Insurers Monitor Shocks to Collateral: Micro Evidence from Mortgage-backed Securities*

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Abstract

This paper examines how insurance companies react to cash flow shocks in commercial mortgage-backed securities (CMBS). Using detailed micro data around the onset of the COVID-19 pandemic, we show that lease expiration predicts commercial real estate mortgage delinquency, particularly for offices due to lower demand. Insurers subsequently sell more exposed CMBS, mirrored by a surge in small banks holding CMBS. These sales do not incur losses, indicating that the underlying information is not fully priced by the market. Our findings reveal that insurance companies actively monitor underlying asset risk and can even gain informational advantages over some banks.

JEL codes: G20, G21, G22, G23

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1. Introduction

Growing risks in mortgage-backed securities, along with perceived failure by intermediaries to perform due diligence and risk management, are considered some of the main causes of the Global Financial Crisis (Chen et al., 2020). For commercial mortgage-backed securities (CMBS), such risks arise due to the uncertainty about cash flows generated by the underlying mortgages. While monitoring these cash flows is particularly challenging due to the complex structure of CMBS and their multiple underlying assets (Ghent, Torous and Valkanov, 2019), studying investor reactions to salient cash flow shocks can reveal whether and how they monitor risks in these complex securities. Differences in investors' due diligence and risk-bearing capabilities in turn pin down how looming commercial real estate (CRE) risks are distributed across financial intermediaries.

In this paper, we examine how cash flow shocks driven by lease expirations and structural changes in office demand affect both mortgage performance and institutional investor behavior. Using detailed micro data around the onset of the COVID-19 pandemic, we show that lease expiration predicts commercial real estate mortgage delinquency, and particularly so for offices. Insurers—one of the largest investor groups in mortgage-backed securities—sell more exposed CMBS before delinquencies materialize, suggesting that they actively monitor these risks. As insurers reduce their CMBS exposure, we document a noticeable increase in private-label CMBS holdings by small banks that subsequently incur losses.

To understand if insurers can gain informational advantages, we first establish whether lease expirations actually predict delinquency in a way that sophisticated investors could anticipate. Using comprehensive data on commercial mortgages in CMBS deals, containing detailed loan and property characteristics as well as information about lease contracts between borrowers and their core tenants, we find that lease expiration increases CRE loan default risk for offices, especially following COVID-19 when hybrid work arrangements reduced office demand (Barrero, Bloom and Davis, 2021) and, thus, rental income from CRE.

The mortgage data enable us to observe the default status of each loan while also capturing relevant information about the underlying properties, including their location and designated use, as well as rental contract characteristics such as lease expiration dates for different types of properties. Changes in rental cash flows are more common when tenant lease contracts expire, since elevated early termination fees can incentivize tenants to retain their lease until it expires.[1] The lease-expiration timing generates a negative cash flow shock for borrowers if they need time to find a new tenant or if they cannot renew the lease at a similar rent.

Using the COVID-19 pandemic as a shock to the demand for office space, we estimate a difference-in-differences specification and show that lease expiration triggers increases in delinquencies, with a stronger effect after COVID-19. These effects are economically meaningful, with lease expiration being associated with about 1.3 percentage points higher delinquency among office-linked loans in the baseline period, and an additional 1.2 percentage point increase in the post-pandemic period.

A challenge in establishing a causal link between lease expiration dates and delinquency rates is that these dates could coincide with other shocks that cause delinquency, e.g., other shocks that lower demand for CRE. Similarly, if mortgages with leases expiring have floating interest rates, concurrent increases in reference interest rates can also cause an increase in delinquency rates. We address these challenges by leveraging the granularity of our data, which allow us to include a rich set of fixed effects that capture several static and time-varying confounding factors that could affect delinquency rates. In addition, our identification strategy exploits lease expiration dates set well before the COVID-19 shock, so that the timing of lease termination is plausibly exogenous to pandemic-induced structural shifts in CRE demand.

We then document how large insurance companies' exposure to offices through their CMBS holdings is, and the extent to which these investors monitor cash flow risk caused by lease expiration. If lease agreement information is monitored by investors, and market prices do not reflect this change in fundamental values, then they should be more likely to sell CMBS with a larger share of mortgages linked to leases expiring when faced with unexpected shocks to collateral demand.

To evaluate this possibility, we complement our comprehensive monthly panel data on CMBS deals and mortgages against CRE with granular information on the asset portfolios of U.S. insurance companies. Insurance companies are indeed a large group of investors in

[1] This should hold true under the condition that the costs of terminating the rental contract early are higher than the savings from moving to a smaller rental object, in particular office space.

CMBS, holding close to one-fourth of newly issued private-label CMBS between 2017 and 2022. We also find that the fraction of insurers' private-label CMBS portfolio exposed to offices peaks in 2020, and decreases afterwards, which is consistent with lower demand for CMBS with office exposures among those investors. Nonetheless, insurers remain largely exposed to cash flow risks arising from lower office demand. In our sample, the median insurance company holds a private-label CMBS portfolio with an average exposure of about 26% to offices. This potentially dwarfs banks' exposure to other CRE-related risks, often of indirect nature (Acharya et al., 2024).

We then test if insurers monitor cash flow risks in their CMBS portfolio by asking if bonds more sensitive to different cash flow shocks are more likely to be sold following the sudden, unexpected increase in risk caused by COVID-19. Our identification strategy relies on the idea that pandemic-driven lower demand for CRE constitutes an unexpected shock to CMBS cash flows, with different effects across property collateral types. We find that most CMBS have the majority of their cash flow shocks induced by lease expiration occurring within six years. Informed by this threshold, we estimate a difference-in-differences specification to assess whether CMBS with exposure to office-linked loans whose main leases expire within six years are more likely to be sold after the pandemic.

The richness of our data allows us to include insurer by time and insurer by bond fixed effects, on top of time-varying coupon type, risk classification, and lagged downgrade fixed effects. This addresses concerns that our estimates may be contaminated by other time-varying insurer shocks or bond characteristics. Moreover, it allows us to capture changes in trading behavior within an asset class with similar capital costs for insurers, and rules out portfolio rebalancing in response to ratings downgrades.

Consistent with the idea that they infer risks from shocks to expected cash flows, we find that insurance companies are more likely to sell CMBS which are exposed to offices with leases expiring within six years. This suggests that they can identify how different property types are affected by the pandemic, and the nature of cash flow risks caused by lower demand for offices. Treated bonds (those exposed to office lease expiration within six years) are over 2 percentage points more likely to be sold by insurers in the post-COVID period than comparable bonds which are not exposed to office lease expiration within six years. This sensitivity to underlying lease expiration in the medium term indicates that the insurance sector expects a whole asset class—commercial real estate—to be affected by the pandemic shock for a longer duration.

The hypothesis that insurers trade based on information acquired through monitoring the collateral pool of private-label CMBS implicitly assumes that such information is not priced by the market. If market participants had fully incorporated the higher risk of more exposed bonds, insurers would be unable to profit from such insights and, instead, realize lower proceeds when selling these assets. We test this mechanism by comparing realized gains and losses from the sales of treated and non-treated bonds. We find no evidence of poorer realized performance for treated bonds; if anything, insurers earn relatively higher trading returns on office-exposed CMBS. This pattern contrasts with sales following credit rating downgrades—events that are typically associated with price declines and forced sales (Ellul, Jotikasthira and Lundblad, 2011).

Insurers adjust to risks in CMBS also along other margins. First, the share of CMBS with office exposure acquired by insurers falls after 2020, along with the share of CMBS exposed to cash flow shocks via lease expiration. Second, insurers demand higher coupons for holding office-exposed CMBS originated after the pandemic. These findings corroborate the idea that insurers monitor risks to their CMBS portfolio, and learn about structural changes that make certain types of collateral more prone to cash flow-induced losses.

If insurers reduce their exposure to private-label CMBS, other investors are acquiring these risky assets. Since monitoring of securitized assets is costly, it is possible that less sophisticated investors are less sensitive to lurking risk and end up holding larger shares of private-label CMBS after the pandemic. In line with this view, we document a striking rise in the holdings of private-label CMBS by banks after 2020, especially by small and medium-sized banks. The number of small banks that hold private-label CMBS *nearly doubles* between 2020 and 2023. Banks exposed to private-label CMBS subsequently experience weaker realized performance in their securities portfolios, with losses amounting to roughly a 1% relative decline in Tier 1 capital during 2022–2023.

Since small banks are in general not exposed to large office-linked loans (Glancy and Kurtzman, 2024), this development could be explained by additional risk-bearing capacity. However, to the extent that small banks have lower risk-management capabilities (Ellul and Yerramilli, 2013), it is also consistent with the idea that better informed insurers offload part of their office-borne CMBS risks to less well informed small banks. Moreover, contrary to insurers, other investors do not seem to demand higher coupons from office-exposed CMBS issued after the pandemic, suggesting these investors are indeed less sensitive to such risks. In summary, our findings point to how investors' ability to monitor risks in complex assets contributes to the transfer of risks caused by systematic shocks.

Related literature. Our paper contributes to the literature studying securitized assets and mortgage-backed securities in particular.[2] This literature has documented how risks in mortgage-backed securities (MBS) affected institutional investors during the Global Financial Crisis. Several papers investigate how MBS characteristics such as equity retention (Begley and Purnanandam, 2017) and retention structure (Flynn, Ghent and Tchistyi, 2020) are used by originators to signal asset quality. Ghent, Torous and Valkanov (2019) show how more complex CMBS underperformed during the Global Financial Crisis, with complexity contributing to both obfuscating collateral quality and allowing for cash flows to be diverted towards residual tranches. Furthermore, investors do not price this complexity-induced default risk. These studies emphasize the difficulty in assessing risks in MBS, which requires costly infrastructure to be performed (Hanson and Sunderam, 2013).

Our contribution is to show that despite these due-diligence challenges and being typically viewed as less capable of doing so, institutional investors such as insurance companies monitor detailed, time-varying property and lease contract characteristics that predict CMBS losses, and they divest on the basis of such information.

As such, we also relate to a broad literature that studies insurance companies' portfolio decisions, and how they react to risks in their asset portfolio.[3] This literature documents that insurance companies react to changes in observable risk such as downgrades, and highlights how regulation affects insurers' reaction to asset risk (Ellul, Jotikasthira and Lundblad, 2011; Chen et al., 2020; Becker, Opp and Saidi, 2022; Sen, 2023). We contribute to this literature by showing that insurers adjust their CMBS portfolios in response to anticipated cash flow risks embedded in the collateral pool, rather than market-wide or regulatory signals. The type of

[2] See, for example, DeMarzo and Duffie (1999), DeMarzo (2005), Demiroglu and James (2012), Ashcraft, Gooriah and Kermani (2019), and Aiello (2022).

[3] See, among others, Chodorow-Reich, Ghent and Haddad (2021), Ge and Weisbach (2021), Koijen and Yogo (2022), Bretscher et al. (2022), Ellul et al. (2022), Koijen and Yogo (2023), O'Hara, Rapp and Zhou (2025), and Bhardwaj, Ge and Mukherjee (2025).

monitoring we study involves assessing loan-level characteristics, such as lease rollover exposure, that predict future deterioration in performance and eventual downgrades. Unlike the fire sales documented in Ellul, Jotikasthira and Lundblad (2011), these transactions do not appear to be driven by capital constraints or regulatory pressures. This distinction highlights that insurers engage in active, information-based monitoring of complex securitized assets, rather than simply reacting to observable changes in credit quality.

In addition, we relate to the literature exploring the impact of work-from-home adjustments in CRE mortgage default risk. Thus far, this literature has not documented a direct link between lower office demand and CRE mortgage default (Van Nieuwerburgh, 2022).[4] Moreover, Jiang et al. (2023) explore how losses from CRE loan portfolios affect the solvency of U.S. banks, and Glancy and Kurtzman (2024) consider how differences in small banks' CRE loan portfolios govern reduced exposure to loans whose poor performance was driven by lower office demand. Hinzen, Severino and Nieuwerburgh (2025), however, argue that despite this lower exposure of regional banks to highly affected CRE markets, these lenders are nonetheless at risk due to under-collateralization and higher portfolio concentration.

We provide a detailed account of how insurers are affected by CRE risks through their CMBS holdings. Our documented insurer responses to shocks that are expected to materialize in the medium term suggest that market participants expect the office demand shock to have a long duration. Finally, the exposure of small banks to CRE risks through their holdings of CMBS has been largely ignored so far. As CRE risks have shifted across the financial sector, in particular to small banks through their CMBS exposure, they start experiencing losses. In that sense, any comprehensive analysis of how CRE risks will affect financial stability should account for both banks' and non-banks' CMBS exposures alike.

2. Lease Expiration, Cash Flow Shocks, and CRE Mortgage Default

In this section, we develop hypotheses that will guide our empirical analysis. First, sudden drops in demand for office space lead to fewer occupied offices after leases expire, either

[4] As in our study, Glancy and Wang (2024) highlight the importance of lease expiration in the post-COVID period, showing that it affects office vacancies and loan performance. Both studies provide direct evidence of the importance of cash flow-triggered mortgage default for commercial real estate. Several papers study the relevance of strategic and cash-flow motives for default of *residential* mortgages (Ganong and Noel, 2023; Bhutta, Dokko and Shan, 2017; Gerardi et al., 2018), with less attention devoted to *commercial* mortgages.

by downsizing or lack of renewal, and longer search times for new tenants. This results in lower income from new leases, reducing overall lease revenue. As a result, to the extent that borrowers rely on such income to repay mortgages, mortgage default rates should increase, especially during periods of lower demand for office space.

Hypothesis 1: *Lease expiration persistently increases defaults of mortgages against offices after the COVID-19 cash flow shock, whereas other types of collateral, especially retail, see defaults immediately and are, thus, less sensitive to lease expiration.*

Since U.S. insurers frequently hold CMBS, any increase in the riskiness of these assets could influence their investment decisions. First, if insurance companies can observe lease expirations, the increased likelihood of future delinquencies due to lease expirations should make CMBS with a higher proportion of soon-to-expire mortgages less attractive to hold. Since lower demand increases the persistence of default triggered by lease expiration, investors are more likely to monitor characteristics associated with cash flow risks following the pandemic-linked shock to CRE demand, which we infer by actions that suggest preceding acquisition and processing of related information. If markets do not incorporate this information, investors are subsequently more prone to selling CMBS with a larger exposure to cash flow shocks after the pandemic.

Hypothesis 2: *Conditional on monitoring, insurers should sell CMBS with relatively more mortgages against offices undergoing lease expiration after the COVID-19 cash flow shock.*

Mortgage-backed securities are complex assets, and assessing risks for these assets is costly and often accessible only to sophisticated institutional investors (Hanson and Sunderam, 2013). Even if insurers possess the ability to monitor the cash flow risks associated with lower CRE demand and lease expiration, as hypothesized, other intermediaries might not. In that case, if insurers sell CMBS with a larger exposure to cash flow risks, and if intermediaries differ in their monitoring capacity, CMBS sales by insurers should be accompanied by increasing holdings of less sophisticated investors.

Hypothesis 3: *If monitoring capacity is heterogeneous, risky CMBS should, on average, flow from insurers to less sophisticated investors.*

3. Data Description

Our data come from two main sources: Trepp and the National Association of Insurance Commissioners (NAIC). Trepp is a leading provider of commercial real estate-collateralized products data (Flynn, Ghent and Tchistyi, 2020), collecting origination information from CRE mortgages, CMBS deals and bonds, which is obtained from various sources. The data include detailed information such as property type and location, mortgage maturity, amount, interest rates, and delinquency information for each distribution date. We classify loans according to the use of the property serving as collateral for the loan. We distinguish between *Office*, *Retail*, and further property types.[5] The data also contain information on lease agreements between borrowers and tenants. We focus on the lease information for the largest tenant only. Appendix-Table A.1 shows that the availability of lease expiration data varies by property type, with Office and Retail as the only two property types for which the date of lease expiration of the main tenant is available for more than 50% of the observations. For this reason, we mainly consider these two property types throughout the paper.

We obtain holdings and trades of fixed income assets of all insurance companies in the U.S. from the National Association of Insurance Commissioners (NAIC). The holdings data are based on NAIC Schedule D Part 1, and contain CUSIP-level end-of-year holdings of fixed income securities, including CMBS. The trading information is obtained from NAIC Schedule D, Parts 3 and 4, which contain information on acquisitions and dispositions of fixed income assets by insurance companies, respectively. We identify actual trades (sales and purchases) using a procedure similar as in Becker, Opp and Saidi (2022), which we describe in Appendix C.

We restrict our analysis to the post-2017 period.[6] This ensures that we mitigate concerns

[5]These are classified as *Multifamily*, *Mixed Use*, *Healthcare-Nursing*, *Lodging-Restaurants*, *Industrial and Warehouses*, and *Other*. The details of how these types are obtained, along with other details of our data cleaning procedure, can be found in Appendix B.

[6]Our Trepp sample covers CMBS information until June 2022.

about the influence of the Global Financial Crisis (GFC), e.g., through elevated delinquency rates responding to demand shocks that originated during the GFC. Table 1 shows the summary statistics of the mortgages in our sample. Panel A focuses on all properties, which have a median lease expiring in 2024 and a median mortgage maturity of 10 years. We classify a loan as delinquent if payments are past due for at least 90 days. On average, less than 1% of all loans are delinquent in our sample period, around 12% of our loans have floating interest rates, and less than 1% are recourse loans.

Since our analysis mostly focuses on offices and retail CRE, we provide a breakdown of the characteristics of the mortgages used to finance these property types in Panels B and C of Table 1, respectively. Relative to retail, offices have floating interest rates more frequently, lower delinquency rates, and similar maturity. Moreover, the mean and the median share of each property occupied by the largest tenant is smaller in offices than in retail.

Finally, we use FDIC's Consolidated Reports of Condition and Income (Call Reports) data for our analysis of bank holdings of private-label CMBS. Further details about the data series are available in Appendix B.

4. Cash Flow Shocks and Mortgage Delinquencies

4.1. The Role of Lease Expiration

First, focusing on mortgages whose lease expiration dates occur between 2017 and 2022, we evaluate the importance of lease expiration-induced cash flow shocks to borrowers in driving delinquency rates. During this sample period, we examine delinquency rates in the time window of one year prior and one year after the expiration date of the main lease. Given our definition of a loan being delinquent if it is at least 90 days, or about 3 months, past due, we expect to see delinquency rates increase comparatively more only after the third month in which a lease expires.

Figure 1 shows the average delinquency rates for all property types for which such information is available. As expected, we observe that delinquency rates increase, with the sharpest increase occurring exactly in the fourth month after the lease expiration date. This is in line with the idea that cash flow shocks from lease expiration induce borrowers to stop making payments on their mortgages. This may be because the existing borrower cannot readily find a new tenant or because the lease generates lower income than the previous one. Moreover, delinquency rates seem to converge back to their pre-lease expiration trend approximately 10 months after lease expiration, which indicates that borrowers resume their payments once a new tenancy agreement is secured. This further illustrates the importance of cash flow shocks to the default behavior of CRE borrowers.

