Determinants of Recent CRE Delinquency: Implications for the Banking Sector *

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Abstract

Rising interest rates and structural shifts in the demand for space have strained CRE markets and prompted concern about contagion to the largest CRE debt holder: banks. We use confidential loan-level data on bank CRE portfolios to examine banks' exposure to at-risk CRE loans. We investigate (1) what loan characteristics are associated with delinquency and (2) how the portfolio composition of major CRE lenders affects their exposure to losses. Loan maturities, higher LTVs, larger property sizes, and greater local remote work tendencies are all associated with weaker loan performance, particularly for office loans. The comparatively modest aggregate delinquency rates for small banks can mostly be explained by their having fewer large-sized office loans in their portfolio relative to other lenders.

Keywords: commercial real estate, banks, CMBS

JEL Classification: G21, G22, G23, R33

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1. INTRODUCTION

Higher interest rates and shifts in where people work and shop have created significant stress in pockets of the commercial real estate (CRE) market (Board of Governors of the Federal Reserve System, May 2023). As CRE is the largest loan category on banks' books, these development have caused concern about CRE loan losses exacerbating other recent banking sector strains (Acharya et al., 2023).[1] Analyzing such effects is complicated by a lack of detailed data on banks' CRE loan holdings. Due to this data limitation, researchers have mostly relied on aggregate bank portfolio data (Faria-e Castro and Jordan-Wood, 2023, 2024), or data from CRE segments with more public reporting (Gupta et al., 2022; Jiang et al., 2023; Glancy and Wang, 2023) to glean information on risks posed to the banking sector. However, banks serve a selected segment of the market (Glancy et al., 2022), and recent CRE stresses have been highly uneven (Marsh and Pandolfo, 2024), so extrapolating across different portions of the CRE market is difficult.

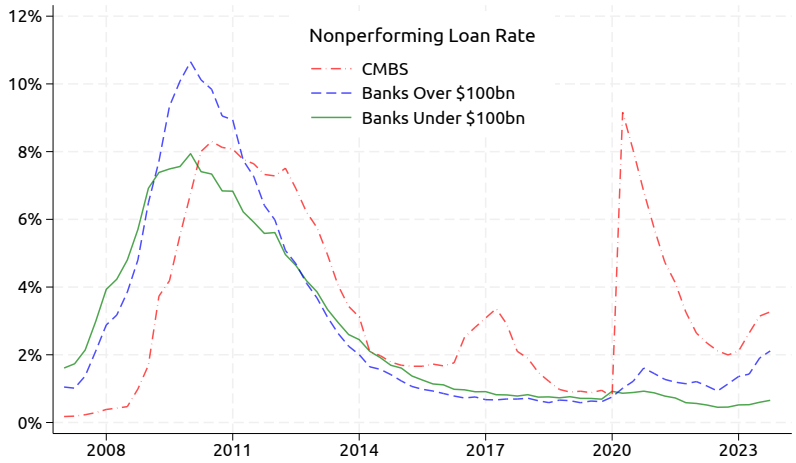
Indeed, Figure 1 shows that loan performance differs markedly across different types of CRE lenders. Though, nonperforming loan rates (NPLs) for bank and commercial mortgage-back securities (CMBS) loans were comparable during the global financial crisis (GFC) of 2007–09, periods of strain since the GFC have been more confined to CMBS markets; CMBS delinquencies (red) rose moderately in 2016 and spiked at the onset of COVID, while delinquencies at large (blue) and small (green) banks remained under 2 percent during these episodes.[2] More recently, delinquency rates for CMBS and large banks rose by similar amounts over the course of 2023, but the performance of CRE loans at smaller banks has remained strong.

In this paper, we compile data from a variety of sources to analyze the performance of bank CRE loans, and identify the factors contributing to these recent differences in loans performance. The analysis proceeds in two steps. First, we use loan-level panel data on CRE loan performance to

[1] As of March 6th, 2024 H.8 data, total outstanding CRE loans were estimated to be about $3.0 trillion, compared to $2.8, $2.6 and $1.9 trillion, for C&I, residential real estate and consumer loans, respectively.

[2] Even during the GFC, NPLs for loans secured by existing properties rose less at banks than for CMBS. However, bank NPLs were pulled up by a near 20 percent delinquency rate for construction and land development loans (a segment not served by CMBS). See Appendix Figure A.1 for a decomposition of bank NPLs by subcategory.

