan R. G. 2002. Does distance still matter? The information revolution in small business lending. *The journal of Finance*, 57, 2533-2570.
- Purnanandam, A. 2011. Originate-to-distribute model and the subprime mortgage crisis. *The review of financial studies*, 24, 1881-1915.
- Roberts, G., Lafuente J. and Darviris T. 2015. Climatic risk toolkit-the impact of climate change in the non-domestic real estate sector of eight European countries. *London: Royal Institution of Chartered Surveyors*.
- Titman, S. and Tsyplakov S. 2010. Originator performance, CMBS structures, and the risk of commercial mortgages. *The Review of Financial Studies*, 23, 3558-3594.
- Vigdor, J. 2008. The economic aftermath of Hurricane Katrina. *Journal of Economic Perspectives*, 22, 135-154.
- Zhu, B. and Fuerst F. 2022. Natural Hazard Exposure and REIT Equity Risk. *Working Paper*.

## Figure 1: Climate Hazards across Zip Code Areas

Figure 1A: Ex-post Estimated Annual Loss Ratio related to Hurricane and Strong Wind

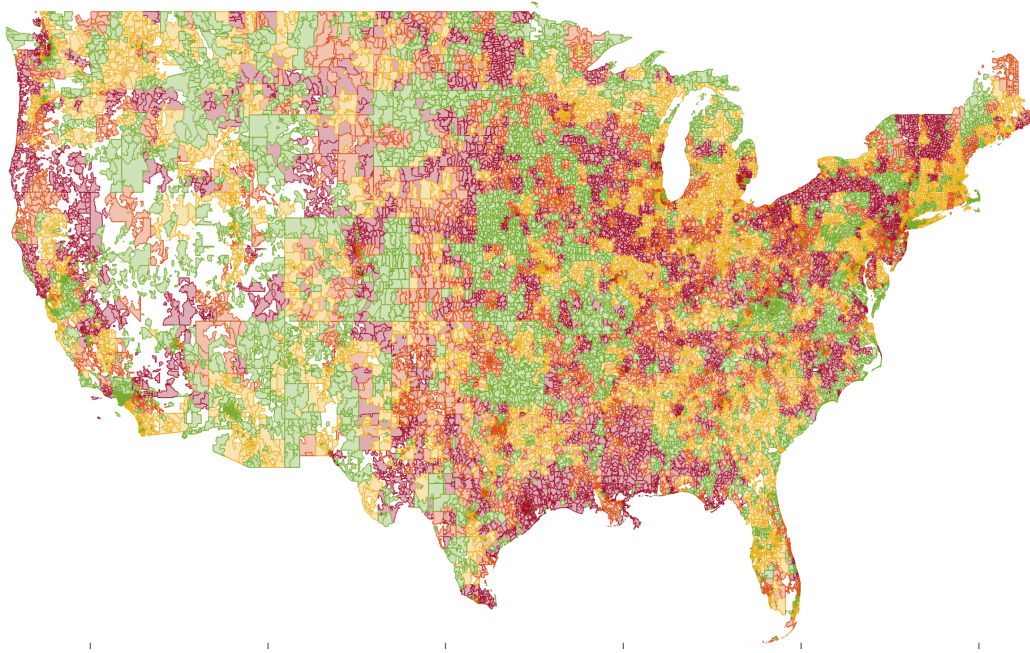
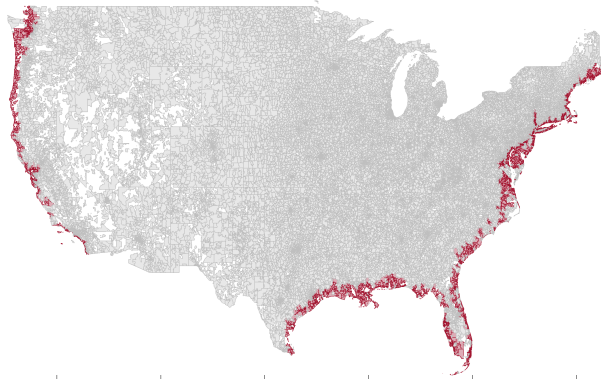
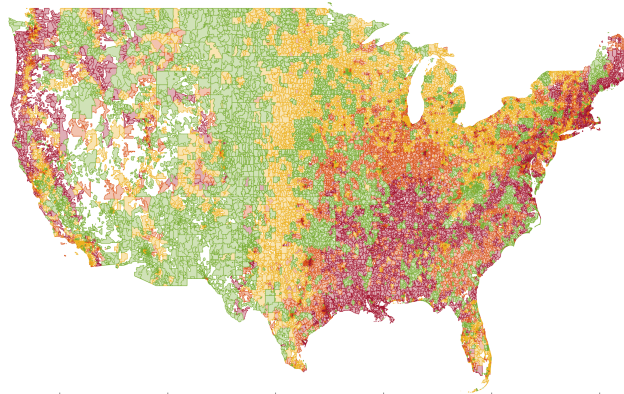


Figure 1B: Flood Risk under the High-Emissions Global Warming Scenario in the Late Century

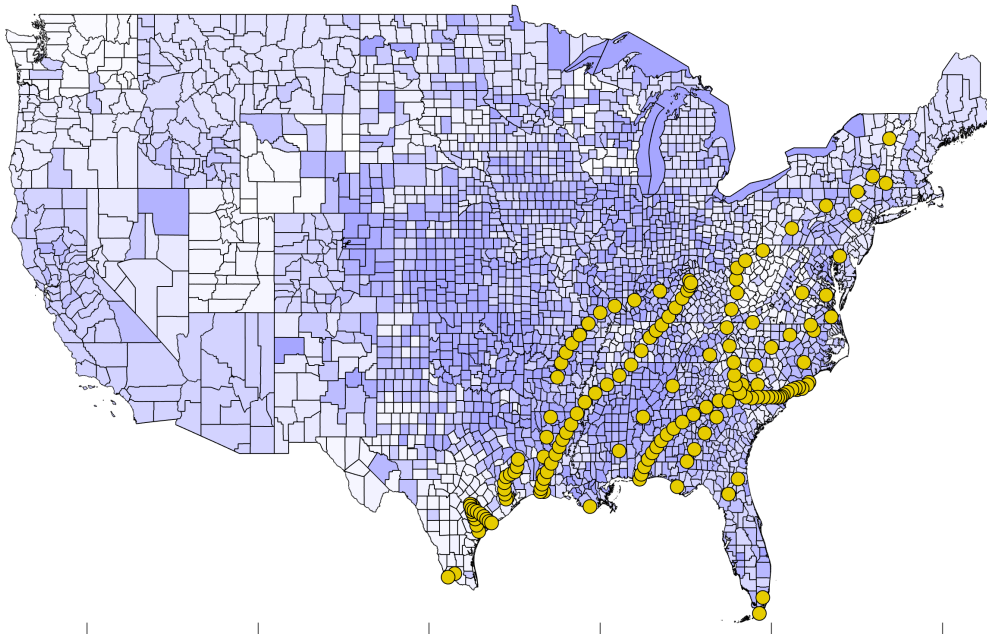
Figure 1C: Sea Level Rise Risk under the High-Emissions Global Warming Scenario in the Late Century



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 1: 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 3: CMBS Loan Allocation across Zip Code Areas with Highest and Lowest Climate Risks

Figure 3A: Loan Amount (Billion USD) Allocated in Zipcodes with Highest and Lowest Climate Risk