This preliminary analysis, however, does not account for potential differences in delinquency rates depending on the use of the property. There are reasons to assume that such differences exist. First, the specific use of the property might limit a borrower's ability to find a new tenant. For example, it may be more difficult to re-purpose office space for other uses, which can increase search costs and lower expected revenue after an existing lease expires. Second, firms in different sectors might be more likely to renew their lease contracts, and to the extent that these firms select into different types of properties, this would differentially affect borrowers depending on the property they are financing with their loan. Third, it may be borrower-specific characteristics that matter. For example, some borrowers who take out mortgages against certain types of properties might struggle more to find new tenants, which would be the case if search frictions are different when looking for office or retail tenants.

Against this background, we split our sample into two subsamples: offices and retail properties. Figure 2 shows a remarkable difference in delinquency behavior for these different property types. The plot on the left-hand side shows sharp increases in delinquency rates of offices following the end of the main lease agreement. By contrast, the plot on the right-hand side suggests that increases in delinquency rates of retail properties are more short-lived, with shocks introduced by the end of lease agreements being more transitory in nature. Overall, these results indicate that cash flow shocks are strong predictors of office delinquencies, but less so for retail properties.

So far, we have examined delinquencies focusing on the exact timing of the lease expiration for a specific property, but not explicitly considering the delinquency behavior of mortgages without leases expiring. This difference in exposure to cash flow shocks caused by lease expiration can be particularly relevant in the post-COVID period, as lower demand for offices could interact with these contractual terms and lead to more persistent losses for landlords. To the extent that lower CRE demand amplifies cash flow shocks, one would expect mortgages with leases expiring in the post-COVID period to perform worse than mortgages which are not subject to such cash flow shocks.

We assess differences in delinquency rates of properties with and without leases expiring by looking at office/retail properties for which we have lease expiration information (i.e., we know if the main lease expires or not), and zoom in on the immediate period before/after the start of the COVID-19 pandemic. We compare the average delinquency rate of loans with leases expiring in 2021-2022 with the average delinquency rate of loans without leases expiring in these two years.

The results are shown in Figure 3. The left-hand side plot shows a striking pattern for office mortgages with and without leases expiring in 2021-2022. Delinquency rates for the latter group are pretty much stable throughout the entire period, whereas there is a large spike in delinquency rates for mortgages the main leases of which expired in 2021-2022. This further indicates that cash flow shocks are a relevant determinant of office mortgage default, and that aggregate delinquency rates do not necessarily capture the extent to which work-from-home arrangements trigger CRE mortgage default given their effect on office demand.

By contrast, the trajectory of retail mortgage delinquencies on the right-hand side of Figure 3 shows a different pattern. Delinquency rates spike immediately at the onset of the COVID-19 pandemic, which coincides with lockdown periods during which retail stores did not generate income to tenants. Following that initial shock, mortgages with leases expiring in 2021-2022 demonstrate persistently higher delinquency rates, which suggests that lease expiration matters for the adjustment to the initial shock. In other words, while cash flow shocks do not seem to *cause* mortgages to go from performing to non-performing in the case of retail, they do seem to affect the *persistence* of the initial increase in delinquency rates.

By zooming in on offices rather than retail properties, we can focus on structural changes in the demand for office space without explicitly considering the implications of the 2020 lockdowns for businesses. Furthermore, if institutional investors trade CMBS holdings before losses materialize, then one would expect their trading behavior to be based on office exposure if these mortgage losses can be predicted by shocks to expected cash flows.

4.2. The Effect of Lease Expiration on Mortgage Delinquency

Our motivating evidence suggests a key role for lease expiration dates in driving delinquency behavior for CRE mortgage borrowers, especially for office properties. Nevertheless, there are multiple other factors that could be driving the delinquency dynamics we observe for properties subject to lease expiration. For example, lease expiration dates could correlate with systematic or region-specific shocks that affect the U.S. economy in specific times, such as the Global Financial Crisis and the onset of the COVID-19 pandemic. Moreover, loans for which we have lease expiration data could also have specific characteristics, such as floating interest rates, which can make them more susceptible to increases in delinquency in times of higher interest rates.

To evaluate the relationship between lease expiration and mortgage default, we leverage the richness of our data, allowing us to compare otherwise similar mortgages that have leases expiring and not. First, we estimate the following specification:

$$I_{jrt}^{D90} = \alpha_j + \alpha_{rt} + \alpha_{j(floating)t} + \sum_{\iota \in [-15,15] \setminus \{3\}} \delta_\iota D_{jt}^\iota + \varepsilon_{jrt}, \tag{1}$$

where I_{jrt}^{D90} is an indicator variable equal to 1 if loan j, for a property located in city r, is delinquent for more than 90 days in year-month t, D_{jt}^ι equals 1 if loan j is ι months after lease expiration in year-month t. α_j and α_{rt} are loan and city by year-month fixed effects, which allow us to control for time-invariant loan-level and time-varying regional characteristics that might influence default rates. $\alpha_{j(floating)t}$ are interest rate type by year-month fixed effects to capture differences in delinquency between floating and fixed interest rate loans. We only include loans for which we have lease expiration information,[7] and cluster standard errors at the loan level.

The coefficients of interest, δ_ι, capture the percent difference in delinquency rates ι months before and after lease expiration, relative to three months after the lease expires. Importantly, the use of comprehensive fixed effects ensures this variation does not correspond to time-varying regional shocks or to index rate characteristics of the mortgages that could also

[7] This is to avoid including loans with leases expiring in our control group (which could happen for loans for which we do not observe that information, but might experience a lease expiration nonetheless).

influence delinquency behavior.

Since lower office demand caused by work-from-home (WFH) arrangements might affect CRE mortgage default rates, we estimate (1) separately for the period before and after the COVID-19 pandemic started (where we consider March 2020 as the beginning of the pandemic). Intuitively, if borrowers face lower demand for their properties due to structural changes associated with work-from-home preferences, then one would expect the cash flow shocks introduced by lease expiration to be long-lasting. Conversely, absent demand shocks, the initial drop in cash flows would cease after the borrower manages to find a new tenant, and delinquency rates would slowly transition back to their pre-lease expiration levels.

The results are shown in Figure 4, indicating that WFH demand adjustment affected the persistence of the effect of cash flow shocks on delinquency rates. While the initial effect is similar in both periods, delinquency rates in the post-COVID period start to diverge further ten months after lease expiration. Our point estimates indicate that, relative to three months following lease expiration, a mortgage experiences a one percentage point higher delinquency rate 15 months after lease expiration before the pandemic. The effects of the cash flow shock induced by lease expiration are longer-lasting in the post-COVID period, with delinquency rates gradually becoming larger following lease expiration. The difference in relative delinquency between 3 months after lease expiration and 15 months after lease expiration is about four percentage points, almost four times the respective point estimate from the pre-COVID period.

To formally estimate the differences in post-lease expiration delinquency behavior before and after the onset of the pandemic, we estimate a triple differences specification:

$$\begin{aligned}
I_{jrt}^{D90} = {} & \alpha_j + \alpha_{rt} + \alpha_{j(floating)t} + \gamma_1 Post\ Expiration_{jt} \\
& + \beta_1 Post\ Expiration_{jt} \times Post\ Covid_t + \beta_2 Post\ Expiration_{jt} \times Ind\ Office_j \\
& + \beta_3 Post\ Covid_{jt} \times Ind\ Office_j \\
& + \beta_4 Post\ Expiration_{jt} \times Post\ Covid_t \times Ind\ Office_j + \varepsilon_{jrt},
\end{aligned} \tag{2}$$

where $Post\ Covid_t$ is a dummy equal to 1 after March 2020, $Post\ Expiration_{jt}$ equals 1 if loan j had its main lease expiration before or in year-month t, and $Ind\ Office_j$ equals 1 if loan j is linked to an office. The coefficient of interest β_4 captures the difference in the effect of lease expiration-induced cash flow shocks on delinquency rates since the onset of the pandemic.

The results are in Table 2. Across all specifications, the coefficient on the triple interaction term is positive and statistically significant, and the economic magnitude is relevant. The baseline effect of lease expiration on mortgage delinquency increases by about 1.2 percentage points, meaning the effect of cash flow shocks on delinquency rates is twice as strong after the COVID-19 pandemic. Cash flow shocks increase delinquency rates by more than 2 percentage points when compared to the average delinquency rate of 0.6% for properties without expired leases in the post-COVID period. This is an economically significant effect, with delinquency rates of office mortgages whose main tenancy agreement expired being more than four times as large as delinquency rates of mortgages that do not experience such cash flow shocks. These results reinforce the notion that demand shocks caused by hybrid work arrangements, which became prevalent after the beginning of the COVID-19 pandemic, further exacerbate the effects of cash flow shocks on CRE mortgage delinquency rates.

CMBS exposure to regional work-from-home characteristics. Our analysis hinges on the observation that by being relatively more affected by hybrid work arrangements, demand for office properties is also relatively more affected by the COVID-19 shock, thereby leading to more persistent cash flow shocks to rent revenue. Importantly, another dimension of heterogeneity in exposure to work-from-home adjustments refers to regional characteristics. For instance, cities like San Francisco or New York are perceived to be more affected by hybrid work arrangements than others (Gupta, Mittal and Nieuwerburgh, 2023).

While we cannot directly measure demand for office space, we can nevertheless assess how mortgages in our sample correlate with measures that reflect regional sensitivity to work-from-home arrangements. For this purpose, we use the measure of jobs that can be performed remotely by Dingel and Neiman (2020), which should broadly indicate which areas are more likely to be affected by work-from-home arrangements. Figure A.2 in the Appendix shows the distribution of the percentage of teleworkable jobs in an MSA, for office-linked mortgages in our sample and for all MSAs. Relative to the distribution across all MSAs, office-linked mortgages are indeed located in areas with higher sensitivity to work-from-home shocks.

5. Do Insurers Monitor Cash Flow Risks?

We have documented a link between expected changes in the tenancy agreement of a specific office and default rates of the mortgage linked to that property, which has implications for assets whose cash flows depend on the performance of these CRE mortgages. In particular, insurance companies' cash flows obtained from their holdings of CMBS might be compromised if the underlying mortgages become non-performing.

This raises several fundamental questions. What is the extent and dynamics of the exposure of insurance companies to office CRE through their holdings of CMBS? Given the predictable nature of expected cash flow shocks to mortgage payments, do insurance companies monitor such risks and sell bonds based on cash flow shocks to mortgage CRE? Finally, does lower office demand in the post-pandemic period affect the trading behavior of these intermediaries? We explore these issues next.

5.1. Insurer Holdings of WFH-sensitive CMBS

We start by leveraging our data to document the importance of insurance companies for the private-label CMBS market, and to characterize their exposure to shocks linked to office collateral. We are in a unique position to do so, given our access to detailed CMBS information (including origination dates) and granular data on the asset portfolio of insurance companies.

First, we consider end-of-year outstanding balances and amounts issued for all private-label CMBS in our sample, and identify which bonds are held by insurance companies at the end of each year. Figure 5 shows that insurance companies are one of the main investors in CMBS markets. By the end of 2022, insurance companies hold about \$200 billion out of \$800 billion outstanding (Panel A). Similarly, between 2017 and 2019, insurance companies acquired around 20% of the total amount of new issues of private-label CMBS in a given year (Panel B). Interestingly, the share of new CMBS originations held by insurers drops to about 17% in 2022. This reduction in the overall amount of CMBS held by insurance companies would be consistent with lower insurer demand, which could arise as lower office demand translates to higher mortgage default rates.

We further explore the dynamics of CMBS holdings by insurance companies and document the exposure of the latter's CMBS portfolio to office CRE collateral. We classify a bond as exposed if it has *any* mortgages financing office properties within its pool of collateral. We then calculate the share of CMBS exposed to offices out of the entire portfolio of private-label CMBS held by insurance companies.

Figure 6 shows the share invested in *non-exposed* bonds for each year. One can see that the share of CMBS exposed to offices increases up until 2020, at which point this trend is reversed. In particular, insurance companies increase the share of CMBS *not exposed* to offices in 2021 and 2022 by about five percentage points. This further suggests that insurers reacted to risks arising from lower demand for office space by adjusting their holdings of CMBS.

Next, we document the exposure of insurers to risks related to expiring tenancy agreements of mortgage-financed offices. We calculate the percent share of mortgages against offices in each deal associated with a CMBS in our sample as of June 2022. We also compute the share of this portfolio of office-linked CMBS with underlying leases expiring between 2023 and 2026. Intuitively, this percentage represents how exposed to office mortgages a particular bond is, abstracting from seniority considerations.

The left panel of Figure 7 considers exposure to any office properties, and the right panel considers exposure to office properties with at least one underlying mortgage with a tenancy agreement expiring between 2023-2026. The median insurance company has its private-label CMBS with an average exposure of about 26% to office properties and 4.6% to office properties with tenancy agreements expiring in 2023-2026. Importantly, there is considerable heterogeneity in the size of the average exposure of CMBS to offices among insurance companies, with the top decile of the distribution of insurers having an average exposure of 39% of their portfolio to offices and 10% to offices with underlying lease expiration.

5.2. CMBS Exposure to Cash Flow Shocks and Trading Behavior

We next exploit exposure heterogeneity across CMBS to estimate the effect of expected cash flow shocks on insurers' trading behavior. Insurance companies might anticipate the effect of work-from-home (WFH) shocks on the cash flows and on the value of their CMBS, and therefore attempt to sell these bonds. Moreover, even if insurance companies do not trade CMBS based on office exposure alone, they could still anticipate how shocks to their assets caused by upcoming lease expiration could lead to losses from mortgage default.

Each CMBS can be composed of multiple mortgages whose underlying leases expire in different years. This gives rise to a dynamic structure for the share of the expected losses due to default following lease expiration. For example, consider a CMBS with four underlying equal-sized mortgages, all of which finance offices occupied by a single tenant. Assume that two leases expire in two years, one lease expires in three years, and one lease expires in six years. Such a CMBS would have 50% of its expected cash flow shocks materializing in two years, 75% of its expected cash flow shocks materializing within three years, and all expected cash flow shocks would materialize within six years. Thus, the time-sensitive nature of the expected cash flow shocks, along with the structure of CMBS, leads to heterogeneity in exposure to expected losses due to office mortgage default across different bonds.

To illustrate this point, we construct the distribution of expected cash flow shocks across future lease expiration years for all CMBS held by insurance companies. For each deal in our sample, we calculate the share of its largest underlying leases expiring in τ years. Formally, for a given deal d, we calculate:

$$Share(\%)^{\tau}_{dt} = \sum_{j \in J^d_t} \frac{\omega^{\tau}_{jt} \times Balance_{jt}}{\sum_{\tau} \omega^{\tau}_{jt} \times Balance_{jt}} \times 100, \tag{3}$$

where $\omega^{\tau}_{jt} \in [0, 100]$ denotes the share of mortgage j's contract at the end of year t that expires in τ years, $Balance_{jt}$ is mortgage j's outstanding balance at the end of year t, and J^d_t is the set of underlying mortgages in deal d at the end of year t.

Figure 8 shows the resulting distribution after averaging $Share(\%)^{\tau}_{dt}$ across all years in our sample, separately for offices and retail. A large share of expected cash flow shocks materializes only within three to six years relative to each year in which we obtain outstanding balances. The average bond in our sample experiences only around 16% of its cash flow shocks within two years. Hence, it would be incorrect to measure a bond's exposure to expected cash flow shocks limiting the analysis to bonds with leases expiring in the following one or two years since, on average, a large share of the shocks is yet to materialize.

The average bond in our sample has around 50% of its expected cash flow shocks to office mortgages materializing *within six years*. This provides us with a natural threshold against which to compare individual bonds. To understand if insurance companies trade based on expected cash flow shocks, we test if they sell private-label CMBS with larger exposure to office mortgages with leases expiring in the near future more frequently after the pandemic started. We define a bond j in year t as *treated* if it has leases expiring within six years relative to year t. Hence, our control group consists of bonds whose expected cash flow shocks materialize only after most cash flow shocks have *already materialized for the average CMBS*. Intuitively, if insurers discount future cash flows (at any non-zero rate), they should value losses in the short to medium term more than any long-run losses.

We then estimate the following specification:

$$\begin{aligned} I_{ijt}^{sold} = & \alpha_{it} + \alpha_{ij} + \alpha_{j(coupon)t} + \alpha_{j(NAIC)t} + \alpha_{j(downgrade_{t-1})t} \\ & + \beta_1 \times Treat_{jt}^{Exp\ Office} + \beta_2 Post\ Covid_t \times Treat_{jt}^{Exp\ Office} + \varepsilon_{ijt}, \end{aligned} \tag{4}$$

where I_{ijt}^{sold} is a dummy which equals 1 if bond j was sold by insurer i in year t, $Post\ Covid_t$ equals 1 after 2019, and $Treat_{jt}^{Exp\ Office}$ equals 1 if bond j is exposed to office-linked mortgages whose main lease expires within six years (excluding year t). We do not include delinquent loans when creating the lease expiration treatment dummies so as to avoid capturing the effect of concurrent losses. α_{it}, α_{ij}, $\alpha_{j(coupon)t}$, $\alpha_{j(NAIC)t}$ and $\alpha_{j(downgrade)t-1}$ are, respectively, insurer by year, insurer-security, coupon type by year, NAIC designation by year and lagged downgrade by year fixed effects.[8]

This battery of time-varying fixed effects safeguards that our estimated effect does not stem from portfolio adjustments resulting from shocks to insurers (Ge and Weisbach, 2021), sales driven by downgraded assets, with potentially higher capital requirements, or due to regulatory reasons (Ellul, Jotikasthira and Lundblad, 2011; Becker, Opp and Saidi, 2022).

The results are in Table 3 and indicate that insurers do take into account how bonds are affected by cash flow shocks in the short to medium term when selling CMBS. In column 1, we estimate (4) and find that insurance companies are 2.7 percentage points more likely to sell bonds which have office mortgages that expire in the next six years after the COVID-19 pandemic than before. The mean of the dependent variable I_{ijt}^{sold} equals 8% for private-label

[8]We defined downgrading based on NAIC designations. Hence, a bond j is marked as downgraded in year t it had a NAIC designation in year $t-1$ greater than its NAIC designation in year $t-2$.

CMBS, indicating a meaningful economic effect from exposure to cash flow shocks expected to materialize in the short to medium term.

This effect is robust to other characteristics of the mortgage pool of a given CMBS that could affect the likelihood of selling the bond. In particular, we account for the fact that $Treat_{jt}^{Exp\ Office}$ reflects de facto an interaction between any office exposure and lease expiration within six years, which we control for in turn.