Figure 1: Nonperforming Loan Rates Over Time



Notes: Each figure plots CRE nonperforming loan rates over time for non-agency CMBS loans (red) and for CRE loans from banks with more (blue) and less (green) than $100 billion in assets. Nonperforming loans are loans that are 30 days or more past due or nonaccrual, plotted as a share of aggregate outstanding balances. Calculations exclude defeased and REO loans.
Sources: Call Reports, Morningstar, and authors' calculations.

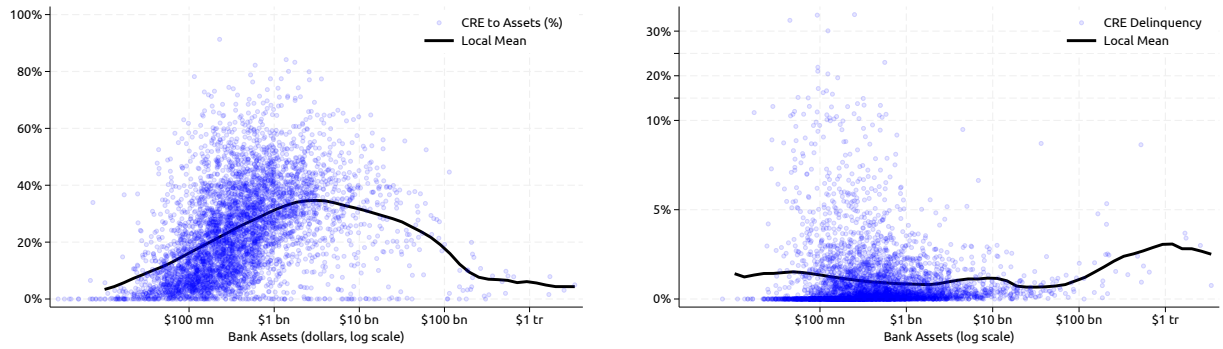
investigate what factors are associated with greater loan delinquency and why loan performance differs between banks and CMBS. To accomplish this, we combine, harmonize, and analyze data from CMBS filings and confidential data from large banks' stress tests. We find that office loans held in CMBS pools are nearly 4 percentage points more likely to go delinquent than those held by banks. This effect is driven nearly entirely by bank loans being secured by smaller properties, having lower LTVs, and being more likely to have recourse. For other property types, CMBS also underperform bank loans, but the difference is smaller and not as clearly attributable to other observable characteristics.[3]

In the second part of the paper, we investigate potential drivers of the strong performance at small banks. Studying the performance of CRE loans at large banks (i.e., banks with over $100 billion in assets) is useful as (1) that is where performance has deteriorated more and (2) data availability enables more-detailed analysis. However, it is smaller banks that are highly exposed to CRE loans. Indeed, Figure 2 shows that it is banks with between $1 billion and $10 billion in assets that tend to

[3]We provide some suggestive evidence that a greater tendency to modify loans may contribute to these unobserved differences.

have the highest concentrations in CRE (left), and that CRE loan delinquency for such banks was quite low for these banks as of the end of 2023 (right). These results indicate that the deterioration in loan performance experienced *to date* is unlikely to cause significant problems for the banking sector. However, if troubles for CRE loans at CMBS and large banks portend similar problems at smaller banks, more significant stress may be looming. To understand such risks, we need to evaluate why CRE loans at small banks have remained comparatively resilient.

Figure 2: CRE Exposure by Bank Size



(a) CRE Concentrations

(b) CRE Delinquency

Notes: Figure plots CRE as a share of assets (left) and CRE delinquency (right) by bank size. CRE includes nonfarm, nonresidential, multifamily and construction and land development loans. Blue dots report CRE shares/delinquency rates at individual banks, while the black line plots an estimate of the average CRE shares/delinquency rates for banks of a given size (based on a local mean smoothing). The scale for the y-axis changes in the right figure after 10% to increase the visibility of differences in performance of banks within typical ranges.
Sources: Call Reports, and authors' calculations.

While detailed loan-level data on loan characteristics and performance are generally not available for small banks, some broad characteristics pertaining to loan sizes, property types, and locations tend are available due to the public reporting of mortgage liens. We can therefore estimate a model of loan performance using data from large banks and investigate the degree to which these observable factors can explain the strong performance of small banks. We show that small banks lend against smaller properties and have fewer office loans in troubled markets. These differences can account for much of small banks' superior CRE loan performance.