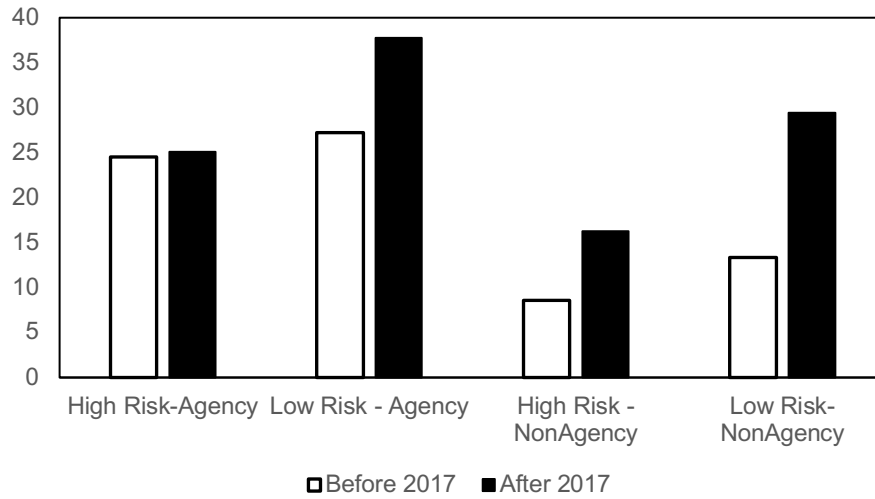
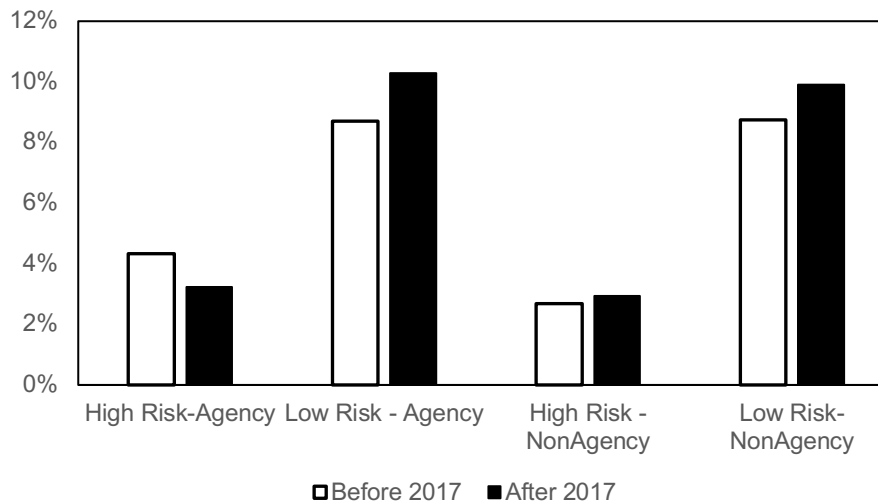
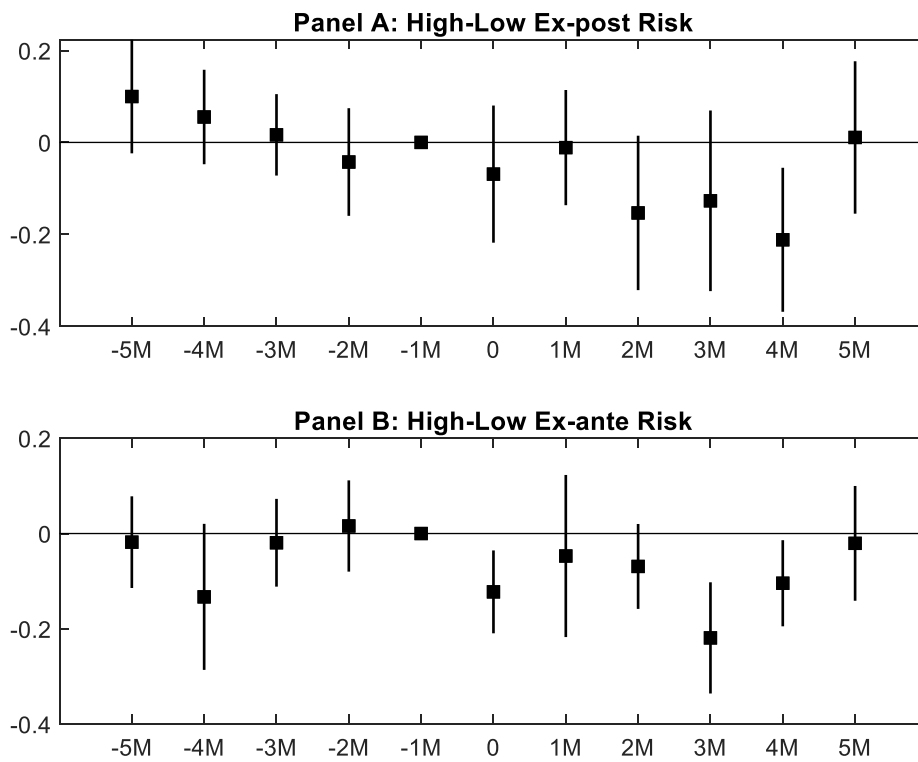


Figure 3B: Share of Loans Allocated in Zipcodes with Highest and Lowest Climate Risk



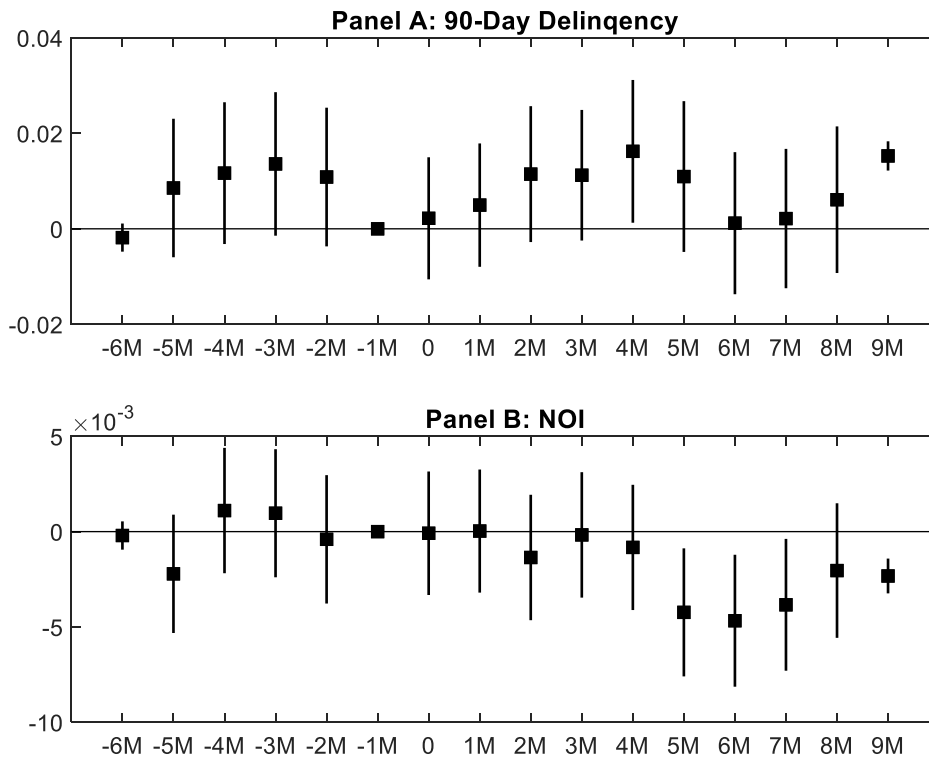
Note: Figure 3A (B) presents the loan amount (loan share) allocated in high- and low-risk zipcodes. High-risk zip codes are defined as those within the top 25% for ex-post hurricane and tornado risks, the top 25% for ex-ante future flood risk, and areas at risk from sea level rise. Low-risk zip codes are defined as those within the bottom 25% for ex-post hurricane and tornado risks, the bottom 25% for ex-ante future flood risk, and areas without sea level rise risk.

**Figure 4: 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  $\alpha_k$  and the lines indicate a 95% confidence interval.

**Figure 5: Impact of Hurricanes and Tornadoes 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  $\alpha_k$  and the lines indicate a 95% confidence interval.