In column 2, we include a dummy variable for the existence of any offices in the underlying pool of mortgages of bond j in year t, I_{jt}^{Office}. In spite of incorporating this control variable along with its interaction with the post-COVID indicator, our estimate remains virtually unaltered. This implies that the presence of office collateral affects the likelihood of sales only for those mortgages with cash flow shocks that are expected to materialize in the short to medium term and after COVID-19.

In the same way, we account for lease expirations more generally. In column 3, we include a dummy variable that equals 1 for CMBS with *any* mortgage with a lease expiring within six years starting in year t, I_{jt}^{Exp}. In line with the idea that insurers are sophisticated enough to understand how collateral type and lease characteristics jointly determine expected mortgage default, we find that underlying lease expiration affects only the post-COVID sales probability for bonds associated with office collateral. Furthermore, lease expiration and office properties play no role for insurance companies' selling decisions before the onset of the COVID-19 pandemic either. This lends support to our conjecture that insurance companies learn about the increase in riskiness of the underlying collateral of CMBS posed by work-from-home demand shocks.

Our evidence in Section 4 reveals contrasting patterns between office and retail loan delinquency rates. Loans linked to retail experience a spike in delinquency right at the onset of the pandemic, which would also pose a risk to holders of CMBS exposed to retail properties. Importantly, this risk is less sensitive to lease expiration, suggesting that the latter is less relevant for retail-exposed CMBS in comparison to office-exposed CMBS. Column 4 of Table 3 tests this idea by further breaking down the collateral and the lease-expiration dummies into mutually exclusive property types. In particular, the dummies $I_{jt}^{Exp\ Retail}$ and $I_{jt}^{Exp\ Other}$ equal 1 if bond j has underlying retail or other mortgages, respectively, with leases expiring within six years, where *Other* is a residual category for any loans with lease expiration information not linked to $Office$ or $Retail$ units. Moreover, I^{Retail}_{jt} is a dummy that equals 1 if bond j has any exposure to retail units in year t.

The coefficient of interest, β_2, drops somewhat after adding these refined controls but remains statistically significant, confirming that insurers are sensitive to cash flow risks for offices after COVID-19. Overall, our evidence supports the idea that insurers do not only monitor cash flow risks but are also sufficiently sophisticated to disentangle how these risks affect different types of CMBS collateral.

The results in Table 3 rely on the dynamic nature of our shocks, which uncovers how heterogeneity across bonds that have cash flow shocks expected to materialize in the short to medium run leads to different trading behavior. To understand how our results are sensitive to using a six-year cutoff to define our treatment, we re-estimate (4), defining $Treat^{Exp\ Office}_{jt}$ as equal to 1 for exposures within three or four, rather than six, years. These thresholds represent moments after which roughly 25% and 33% of the office-borne cash flow shocks have materialized for the average CMBS.

Appendix-Table A.2 shows that our results are robust to using these alternative thresholds. Moreover, the point estimates of β_2 are larger for the longer (four-year) horizon (columns 5 to 8) as compared to the shorter (three-year) horizon (columns 1 to 4). The reason is that thresholds implied by shorter horizons lead the control group to include bonds exposed to some medium-term shocks (those occurring in five and six years' time) as well. This lends further support to the idea that insurance companies monitor the actual timing of potential cash flow shocks to office-linked mortgages.

To bolster our identification assumption that insurers would not have reacted differently to shocks affecting the cash flow risks of CMBS exposed to offices with leases expiring within six years in the absence of the pandemic, we also estimate a dynamic difference-in-differences regression:

$$\begin{aligned} I^{sold}_{ijt} &= \alpha_{it} + \alpha_{ij} + \alpha_{j(coupon)t} + \alpha_{j(NAIC)t} + \alpha_{j(downgrade_{t-1})t} \\ &\quad + \beta Treat^{Exp\ Office}_{jt} + \sum_{\iota \neq 2019} \delta_\iota Treat^{Exp\ Office}_{j\iota} + \theta Controls_{jt} + \varepsilon_{ijt}, \end{aligned} \tag{5}$$

where each $Treat^{Exp\ Office}_{j\iota}$ is a dummy variable which equals 1 in year $\iota \neq 2019$ if bond j is exposed to office-linked mortgages whose main lease expires within six years (excluding year ι), and $Controls_{jt}$ includes the same set of bond-level controls as in column 3 of Table 3.

One can see in Figure A.3, which plots our estimated coefficients δ_ι, that most of the effect we capture takes place in 2020 and in 2022, with a spike in sales of CMBS with more exposure to cash flow risks posed by lease expiration. Reassuringly, we find no visual evidence for violation of parallel trends, supporting our identification assumption that office lease expiration becomes a salient feature of CMBS only after the onset of the pandemic.

To what extent do these sales represent actual portfolio rebalancing, rather than minor adjustments in insurers' asset portfolios? To answer this question, we follow the approach from Ge and Weisbach (2021), and re-estimate specification 4 using as dependent variable the par value of the sales of bond j in year t divided by the par value of the same bond in the previous year, $Share\ Par\ Value\ Sold_{ijt}$. The results are in Appendix-Table A.3. Across all specifications, the coefficient of interest β_2 is positive and significant, indicating that after COVID-19 a larger share of bonds exposed to cash flow shocks was sold by insurers, as measured by the share of par value sold. Our findings are robust to this alternative specification and, thus, capture meaningful adjustments in the asset portfolio of insurance companies.

5.3. CMBS Trading and Realized Gains and Losses

The results so far suggest that insurers actively monitor underlying lease expiration information embedded in complex CMBS structures to identify and sell assets exposed to imminent cash flow shocks. Naturally, if other market participants systematically observe and process the same information, the riskiness of CMBS exposed to such cash flow risks would already be incorporated into market prices. In that case, insurers would have little to gain from acting on this information alone, since expected losses would already be reflected in valuations.

To assess whether this holds in practice, we examine realized gains and losses reported by insurers on their trading activities. These realized gains and losses correspond to the difference between the sale proceeds of an asset and its book value. Because sales revenue reflects transaction prices, this approach allows us to capture potential losses at a discount—precisely what would occur if the market had repriced CMBS following COVID-19. Using this information, we estimate the following specification:

$$Realized\ gain\ over\ BACV_{ijt} = \alpha_{it} + \alpha_j + \alpha_{j(coupon)t} + \alpha_{j(NAIC)t} + \alpha_{j(downgrade_{t-1})t} + \beta_1 Treat_{jt}^{Exp\ Office} + \beta_2 Post\ Covid_t \times Treat_{jt}^{Exp\ Office} + \varepsilon_{ijt}, \tag{6}$$

where the dependent variable, $Realized\ gain\ over\ BACV_{ijt}$, measures realized gains or losses on the sale of bond j by insurer i in year t, relative to the book value of bond j in the previous year. The treatment variable $Treat_{jt}^{Exp\ Office}$ and the fixed effects α_{it}, $\alpha_{j(coupon)t}$, $\alpha_{j(NAIC)t}$, and $\alpha_{j(downgrade_{t-1})t}$ are defined as before, where α_j denotes bond-level fixed effects. As realized gains and losses are observed for bonds that are sold, we estimate (6) using only bonds sold, compromising our ability to include insurer-bond fixed effects α_{ij}, which would require multiple sales of the same bond by a given insurer.

The coefficient of interest, β_2, captures the differential realized gain or loss for treated bonds (those exposed to office lease-expiration risk) sold in a given year relative to non-exposed bonds sold in the same period. If market prices adjust post COVID-19 to reflect the heightened risk of these exposures, we would expect a *negative* estimated β_2 as the proceeds received by insurers for these assets would be lower than those for comparable non-exposed assets, controlling for other price-relevant characteristics such as ratings downgrades.

Table 4 shows the results. Across all specifications, we find no evidence that treated bonds were sold at a discount after COVID-19. If anything, exposure to office collateral is associated with *positive* realized gains or losses post–COVID-19, whereas exposure to retail collateral is associated with *negative* outcomes. This pattern underscores that CMBS prices do respond to salient features of collateral performance—consistent with the divergent delinquency dynamics observed for offices and retail properties at the onset of the pandemic (Figure 3). In contrast, we find no systematic relationship between exposure to *lease-expiration risk* in offices and realized gains or losses on insurers' securities sales.

Finally, we validate that realized gains and losses capture meaningful variation in the underlying value of bonds sold by insurers by examining the effects of ratings downgrades, which are known to trigger sales by constrained insurers (Ellul, Jotikasthira and Lundblad, 2011). Appendix-Table A.4 confirms that private-label CMBS downgraded in the previous year exhibit worse trading returns relative to comparable non-downgraded CMBS.

5.4. CMBS Acquisitions by Insurance Companies

Having documented that exposure to underlying cash flow shocks affects insurance companies' trading behavior, and given the dynamics of CMBS portfolio exposure to offices shown in Figures 5 and 6, we next consider insurers' purchasing behavior: are insurance companies also less willing to acquire private-label CMBS exposed to office CRE? Lower willingness to hold office-linked CMBS can manifest itself through smaller acquisition of these assets by insurers after COVID-19. Additionally, to the extent that insurers demand higher returns for holding assets perceived as riskier, newly issued office-exposed CMBS held by insurers should offer higher returns.

We start by considering how risk characteristics of private-label CMBS acquired by insurers change over the years, focusing on office exposure and cash flow risks represented by lease expiration. Figure 9 shows the distribution of office exposure for all private-label CMBS acquired by insurance companies before and after COVID-19. Importantly, there is a large jump in the share of CMBS acquired in 2020-2022 which have no underlying office-linked collateral, with close to 30% of the bonds acquired in 2022 having no exposure to office CRE. We observe a similar pattern when considering exposure to cash flow shocks represented by lease expiration taking place within six years, our treatment measure. Figure 10 plots the corresponding distribution, before and after the COVID-19 pandemic. There is a shift towards the left of the distribution, with a larger share of the bonds acquired in the post-COVID period having no exposure to short- and medium-term cash flow shocks to office CRE. In particular, there is an increase of about 10% in the share of CMBS acquired in the post-COVID period that have no mortgages linked to office CRE whose main lease expires within six years.

The drastic reduction in holdings of cash flow risk-sensitive CMBS by insurers indicates that these investors adjust their exposure to risks along the extensive margin, by acquiring private-label CMBS with smaller exposure to offices. This adjustment can also occur along the intensive margin if lower willingness to hold office-exposed CMBS leads insurers to require higher returns in order to invest in office-linked CMBS after COVID-19.

To test this, we analyze how the coupons of newly issued private-label CMBS vary based on their exposure to offices, before and after the pandemic, by estimating the following specification at the bond issuance level:

$$\begin{aligned} Coupon_{jt} =& \alpha_{j(maturity)t} + \beta_1 Office_j\% + \beta_2 Post\ Covid_t \times Office_j\% \\ & + \beta_3 Office_j\% \times NAIC\ Held_{jt} + \beta_4 Post\ Covid_t \times Office_j\% \times NAIC\ Held_{jt} \\ & + \gamma_1 NAIC\ Held_{jt} + \gamma_2 Post\ Covid_t \times NAIC\ Held_{jt} + \Gamma X_j + \varepsilon_{jt}, \end{aligned} \tag{7}$$

where $Coupon_{jt}$ denotes the coupon offered by bond j issued in quarter t in percentage points, $Post\ Covid_t$ is an indicator variable that equals 1 after 2020Q1, $Office_j\%$ is the share (in %) of bond j at origination that is exposed to offices, $\alpha_{j(maturity)t}$ are bond maturity (in years) by year-quarter fixed effects, and X_j is a vector of bond-level controls. The ownership indicator variable, $NAIC\ Held_{jt}$, equals 1 if bond j is held by an insurance company at the end of the respective year, and reflects differences in the pricing of risk by insurers relative to other investors. Control variables include a dummy for investment grade bonds, the % share of the pool in the largest state, the number of loans of the deal to proxy for deal complexity (Ghent, Torous and Valkanov, 2019), a dummy for horizontal risk retention (Flynn, Ghent and Tchistyi, 2020), bond j's subordination percentage at origination, the weighted average LTV and debt-service coverage ratio of the deal at securitization, and a dummy for conduit loans.

Column 1 of Table 5 shows the results without accounting for differences between CMBS held by insurers vs. other investors, assuming that changes in office risks after the pandemic were not priced in differently by investors. The negative estimate masks significant underlying heterogeneity. When we account for CMBS ownership in column 2, we find that bonds from deals with a larger share invested in office loans command a coupon premium, especially after COVID-19, when they are held by insurance companies as compared to bonds held by other investors. A one percentage point increase in the office exposure of a deal translates to approximately 2 basis points higher coupon rates if the bond is held by any insurer after COVID-19. This effect is robust to the inclusion of bond-level controls and lead underwriter fixed effects in columns 3 and 4.

Overall, the changes in acquisition behavior by insurers documented in this section further corroborate that they do monitor work-from-home triggered changes in office loan risk. Higher office percentage in general has a negative effect on coupons for CMBS, including those held by other intermediaries. This could be explained by different risk perception by these investors, and ultimately affects the allocation of cash flow risks across intermediaries. We next analyze how such risks migrate from insurers to other intermediaries.

6. Migration of CRE Cash Flow Risks from Insurance to Other Firms

The evidence so far suggests that insurers are able to monitor risks in securitized assets that arise from lower office demand after the pandemic, and reduce their exposure to these private-label CMBS. In this section, we turn to the question of who acquires these assets in an attempt to understand which intermediaries become more exposed to WFH-borne risks and why these other investors are willing and able to acquire more exposed CMBS.

6.1. Who Purchases Private-label CMBS from Insurers?

We first analyze the purchasers of private-label CMBS from insurance companies in our sample period. To this end, we categorize the buyers into three groups: banks, insurance companies, and others (which includes uncategorized buyers and instances where the buyer name is not specified in the data). Figure A.4 illustrates the trends in these categories over time. The overwhelming majority of sales are for bank buyers, which is also true for office-exposed CMBS (Figure A.5).[9]

To test more formally whether insurance companies sell off CRE-related cash flow risks to banks, we re-estimate the same specifications as in Table 3, but replace the dependent variable with a sales indicator that is equal to one only for the subset of sales to banks. That is, the dependent variable equals zero if insurer i sold any fraction of security j in year t to any non-bank purchaser or nothing at all.

In Table 6, the coefficient on treated CMBS after COVID, β_2 in (4), is positive—as in Table 3—and statistically significant across all specifications. The estimated coefficient in the most conservative regression specification (column 4), where we explicitly control for differential sales behavior for any other type of collateral and lease expiration separately, amounts to more than 80% of the respective coefficient in column 4 of Table 3. This indicates that

[9] We exclude three major buyers: FA REINSURANCE, RESOLUTION LIFE, COINSURANCE TALCOTT-ALLIANZ.

sales are more likely to banks if the CMBS is related to office properties with leases expiring within six years in the post-COVID period.

For completeness, Appendix-Table A.5 examines sales from insurance companies to other insurance companies by adjusting the dependent variable accordingly. The results suggest none of the effects for sales to insurers if the CMBS in question is related to office properties with leases expiring within six years. Moreover, we show in Figure A.6 the share of the portfolio of private-label CMBS held by insurers exposed to lease expiration within six years as captured by $Treat_{jt}^{Exp\ Office}$. There is a sharp drop in the share of insurers' CMBS portfolio exposed to cash flow shocks after 2019, consistent with the idea that insurers reduce their exposure to cash flow risks by selling exposed bonds to other types of investors, as indicated in Table 6.

Overall, these results can be interpreted as suggesting a transfer of this particular risk from insurance companies to banks.

6.2. Bank Holdings of Private-label CMBS

Purchaser information reported by insurers suggests most of the buyers of private-label CMBS with office exposure are banks, as shown in Figure A.5. Nonetheless, these banks might be acting as dealers on behalf of other buyers, which limits the conclusions we can draw from reported buyer information on NAIC files.

To better understand the extent to which banks acquire more CMBS after the pandemic, we use Call Reports data and construct bank-level holdings of private-label CMBS. In this manner, we first document how aggregate holdings of private-label CMBS evolve over time for banks of different sizes.

Figure 11 shows a noticeable increase in holdings of CMBS by small and medium-sized banks (i.e., those with assets under $100 billion) from 2021 onwards. This pattern is more striking relative to 2017 and 2018, when the aggregate amount of private-label CMBS holdings by banks was at similar levels but with a substantially smaller role played by small and medium-sized banks. This bigger role could be explained by a larger exposure to private-label CMBS by those institutions that held CMBS in the past, or by a larger number of banks investing in these assets. Figure 12 shows that the latter is the main driving force. In Panel

A, we see that the number of small banks (total assets under $10 billion) that hold private-label CMBS nearly doubles between March 2020 and December 2023. Moreover, these "new entrants" are holding meaningful shares of private-label CMBS: the median small bank has more than 1% of their assets invested in private-label CMBS, as shown in Panel B.

Between 2020 and 2022, holdings of private-label CMBS by small and medium-sized banks nearly doubled from $9 billion to $17 billion. This increase closely mirrors changes in insurers' portfolios. Prior to the pandemic, insurers had steadily increased their holdings of CMBS exposed to offices with leases expiring within six years, adding approximately $8 billion annually. However, this pattern reversed during 2020-2022, with exposed CMBS holdings decreasing by $0.1 billion (Figure A.6). This decline reflects insurers' reduced appetite for assets vulnerable to cash flow shocks from office lease expiration. The matching magnitudes and timing of these shifts lend further support to a redistribution of exposed CMBS from insurers back to the banking sector.

To understand how this unprecedented increase in the number of small banks investing in CMBS is related to the characteristics of these banks, we divide our sample of small banks into three types: banks that held private-label CMBS between 2017 and March 2020, banks that held private-label CMBS *only after* March 2020, and banks that did not hold any private-label CMBS between 2017 and 2023. Appendix-Table A.6 shows mean values of selected characteristics for these three different bank types. Banks that began investing in private-label CMBS after COVID-19 are smaller than those that invested in CMBS before the pandemic, but have similar leverage, exposure to CRE loans, and have a similar share of their total assets and securities invested in private-label CMBS. Banks that did not invest in CMBS (column 3) are smaller, have lower exposure to non-owner-occupied CRE loans, and are more levered than banks that invested in private-label CMBS between 2017 and 2023.

Banks increasing their holdings of private-label CMBS suggests that risks in CMBS with office-linked mortgages flow from the insurance sector to the banking sector. What explains this shift in CMBS ownership from insurers to banks, especially small banks? To the extent that small banks make smaller loans (Ghent and Valkanov, 2016; Glancy et al., 2022), they are unlikely to originate loans that can be used to finance offices, meaning they are not exposed to risks related to the effects of hybrid work arrangements on office vacancies.[10]

[10] https://www.nytimes.com/2024/07/24/business/banks-loans-commercial-real-estate.html sug-

This has two implications. First, by investing in office-exposed CMBS, these small banks would effectively diversify their CRE exposure, potentially equipping them with greater risk-bearing capacity. Additionally, small banks' ability to perform due diligence in CMBS might be limited, which would facilitate sales of office-exposed CMBS by insurance companies to small banks. While both forces could be at play, we have provided evidence of insurers' ability to monitor risks in securitized assets, which in turn facilitates the transfer of these risks to the banking sector.