The rest of the paper proceeds as follows: Section 2 reviews an array of factors identified in the

literature that could contribute to differences in loan performance across CRE lenders. Section 3 presents evidence that a number of characteristics typically associated with bank CRE lending—namely recourse, smaller properties, lower LTVs, and a greater ability to modify loans—are associated with better loan performance. Section 4 extrapolates findings to small banks, and presents evidence that small banks' lack of large-sized office loans accounts for their better loan performance. Section 5 concludes.

2. LITERATURE ON DIFFERENCES BETWEEN BANK AND CMBS CRE LOANS

To guide our analysis of the factors potentially contributing to the differences in loans performance shown in Figure 1, we first review the literature pertinent to this question. We split this discussion into two parts, first discussing the factors that could mitigate CRE losses for banks relative to CMBS and second discussing factors that could amplify such losses.

2.1. Factors Supporting Bank Loan Performance

Modification Ability The first factor supporting bank loan performance is that banks are more able to modify distressed loans to preempt foreclosure (Black et al., 2017, 2020; Glancy et al., 2023b). While CMBS face limitations to modifying loans due to IRS policies, stipulations in pooling and servicing agreements, and conflicts of interest across disparate investors, banks face comparatively modest impediments. Indeed, bank regulators released a policy statement on CRE loan workouts in 2023 reaffirming that "prudent CRE loan accommodations and workouts are often in the best interest of the financial institution and the borrower" and providing guidance on supervisory treatment of such actions.[4]

Loan accommodations were likely a critical driver of why delinquency for bank CRE loans rose so little at the onset of COVID in Figure 1. Glancy et al. (2023b) show that while delinquency rose notably for CMBS loans— for hotel loans, in particular—banks instead saw a dramatic rise in the use of forbearance. Namely, bank borrowers were able to receive short-term accommodations to

[4]The guidance is available here: https://www.federalreserve.gov/supervisionreg/srletters/SR2305a1.pdf

deal with temporary cash flow shocks. While forbearance is less likely to be helpful in the current environment given that the difficulties are likely of a longer-term nature, banks similarly face fewer impediments to longer-term workouts. CRE foreclosures tend to be associated with significant deadweight losses, particularly when the market is experiencing liquidity strains (Brown et al., 2006). More substantial workouts, even if they involve the bank charging off a portion of the loan, could mitigate losses relative to foreclosure. CMBS are not prohibited from such actions—for example, Flynn Jr. et al. (2023) show that a 2009 change in IRS policies facilitated renegotiation—but frictions tend to be higher, raising the risk of most costly resolutions.

Recourse and Lower Leverage A second factor supporting the performance of bank CRE loans is that borrowers typically have more equity at stake. First, bank loans typically have lower LTVs, which gives more room for property values to fall before the lender starts taking losses (Glancy et al., 2022). Second, bank CRE loans are predominantly recourse loans, meaning that borrowers have assets besides the subject property at stake if they default. Glancy et al. (2023a) show that about three-fourths of CRE loans from large U.S. banks have recourse (on an unweighted basis). The authors demonstrate that these recourse loans receive more favorable underwriting terms and were less likely to require forbearance at the onset of the pandemic, both consistent with recourse supporting loan performance. Recourse might be particularly valuable to lenders in the current environment, as the economy is generally performing well outside of pockets of stress in the CRE market. If sponsors or guarantors have other assets of value—for example, equity in other properties—owners will be more willing and able to maintain payments on loans secured by troubled properties. In contrast, CMBS loans are generally non-recourse (barring springing guarantees for particular "bad acts"). As such, CMBS borrowers may be more willing to walk away from a property even if they have the ability to service the debt on it.

Differences in Loan Size/Location A third factor potentially contributing to differences in loan performance are that banks tend to lend against smaller properties than CMBS (Ghent and Valkanov, 2016; Glancy et al., 2022).[5] While loans against larger properties are not inherently riskier, they have underperformed in the current environment. Part of this effect likely reflects location; high priced properties are disproportionately located in central business districts (CBDs). Amid the shift to working from home, CBDs have experienced declines in commuting activity (Monte et al., 2023) and commercial rents (Rosenthal et al., 2022), and a greater deterioration in property occupancy and income following lease expirations (Glancy and Wang, 2023). Relative to CMBS, office loans at banks, and especially small banks, are more likely to be in suburban markets, which have been less affected by the shift to remote work.[6] Even within a city, larger offices likely have a tenant mix placing them at a greater risk of departures (e.g., multi-location tech companies).