**Table 1: Summary Statistics of Loans**

<b>Panel A: At Securitization (2011 to 2018)</b>					
	<b>Mean</b>	<b>Std</b>	<b>Max</b>	<b>Min</b>	
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	
Over Statement	0.003	0.035	1.259	0	
Loan Rate	0.043	0.008	0.104	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	
Built between 2000 and 2010	0.172	0.378	1	0	

<b>Panel B:</b>	<b>Retention Loans</b>		<b>Non Retention Loans</b>		<b>Diff</b>
	<b>Mean</b>	<b>Std</b>	<b>Mean</b>	<b>Std</b>	<b>Mean</b>
Time Lag (month)	2.524	2.541	5.330	5.188	-2.807***
Originator is the underwriter	0.452	0.498	0.145	0.352	0.307***
Loan originated by non-underwriters	0.448	0.497	0.228	0.420	0.220***
Over Statement	0.004	0.032	0.003	0.035	0.000
Loan Rate	0.048	0.007	0.043	0.008	0.006***
Debt service coverage ratio	2.312	2.683	2.104	2.642	0.208***
LTV	0.593	0.142	0.668	0.116	-0.075***
Occupancy	0.930	0.081	0.930	0.077	0.000
Loan Term (month)	111	23	119.113	52.445	-7.970***
Interest Only Loan	0.307	0.461	0.089	0.285	0.218***
Built before 1960	0.159	0.366	0.153	0.360	0.007
Built between 1960 and 1970	0.083	0.276	0.127	0.333	-0.044***
Built between 1970 and 1980	0.116	0.320	0.158	0.365	-0.042***
Built between 1980 and 1990	0.189	0.392	0.204	0.403	-0.015***
Built between 1990 and 2000	0.120	0.325	0.123	0.328	-0.002
Built between 2000 and 2010	0.206	0.404	0.170	0.375	0.036***

<b>Panel C: At Distribution (2011 to 2018)</b>					
	<b>Mean</b>	<b>Std</b>	<b>Max</b>	<b>Min</b>	
Delinquency (more than 90 days)	0.351%	5.914%	1	0	
Employment	34650	38357	292915	4	
Business Concentration	0.165	0.067	1	0.075	
NOI (1000USD)	2627	7080	374828	0	
LTV	0.627	0.141	1	0.0096	
Remaining Loan Term (month)	95	46	443	0	

<b>Panel D:</b>	<b>Retention Loans</b>		<b>Non Retention Loans</b>		<b>Diff</b>
	<b>Mean</b>	<b>Std</b>	<b>Mean</b>	<b>Std</b>	<b>Mean</b>
Delinquency (more than 90 days)	0.056%	2.368%	0.371%	6.079%	-0.315%***
Employment	40853	45814	34231	37764	6622***
Business Concentration	0.166	0.067	0.165	0.067	0.001
NOI (1000USD)	4025	10819	2533	6743	1493***
LTV	0.588	0.146	0.630	0.141	-0.042***
Remaining Loan Term (month)	105	23	95	47	11***

Note: This table reports the descriptive statistics for CMBS loans included in our sample. Panel A presents the statistics for the time lag between origination and securitization, a dummy for whether the loan originator is the underwriter of the deal, a dummy for loans originated by non-underwriters, the difference between the reported NOI at securitization and the realized

NOI in the year of securitization (overstatement), the loan rate at securitization, the debt service coverage ratio at securitization, the loan-to-value ratio at securitization (LTV), occupancy at securitization, the loan term at securitization, a dummy for interest-only loans, and dummies for properties built in various year groups. Panel B compares the aforementioned loan characteristics for risk retention and non-risk-retention loans. Panel C reports the statistics over 2011 and 2018 for over-90-day delinquency rate, the number of establishments at the zipcode level (employment), the zipcode-level Herfindahl index for industry sector concentration (business concentration), net operating income at distribution (NOI), the loan-to-value ratio at distribution (LTV), and the remaining loan term at distribution. Panel D compares the loan characteristics mentioned in Panel C for risk retention and non-risk-retention loans.

**Table 2: Summary Statistics of Deals**

<b>Panel A: Securitization (2011 to 2018)</b>					
	<b>Mean</b>	<b>Std</b>	<b>Max</b>	<b>Min</b>	
Risk Retention Deal	23%	42%	1	0	
Non Agency Deal	81%	39%	1	0	
Below-AAA (437 Deals)	0.284	0.133	0.873	0	
Below-BBB (437 Deals)	0.085	0.073	0.570	0	
WAC	0.045	0.008	0.083	0.011	
WADSCR	2.324	2.890	65.33	1	
WAOCC	0.933	0.043	1	0.61	
WALTV	0.592	0.098	0.89	0.0139	
WA Term	108	34	345	15	
Deal Size (Million USD)	771	425	2144	1	
WA Emp	45731	51881	285071	2411	
WA BusiConcen	0.171	0.055	0.695	0.086	

<b>Panel B:</b>	<b>Retention Deals</b>		<b>Non Retention Deals</b>		<b>Diff Mean</b>
	<b>Mean</b>	<b>Std</b>	<b>Mean</b>	<b>Std</b>	
Below-AAA (437 Deals)	0.295	0.166	0.280	0.117	0.014
Below-BBB (437 Deals)	0.098	0.090	0.080	0.064	0.018**
WAC	0.045	0.007	0.045	0.008	0.000
WADSCR	2.352	0.690	2.316	3.269	0.036
WAOCC	0.928	0.046	0.934	0.042	-0.006
WALTV	0.555	0.079	0.603	0.100	-0.048***
WA Term	104	25	109	36	-4.463
Deal Size (Million USD)	771	342	771	447	-0.182
WA Emp	50762	55980	44241	50578	6521***
WA BusiConcen	0.193	0.068	0.164	0.049	0.029***

Note: This table presents the descriptive statistics for the CMBS deals in our sample. Panel A provides statistics on the risk-retention deals, non-agency deals, the proportion of loans rated below AAA (Below-AAA), the proportion rated below BBB (Below-BBB), the weighted average coupon (WAC), weighted average debt service coverage ratio (WADSCR), weighted average occupancy rate (WAOCC), the weighted average loan-to-value ratio at securitization (WALTV), weighted average loan term (WA Term), deal size, the weighted average number of establishments per zipcode (WA Emp), and weighted average Herfindahl-Hirschman Index (HHI) of sectoral establishments (WA BusiConcen). Panel B compares these loan characteristics between risk-retention and non-risk-retention deals.

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

<b>Panel A: Year</b>		<b>Hurricanes</b>	<b>Tornadoes</b>
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%

<b>Panel B: Loan</b>	<b>Mean</b>	<b>Std</b>	<b>Max</b>	<b>Min</b>
PostH*DamageH	0.027%	0.149%	2.896%	0
PostT*DamageT	1.237%	4.669%	65.524%	0
DamageH	0.185%	0.361%	3.397%	0
DamageT	10.514%	7.815%	65.524%	0

<b>Panel C:</b>	<b>Retention Deals</b>		<b>Non Retention Deals</b>		<b>Diff Mean</b>
	<b>Mean</b>	<b>Std</b>	<b>Mean</b>	<b>Std</b>	
PostH*DamageH	0.041%	0.207%	0.026%	0.143%	0.015%***
PostT*DamageT	0.974%	3.861%	1.259%	4.732%	-0.285%***
DamageH	0.188%	0.358%	0.185%	0.361%	0.003%
DamageT	9.326%	7.200%	10.616%	7.857%	-1.290%***

<b>Panel D: Share of Loans in Zipcodes</b>	<b>Mean</b>	<b>Std</b>	<b>Max</b>	<b>Min</b>
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