6.3. Bank Losses

The evidence on insurers' trading behavior indicates that these investors actively sell CMBS exposed to expected cash flow shocks, suggesting that the performance of such bonds is likely to deteriorate over time. Consequently, the growing presence of small banks in private-label CMBS markets raises the possibility that these institutions subsequently face losses in their securities portfolios. To assess this hypothesis, we examine realized gains and losses on banks' securities holdings, comparing institutions exposed and not exposed to private-label CMBS. We estimate the following specification:

$$\frac{Securities\ Losses_{it}}{Assets_{it-1}} = \alpha_i + \alpha_t + \beta_1 Treat_{it-1} + \beta_2 X_{it} + \sum_{\tau \neq 2020} \delta_\tau Treat_{i\tau-1} + \sum_{\tau \neq 2020} \Gamma_\tau \times X_{i\tau} + \varepsilon_{it}, \quad (8)$$

where the dependent variable, $\frac{Securities\ Losses_{it}}{Assets_{it-1}}$, measures realized gains or losses on held-to-maturity and available-for-sale securities of bank i in year t, scaled by total assets in the previous year and expressed in percentage points. The treatment indicator, $Treat_{it-1}$, equals 1 if bank i held private-label CMBS in year $t-1$. The specification includes bank (α_i) and year (α_t) fixed effects to absorb time-invariant heterogeneity across banks and aggregate shocks common to all institutions. Standard errors are clustered at the bank level.

We further include a vector of time-varying bank-level controls, X_{it}, to account for other factors influencing securities performance but unrelated to CMBS exposure. These controls include lagged shares of (i) treasury securities, (ii) agency MBS, (iii) long-duration assets, and (iv) short-duration assets, all out of total securities held. We also include total securities rela-

gests that small banks did not incur substantial losses on their CRE loans due to reduced office exposure.

tive to total assets as well as lagged total assets as controls. We further allow the importance of each characteristic to vary across years by estimating time-varying coefficients.

The coefficients of interest, δ_τ, capture differences in securities portfolio performance between banks that hold private-label CMBS and those that do not in the year prior, relative to the baseline period (late 2020). The results, reported in Figure 13, reveal a pronounced relative decline in realized gains and losses for banks exposed to private-label CMBS in 2022 and 2023. Importantly, we find no evidence of differential pre-trends prior to the pandemic, supporting the validity of our design.

The timing of this decline coincides with the stabilization in the number of small banks holding private-label CMBS (Figure 12). In 2022-2023, treated banks experience approximately 6 basis points lower realized performance in their securities portfolios (relative to total assets) compared with non-exposed banks. Given that the ratio of Tier 1 capital to total assets for small banks averages around 11%, this loss corresponds to roughly a 1% relative decline in Tier 1 capital for banks holding private-label CMBS.

7. Financial Stability and Policy Implications

Our empirical findings reveal how institutional investors assess and respond to underlying risks in MBS. Given the systemic importance of both insurers and CRE loans in financial markets, these findings have direct implications for financial stability and policy, which we outline below.

7.1. Institutional Investors and Risk in Securitized Assets

The central role of asset-backed securities in the Global Financial Crisis (GFC) led regulators to overhaul securitization regulation, focusing on better aligning originator incentives and strengthening investor risk assessment. Post-GFC reforms introduced due diligence requirements that mandate investors to evaluate risk characteristics of underlying exposures in securitized positions.[11] These requirements were designed to address investors' apparent failure to monitor securitization risks before the crisis. Our analysis of insurers' CMBS trading following the pandemic demonstrates that sophisticated institutional investors can

[11] See, for example, Chapter 2, Article 5 in EBA (2017).

effectively assess and actively monitor risks in their securitized-asset portfolios. This strongly suggests that at least the largest, most systemically important banks always had this ability to start with.

However, as insurance companies adjust their portfolios in response to mounting risks, we observe a dramatic increase in private-label CMBS holdings by small banks. This redistribution reveals substantial heterogeneity in financial intermediaries' risk-management capabilities and raises concerns about less sophisticated investors increasing their exposure to these assets precisely when their risks are rising. The situation is particularly concerning given that default risks from hybrid work arrangements are materializing gradually through cash flow shocks, suggesting both insurers and banks may face significant future losses from CRE mortgage defaults. These findings underscore that even sophisticated risk-assessment capabilities cannot substitute for robust capital requirements, which remain essential for ensuring investors can absorb unexpected losses and internalize financial stability risks.

7.2. Commercial Real Estate Mortgage Default Risk

The COVID-19 pandemic triggered an unprecedented shift in work arrangements, fundamentally altering CRE valuations through the widespread adoption of hybrid work. These structural changes in asset prices have raised financial stability concerns, given that CRE serves as collateral for bank loans and underlies CMBS. Our study fills an important gap by demonstrating how the sensitivity to borrower income and the timing of cash flow shocks matter for the transmission of lower office demand to credit risk.

Our results address several key policy challenges. First, they demonstrate the critical importance of property-specific contract information, particularly lease expiration dates, in identifying mortgages materially dependent on cash flows. This informs the implementation of revised banking standards ("Basel 3.1") currently under consideration by prudential regulators globally. These standards differentiate mortgages based on whether they are "*materially dependent on cash flows generated by the property*" (CRE20 in BCBS, 2022) for credit risk capitalization. The UK's Prudential Regulation Authority (PRA), for instance, proposes in its Basel 3.1 consultation to "assign risk weights to mortgage exposures depending on whether repayment of the loan is materially dependent on the cash flows generated by the property."[12]

Second, we have shown that aggregate delinquency rates alone provide an incomplete and potentially misleading picture of CRE credit risk, as they fail to capture the forward-looking risks from post-COVID changes in office demand. Our findings demonstrate that granular data, particularly the monitoring of tenancy agreement characteristics, are crucial for accurate credit risk assessment.

8. Conclusion

In this paper, we examine how cash flow shocks from commercial property leases affect mortgage delinquencies, and assess insurers' monitoring of these risks in securitized assets. Using detailed data on commercial mortgages in CMBS deals combined with insurers' portfolio and trading behavior, we document that borrower cash flow shocks significantly impact CRE loan defaults following the COVID-19 pandemic. For office properties specifically, we find that lease expiration becomes a stronger predictor of default during the pandemic, possibly driven by reduced office demand due to work-from-home arrangements.

Our analysis reveals that insurers actively manage these risks by reducing their exposure to vulnerable CMBS before delinquencies materialize. These sales do not occur at a loss, underscoring that insurers act on information not yet fully reflected in market prices rather than engaging in fire sales. This finding challenges the common view that institutional investors do not (sufficiently) monitor underlying asset risks. As existing leases expire and need to be renewed, our results point to a likely build-up of default risk and highlight which CRE loan features are most relevant for tracking such risks. We also highlight the implications of the transfer of CMBS risks to small banks, which points to heterogeneity in monitoring ability across investors in the CMBS market.

These findings have broader implications for financial policy. Heterogeneity in investors' ability to monitor complex securities can lead to systematic reallocation of risk across the financial sector. This process can shift the locus of risk rather than eliminate it, amplifying small banks' vulnerabilities when asset fundamentals deteriorate. Although our analy-

[12]See https://www.bankofengland.co.uk/prudential-regulation/publication/2022/november/implementation-of-the-basel-3-1-standards.

sis focuses on U.S. CMBS data, these mechanisms likely operate similarly in other markets and countries. Given the systemic importance of both insurers and mortgages in financial markets, our findings underscore the need for continued scrutiny and monitoring of risks stemming from structural changes in office demand.

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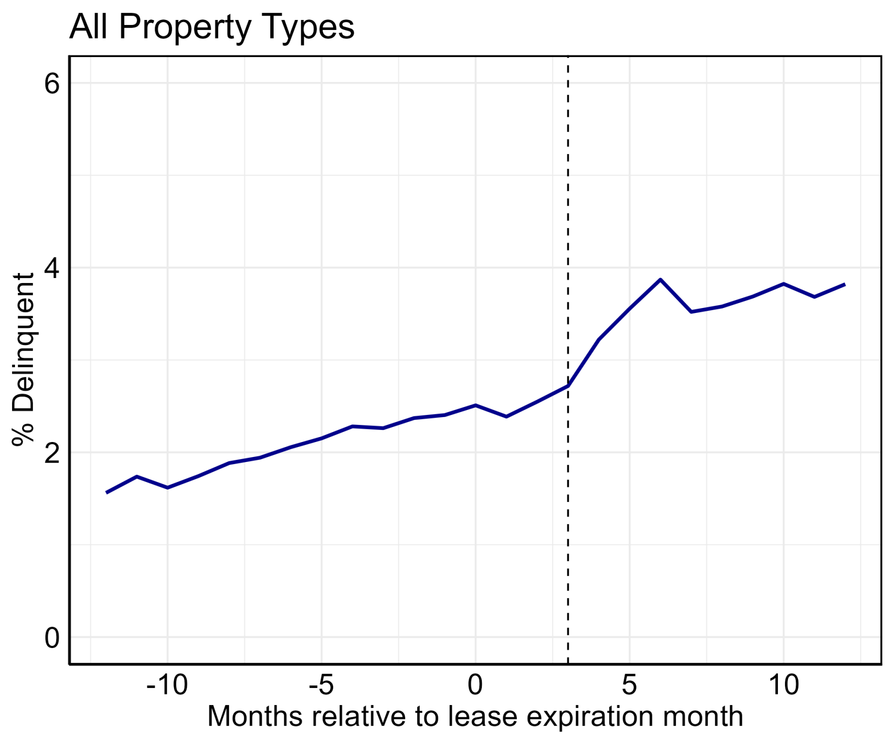
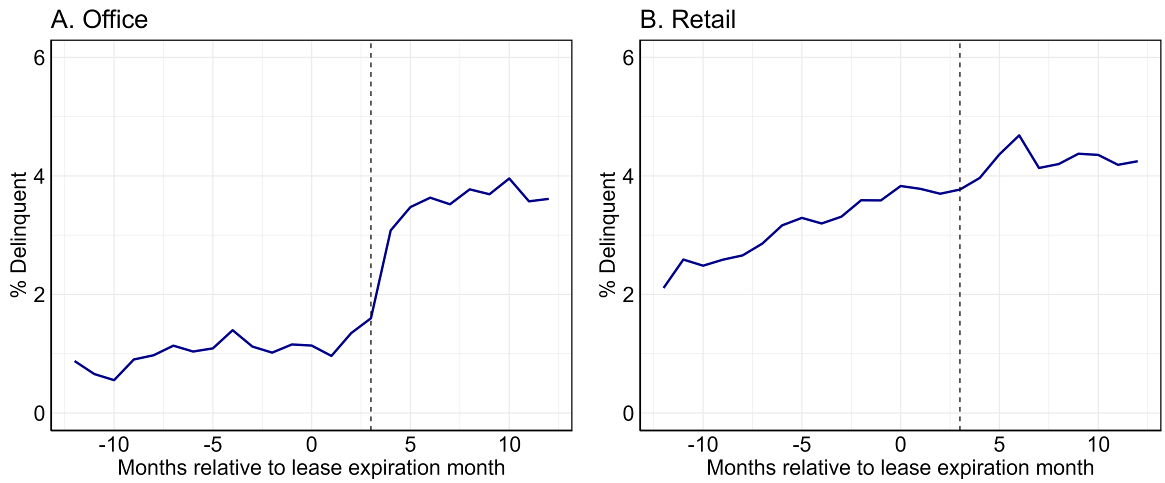
FIGURES

Figure 1: Changes in Delinquency Around Lease Expiration Dates



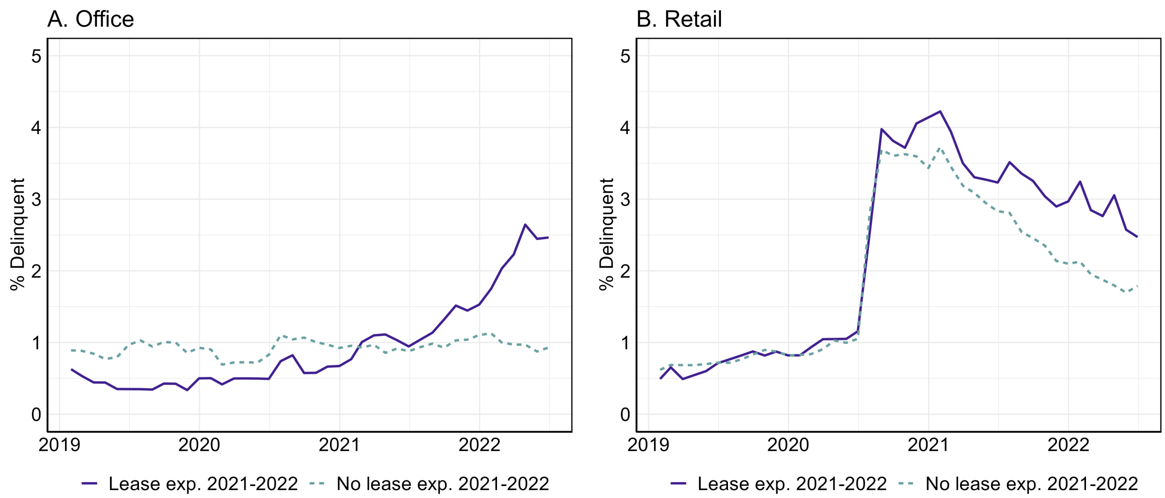
Notes: This figure shows average delinquency rates in each month relative to lease expiration, for properties with leases expiring between 2017 and June 2022. Delinquency is a dummy variable which equals 1 if a mortgage is at least 90 days past due. Sources: Trepp loan data and authors' calculations.

Figure 2: Changes in Delinquency Around Lease Expiration Dates for Office and Retail



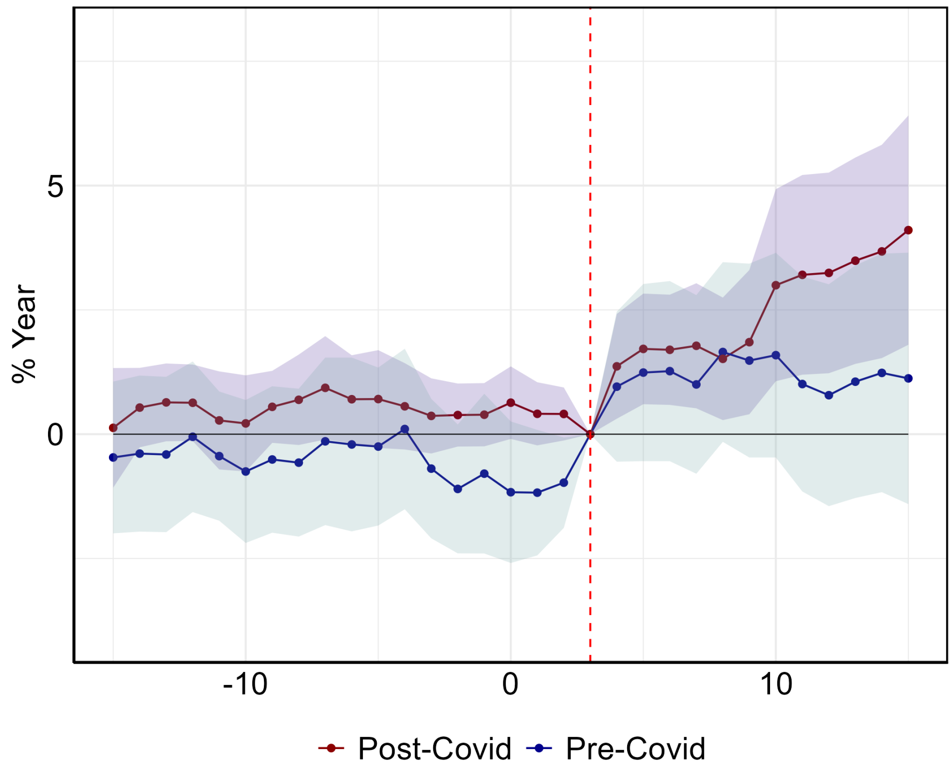
Notes: This figure shows average delinquency in each month relative to lease expiration, for properties with leases expiring between 2017 and June 2022. **Panel A** shows delinquency rates for properties classified as *Office*. **Panel B** shows delinquency rates for properties classified as *Retail*. Delinquency is a dummy variable which equals 1 if a mortgage is at least 90 days past due. The vertical line marks three months after lease expiration. Sources: Trepp loan data and authors' calculations.

Figure 3: Delinquency Rates of Mortgages With and Without Leases Expiring in 2021-2022



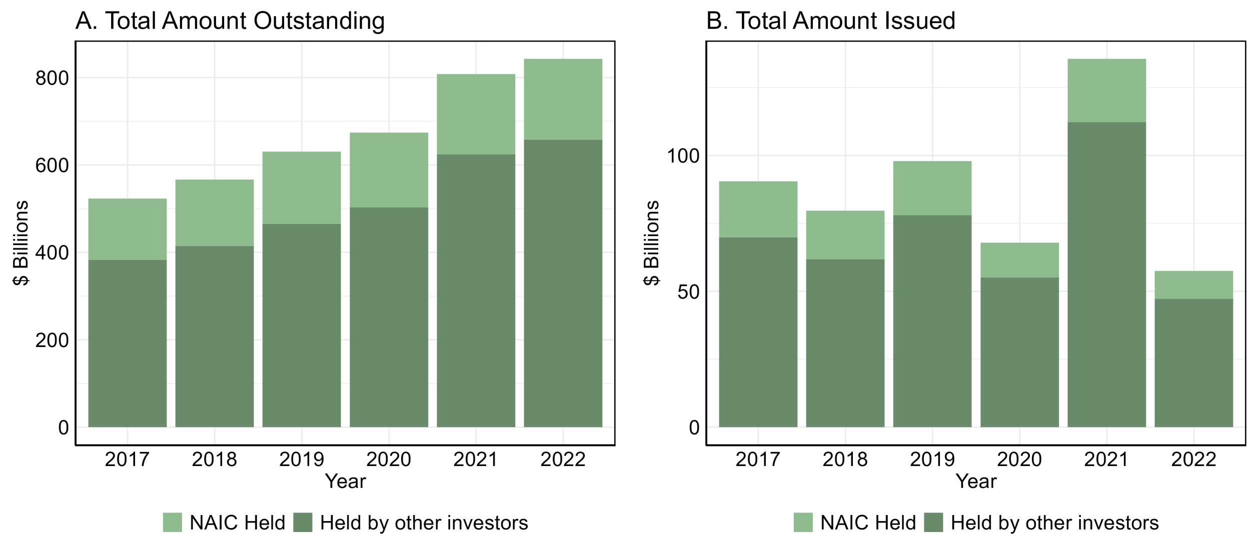
Notes: This figure shows average delinquency rates for mortgages *with* leases expiring in 2021-2022, and mortgages *without* leases expiring in these two years. **Panel A** shows delinquency rates for properties classified as *Office*. **Panel B** shows delinquency rates for properties classified as *Retail*. Delinquency is a dummy variable which equals 1 if a mortgage is at least 90 days past due. Sources: Trepp loan data and authors' calculations.