Size may also interact with some of the other factors discussed as influencing bank loan performance. For one, the ability to modify loans is more beneficial when firms have weaker bargaining positions, as strategic renegotiation is less of a concern (Hackbarth et al., 2007). Additionally, recourse supports loan performance more when the loan size is small relative to the guarantor's other assets.

Better Screening A last factor potentially supporting the performance of bank loans is better screening incentives given that bank lenders typically retain all of the credit risk. Work on the CMBS market before the GFC provides evidence that adverse selection (An et al., 2011) and moral hazard regarding screening incentives (Ashcraft et al., 2019) reduce the quality of loans in CMBS pools. In response, as part of the Dodd-Frank Act, regulators implemented risk retention requirements to reduce such agency problems (Flynn Jr et al., 2020). Nonetheless, Griffin and Priest (2023) present evidence that agency conflicts between originators and CMBS investors persist, and may create underwriting weaknesses that are revealed during times of stress.

[5] By virtue of their diversified customer base, CMBS are able to fund larger loans that would generate too much concentration risk for a balance sheet lender.

[6] Glancy and Wang (2023) show that small and regional banks have a lower exposure to CBD markets than other lenders and that this difference is predominantly explained by differences in loan size.

2.2. *Factors that May Hinder Bank Loan Performance*

Specialization in Riskier Loans While greater renegotiation flexibility may support the performance of any given bank loan, this effect may give banks an advantage in financing riskier properties where such flexibility is more valuable (Black et al., 2017, 2020). One clear dimension along which risk differs is that CMBS lend against income-producing properties, whereas banks originate more bridge and construction loans. The performance of bridge and construction loans can be more dependent on the particular business model of the borrower and thus subject banks to the risk that properties are more difficult to lease-up than expected or fail to earn returns sufficient to recoup the alteration costs. Consistent with these loans being riskier, construction and land development loans receive higher FDIC fee assessments,[7] receive higher capital requirements when LTV limits are not met (Glancy and Kurtzman, 2022) and disproportionately contributed to bank failures during the GFC (Friend et al., 2013).

More Financially Constrained Borrowers A final difference between bank and CMBS loans is that banks may cater to more financially constrained borrowers. Roughly half of CMBS lending goes to public or institutional buyers, compared to only 10 percent of bank lending (Glancy et al., 2023b). These larger sponsors with more diversified funding sources would be more able to maintain loan payments in the face of a disruption to property cash flows (assuming they find it optimal to do so). Similar selection effects occur outside the CRE market, where banks disproportionately serving smaller, younger and riskier firms, while more established firms utilize market financing (Petersen and Rajan, 1994; Bolton and Freixas, 2000).

[7] See FDIC Law, Regulations, Related Acts, Title 12 Chapter III Subchapter B Appendix C to Subpart A to Part 327 available at https://www.ecfr.gov/current/title-12/chapter-III/subchapter-B/part-327.

3. LOAN PERFORMANCE AT LARGE BANKS

This section uses loan-level bank and CMBS data to investigate the loan and property characteristics affecting CRE loan performance in 2023.

3.1. Methodology

As the last section discusses, there are a host of factors that may contribute to differences in the performance of bank and CMBS loans. We now empirically examine how much these factors matter in the current environment. Data on bank loans comes FR Y-14Q filings (the data underlying bank stress tests), which provide loan-quarter information on loans with committed values over $1 million from banks with over $100 billion in assets. CMBS data comes from Morningstar, which compiles loan-month data from CMBS disclosures.[8] We classify lenders by who holds the loan, rather than who originates it, so bank-originated loans in CMBS pools are considered CMBS loans.

Though banks below the Y-14 reporting threshold tend to have higher concentrations in CRE on average, an advantage of the Y-14 sample is that it covers the group of banks for which CRE loan performance has actually deteriorated. This analysis is thus useful for examining the factors causing CRE loans to go deliquent. While we cannot analyze the performance of CRE loans at smaller banks in such detail, we can assess the performance of Y-14 loans with characteristics resembling those of small banks (i.e., smaller loans in smaller markets) to explore the implications for smaller banks. We conduct this exercise in Section 4.