<b>Panel E:</b>	<b>Retention Deals</b>		<b>Non Retention Deals</b>		<b>Diff Mean</b>
	<b>Mean</b>	<b>Std</b>	<b>Mean</b>	<b>Std</b>	
Lowest Hazard (Ex-Post)	28.03%	24.98%	20.60%	23.98%	7.43%***
Second Lowest Hazard (Ex-Post)	27.67%	22.21%	30.57%	25.02%	-2.89%
Second Highest Hazards (Ex-Post)	26.29%	23.33%	28.60%	25.84%	-2.32%
Highest Hazards (Ex-Post)	18.00%	18.32%	20.23%	20.85%	-2.22%
Lowest Flood Risk (Ex-Ante)	32.15%	23.15%	33.03%	25.85%	-0.88%
Second Lowest Flood Risk (Ex-Ante)	7.29%	10.78%	10.33%	17.79%	-3.04%***
Second Highest Flood Risk (Ex-Ante)	17.65%	15.66%	18.88%	17.61%	-1.22%
Highest Flood Risk (Ex-Ante)	39.18%	28.96%	34.43%	30.05%	4.76%
Sea Level Rise Risk (Ex-Ante)	38.83%	28.49%	35.38%	28.60%	3.44%

Note: This table presents descriptive statistics on the climate risk exposure of CMBS deals. Panel A details the number of loans affected by hurricanes and tornadoes with damages exceeding one billion dollars each year. Panel B reports the realized damages from such events, along with historical building loss ratios attributable to hurricanes and tornadoes. Panel C compares the variables from Panel B between risk-retention and non-risk-retention loans. Panel D provides statistics on the proportion of loans in CMBS deals located in zip codes with varying levels of climate hazard exposure. Panel E compares the variables from Panel D between risk-retention and non-risk-retention deals.

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

<i>Dependent Variable:</i>	(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	(5) Share of Loans in 25% Zipcodes with Second Highest Hazard	(6) Share of Loans in 25% Zipcodes with Highest Hazard
<i>Retention Deal</i>	-0.0236** (0.0119)	0.0747** (0.0349)	0.0122 (0.0319)	-0.0318 (0.0375)	-0.0666** (0.0293)
<i>WA Emp</i>	-0.0081 (0.0119)	-0.0969*** (0.0332)	0.0209 (0.0258)	0.0790** (0.0395)	-0.0021 (0.0261)
<i>WA BusiConcen</i>	-0.1122 (0.1066)	0.8557** (0.3448)	-0.8627*** (0.2593)	-0.2668 (0.3130)	0.2662 (0.2112)
<i>WADSCR</i>	0.0019 (0.0018)	-0.0092** (0.0038)	0.0013 (0.0026)	0.0026 (0.0027)	0.0053 (0.0048)
<i>WALTV</i>	0.1886** (0.0925)	-0.4962** (0.2185)	0.1995 (0.1780)	-0.0416 (0.2003)	0.3440 (0.2734)
<i>WAOCC</i>	-0.1013 (0.1787)	0.0323 (0.3524)	-0.0988 (0.3555)	0.0474 (0.3604)	0.0074 (0.2672)
<i>OverStatement</i>	-0.1789 (0.1622)	0.8427 (0.6619)	-0.4642* (0.2755)	-0.1680 (0.4838)	-0.2145 (0.3716)
<i>WAC</i>	4.0218*** (1.4358)	-1.4586 (1.6142)	-2.6779* (1.5757)	-1.2729 (2.3637)	5.4513*** (1.7849)
<i>WA Term</i>	0.0401 (0.0312)	0.0055 (0.0410)	-0.0621 (0.0661)	0.1719*** (0.0573)	-0.1144** (0.0513)
<i>Interest Only</i>	0.0979** (0.0423)	-0.0676* (0.0398)	-0.0191 (0.0358)	0.0333 (0.0593)	0.0519 (0.0426)
<i>Deal Size</i>	-0.0048 (0.0126)	0.0384** (0.0170)	-0.0063 (0.0276)	0.0108 (0.0270)	-0.0422 (0.0273)
<i>Share BuiltYear</i>	Yes	Yes	Yes	Yes	Yes
<i>Share PropType</i>	Yes	Yes	Yes	Yes	Yes
<i>Deal Type FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Year_month FE</i>	Yes	Yes	Yes	Yes	Yes
<i>No. of obs</i>	556	556	556	556	556
<i>R<sup>2</sup></i>	0.2413	0.3192	0.2321	0.2058	0.2052

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the weighted average climate hazard exposure (Column 1) and share of properties in zipcodes 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 the weighted average zipcode-level number of establishments (WA Emp), the weighted average HHI of sectoral establishments' business concentration (WA BusiConcen), the share of overstated loans, the weighted average debt service coverage ratio (WADSCR), the weighted average loan-to-value ratio (WALTV), the weighted average occupancy rate (WA OCC), the weighted average loan term (WA Term), the share of interest-only loans, and deal size. We also include the share of loans within different construction year groups, the share of properties of different property types, a deal type dummy, and a year-month dummy for securitization. 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)**

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Dependent Variable:</i>	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
<i>Retention Deal</i>	0.0604* (0.0339)	-0.0036 (0.0252)	-0.0086 (0.0236)	-0.0746** (0.0353)	-0.1008*** (0.0373)	-0.1000*** (0.0323)
<i>Other Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Share BuiltYear</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Share PropType</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Deal Type FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year_month FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of obs</i>	556	556	556	556	556	556
<i>R<sup>2</sup></i>	0.2473	0.3347	0.3548	0.4341	0.4209	0.3938

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 1 to Column 4), the share of properties in zipocodes with sea level rise risk (Column 5), and the share of loans in zipcodes with flood and/or sea level rise risk (Column 6). 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 the weighted average zipcode-level number of establishments (WA Emp), the weighted average HHI of sectoral establishments' business concentration (WA BusiConcen), the share of overstated loans, the weighted average debt service coverage ratio (WADSCR), the weighted average loan-to-value ratio (WALTV), the weighted average occupancy rate (WA OCC), the weighted average loan term (WA Term), the share of interest-only loans, and deal size. We also include the share of loans within different construction year groups, the share of properties of different property types, a deal type dummy, and a year-month dummy for securitization. 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**

<i>Dependent Variable: Time Lag between Securitization and Origination</i>	(1) All Originators	(2) Excluding Conduit Lenders
<i>PostHT× DamageHT</i>	-0.1284** (0.0511)	-0.2288*** (0.0676)
<i>PostHT× DamageHT× Retention</i>	0.1944 (0.1898)	0.4669** (0.2242)
<i>DamageHT</i>	0.0406 (0.0422)	0.0485 (0.0538)
<i>DamageHT×Retention</i>	-0.0792 (0.1157)	-0.1482 (0.1286)
<i>Retention</i>	0.0783** (0.0303)	-0.0050 (0.0360)
<i>Emp</i>	0.0023 (0.0028)	0.0039 (0.0035)
<i>BusiConcen</i>	0.0521 (0.0348)	0.0901* (0.0460)
<i>OverStatement</i>	-0.1673 (0.1559)	-0.2328* (0.1351)
<i>DSCR</i>	0.0301*** (0.0045)	0.0231*** (0.0052)
<i>LTV</i>	-0.1271** (0.0509)	-0.1480** (0.0589)
<i>OCC</i>	-0.0637** (0.0317)	-0.0372 (0.0383)
<i>Term</i>	-0.0020*** (0.0002)	-0.0015*** (0.0003)
<i>Loan Rate</i>	13.0722*** (1.4432)	12.0940*** (1.8772)
<i>Interest Only</i>	-0.0568*** (0.0140)	-0.0337** (0.0170)
<i>Construction Year FE</i>	Yes	Yes
<i>Property Type FE</i>	Yes	Yes
<i>MSA FE</i>	Yes	Yes
<i>Year_month FE</i>	Yes	Yes
<i>Originator FE</i>	Yes	Yes
<i>No. of obs</i>	47102	27995
<i>R<sup>2</sup></i>	0.5424	0.5782

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. Control variables include the log of zipcode level establishment number, HHI of sectoral establishments at the zipcode (BusiConcen), NOI overstatement (OverStatement), debt service coverage ratio (DSCR), loan to value ratio (LTV), occupancy rate (OCC), loan term, loan rate, and a dummy variable for interest only loan. The values for the control variables are from the securitization period. 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**