Figure 4: Delinquency Rates Around Lease Expiration Dates—Office WFH Sensitivity



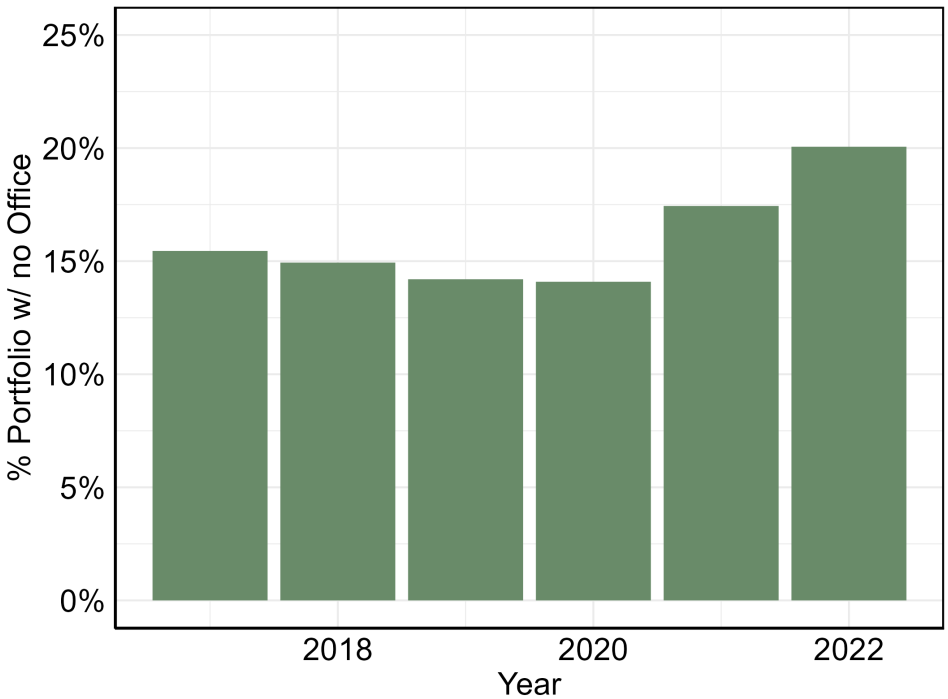
Notes: This figure shows the effects of lease expiration on delinquency rates of properties classified as *Office*. The level of observation is loan j in city r in year-month t, which refers to the distribution month of each securitized mortgage. The sample period is Jan/2017 to Jun/2022. The dependent variable I_{jrt}^{D90} is a dummy variable which equals 1 if a loan is at least 90 days past due. The δ_ι estimates from specification (1) show delinquency rates relative to three months after the lease expiration month. The vertical line marks three months after lease expiration. "Pre-Covid" includes all months before March 2020, and "Post-Covid" includes all months after March 2020. Shaded areas correspond to the 95 percent confidence intervals around point estimates. Standard errors are clustered at the loan level. Sources: Trepp and authors' calculations.

Figure 5: Insurance Holdings of CMBS



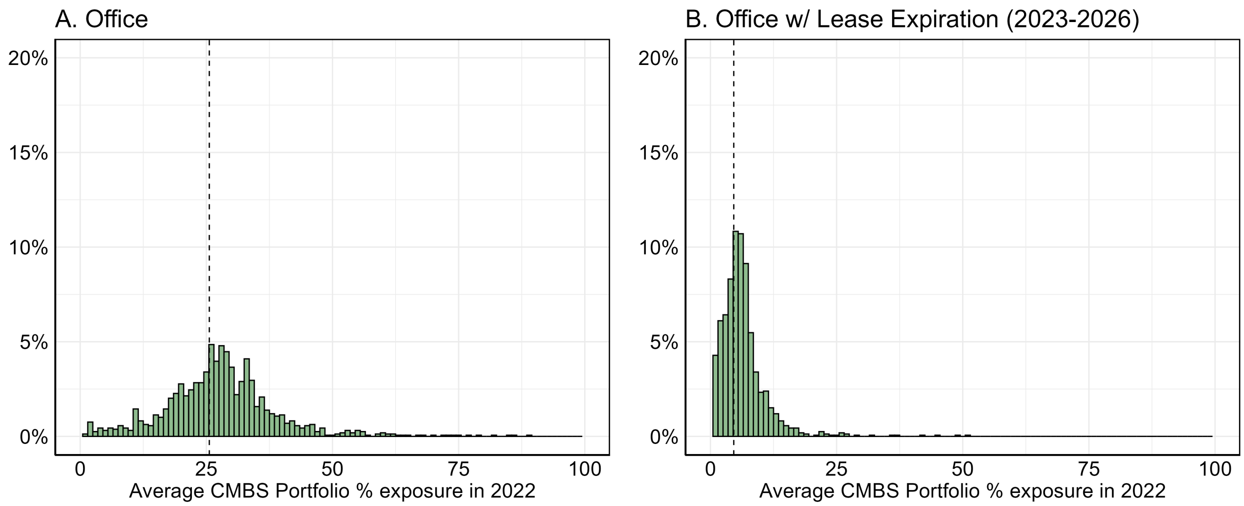
Notes: This figure shows the total amount outstanding (**Panel A**) and amount originated (**Panel B**) of private-label CMBS per year, differentiating between the amount held by insurance companies and that held by other investors. We identify holdings of insurance companies using NAIC Schedule D, Part 1. Insurer-held amounts are calculated as the sum of the BACV of the CMBS held by insurers. Amount held by other investors is the residual value relative to the total original balance outstanding/originated in a given year. Both plots exclude interest-only and agency CMBS. Source: Trepp, NAIC, and authors' calculations.

Figure 6: % CMBS Portfolio Without Office Exposure



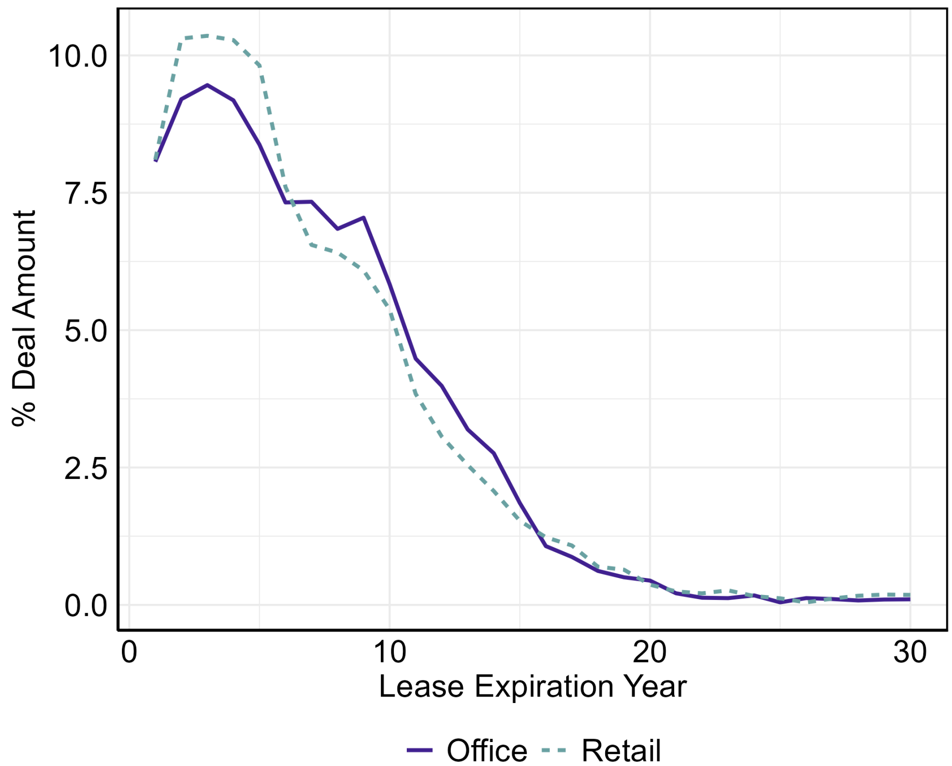
Notes: This figure shows the share of insurance companies' private-label CMBS portfolio not exposed to *any* mortgages linked to properties classified as *Office*. Shares are calculated aggregating BACV for exposed and non-exposed CMBS, where exposure is defined as any percentage of the pool of mortgages used to finance office CRE. Source: Trepp, NAIC, and authors' calculations.

Figure 7: CMBS Bonds Held by Insurance Companies—Exposure to Offices



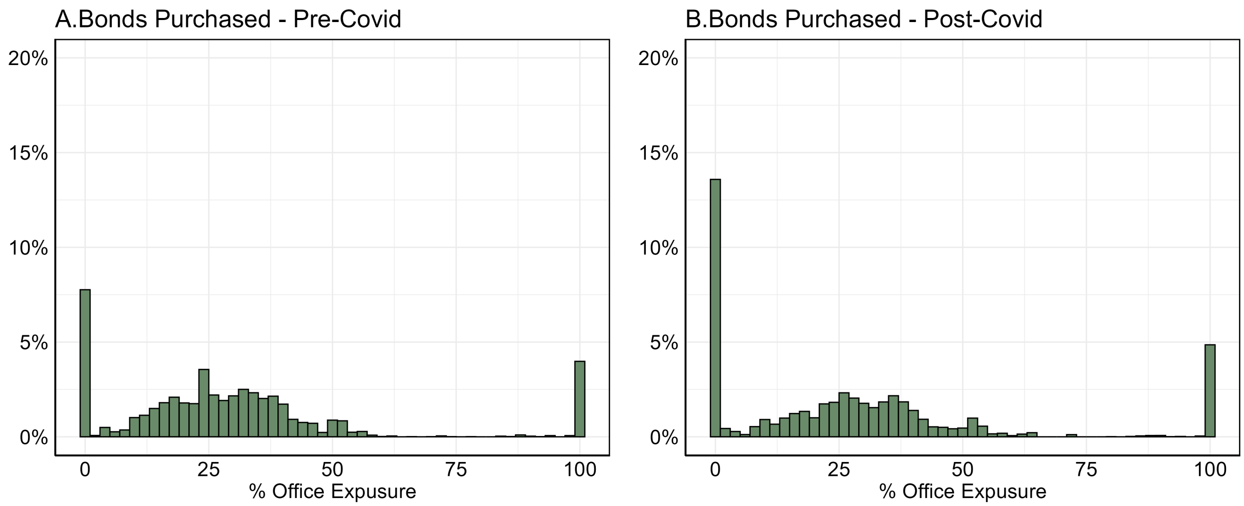
Notes: This figure shows the distribution of office-exposed shares of insurance companies' private-label CMBS portfolio. **Panel A** shows the distribution for any office exposure. **Panel B** shows the distribution conditional on any mortgages having main leases expiring between 2023-2026. Source: Trepp, NAIC, and authors' calculations.

Figure 8: CMBS Cash Flow Shock Dynamics



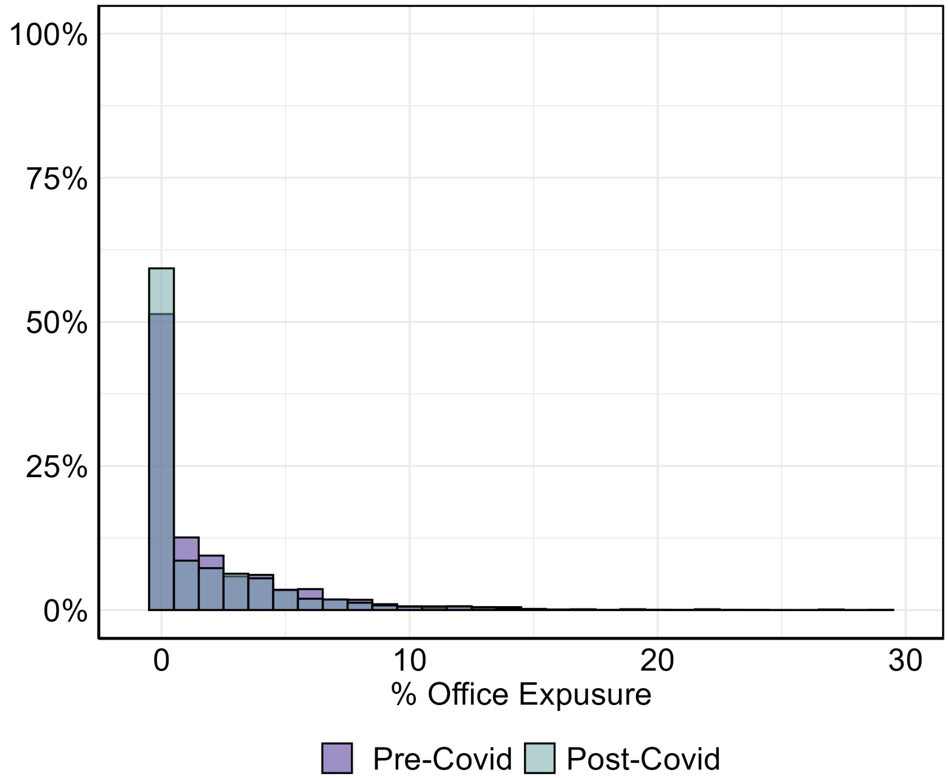
Notes: This figure shows the average distribution of expected cash flow shocks for deals in our sample in each lease expiration year after the reference year. We first calculate, for each deal in a given year, what share of mortgages have leases expiring in τ years. Then, we average these shares, first across bonds of a given property type in a given year, then across years, separately for offices and retail. Source: Trepp, NAIC, and authors' calculations.

Figure 9: Distribution of Office Exposure—CMBS Acquired Before and After COVID-19



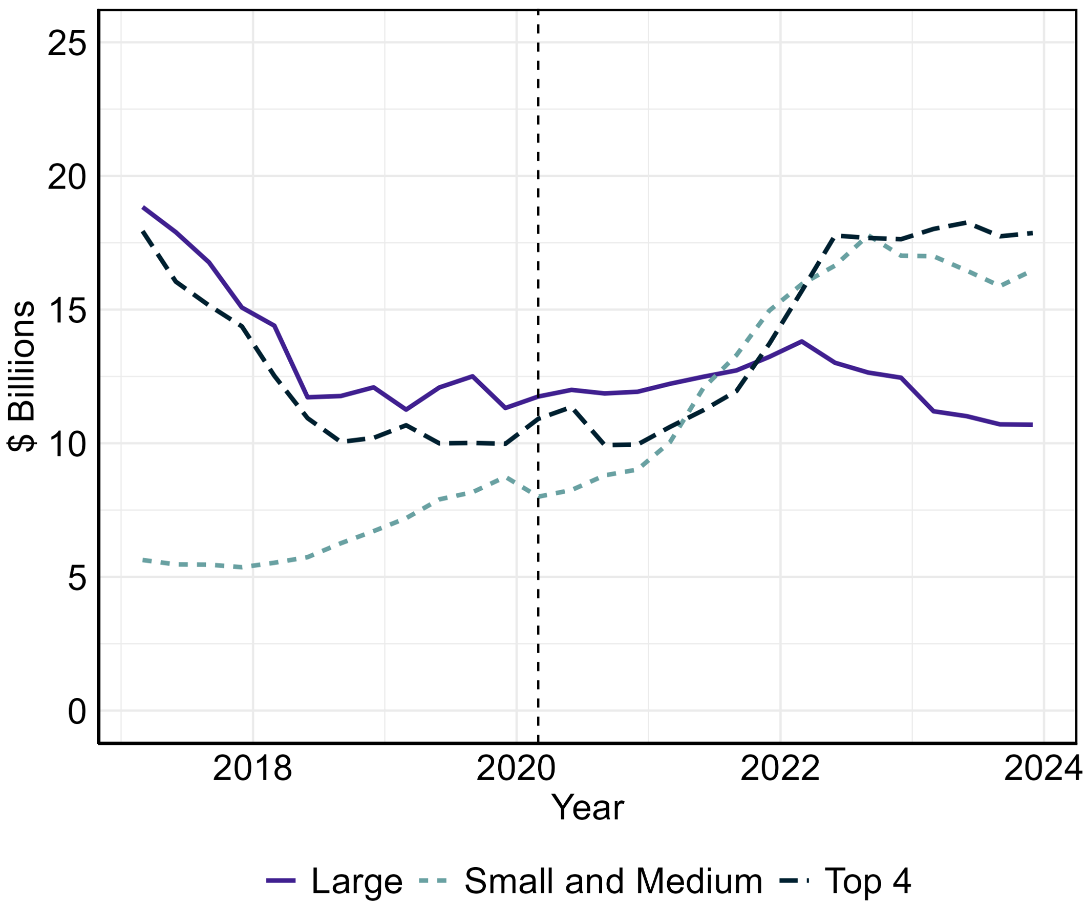
Notes: This figure shows the distribution of office exposures of private-label CMBS acquired by insurance companies, before and after COVID-19. Percent exposure equals the amount of the pool of mortgages linked to office CRE. **Panel A** panel plots the distribution of office exposure for CMBS acquired between 2017-2019. **Panel B** plots the distribution of office exposure for CMBS acquired between 2020-2022. The width of each distribution bar equals 2%. Source: Trepp, NAIC, and authors' calculations.