To investigate how observable characteristics relate to loan performance, we estimate linear regressions of the form:

$$100 \times \text{Delinquent}_{i,23} = \beta_1 \text{CMBS}_i + \beta_2 \text{Maturing}_{i,23} + \beta_3 \text{Office}_i + \gamma' X_{i,23} + \varepsilon_i,$$

[8] We exclude agency deals from the CMBS data, as well as defeased or REO loans. For bank loans, we only include first-lien loan, against already-constructed properties to better align the sample with that of the CMBS market.

where $\text{Delinquent}_{i,23}$ is in indicator for whether loan i is delinquent as of the last observation in 2023.[9] We count loans that are liquidated or performing beyond their maturity date as delinquent. The main independent variables of interest are whether loan i is in a CMBS pool, whether the loan was scheduled to mature in 2023, and whether the loan is secured by an office property. The coefficient on CMBS reflects the difference in delinquency rates for CMBS loans compared to those from large domestic banks, controlling for the two characteristics most strongly related to loan performance: whether they matured (capturing difficulty refinancing in an environment of falling valuations and tight lending standards) and whether the loan is secured by an office property (the property type accounting for most of the rise in delinquencies over 2023).

$X_{i,23}$ is a set of controls which includes other property type dummies.[10] In some specifications, we layer in additional controls to assess whether they can account for some of the difference in delinquency between large banks and CMBS. These additional controls include LTV, property size, a recourse indicator, and geographic characteristics (whether the property is in a CBD or area where more jobs can be done remotely). Observing how β_1 changes as extra controls are added provides information on the extent to which these characteristics can account for differences in loan performance. In the most expansive specifications, we also include controls for the occupancy and debt yield for the property.[11] These controls thus assess the extent to which differences are driven unobserved risks to property performance that materialize as a deterioration in financial performance. Finally, in robustness exercises we conduct similar analysis predicting whether loans receive extensions to assess whether banks are providing more accommodation to stressed borrowers.

[9] The quarter of observations is either 2023:Q4 if the loan is active as of the end of the year or the quarter the loan paid-off or was liquidated otherwise.

[10] These variables are included in every specification but not displayed. Multifamily is the omitted category. Hotel and retail are the next-most-likely loans to be delinquent after office, while industrial delinquency rates are not significantly different from those for multifamily loans.

[11] Debt yield is the ratio of net operating income to the outstanding loan balance and thus reflects the ability of a property's cash flows to pay off the loan. Since income and occupancy would not get updated in the event that a loan pays off in 2023, we measure these financial variables as of a year prior.

3.2. Results

The main estimates are reported in Table 1. Column (1) presents estimates from the most parsimonious specification, which only includes the CMBS, maturing loan, and property type indicators. The results show that CMBS loans are about 2 percentage points more likely to become delinquent, office loans are about 3 percentage points more likely to become delinquent (relative to multifamily loans), and loans that mature are about 11 percentage points more likely to become delinquent. This last effect highlights the significant difficulty borrowers face in refinancing to pay off balloon loans; borrowers who are able to remain current over the life of the loan are frequently failing to pay the loan off as it comes due.

To investigate why CMBS loans have higher delinquency rates, column (2) starts to add controls for different factors discussed in the previous section as potentially contributing to differences in loan performance: the at-origination LTV of the loan, the logarithm of the at-origination property value, and an indicator for whether the loan has recourse. The size and LTV controls account for the fact that CMBS provide higher leverage, on average, and tend to lend against larger properties. Since CMBS loans are essentially entirely non-recourse, the effect of recourse is identified off of differences in the performance of bank-held recourse and non-recourse loans. Therefore, the coefficient on CMBS is now estimated off of the difference in the performance between CMBS loans and non-recourse bank loans.

The findings show that the characteristics associated with bank loans—lower leverage, smaller properties, and recourse—are also associated with stronger loan performance. A one standard deviation higher LTV (0.16) raises the likelihood of the delinquency by about 85 basis points, while a one standard deviation larger size (1.16) increases the delinquency rate by about 95 basis points.[12] Effects of recourse are smaller (and less consistent across specifications), with recourse loans having a delinquency rate that is about 50 basis points lower than similar non-recourse loans. Adding

[12] Variation in property values reflect differences in both size (i.e., square footage) and valuation (i.e., price per square foot). Most of the effects are attributable to differences in size, so we refer to the variable ln(Value at Orig.) as "size" for the sake of brevity.

these three additional controls reduces the coefficient on CMBS from 2.23 to 0.94, indicating that CMBS' tendency to make larger, higher LTV, non-recourse loans accounts for about half of their inferior performance.