<i>Dependent Variable:</i>	(1) Originates for own deal	(2) never underwrit
<i>PostHT×DamageHT</i>	0.0555** (0.0274)	-0.1019*** (0.0370)
<i>PostHT×DamageHT×Retention</i>	-0.5414** (0.2173)	0.5630*** (0.2129)
<i>DamageHT</i>	0.0137 (0.0232)	0.0412 (0.0297)
<i>DamageHT× Retention</i>	-0.1781 (0.1179)	0.1215 (0.1166)
<i>Retention</i>	0.1027** (0.0477)	-0.1475*** (0.0503)
<i>Emp</i>	0.0002 (0.0017)	0.0010 (0.0019)
<i>BusiConcen</i>	0.0055 (0.0213)	0.0203 (0.0247)
<i>OverStatement</i>	-0.0452*** (0.0163)	0.0041 (0.0211)
<i>DSCR</i>	-0.0017* (0.0009)	0.0038** (0.0016)
<i>LTV</i>	0.0364 (0.0257)	0.0810*** (0.0271)
<i>OCC</i>	-0.0156 (0.0241)	0.0425 (0.0296)
<i>Term</i>	-0.0001 (0.0001)	0.0000 (0.0001)
<i>Loan Rate</i>	0.1519 (0.7019)	-1.8743* (0.9726)
<i>Interest Only</i>	0.0010 (0.0076)	0.0013 (0.0092)
<i>Construction Year FE</i>	Yes	Yes
<i>Property Type FE</i>	Yes	Yes
<i>MSA FE</i>	Yes	Yes
<i>Year_month FE</i>	Yes	Yes
<i>Originator FE</i>	Yes	Yes
<i>No. of obs</i>	47102	47102
<i>R<sup>2</sup></i>	0.4725	0.4194

Note: This table reports the results of cross-sectional regressions. Column 1 uses the dummy variable for underwriters selecting their own deals to underwrite as the dependent variable, while Column 2 employs the dummy variable for originators that are non-underwriters as the dependent variable. 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 the log of zipcode level establishment number, HHI of sectoral establishments at the zipcode (BusiConcen), NOI overstatement (OverStatement), debt service coverage ratio (DSCR), loan to value ratio (LTV), occupancy rate (OCC), loan term, loan rate, and a dummy variable for interest only loan. The values for the control variables are from the securitization period. 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**

<i>Dependent Variable:</i>	(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	(5) Share of Loans in 25% Zipcodes with Second Highest Hazard	(6) Share of Loans in 25% Zipcodes with Highest Hazard
<i>PostHT×DamageHT</i>	0.5749 (0.4025)	-1.1397 (1.0624)	0.4801 (0.8914)	0.0981 (0.8592)	0.5615 (0.6924)
<i>PostHT×DamageHT× PreRetention</i>	-0.9521** (0.3864)	1.1450 (0.7655)	0.3836 (0.8630)	-0.0438 (0.9606)	-1.4848** (0.6962)
<i>DamageHT</i>	0.0005 (0.0007)	0.0032 (0.0024)	-0.0002 (0.0020)	-0.0017 (0.0027)	-0.0012 (0.0018)
<i>DamageHT× PreRetention</i>	0.0029*** (0.0009)	-0.0021 (0.0028)	-0.0016 (0.0035)	0.0004 (0.0040)	0.0033 (0.0024)
<i>PreRetention</i>	-0.0106 (0.0286)	-0.0243 (0.0779)	0.1751** (0.0720)	-0.1438 (0.1316)	-0.0070 (0.0377)
<i>Pre Emp</i>	0.0088 (0.0066)	-0.1210*** (0.0351)	0.0243 (0.0333)	0.0627** (0.0284)	0.0340** (0.0146)
<i>PreBusiConcen</i>	0.0279 (0.0612)	0.2612 (0.2135)	-0.1995 (0.1638)	-0.2279 (0.1713)	0.1662 (0.1369)
<i>PreOverStatement</i>	-0.0219 (0.0307)	0.2033 (0.1372)	-0.0293 (0.0734)	-0.1665*** (0.0527)	-0.0075 (0.0495)
<i>PreDSCR</i>	0.0351 (0.0264)	-0.0858 (0.0751)	-0.0417 (0.0743)	0.1225 (0.1061)	0.0050 (0.0714)
<i>PreLTV</i>	0.4055*** (0.0619)	-1.0830*** (0.3357)	-0.1285 (0.3585)	0.0376 (0.2323)	1.1739*** (0.1968)
<i>PreOCC</i>	-0.1343 (0.1049)	0.1322 (0.4647)	0.2293 (0.6020)	-0.2843 (0.4275)	-0.0772 (0.3349)
<i>Pre Term</i>	-0.0089 (0.0126)	0.0981* (0.0540)	-0.0851 (0.0536)	0.0196 (0.0398)	-0.0326 (0.0388)
<i>Pre Loan Rate</i>	1.8556** (0.8276)	-4.4428 (3.3617)	3.5738 (3.0634)	1.0802 (3.9005)	-0.2112 (2.6091)
<i>Pre Interest Only</i>	-0.0126 (0.0271)	0.0462 (0.0837)	-0.1232** (0.0596)	0.0388 (0.0728)	0.0382 (0.0659)
<i>Share of BuiltYear</i>	Yes	Yes	Yes	Yes	Yes
<i>Share of Deal Type</i>	Yes	Yes	Yes	Yes	Yes
<i>Share of PropType</i>	Yes	Yes	Yes	Yes	Yes
<i>Year_month FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Underwriter FE</i>	Yes	Yes	Yes	Yes	Yes
<i>No. of obs</i>	846	846	846	846	846
<i>R<sup>2</sup></i>	0.3819	0.3580	0.2596	0.2513	0.3336

Note: This table reports the results of cross-sectional regressions. The dependent variable is the weighted average climate hazard exposure (Column 1) and the share of properties in zipcodes with the lowest to the highest climate risk (Columns 2 to 6). 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 that determines 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 the log of the zipcode-level number of establishments, the HHI of sectoral establishments at the zipcode, NOI overstatement, the debt service coverage ratio, the loan-to-value ratio, the occupancy rate, loan term, loan rate, and whether the loan is interest-only. The values for these control variables are the face-value weighted averages of all loans in previous deals issued by the underwriter (Pre). We also include the share of loans within different construction year groups, the share of loans of different property types, the share of loans in different deal types, year-month dummies, and underwriter dummies. Heteroskedastic robust standard errors are reported in parenthesis. \*\*\*, \*\* and \* denote significance at the 1%, 5% and 10% level, respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Dependent Variable:</i>	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
<i>PostHT×DamageH</i>	3.7256** (1.8091)	0.5946 (1.3094)	-0.6433 (2.2804)	-3.6224 (2.8132)	2.7413 (2.2540)	-0.0100 (2.1976)
<i>PostHT×DamageH× PreRetention</i>	0.2919 (0.8313)	0.1522 (0.2533)	-0.1043 (0.6425)	-0.1612 (0.9247)	-1.4995** (0.7568)	-0.5997 (0.9319)
<i>DamageH</i>	-0.0020 (0.0657)	-0.0117 (0.0319)	0.0522 (0.0504)	-0.0394 (0.0873)	-0.0826 (0.0673)	-0.0586 (0.0690)
<i>DamageH× PreRetention</i>	0.0077 (0.1272)	-0.0509 (0.0527)	-0.1366 (0.0928)	0.1852 (0.1557)	0.2466 (0.1577)	0.1189 (0.1575)
<i>Retention</i>	0.0222 (0.0734)	-0.0171 (0.0311)	0.0724* (0.0393)	-0.1090 (0.0717)	0.0416 (0.0839)	-0.0584 (0.0608)
<i>Other Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Share of Construct.</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Deal Type FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Share of PropType</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year_month FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Underwriter FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of obs</i>	846	846	846	846	846	846
<i>R<sup>2</sup></i>	0.2213	0.3396	0.3745	0.4086	0.5102	0.4168

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 1 to 4), share of properties in zipcodes with sea level rise risk (Column 5) and share of loans in zipcodes with flood or sea level rise risk (Column 6). 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 the log of the zipcode-level number of establishments, the HHI of sectoral establishments at the zipcode, NOI overstatement, the debt service coverage ratio, the loan-to-value ratio, the occupancy rate, loan term, loan rate, and whether the loan is interest-only. The values for these control variables are the face-value weighted averages of all loans in previous deals issued by the underwriter. We also include the share of loans within different construction year groups, the share of loans of different property types, the share of loans in different deal types, year-month dummies, and underwriter dummies. Heteroskedastic robust standard errors are reported in parenthesis. \*\*\*, \*\* and \* denote significance at the 1%, 5% and 10% level, respectively.