Figure 10: Distribution of Office Exposure with Leases Expiring—CMBS Acquired Before and After COVID-19



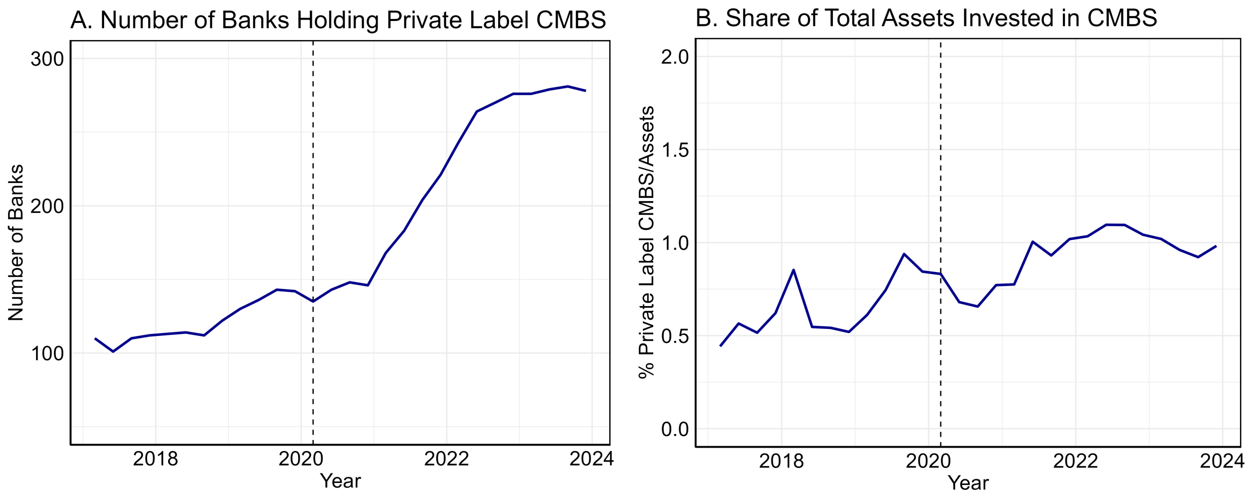
Notes: This figure shows the distribution of treatment exposure of private-label CMBS acquired by insurance companies, before and after COVID-19, based on underlying office-linked lease expiration. Percent exposure equals the amount of the pool of mortgages linked to office CRE whose main lease agreement expires within six years. Source: Trepp, NAIC, and authors' calculations.

Figure 11: Bank Holdings of Private-label CMBS



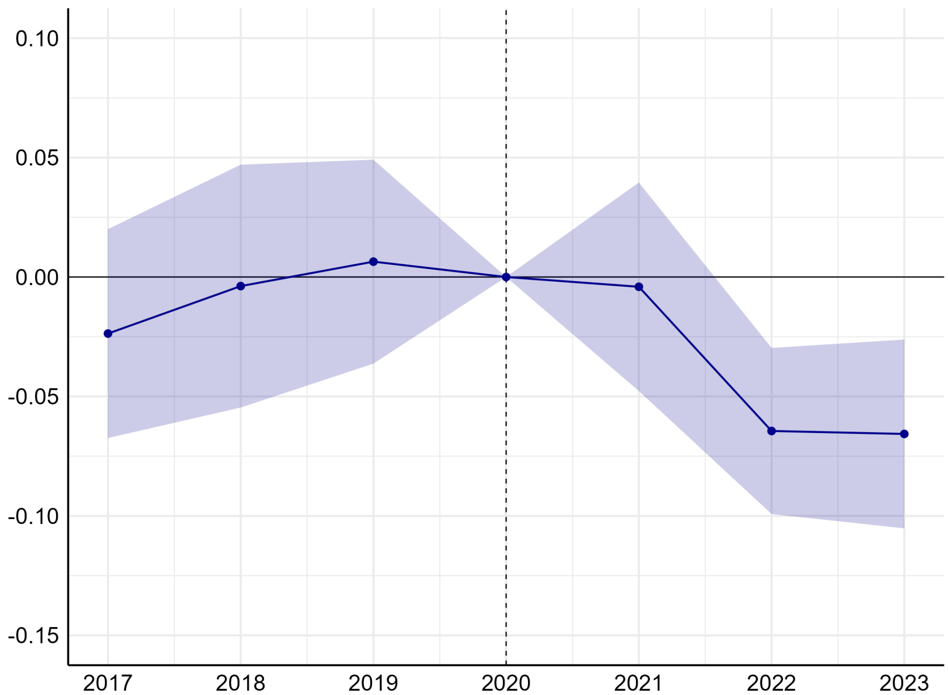
Notes: This figure shows the total amount of private-label CMBS holdings of U.S. banks, including held-to-maturity and available-for-sale assets. Top 4 banks are J.P. Morgan Chase, Bank of America, Citigroup, and Wells Fargo. Large banks are institutions with total assets above $100 billion, medium banks are institutions with total assets between $10 billion and $100 billion, and small banks are institutions with total assets under $10 billion. We also exclude TD Bank from the plots as it shows discontinuity in holdings of private CMBS in 2018 that is not present on the aggregate series. Source: Call Reports and authors' calculations.

Figure 12: Small Banks' Exposure to Private-Label CMBS



Notes: This figure shows the number of small U.S. banks which hold private-label CMBS (Panel A) and the median % share of private-label CMBS out of total assets for small banks with CMBS exposure (Panel B). Small banks are defined as institutions with total assets under $10 billion. Source: Call Reports and authors' calculations.

Figure 13: Bank Holdings of CMBS and Securities Losses



Notes: The plot shows the dynamic effect of banks' exposure to private-label CMBS on realized gains and losses on securities trading, as in (8). Shaded area corresponds to the 95 percent confidence interval around point estimates. Standard errors are clustered at the bank level. Source: Call Reports and authors' calculations.

TABLES

Table 1: Summary Statistics

Panel A. All Properties	Mean	Median	Min	Max	N
Outstanding Balance	12,126,498.41	4,665,665.69	535.94	9,016,115,069.00	7,081,912
Floating Interest Rate	0.12	0.00	0.00	1.00	7,081,912
Delinquency (90 days)	0.01	0.00	0.00	1.00	7,081,912
Recourse Loan	0.01	0.00	0.00	1.00	7,081,912
Loan Term	228.39	120	1	515	7,010,744
Lease Expiration Year	2026	2024	2016	2099	747,189
Largest Tenant % Sqr Ft	45.11	33.44	0.00	100.00	748,523
Panel B. Office	Mean	Median	Min	Max	N
Outstanding Balance	35,592,214.49	17,545,061.17	6,760.18	3,000,000,000.00	276,561
Floating Interest Rate	0.08	0.00	0.00	1.00	276,561
Delinquency (90 days)	0.01	0.00	0.00	1.00	276,561
Recourse Loan	0.02	0.00	0.00	1.00	276,561
Loan Term	112.87	120	1	363	275,307
Lease Expiration Year	2025	2024	2016	2099	209,965
Largest Tenant % Sqr Ft	42.20	29.71	0.00	100.00	211,306
Panel C. Retail	Mean	Median	Min	Max	N
Outstanding Balance	17,123,979.19	7,331,549.50	797.55	2,400,000,000.00	516,328
Floating Interest Rate	0.02	0.00	0.00	1.00	516,328
Delinquency (90 days)	0.02	0.00	0.00	1.00	516,328
Recourse Loan	0.01	0.00	0.00	1.00	516,328
Loan Term	123.63	120	1	360	506,734
Lease Expiration Year	2027	2024	2016	2099	415,663
Largest Tenant % Sqr Ft	45.68	34.52	0.00	100.00	417,838

Notes: This table shows summary statistics from our sample of commercial real estate mortgages. The sample period is from Jan/2017 to Jun/2022. **Panel A** includes summary statistics for all property types in the sample. **Panel B** includes summary statistics for properties classified as *Office*. **Panel C** includes summary statistics for properties classified as *Retail*. Source: Trepp and authors' calculations.

Table 2: The Effect of Lease Expiration on Mortgage Default Before and After COVID-19

	I_{jrt}^{D90}		
	(1)	(2)	(3)
$Post\ Expiration_{jt}$	0.0131***	0.0132***	0.0140***
	(0.0029)	(0.0029)	(0.0033)
$Post\ Covid_t \times Post\ Expiration_{jt}$	-0.0029	-0.0029	-0.0013
	(0.0033)	(0.0033)	(0.0038)
$Post\ Covid_t \times Ind\ Office_j$	-0.0162***	-0.0160***	-0.0216***
	(0.0019)	(0.0019)	(0.0030)
$Post\ Expiration_{jt} \times Ind\ Office_j$	0.0013	0.0014	0.0004
	(0.0062)	(0.0062)	(0.0065)
$Post\ Covid_t \times Post\ Expiration_{jt} \times Ind\ Office_j$	0.0122*	0.0121*	0.0132*
	(0.0064)	(0.0064)	(0.0070)
Observations	842,875	842,875	761,489
R^2	0.42919	0.42924	0.52736
Month-year fixed effects	✓		
Loan ID fixed effects	✓	✓	✓
Month-year × Floating fixed effects		✓	✓
Month-year × City fixed effects			✓

Notes: This table shows the effects of lease expiration on delinquency rates for mortgages linked to different property types, before and after COVID-19, as in (2). The level of observation is loan j in city r in year-month t, which refers to the distribution month of each securitized mortgage. The sample period is Jan/2017 to Jun/2022. The dependent variable, I_{jrt}^{D90}, is a dummy variable which equals 1 if a loan is at least 90 days past due. $Post\ Covid_t$ equals 1 after March 2020, $Post\ Expiration_{jt}$ equals 1 if loan j had its main lease expiration before or in year-month t, and $Ind\ Office_j$ equals 1 if loan j is linked to an office. Standard errors clustered at the loan level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp and authors' calculations.

Table 3: CMBS Trading Difference-in-Differences—Exposure to Lease Expiration

	I^{sold}_{ijt}			
	(1)	(2)	(3)	(4)
$Treat^{Exp\ Office}_{jt}$	0.0092**	0.0103**	0.0028	0.0046
	(0.0042)	(0.0043)	(0.0066)	(0.0054)
$Post\ Covid_t \times Treat^{Exp\ Office}_{jt}$	0.0271***	0.0244***	0.0338***	0.0191***
	(0.0045)	(0.0055)	(0.0083)	(0.0067)
I^{Office}_{jt}		0.0009	-0.0013	0.0046
		(0.0180)	(0.0180)	(0.0181)
$Post\ Covid_t \times I^{Office}_{jt}$		0.0060	0.0057	0.0035
		(0.0073)	(0.0073)	(0.0073)
I^{Exp}_{jt}			0.0103	
			(0.0070)	
$Post\ Covid_t \times I^{Exp}_{jt}$			-0.0124	
			(0.0084)	
$I^{Exp\ Retail}_{jt}$				0.0083
				(0.0064)
$I^{Exp\ Other}_{jt}$				0.0073
				(0.0046)
I^{Retail}_{jt}				-0.0140
				(0.0295)
$Post\ Covid_t \times I^{Exp\ Retail}_{jt}$				0.0081
				(0.0089)
$Post\ Covid_t \times I^{Exp\ Other}_{jt}$				0.0047
				(0.0048)
$Post\ Covid_t \times I^{Retail}_{jt}$				0.0005
				(0.0080)
Observations	203,494	203,494	203,494	203,494
R^2	0.53986	0.53987	0.53988	0.53999
Year × Insurer ID fixed effects	✓	✓	✓	✓
CUSIP × Insurer ID fixed effects	✓	✓	✓	✓
Year × Coupon Type fixed effects	✓	✓	✓	✓
Year × NAIC Designation fixed effects	✓	✓	✓	✓
Year × Lagged Downgrade fixed effects	✓	✓	✓	✓

Notes: This table shows the effect of exposure to underlying lease expiration and offices on the likelihood of sales of private-label CMBS by insurance companies, as in (4). The level of observation is bond j held by insurer i at the end of year t. The sample period is 2017 to 2022. The dependent variable, I^{sold}_{ijt}, is a dummy which equals 1 if bond j was sold by insurer i in year t. $Post\ Covid_t$ equals 1 after 2019. $Treat^{Exp\ Office}_{jt}$ is a dummy which equals 1 if bond j is exposed to office mortgages whose main lease expires within six years (excluding year t). I^{Exp}_{jt}, $I^{Exp\ Retail}_{jt}$, and $I^{Exp\ Other}_{jt}$ are dummy variables which equal 1 if bond j is exposed to mortgages whose main lease expires within six years (excluding year t), for all properties, retail only, and properties that are neither retail nor offices. I^{Office}_{jt} and I^{Retail}_{jt} are dummies which equal 1 for any exposure to offices and retail. Coupon Type is the type of coupon payment for bond j (e.g., fixed rate, floating rate, interest only). Lagged downgrade is a dummy which equals 1 if the bond was downgraded (based on NAIC designation) in year $t-1$. Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Table 4: Insurers CMBS Trading and Realized Gains and Losses

	Realized gain over $BACV_{ijt}$			
	(1)	(2)	(3)	(4)
$Treat_{jt}^{Exp\ Office}$	-0.0029	0.0005	-0.0041	-0.0027
	(0.0040)	(0.0037)	(0.0045)	(0.0040)
$Post\ Covid_t \times Treat_{jt}^{Exp\ Office}$	0.0101***	0.0039	0.0116*	0.0086*
	(0.0039)	(0.0042)	(0.0062)	(0.0049)
I_{jt}^{Office}		-0.0264**	-0.0270**	-0.0226*
		(0.0133)	(0.0135)	(0.0130)
$Post\ Covid_t \times I_{jt}^{Office}$		0.0127**	0.0120**	0.0059
		(0.0059)	(0.0059)	(0.0056)
I_{jt}^{Exp}			0.0072	
			(0.0056)	
$Post\ Covid_t \times I_{jt}^{Exp}$			-0.0110*	
			(0.0065)	
$I_{jt}^{Exp\ Retail}$				0.0070
				(0.0059)
$I_{jt}^{Exp\ Other}$				0.0002
				(0.0030)
I_{jt}^{Retail}				-0.0096
				(0.0194)
$Post\ Covid_t \times I_{jt}^{Exp\ Retail}$				0.0073
				(0.0075)
$Post\ Covid_t \times I_{jt}^{Exp\ Other}$				0.0024
				(0.0029)
$Post\ Covid_t \times I_{jt}^{Retail}$				-0.0196***
				(0.0075)
Observations	14,483	14,483	14,483	14,483
R^2	0.78759	0.78785	0.78798	0.78842
Year × Insurer ID fixed effects	✓	✓	✓	✓
CUSIP fixed effects	✓	✓	✓	✓
Year × Coupon Type fixed effects	✓	✓	✓	✓
Year × NAIC Designation fixed effects	✓	✓	✓	✓
Year × Lagged Downgrade fixed effects	✓	✓	✓	✓

Notes: This table shows the effect of exposure to underlying lease expiration and offices on reported gains and losses conditional on bond sales by insurers, as in 6. The level of observation is bond j held by insurer i at the end of year t. The sample period is 2017 to 2022, and includes only bonds which were sold in each given year. The dependent variable, *Realized gain over* $BACV_{ijt}$, is the ratio of realized gains and losses in a given year, divided by the book value of the asset in the previous year. We exclude outliers of this dependent variable below the 2% and above the 98% percentiles. $Post\ Covid_t$ equals 1 after 2019. $Treat_{jt}^{Exp\ Office}$ is a dummy which equals 1 if bond j is exposed to office mortgages whose main lease expires within six years (excluding year t). I_{jt}^{Exp}, $I_{jt}^{Exp\ Retail}$, and $I_{jt}^{Exp\ Other}$ are dummy variables which equal 1 if bond j is exposed to mortgages whose main lease expires within six years (excluding year t), for all properties, retail only, and properties that are neither retail nor offices. I_{jt}^{Office} and I_{jt}^{Retail} are dummies which equal 1 for any exposure to offices and retail. Coupon Type is the type of coupon payment for bond j (e.g., fixed rate, floating rate, interest only). Lagged downgrade is a dummy which equals 1 if the bond was downgraded (based on NAIC designation) in year $t-1$. Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Table 5: Bond Coupons

	$Coupon_{jt}$			
	(1)	(2)	(3)	(4)
$Office_j\%$	-0.0024***	-0.0091***	-0.0062***	-0.0056***
	(0.0009)	(0.0027)	(0.0023)	(0.0021)
$Post\ Covid_t \times Office_j\%$	-0.0009	-0.0154***	-0.0158***	-0.0154***
	(0.0017)	(0.0042)	(0.0036)	(0.0032)
$Office_j\% \times NAIC\ Held_{jt}$		0.0089***	0.0068***	0.0074***
		(0.0028)	(0.0024)	(0.0021)
$Post\ Covid_t \times Office_j\% \times NAIC\ Held_{jt}$		0.0189***	0.0197***	0.0136***
		(0.0041)	(0.0036)	(0.0033)
$NAIC\ Held_{jt}$		-0.0078	0.2684***	-0.2197**
		(0.0901)	(0.0797)	(0.1076)
$Post\ Covid_t \times NAIC\ Held_{jt}$		-0.8356***	-0.8328***	-0.8189***
		(0.1294)	(0.1133)	(0.1578)
$Prime\ rating_j$			-0.7256***	-0.1250**
			(0.0349)	(0.0515)
$Main\ state\ (share\ in\ \%)_j$			-0.0027***	-0.0014
			(0.0010)	(0.0012)
$Num\ Loans\ at\ Securitization_j$			0.0003	-0.0006
			(0.0012)	(0.0015)
$Horizontal\ Risk\ Retention_j$			0.0572*	0.0668*
			(0.0323)	(0.0356)
$Retail_j\%$				-0.0179***
				(0.0036)
$Post\ Covid_t \times Retail_j\%$				-0.0060
				(0.0060)
$NAIC\ Held_{jt} \times Retail_j\%$				0.0222***
				(0.0034)
$Post\ Covid_t \times NAIC\ Held_{jt} \times Retail_j\%$				0.0120**
				(0.0059)
$Subordination_j\%$				-0.0181***
				(0.0016)
$Weighted\ Avg\ LTV\ at\ Securitization_j$				-0.0083**
				(0.0039)
$Weighted\ Avg\ DSCR\ at\ Securitization_j$				-0.1614***
				(0.0565)
$Conduit_j$				-0.2597**
				(0.1157)
Observations	3,200	3,200	3,200	2,449
R^2	0.56971	0.60990	0.66580	0.68158
Year-quarter × Maturity fixed effects	✓	✓	✓	✓
Lead Underwriter fixed effects			✓	✓

Notes: This table shows a regression of fixed-rate bond coupons of private-label CMBS on the office collateral and insurance ownership before and after COVID-19, as in (7). The level of observation is bond j originated in quarter t. The sample period is 2017 to 2022. The dependent variable $Coupon_{jt}$ is the coupon rate of fixed-rate bond j (in percentage points) originated in quarter t. $Post\ Covid_t$ equals 1 after 2019. $NAIC\ Held_{jt}$ equals 1 if bond j is held by any insurer at the end of the year of origination of the respective quarter t. $Office_j$ % and $Retail_j$ % are the percent shares of each bond j's corresponding deal linked to office and retail loans. $Prime\ rating_j$ equals 1 if the bond is rated at least BBB by S&P or by Fitch, or at least Baa3 by Moody's. $Main\ State\ (share\ in\ \%)_j$ is the share of the deal invested in the main state. $Num\ of\ Loans\ at\ Securitization_j$ is the number of loans in the deal at origination. $Horizontal\ Risk\ Retention_j$ and $Conduit_j$ are dummies for deals of each type, respectively. $Subordination_j\%$ bond j's subordination percentage at origination. $Weighted\ Avg\ LTV\ at\ Securitization_j$ and $Weighted\ Avg\ DSCR\ at\ Securitization_j$ are average LTV and DSCR weighted by loan volume within each deal. Maturity denotes the bond maturity in years. Lead Underwriter is a categorical variable indicating the lead underwriter of each deal. Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Table 6: CMBS Bank Buyer Difference-in-Differences—Exposure to Lease Expiration