**Table 10: Climate Hazards and Loan Performance**

<i>Dependent Variable:</i>	(1) Default Risk	(2) NOI
<i>PostHT×DamageHT</i>	0.1006*** (0.0178)	-0.0202*** (0.0076)
<i>DamageHT</i>	-0.0004 (0.0015)	-0.0051*** (0.0006)
<i>Emp</i>	-0.0008*** (0.0001)	-0.0013*** (0.0000)
<i>EmpConcen</i>	-0.0016 (0.0012)	-0.0020*** (0.0004)
<i>Overstatement</i>	-0.0006 (0.0008)	-0.0173*** (0.0006)
<i>DSCR</i>	0.0006*** (0.0000)	0.0004*** (0.0000)
<i>LTV</i>	0.0641*** (0.0016)	0.0267*** (0.0005)
<i>Loan Rate</i>	0.4302*** (0.0156)	0.2655*** (0.0043)
<i>OCC</i>	0.0016 (0.0010)	0.0003 (0.0003)
<i>Term</i>	-0.0036*** (0.0002)	-0.0037*** (0.0001)
<i>Interest Only</i>	0.0035*** (0.0002)	-0.0080*** (0.0001)
<i>Construction Year FE</i>	Yes	Yes
<i>Property Type FE</i>	Yes	Yes
<i>Originator FE</i>	Yes	Yes
<i>MSA FE</i>	Yes	Yes
<i>Year month FE</i>	Yes	Yes
<i>No. of obs</i>	826,703	826,703
<i>R<sup>2</sup></i>	0.1028	0.3030

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 a dummy variable with a value of one for 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. Control variables include the log of zipcode level establishment number (Emp), HHI of sectoral establishments at the zipcode (BusiConcen), NOI overstatement (OverStatement), debt service coverage ratio (DSCR), loan to value ratio (LTV), occupancy rate (OCC), loan term, loan rate, and a dummy variable for interest only loan. Except for debt service coverage ratio and loan rate, other independent variables, including loan characteristics and local economic conditions, are measured at the time of distribution. 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.

**Table 11: The Pricing of Climate Hazard Exposure in CMBS Loans**

<i>Dependent Variable:</i> <i>Loan Rate at Securitization</i>	(1)	(2)	(3)
<i>Exposure to High Ex- ante Flood Risk</i>	-0.0365 (0.0376)		
<i>Exposure to Sea Level Rise Risk</i>	0.0104 (0.0092)		
<i>Exposure to High Ex- post Risk</i>	0.0039 (0.0091)		
<i>Exposure to Low Ex ante Flood Risk -</i>	0.0360 (0.0377)		
<i>Exposure to Low Ex- post Risk</i>	-0.0326*** (0.0093)		
<i>Exposure to High Risk (OR)</i>		0.0007 (0.0082)	
<i>Exposure to Low Risk(OR)</i>		-0.0294*** (0.0090)	
<i>Exposure to High Risk (AND)</i>			0.0467** (0.0182)
<i>Exposure to Low Risk (AND)</i>			-0.0181 (0.0134)
<i>Emp</i>	-0.0330*** (0.0036)	-0.0324*** (0.0036)	-0.0324*** (0.0036)
<i>BusiConcen</i>	-0.0820** (0.0416)	-0.0788* (0.0417)	-0.0812* (0.0417)
<i>OverStatement</i>	0.0756** (0.0365)	0.0757** (0.0365)	0.0758** (0.0365)
<i>DSCR</i>	-0.0487*** (0.0094)	-0.0487*** (0.0094)	-0.0484*** (0.0094)
<i>LTV</i>	-0.4158*** (0.1042)	-0.4175*** (0.1043)	-0.4173*** (0.1042)
<i>OCC</i>	0.0545 (0.0477)	0.0541 (0.0477)	0.0546 (0.0477)
<i>Term</i>	0.0001 (0.0003)	0.0001 (0.0004)	0.0001 (0.0003)
<i>Interest Only</i>	-0.1874*** (0.0272)	-0.1875*** (0.0272)	-0.1873*** (0.0272)
<i>Construction Year FE</i>	Yes	Yes	Yes
<i>Property Type FE</i>	Yes	Yes	Yes
<i>MSA FE</i>	Yes	Yes	Yes
<i>Year_month FE</i>	Yes	Yes	Yes
<i>Originator FE</i>	Yes	Yes	Yes
<i>No. of obs</i>	47179	47179	47179
<i>R<sup>2</sup></i>	0.4993	0.4992	0.4992

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the loan rate at securitization. Key variables are exposure to various climate risks. Exposure to High/Low Ex-ante Flood Risk is a dummy variable indicating whether the loan is located in the 25% zipcodes with the highest/lowest ex-ante flood risk. Exposure to Sea Level Rise Risk is a dummy variable indicating whether the loan is located in zip codes with future sea level rising risk. Exposure to High/Low ex-post Risk is a dummy variable indicating whether the loan is located in the 25% zip codes with the highest/lowest ex-post hurricane and tornado risk. Exposure to High/Low Risk (OR) is a dummy variable indicating whether the loan is located in the 25% zip codes with the highest/lowest ex-post or ex-ante climate risk. Exposure to High/Low Risk (AND) is a dummy variable indicating whether the loan is located in the 25% zip codes with the highest/lowest ex-post and ex-ante climate risk. Control variables include the log of zipcode level establishment number, HHI of sectoral establishments at the zipcode (BusiConcen), NOI overstatement (OverStatement), debt service coverage ratio (DSCR), loan to value ratio (LTV), occupancy rate (OCC), loan term, loan rate, and a dummy variable for interest only loan. The values for the control variables are from the securitization period. 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.

**Table 12: The Pricing of Climate Hazard Exposure by Loans in Retention and Non-Retention CMBS Deals**

	(1)	(2)	(3)
<i>Exposure to High Ex- ante Flood Risk</i>	-0.0324 (0.0379)		
<i>Exposure to Sea Level Rise Risk</i>	0.0159* (0.0093)		
<i>Exposure to High Ex- post Risk</i>	0.0058 (0.0094)		
<i>Exposure to Low Ex- ante Flood Risk</i>	0.0396 (0.0376)		
<i>Exposure to Low Ex- post Risk</i>	-0.0296*** (0.0098)		
<i>Exposure to High Risk (OR)</i>		0.0054 (0.0084)	
<i>Exposure to Low Risk(OR)</i>		-0.0306*** (0.0093)	
<i>Exposure to High Risk (AND)</i>			0.0541*** (0.0193)
<i>Exposure to Low Risk (AND)</i>			-0.0178 (0.0139)
<i>Exp. High Ex-ante Flood Risk × Retention</i>	-0.0383 (0.0341)		
<i>Exp. Sea Level Rise Risk × Retention</i>	-0.0616** (0.0249)		
<i>Exp. High Ex-post Risk× Retention</i>	-0.0222 (0.0248)		
<i>Exp. Low Ex-ante Flood Risk × Retention</i>	-0.0026 (0.0237)		
<i>Exp. Low Ex-post Risk× Retention</i>	-0.0294 (0.0321)		
<i>Exp. High Risk (OR) × Retention</i>		-0.0547** (0.0249)	
<i>Exp. Low Risk (OR) × Retention</i>		0.0122 (0.0208)	
<i>Exp. High Risk (AND) × Retention</i>			-0.0689 (0.0607)
<i>Exp. Low Risk (AND) × Retention</i>			0.0004 (0.0326)
<i>Retention</i>	-0.0283 (0.0659)	-0.0523 (0.0587)	-0.0634 (0.0563)
<i>Control Variables</i>	Yes	Yes	Yes
<i>Construction Year FE</i>	Yes	Yes	Yes
<i>Property Type FE</i>	Yes	Yes	Yes
<i>MSA FE</i>	Yes	Yes	Yes
<i>Year_ month FE</i>	Yes	Yes	Yes
<i>Originator FE</i>	Yes	Yes	Yes
<i>No. of obs</i>	47179	47179	47179
<i>R<sup>2</sup></i>	0.4997	0.4995	0.4994