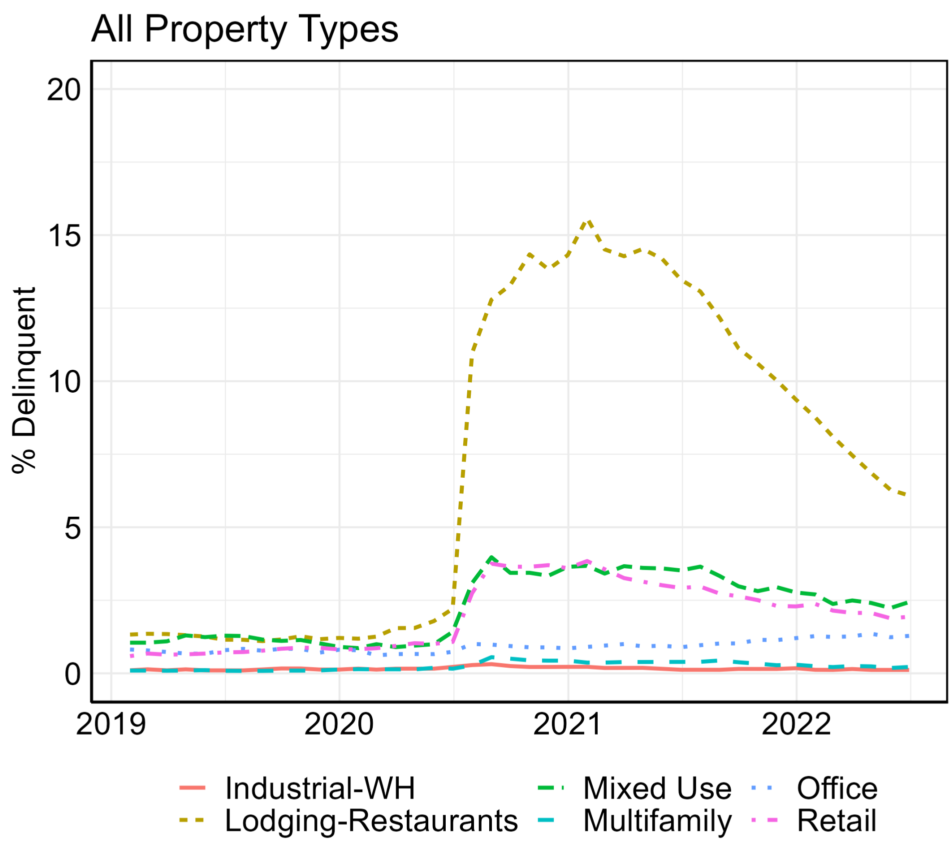
	$I_{ijt}^{sold\ to\ bank}$			
	(1)	(2)	(3)	(4)
$Treat_{jt}^{Exp\ Office}$	0.0084**	0.0097***	0.0036	0.0053
	(0.0034)	(0.0035)	(0.0054)	(0.0043)
$Post\ Covid_t \times Treat_{jt}^{Exp\ Office}$	0.0204***	0.0172***	0.0275***	0.0161***
	(0.0035)	(0.0043)	(0.0066)	(0.0053)
I_{jt}^{Office}		-0.0020	-0.0047	-0.0022
		(0.0127)	(0.0127)	(0.0127)
$Post\ Covid_t \times I_{jt}^{Office}$		0.0071	0.0069	0.0047
		(0.0057)	(0.0057)	(0.0058)
I_{jt}^{Exp}			0.0079	
			(0.0059)	
$Post\ Covid_t \times I_{jt}^{Exp}$			-0.0139**	
			(0.0067)	
$I_{jt}^{Exp\ Retail}$				0.0021
				(0.0053)
$I_{jt}^{Exp\ Other}$				0.0070*
				(0.0039)
I_{jt}^{Retail}				0.0190
				(0.0206)
$Post\ Covid_t \times I_{jt}^{Exp\ Retail}$				0.0091
				(0.0070)
$Post\ Covid_t \times I_{jt}^{Exp\ Other}$				0.0033
				(0.0038)
$Post\ Covid_t \times I_{jt}^{Retail}$				-0.0120*
				(0.0064)
Observations	202,957	202,957	202,957	202,957
R^2	0.49382	0.49383	0.49386	0.49394
Year × Insurer ID fixed effects	✓	✓	✓	✓
CUSIP × Insurer ID fixed effects	✓	✓	✓	✓
Year × Coupon Type fixed effects	✓	✓	✓	✓
Year × NAIC Designation fixed effects	✓	✓	✓	✓
Year × Lagged Downgrade fixed effects	✓	✓	✓	✓

Notes: This table shows the effect of exposure to underlying lease expiration and offices on the likelihood of sales of private-label CMBS by insurers to *banks*. The level of observation is bond j held by insurer i at the end of year t. The sample period is 2017 to 2022. The dependent variable, $I_{ijt}^{sold\ to\ bank}$, is a dummy which equals 1 if bond j was sold by insurer i in year t to a bank. We excluded CMBS holdings with the following buyers: FA REINSURANCE, Resolution Life Insurance, Coinsurance Talcott-Allianz. $Post\ Covid_t$ equals 1 after 2019. $Treat_{jt}^{Exp\ Office}$ is a dummy which equals 1 if bond j is exposed to office mortgages whose main lease expires within six years (excluding year t). I_{jt}^{Exp}, $I_{jt}^{Exp\ Retail}$, and $I_{jt}^{Exp\ Other}$ are dummy variables which equal 1 if bond j is exposed to mortgages whose main lease expires within six years (excluding year t), for all properties, retail only, and properties that are neither retail nor offices. I_{jt}^{Office} and I_{jt}^{Retail} are dummies which equal 1 for any exposure to offices and retail. Coupon Type is the type of coupon payment for bond j (e.g., fixed rate, floating rate, interest only). Lagged downgrade is a dummy which equals 1 if the bond was downgraded (based on NAIC designation) in year $t-1$. Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Appendix

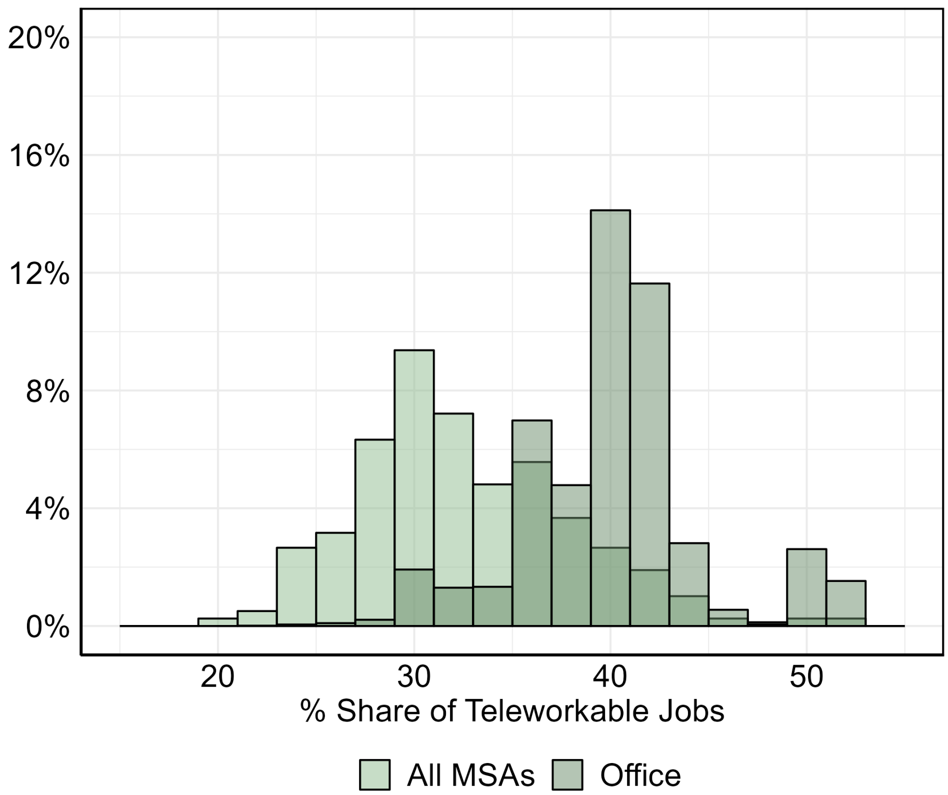
A. Additional Figures and Tables

Figure A.1: Delinquency Rates by Property Type



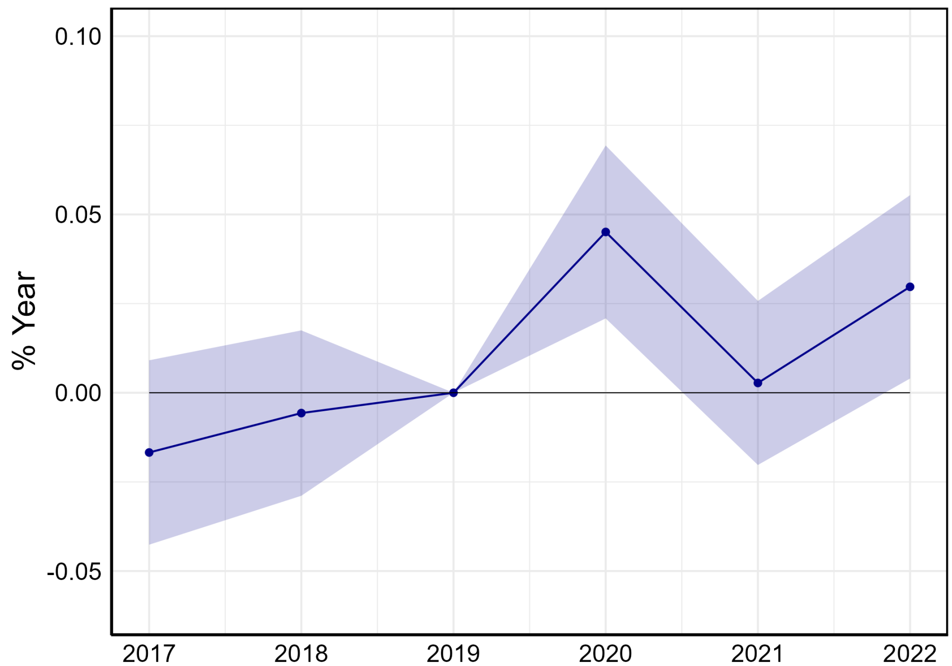
Notes: This Figure reports average delinquency for mortgages linked to different property types. Property types are defined as in Appendix B. Delinquency is a dummy variable which equals 1 if a mortgage is more than 90 days past due. Source: Trepp and authors' calculations.

Figure A.2: Distribution of % Teleworkable Jobs—All MSAs and Office Mortgages



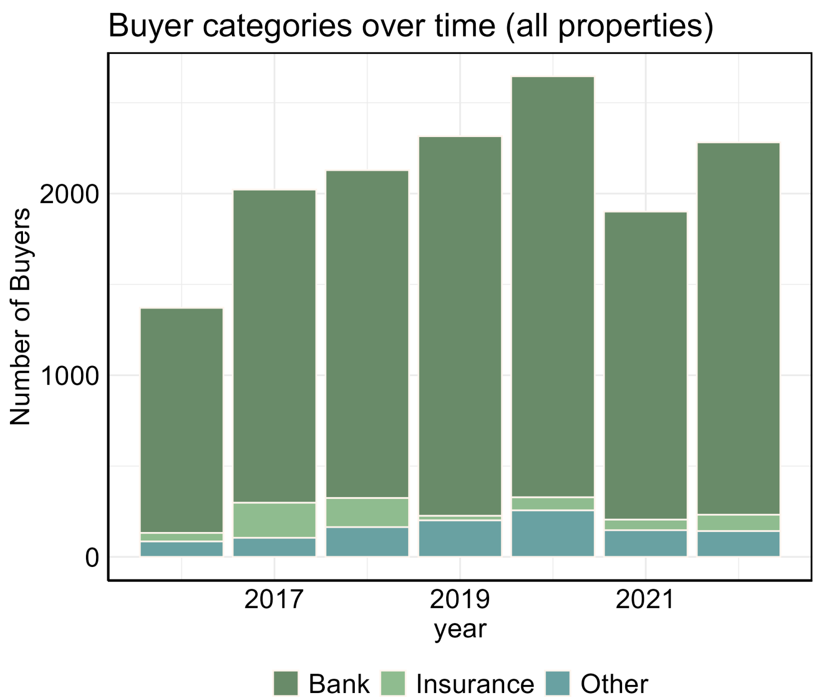
Notes: This figure shows the distribution of the share of jobs in each MSA that can be performed from home, using the measure proposed by Dingel and Neiman (2020). We plot the distribution of all MSAs in the Dingel and Neiman (2020) dataset, and the distribution of the MSAs from the mortgages in the Trepp data, focusing on properties classified as *Office*. The width of each distribution bar is 2%. Source: Trepp and authors' calculations.

Figure A.3: Dynamic Difference-in-Differences: Trading of CMBS Exposed to Cash Flow Risks



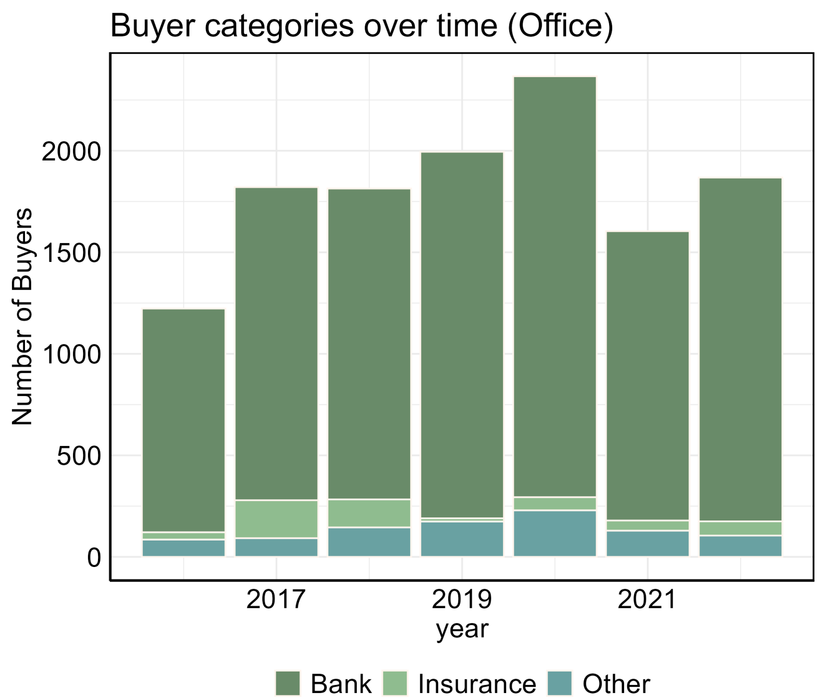
Notes: The plot shows the time-varying effect of exposure to underlying office lease expiration (relative to 2019) on the likelihood of sales of private-label CMBS by insurers, as in (5). Shaded area corresponds to the 95 percent confidence interval around point estimates. Standard errors are clustered at the security level. Source: Trepp, NAIC, and authors' calculations.

Figure A.4: Buyers of CMBS by Category Over Time (All Properties)



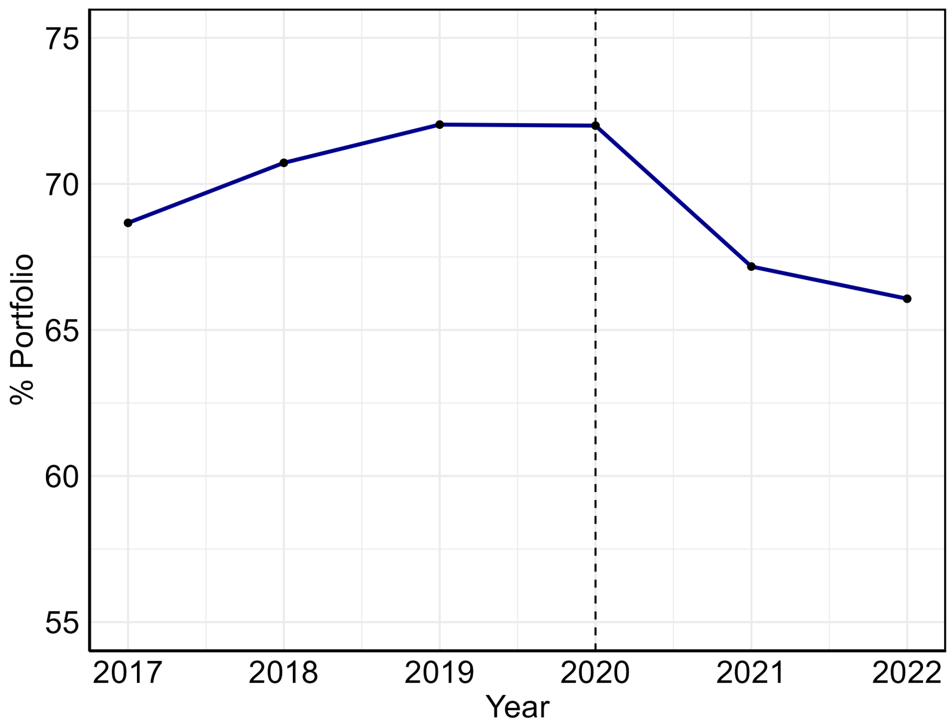
Notes: This figure reports the share of buyers of all private-label CMBS against all properties sold by insurance firms by categories over time. We exclude three major buyers (FA REINSURANCE, RESOLUTION LIFE, COINSURANCE TALCOTT-ALLIANZ). Property types are defined as in Appendix B. Source: Trepp, NAIC, and authors' calculations.

Figure A.5: Buyers of CMBS by Category Over Time (Offices)



Notes: This figure reports the share of buyers of all private-label CMBS against offices sold by insurance firms by categories over time. We exclude three major buyers (FA REINSURANCE, RESOLUTION LIFE, COINSURANCE TALCOTT-ALLIANZ). Property types are defined as in Appendix B. Source: Trepp, NAIC, and authors' calculations.

Figure A.6: Share Insurers' CMBS Portfolio Exposed to Treatment (Office Lease Expiration



Notes: The plot shows the share of the private-label CMBS portfolio of insurance companies at the end of each year, for bonds which have $Treat_{jt}^{Exp\ Office}$ equal 1, that is, bond j has any underlying office-linked mortgages whose leases expire within six years in year t. Source: Trepp, NAIC, and authors' calculations.