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the loan rate at securitization. Key variables are exposure to various climate risks. Key variables are exposure to various climate risks. Exposure to High/Low Ex-ante Flood Risk is a dummy variable indicating whether the loan is located in the 25% zipcodes with the highest/lowest ex-ante flood risk. Exposure to Sea Level Rise Risk is a dummy variable indicating whether the loan is located in zip codes with future sea level rising risk. Exposure to High/Low ex-post Risk is a dummy variable indicating whether the loan is located in the 25% zip codes with the highest/lowest ex-post hurricane and tornado risk. Exposure to High/Low Risk (OR) is a dummy variable indicating whether the loan is located in the 25% zip codes with the highest/lowest ex-post or ex-ante climate risk. Exposure to High/Low Risk (AND) is a dummy variable indicating whether the loan is located in the 25% zip codes with the highest/lowest ex-post and ex-ante climate risk. 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 the log of zipcode level establishment number, HHI of sectoral establishments at the zipcode (BusiConcen), NOI overstatement (OverStatement), debt service coverage ratio (DSCR), loan

to value ratio (LTV), occupancy rate (OCC), loan term, loan rate, and a dummy variable for interest only loan. The values for the control variables are from the securitization period. 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.

**Table 13: The Pricing of Climate Hazard Exposure in CMBS Deals**

<i>Dependent Variable:</i>	(1) <i>WAC</i>	(2) <i>WAC</i>	(3) <i>Below- AAA</i>	(4) <i>Below- AAA</i>	(5) <i>Below- BBB</i>	(6) <i>Below- BBB</i>
<i>Exposure to High Risk (OR)</i>	0.1199 (0.3174)		0.0397 (0.0299)		-0.0147 (0.0263)	
<i>Exposure to Low Risk (OR)</i>	-0.0049 (0.1440)		0.0792* (0.0448)		-0.0002 (0.0274)	
<i>Exposure to High Risk (AND)</i>		0.1781 (0.1093)		-0.0146 (0.0156)		0.0071 (0.0136)
<i>Exposure to Low Risk (AND)</i>		0.0223 (0.0926)		0.0138 (0.0223)		0.0005 (0.0169)
<i>WA Emp</i>	-0.1700*** (0.0466)	-0.1694*** (0.0507)	-0.0138 (0.0112)	0.0182* (0.0110)	0.0178** (0.0077)	0.0180** (0.0079)
<i>WA BusiConcen</i>	-0.0276 (0.5980)	-0.0526 (0.6475)	-0.0563 (0.0904)	0.0754 (0.0828)	0.2896*** (0.1068)	0.2874** (0.1152)
<i>OverStatement</i>	0.4649 (0.3496)	0.4356 (0.3449)	-0.0261 (0.0465)	-0.0305 (0.0538)	-0.0255 (0.0324)	-0.0330 (0.0376)
<i>WADSCR</i>	0.0023 (0.0158)	0.0039 (0.0162)	-0.0297*** (0.0048)	-0.0272*** (0.0048)	-0.0156** (0.0077)	-0.0155** (0.0077)
<i>WALTV</i>	0.8640* (0.4720)	0.9735* (0.4998)	0.5759*** (0.0821)	0.5989*** (0.0773)	0.3813*** (0.0607)	0.3772*** (0.0627)
<i>WAOCC</i>	0.6274 (0.4728)	0.5848 (0.4921)	0.1869 (0.1313)	0.1796 (0.1208)	0.0445 (0.0469)	0.0446 (0.0482)
<i>WA Term</i>	0.5204*** (0.1508)	0.5202*** (0.1526)	-0.0279 (0.0308)	-0.0311 (0.0293)	-0.0353 (0.0238)	-0.0344 (0.0244)
<i>Interest Only</i>	-0.7077*** (0.1198)	-0.7183*** (0.1179)	0.0833*** (0.0191)	0.0768*** (0.0170)	0.0386*** (0.0124)	0.0380*** (0.0120)
<i>Deal Size</i>	-0.1699*** (0.0541)	-0.1706*** (0.0554)	-0.0462*** (0.0148)	-0.0532*** (0.0142)	-0.0299*** (0.0114)	-0.0300*** (0.0115)
<i>Share BuiltYear</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Share PropType</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Deal Type FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year month FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of obs</i>	556	556	437	437	437	437
<i>R<sup>2</sup></i>	0.5959	0.5991	0.7742	0.7684	0.4865	0.4865

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the initial weighted average coupon rate (Column 1 and 2), AAA subordination level (Column 3 and 4) and BBB subordination level (Column 5 and 6). Key variables are exposure to various climate risks. Exposure to High/Low Risk (OR) is the share of loans in the deal located in the 25% zip codes with the highest/lowest ex-post or ex-ante climate risk. Exposure to High/Low Risk (AND) is the share of loans in the deal located in the 25% zip codes with the highest/lowest ex-post and ex-ante climate risk. Other control variables include the weighted average zipcode-level number of establishments (WA Emp), the weighted average HHI of sectoral establishments' business concentration (WA BusiConcen), the share of overstated loans, the weighted average debt service coverage ratio (WADSCR), the weighted average loan-to-value ratio (WALTV), the weighted average occupancy rate (WA OCC), the weighted average loan term (WA Term), the share of interest-only loans, and deal size. We also include the share of loans within different construction year groups, the share of properties of different property types, a deal type dummy, and a year-month dummy for securitization. Heteroskedastic robust standard errors are reported in parenthesis. \*\*\*, \*\* and \* denote significance at the 1%, 5% and 10% level, respectively.

**Table 14: The Pricing of Climate Hazard Exposure in Retention and Non-Retention CMBS Deals**

<i>Dependent Variable:</i>	(1) <i>WAC</i>	(2) <i>WAC</i>	(3) <i>Below- AAA</i>	(4) <i>Below- AAA</i>	(5) <i>Below- BBB</i>	(6) <i>Below- BBB</i>
<i>Exposure to High Risk (OR)</i>	0.0446 (0.4107)		0.0018 (0.0316)		0.0028 (0.0265)	
<i>Exposure to Low Risk (OR)</i>	-0.1384 (0.1764)		0.0050 (0.0182)		-0.0334 (0.0293)	
<i>Exp. High Risk (OR) × Retention</i>	0.2404 (0.4639)		0.1831*** (0.0602)		-0.0522 (0.0832)	
<i>Exp. Low Risk (OR) × Retention</i>	0.3637* (0.2132)		0.0508 (0.0487)		0.1059* (0.0572)	
<i>Exposure to High Risk (AND)</i>		0.2144* (0.1241)		-0.0360** (0.0167)		0.0082 (0.0123)
<i>Exposure to Low Risk (AND)</i>		0.0043 (0.1100)		-0.0121 (0.0193)		-0.0081 (0.0199)
<i>Exp. High Risk (AND) × Retention</i>		-0.3216** (0.1393)		0.1525*** (0.0540)		0.0169 (0.0237)
<i>Exp. Low Risk (AND) × Retention</i>		0.0079 (0.1475)		0.1141* (0.0639)		0.0423 (0.0410)
<i>Retention</i>	0.0027 (0.1073)	0.2854 (0.1761)	-0.0360 (0.0258)	-0.1647*** (0.0580)	0.0018 (0.0082)	-0.0206 (0.0316)
<i>Control Variables</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Share BuiltYear</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Share PropType</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Deal Type FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year month FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of obs</i>	556	556	437	437	437	437
<i>R<sup>2</sup></i>	0.5411	0.5459	0.7352	0.7397	0.3938	0.3858

Note: This table reports the results of cross-sectional regressions for deals. The dependent variable is the initial weighted average coupon rate (Column 1 and 2), AAA subordination level (Column 3 and 4) and BBB subordination level (Column 5 and 6). Exposure to High/Low Risk (OR) is the share of loans in the deal located in the 25% zip codes with the highest/lowest ex-post or ex-ante climate risk. Exposure to High/Low Risk (AND) is the share of loans in the deal located in the 25% zip codes with the highest/lowest ex-post and ex-ante climate risk. 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.



## Appendix:

### Table A1: Distribution of Loans

<b>Year</b>	<b># Mortgage Origination</b>	<b># Mortgage Securitization</b>	<b># Deals</b>
2010	911	-	
2011	2709	2323	15
2012	3744	3348	36
2013	4918	4826	59
2014	6199	5345	68
2015	8595	7182	73
2016	7168	7908	68
2017	8787	8814	69
2018	4071	7356	49

<b>Property Type</b>	<b># Mortgage</b>	<b>% Mortgage</b>
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%

**Table A2: Robustness Tests Concerning Income Overstatement**

<i>Dependent Variable:</i>	(1) Time Lag between Securitization and Origination	(2) Originations for its own deal	(3) never underwrit	(4) Default Risk	(5) NOI	(6) NOI Over Statement
<i>PostHT×DamageHT</i>	-0.3194*** (0.0850)	0.0565** (0.0276)	-0.0993*** (0.0367)	0.0883*** (0.0173)	-0.0289*** (0.0077)	0.0290* (0.0153)
<i>PostHT×DamageHT × Retention</i>	0.7121** (0.3117)	-0.5544** (0.2278)	0.5568** (0.2215)			
<i>DamageHT</i>	0.0682 (0.0674)	0.0125 (0.0237)	0.0390 (0.0303)	-0.0014 (0.0016)	-0.0043*** (0.0006)	-0.0158 (0.0117)
<i>DamageHT× Retention</i>	-0.1719 (0.1782)	-0.1646 (0.1182)	0.1173 (0.1166)			
<i>Retention</i>	-0.0196 (0.0445)	0.1058** (0.0458)	-0.1492*** (0.0482)			
<i>Control Variables</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Construction Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Property Type FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>MSA FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year_month FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Originator FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of obs</i>	27532	46338	46338	813543	813543	47102
<i>R<sup>2</sup></i>	0.5741	0.4732	0.4181	0.1041	0.3006	0.0780

Note: From Columns 1 to 5, we investigate whether results remain robust when we exclude loans with high NOI overstatement (over 5%). The dependent variable is the time lag between securitization and origination (Column 1), a dummy variable for underwriters selecting their own deals to underwrite (Column 2), a dummy variable for originators that are non-underwriters (Column 3), 90 day delinquency (Column 4) and Net operating income (Column 5). Column 6 investigates the relationship between NOI Over Statement and Climate Hazard using all samples without excluding any loan. The dependent variable is a dummy variable, equalling one when the loan shows NOI overstatement at securitization. Post HT is a dummy variable with a value of one for 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 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 A3: Climate Hazard and Loan Performance for Retention and Non-Retention Loans**

<i>Dependent Variable:</i>	(1) Default Risk	(2) NOI
<i>PostHT×DamageHT</i>	0.1228*** (0.0200)	-0.0371*** (0.0082)
<i>DamageHT</i>	-0.0003 (0.0016)	-0.0036*** (0.0006)
<i>PostHT×DamageHT</i> <i>× Retention</i>	-0.2609*** (0.0421)	0.1173*** (0.0257)
<i>DamageHT</i> <i>× Retention</i>	0.0018 (0.0024)	-0.0075*** (0.0009)
<i>Retention</i>	-0.0040*** (0.0003)	-0.0035*** (0.0001)
<i>Zipcode Emp</i>	-0.0007*** (0.0001)	-0.0013*** (0.0000)
<i>Zipcode EmpConcen</i>	-0.0015 (0.0010)	-0.0019*** (0.0004)
<i>Overstatement</i>	-0.0006 (0.0005)	-0.0065*** (0.0002)
<i>DSCR_Secur</i>	0.0006*** (0.0000)	0.0004*** (0.0000)
<i>LTV</i>	0.0642*** (0.0016)	0.0257*** (0.0005)
<i>Loan Rate_Secur</i>	0.4426*** (0.0157)	0.3104*** (0.0043)
<i>OCC_Secur</i>	0.0013 (0.0009)	-0.0000 (0.0003)
<i>Term_Secur</i>	-0.0034*** (0.0002)	-0.0035*** (0.0001)
<i>Interest Only</i>	0.0041*** (0.0002)	-0.0074*** (0.0001)
<i>Construction Year FE</i>	Yes	Yes
<i>Property Type FE</i>	Yes	Yes
<i>Originator FE</i>	Yes	Yes
<i>MSA FE</i>	Yes	Yes
<i>Year month FE</i>	Yes	Yes
<i>No. of obs</i>	826703	826703
<i>R<sup>2</sup></i>	0.1030	0.3041

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. 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 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 A4: Underwriting Standards for Retention and Non-Retention Loans**

<i>Dependent Variable:</i>	(1)	(2)	(3)	(4)
	DSRC	LTV	DSRC	LTV
<i>Exp. High Risk</i>	-0.1550 (0.1014)	0.0010 (0.0034)		
<i>Exp. High Risk</i> <i>× Retention</i>	0.0065 (0.2018)	-0.0194* (0.0118)		
<i>PostHT× DamageHT</i>			-0.5796** (0.2462)	-0.0145 (0.0100)
<i>DamageHT</i>			-0.1910 (0.1917)	0.0102 (0.0078)
<i>PostHT× DamageHT×</i> <i>Retention</i>			-0.1387 (0.9273)	0.0372 (0.0376)
<i>DamageHT×</i> <i>Retention</i>			-0.8012 (0.5249)	-0.0520** (0.0213)
<i>Retention</i>	-0.3676*** (0.0581)	-0.0086*** (0.0022)	-0.2698*** (0.0727)	-0.0047 (0.0029)
<i>Zipcode Emp</i>	0.0872*** (0.0120)	-0.0076*** (0.0005)	0.0996*** (0.0121)	-0.0081*** (0.0005)
<i>Zipcode BusiConcen</i>	0.0647 (0.1544)	-0.0354*** (0.0072)	0.0124 (0.1632)	-0.0312*** (0.0066)
<i>OverStatement</i>	-0.2047*** (0.0594)	-0.0142*** (0.0039)	-1.8852*** (0.2015)	0.0712*** (0.0082)
<i>Term_Secur</i>	-0.0092*** (0.0004)	0.0108** (0.0051)	-0.0092*** (0.0003)	-0.0000 (0.0000)
<i>Interest Only</i>	0.5012*** (0.0534)	-0.0000 (0.0000)	26.5429*** (1.7928)	-0.6324*** (0.0726)
<i>Construction Year FE</i>	Yes	Yes	Yes	Yes
<i>Property Type FE</i>	Yes	Yes	Yes	Yes
<i>MSA FE</i>	Yes	Yes	Yes	Yes
<i>Year_month FE</i>	Yes	Yes	Yes	Yes
<i>Originator FE</i>	Yes	Yes	Yes	Yes
<i>No. of obs</i>	47179	47179	47102	47102
<i>R<sup>2</sup></i>	0.2360	0.5026	0.2429	0.5051

Note: This table compares the underwriting standards for retention and non-retention loans. The dependent variable is debt service coverage ratio (Column 1 and 3) and loan to value ratio (column 2 and 4). 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. 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 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.