Table A.1: Property Types and Lease Expiration Information

Property Category	# without lease expiration	# with lease expiration	% with lease expiration
Healthcare-Nursing	464727	51	0.01
Industrial-WH	147055	53515	26.68
Lodging-Restaurants	208574	180	0.09
Mixed Use	66103	56571	46.11
Multifamily	5057710	831	0.02
Office	66596	209965	75.92
Other	223293	10413	4.46
Retail	100665	415663	80.50

Notes: This table shows the number of observations in our CRE mortgage sample for which the lease expiration information is included, and the number of observations for which the lease expiration information is missing. Sample is from Jan/2017 to Jun/2022. Breakdown is provided by property type. Source: Trepp and authors' calculations.

Table A.2: CMBS Trading Difference-in-Differences—Exposure to Lease Expiration (Extension)

	I_{ijt}^{sold}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treat_{jt}^{Exp\ Office}$	0.0040	0.0058*	0.0035	0.0039	0.0051	0.0065*	0.0042	0.0037
	(0.0030)	(0.0031)	(0.0037)	(0.0033)	(0.0034)	(0.0035)	(0.0044)	(0.0039)
$Post\ Covid_t \times Treat_{jt}^{Exp\ Office}$	0.0193***	0.0152***	0.0102**	0.0134***	0.0239***	0.0203***	0.0197***	0.0161***
	(0.0038)	(0.0042)	(0.0051)	(0.0045)	(0.0040)	(0.0046)	(0.0057)	(0.0050)
I_{jt}^{Office}		-9.56×10^{-5}	0.0028	0.0039		0.0007	0.0009	0.0042
		(0.0181)	(0.0180)	(0.0183)		(0.0180)	(0.0181)	(0.0182)
$Post\ Covid_t \times I_{jt}^{Office}$		0.0147**	0.0095	0.0110		0.0102	0.0098	0.0076
		(0.0066)	(0.0070)	(0.0069)		(0.0068)	(0.0069)	(0.0070)
I_{jt}^{Exp}			0.0090*				0.0053	
			(0.0050)				(0.0057)	
$Post\ Covid_t \times I_{jt}^{Exp}$			0.0140**				0.0018	
			(0.0066)				(0.0070)	
$I_{jt}^{Exp\ Retail}$				0.0068				0.0078
				(0.0042)				(0.0051)
$I_{jt}^{Exp\ Other}$				0.0084***				0.0059*
				(0.0030)				(0.0035)
I_{jt}^{Retail}				-0.0142				-0.0137
				(0.0301)				(0.0299)
$Post\ Covid_t \times I_{jt}^{Exp\ Retail}$				0.0094				0.0083
				(0.0061)				(0.0071)
$Post\ Covid_t \times I_{jt}^{Exp\ Other}$				-0.0049				0.0008
				(0.0036)				(0.0040)
$Post\ Covid_t \times I_{jt}^{Retail}$				0.0070				0.0036
				(0.0069)				(0.0073)
Observations	203,494	203,494	203,494	203,494	203,494	203,494	203,494	203,494
R^2	0.53975	0.53979	0.53989	0.53994	0.53980	0.53982	0.53983	0.53993
Year × Insurer ID fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
CUSIP × Insurer ID fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year × Coupon Type fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year-NAIC Designation fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year × Lagged Downgrade fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows the effect of exposure to underlying lease expiration and offices on the likelihood of sales of private-label CMBS by insurance companies. The level of observation is bond j held by insurer i at the end of year t. The sample period is 2017 to 2022. The dependent variable I_{ijt}^{sold} is a dummy which equals 1 if bond j was sold by insurer i in year t. $Post\ Covid_t$ equals 1 after 2019. $Treat_{jt}^{Exp\ Office}$ is a dummy which equals 1 if bond j is exposed to office mortgages whose main lease expires within three years (threshold = 25%, in columns 1-4) or within four years (threshold = 33%, in columns 5-8), excluding year t. I_{jt}^{Exp}, $I_{jt}^{Exp\ Retail}$, and $I_{jt}^{Exp\ Other}$ are dummy variables which equal 1 if bond j is exposed to mortgages whose main lease expires within three years (threshold = 25%) or four years (threshold = 33%), excluding year t, for all properties, retail only, and properties that are neither retail nor offices. I_{jt}^{Office} and I_{jt}^{Retail} are dummy variables which equal 1 for any exposure to offices/retail. Coupon Type is the type of coupon payment for bond j (e.g., fixed rate, floating rate, interest only). Lagged downgrade is a dummy which equals 1 if the bond was downgraded (based on NAIC designation) in year $t-1$. Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Table A.3: CMBS Portfolio Difference-in-Differences—Exposure to Lease Expiration

	$Share\ Par\ Value\ Sold_{ijt}$			
	(1)	(2)	(3)	(4)
$Treat_{jt}^{Exp\ Office}$	0.0037	0.0049	0.0013	0.0033
	(0.0037)	(0.0038)	(0.0060)	(0.0049)
$Post\ Covid_t \times Treat_{jt}^{Exp\ Office}$	0.0245***	0.0213***	0.0258***	0.0127**
	(0.0040)	(0.0048)	(0.0075)	(0.0059)
I_{jt}^{Office}		0.0046	0.0036	0.0068
		(0.0165)	(0.0165)	(0.0166)
$Post\ Covid_t \times I_{jt}^{Office}$		0.0070	0.0068	0.0049
		(0.0065)	(0.0065)	(0.0065)
I_{jt}^{Exp}			0.0050	
			(0.0064)	
$Post\ Covid_t \times I_{jt}^{Exp}$			-0.0060	
			(0.0075)	
$I_{jt}^{Exp\ Retail}$				0.0058
				(0.0060)
$I_{jt}^{Exp\ Other}$				0.0016
				(0.0041)
I_{jt}^{Retail}				0.0069
				(0.0246)
$Post\ Covid_t \times I_{jt}^{Exp\ Retail}$				0.0094
				(0.0080)
$Post\ Covid_t \times I_{jt}^{Exp\ Other}$				0.0078*
				(0.0043)
$Post\ Covid_t \times I_{jt}^{Retail}$				-0.0007
				(0.0070)
Observations	202,064	202,064	202,064	202,064
R^2	0.54607	0.54608	0.54608	0.54620
Year × Insurer ID fixed effects	✓	✓	✓	✓
CUSIP × Insurer ID fixed effects	✓	✓	✓	✓
Year × Coupon Type fixed effects	✓	✓	✓	✓
Year × NAIC Designation fixed effects	✓	✓	✓	✓
Year × Lagged Downgrade fixed effects	✓	✓	✓	✓

Notes: This table shows the effect of exposure to underlying lease expiration and offices on share of the par value of bonds sold in a given year. We estimate the same specification as in (4), but with the share of the par value of a bond sold as the dependent variable. Appendix B has the details on the construction of this variable. The level of observation is bond j held by insurer i at the end of year t. The sample period is 2017 to 2022. The dependent variable, $Share\ Par\ Value\ Sold_{ijt}$, is the par value of the sales of bond j divided by the par value of the same bond in the previous year. $Post\ Covid_t$ equals 1 after 2019. $Treat_{jt}^{Exp\ Office}$ is a dummy which equals 1 if bond j is exposed to office mortgages whose main lease expires within six years (excluding year t). I_{jt}^{Exp}, $I_{jt}^{Exp\ Retail}$, and $I_{jt}^{Exp\ Other}$ are dummy variables which equal 1 if bond j is exposed to mortgages whose main lease expires within six years (excluding year t), for all properties, retail only, and properties that are neither retail nor offices. I_{jt}^{Office} and I_{jt}^{Retail} are dummies which equal 1 for any exposure to offices and retail. Coupon Type is the type of coupon payment for bond j (e.g., fixed rate, floating rate, interest only). Lagged downgrade is a dummy which equals 1 if the bond was downgraded (based on NAIC designation) in year $t-1$. Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Table A.4: CMBS Trading and Realized Gains —Ratings Downgrading

	Realized gain over $BACV_{ijt}$		
	(1)	(2)	(3)
$I_{jt-1}^{Downgrade}$	-0.0067*	-0.0062*	-0.0059
	(0.0037)	(0.0037)	(0.0038)
I_{jt}^{Retail}			-0.0081
			(0.0175)
I_{jt}^{Office}			-0.0281**
			(0.0127)
$Post\ Covid_t \times I_{jt}^{Retail}$			-0.0076*
			(0.0040)
$Post\ Covid_t \times I_{jt}^{Office}$			0.0167***
			(0.0051)
Observations	14,486	14,483	14,483
R^2	0.76962	0.78699	0.78777
Year × Insurer ID fixed effects	✓	✓	✓
CUSIP fixed effects	✓	✓	✓
Year × Coupon Type fixed effects		✓	✓
Year × NAIC Designation fixed effects		✓	✓

Notes: This table shows the effect of ratings downgrading on reported gains and losses conditional on sales. The level of observation is bond j held by insurer i at the end of year t. The sample period is 2017 to 2022, and includes only bonds which were sold in each given year. The dependent variable, *Realized gain over* $BACV_{ijt}$, is the ratio of realized gains and losses in a given year, divided by the book value of the asset in the previous year. We exclude outliers of this dependent variable below the 2nd percentile or above the 98th percentile. $I_{ijt-1}^{Downgrade}$ is a dummy which equals 1 if bond i sold by insurer j has been downgraded in year $t-1$. I_{jt}^{Office} and I_{jt}^{Retail} are dummies which equal 1 for any exposure to offices and retail. Coupon Type is the type of coupon payment for bond j (e.g., fixed rate, floating rate, interest only). Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Table A.5: CMBS Insurance Buyer Difference-in-Differences—Exposure to Lease Expiration

	$I_{ijt}^{sold\ to\ insurer}$			
	(1)	(2)	(3)	(4)
$Treat_{jt}^{Exp\ Office}$	0.0015***	0.0013**	0.0016**	0.0008
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
$Post\ Covid_t \times Treat_{jt}^{Exp\ Office}$	0.0003	0.0008	0.0015	0.0013
	(0.0006)	(0.0008)	(0.0010)	(0.0010)
I_{jt}^{Office}		-0.0003	-0.0005	-0.0002
		(0.0011)	(0.0011)	(0.0012)
$Post\ Covid_t \times I_{jt}^{Office}$		-0.0013	-0.0012	-0.0011
		(0.0009)	(0.0009)	(0.0009)
I_{jt}^{Exp}			-0.0005	
			(0.0009)	
$Post\ Covid_t \times I_{jt}^{Exp}$			-0.0010	
			(0.0010)	
$I_{jt}^{Exp\ Retail}$				0.0004
				(0.0009)
$I_{jt}^{Exp\ Other}$				0.0008
				(0.0006)
I_{jt}^{Retail}				-0.0004
				(0.0009)
$Post\ Covid_t \times I_{jt}^{Exp\ Retail}$				-0.0012
				(0.0009)
$Post\ Covid_t \times I_{jt}^{Exp\ Other}$				-0.0005
				(0.0006)
$Post\ Covid_t \times I_{jt}^{Retail}$				0.0017*
				(0.0010)
Observations	202,957	202,957	202,957	202,957
R^2	0.45814	0.45815	0.45816	0.45816
Year × Insurer ID fixed effects	✓	✓	✓	✓
CUSIP × Insurer ID fixed effects	✓	✓	✓	✓
Year × Coupon Type fixed effects	✓	✓	✓	✓
Year × NAIC Designation fixed effects	✓	✓	✓	✓
Year × Lagged Downgrade fixed effects		✓	✓	✓

Notes: This table shows the effect of exposure to underlying lease expiration and offices on the likelihood of sales of private-label CMBS by insurance companies to *insurers*. The level of observation is bond j held by insurer i at the end of year t. The sample period is 2017 to 2022. The dependent variable, $I_{ijt}^{sold\ to\ insurer}$, is a dummy which equals 1 if bond j was sold by insurer i in year t to another insurer. We excluded CMBS holdings with the following buyers: FA REINSURANCE, Resolution Life Insurance, Coinsurance Talcott-Allianz. $Post\ Covid_t$ equals 1 after 2019. $Treat_{jt}^{Exp\ Office}$ is a dummy which equals 1 if bond j is exposed to offices whose main lease expires within six years (excluding year t). I_{jt}^{Exp}, $I_{jt}^{Exp\ Retail}$ and $I_{jt}^{Exp\ Other}$ are also variables which equal 1 if bond j is exposed to mortgages whose main lease expires within six years (excluding year t), for all properties, retail only, and properties that are neither retail nor offices. I_{jt}^{Office} and I_{jt}^{Retail} are dummies which equal 1 for any exposure to offices and retail. Coupon Type is the type of coupon payment for bond j (e.g., fixed rate, floating rate, interest only). Lagged downgrade is a dummy which equals 1 if the bond was downgraded (based on NAIC designation) in year $t-1$. Standard errors clustered at the security level in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sources: Trepp, NAIC, and authors' calculations.

Table A.6: Small Bank Characteristics by CMBS Ownership

	CMBS Before COVID-19	CMBS Only After COVID-19	No CMBS
Total Assets (000s)	1,751,887	1,267,447	707,091
% Non-owner occ CRE loans	16.35	17.16	13.28
% Private CMBS over total assets	1.18	1.26	0
% Private CMBS	1.98	2.37	0
% Short term securities	2.93	2.76	5.55
% US Treasury	8.22	9.56	16.39
% State and Municipal Bonds	28.64	28.67	27.51
% Other Debt Securities	3.28	3.42	1.95
% Foreign Debt Securities	0.13	0.10	0.09
% Agency MBS	10.43	9.83	7.53
Tier 1 Leverage	10.85	10.81	11.57

Notes: This table shows average values for selected characteristics for three types of small banks over the four quarters of 2023. The first column includes all banks that hold private-label CMBS between 2017 and March 2020. The second column includes all banks that hold private-label CMBS only after March 2020. The last column includes all remaining banks, i.e., banks that do not hold any private-label CMBS between 2017 and 2023. Source: Call Reports and authors' calculations.

B. Data Construction

Our data comes from two main sources, Trepp and NAIC, and are complemented by Call Reports data for our bank level analysis. In what follows, we document the data cleaning procedures for each of the two data sources, and show how we obtain measures of exposure to cash flow shocks at the CMBS level.

Trepp CRE mortgage data. Mortgage data is informed at the loan level with frequency dictated by distribution dates (*ddate*). We use these distribution dates as our main date variables in the loan level analysis. In constructing our sample for the analysis, we exclude:

- Observations without *city* information;
- Observations with an outstanding balance lower than $ 500;
- Observations for which lease expiration is patchy, that is, when lease expiration information exists for certain months, ceases to be included, and is again included afterwards;
- Observations which have more than one broad property type associated with it in the year in our sample.

Furthermore, we use information from the variable *proptype*, informed by Trepp, to construct the broad property types which we use in our analysis. The variable *proptype* has a large number of stringers indicating the use of the property serving as collateral for each mortgages. We aggregate these strings into eight different property types: *Office*, *Retail*, *Multifamily*, *Mixed Use*, *Healthcare-Nursing*, *Lodging-Restaurants*, *Industrial and Warehouses*, and the residual category *Other*. Examples of how we bin different *proptype* into our broader property type category are:

- **Office** includes *proptype* strings such as "Office" "Office/Hdqr","Office Building" and "office properties";
- **Retail** includes *proptype* strings such as "Retail", "Retail Unanchored", "Retail Anchored" and "Retail Mall";

- **Multifamily** includes *proptype* strings such as “Multi-Tenant”, “Multifamily” and “Multi-family”;
- **Mixed Use** includes *proptype* strings such as “Mixed-Use”, “Office/Warehouse”, “Multifamily/Retail” and “Offc/Retail/Mltfmly”;
- **Healthcare-Nursing** includes *proptype* strings such as “Nursing Home”, “Medical Office”, “Assisted Living” and “Medical Office”;
- **Lodging-Restaurants** includes *proptype* strings such as “Hospitality”, “Lodging Full Service”, “Restaurant” and “Hotel”;
- **Industrial and Warehouses** includes *proptype* strings such as “Industrial”, “Self-Storage”, “Warehouse” and “Industrial/warehouse”.

The full list of strings and their respectively classification can be obtained upon request. Following this procedure, we obtain the loan level monthly panel summarized in Table 1.

Call Reports. We obtain bank level data at quarterly frequency from the Reports of Condition and Income (call reports), available at https://cdr.ffiec.gov/public/ManageFacsimiles.aspx. We construct our series of holdings of private CMBS by following the construction of the LM763063653.Q and LM763063693.Q variables at the bank level. Detailed instructions for the construction of these two series can be found here https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=LM763063653&t= and in https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=LM763063693&t=.[13]

We define *short-duration asset holdings* as the reported value of debt securities with remaining maturity of less than one year. We define *long-duration asset holdings* the sum of reported values of government securities with over 5 years maturity (lines A553 and A554) plus the sum of mortgage pass-through securities with over 5 years maturity (lines A559 and A560).

[13] We exclude TD Bank from the analysis as its holdings of private-label CMBS suddenly drop in 2018, and no discontinuous drop is observed in either of the aggregate series. Our small bank analysis is identical as TD Bank would not be classified as a small bank.

B.1. CMBS and Insurer Level Exposure to Underlying Loan Characteristics

Since NAIC data is at annual frequency and Trepp data is at distribution date frequency (monthly), we follow an aggregation procedure to plug loan information into CMBS. Specifically, we collect deal level information corresponding to December of each year (and June for 2022, the last month in our sample from Trepp), and add this information to the bonds linked to each deal.

Specifically, let $TotAmt_{djt}$ denote the total amount outstanding of the pool of loans of deal d which is linked to bond j and $TotAmt_{djt}^{Offices}$ denote the same amount for loans linked to office properties. Then bond j's exposure to offices in year t is defined as $T_{jt}^{Office} \equiv \frac{TotAmt_{djt}^{Offices}}{TotAmt_{djt}}$. This exposure variable is used to construct dummy variables for positive exposure to offices using variables analogous to $TotAmt_{djt}^{Offices}$ that only include amount for loans with leases expiring within τ years.

To obtain insurer level exposures, we calculate a weighted average exposure at the bond level (weighted by BACV), times the size of the portfolio of private-label CMBS for each insurer.

C. Identifying Active Sales and Acquisitions

The results in Section 5 rely on measures of active asset sales and acquisitions by insurers, obtained from NAIC Schedule D, parts 3 and 4. We identify active sales using a procedure similar to Becker, Opp and Saidi (2022). First, we use the information contained in the variable *name of the purchaser* to exclude entries with keywords associated with *maturity*, *redemption*, *repayment* and *default*, for example. We also impose the requirement of strict positive or negative value in the variable *realized gain(loss) on disposal*. Finally, we further exclude observations for which maturity dates coincide with the report date.

To classify active acquisitions, we identify a series of keywords for the *vendor* variable which contain information not associated with active acquisitions. These keywords include references to *exchange*, *capitalization*, *merger* and *transfer*, for example. The full list of keywords, alongside the R code, can be obtained from the authors upon request.