Column (3) adds in geographic characteristics of the property securing the loan: whether the property is in a CBD and the share of jobs in the MSA that are identified as being able to be done at home by Dingel and Neiman (2020).[13] The results indicate that delinquency rates are about 2 percentage points higher in CBDs, but only modestly higher for cities more exposed to a potential shift to remote work; a one standard deviation increase in the teleworkable share (0.046) only increases delinquency by about 25 basis points. Adding the extra geographic controls causes the estimated coefficient on CMBS to increase a bit; though banks generally do less lending in adversely affected markets, this is mostly do to size differences which were accounted for by the specification in column (2).

Column (4) adds two variables pertaining to the property's financial situation: the property occupancy and an indicator for whether the property's debt yield (net income as a share of the loan balance) is under 8 percent. These controls thus account for whether differences in performance are driven by variation in occupancy or cash flow risks across lenders. Low occupancy and high debt yields are highly predictive of delinquency: a 10 percentage point drop in occupancy raises the probability of delinquency by 1.5 percentage points and a low debt yield raises the probability of delinquency by about 1.9 percentage points.

While the overperformance of bank loans can be partially explained by observable characteristics, there remains a large unobserved component. CMBS loans are about 1.4 percentage points more likely to go delinquent than bank loans with similar underwriting terms and even similar financial performance. One explanation for this result is that banks are more able to renegotiate stressed loans. Some suggestive evidence of this can be found in Table A.1, which shows that

[13] CBDs are identified by the share of offices in the ZIP code that RCA identifies as being in CBD. Though this is technically a continuous measure, almost all loans take a value of 0 or 1, so it can effectively be considered a CBD indicator variable.

Table 1: Loan Performance By Lender Type

	$100 \times \text{Delinquent}_{i,23}$							
	Full Sample				Offices			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CMBS	2.23**	0.94*	1.21**	1.37**	4.12**	-1.53	-1.39	-0.77
	(0.28)	(0.37)	(0.35)	(0.35)	(0.67)	(1.19)	(1.29)	(1.27)
Maturing	11.34**	11.02**	11.40**	11.05**	18.24**	17.36**	17.13**	16.16**
	(0.89)	(0.89)	(0.96)	(0.97)	(1.76)	(1.76)	(1.87)	(1.81)
Office	3.43**	2.63**	2.64**	2.37**				
	(0.33)	(0.30)	(0.33)	(0.34)				
LTV at Orig.		5.43**	6.05**	4.42**		14.39**	15.33**	12.30**
		(0.78)	(1.02)	(0.98)		(1.90)	(2.02)	(1.93)
ln(Value at Orig.)		0.82**	0.71**	0.47**		1.86**	1.39**	1.02**
		(0.11)	(0.11)	(0.10)		(0.30)	(0.32)	(0.31)
Recourse		-0.50^{+}	-0.10	-0.18		-3.87**	-3.93**	-3.76**
		(0.26)	(0.23)	(0.24)		(1.04)	(1.10)	(1.06)
CBD			1.99**	1.71**			4.10**	2.85**
			(0.48)	(0.40)			(1.02)	(0.99)
Teleworkable Share			5.15**	2.91			15.84**	11.55*
			(1.83)	(1.85)			(5.43)	(5.37)
Occupancy				-14.89**				-19.34**
				(1.62)				(2.53)
Debt Yield<.08				1.91**				6.59**
				(0.45)				(1.07)
R^2_a	0.053	0.059	0.063	0.082	0.065	0.088	0.091	0.128
Observations	59,202	59,118	54,336	53,626	7,852	7,832	7,190	7,065
Other Property Fixed Effects?	✓	✓	✓	✓				

Notes: This table presents estimates from the equation:

$$100 \times \text{Delinquent}_{i,23} = \beta_1 \text{CMBS}_i + \beta_2 \text{Maturing}_{i,23} + \beta_3 \text{Office}_i + \gamma' X_{i,23} + \varepsilon_i$$

where $\text{Delinquent}_{i,23}$ is an indicator for whether loan i is delinquent as of the last observation in 2023 (2023:Q4 if the loan is active as of the end of the year, or the quarter the loan was paid-off or liquidated otherwise). Loans that are liquidated or performing beyond their maturity date count as delinquent. The main independent variables of interest are whether loan i is in a CMBS pool, whether the loan was scheduled to mature in 2023, and whether the loan is secured by an office property. Fixed effects for other property types are included by not displayed (multifamily is the omitted category). Column (2) adds controls for whether the loan has recourse, the at-origination LTV, and the logarithm of the property value at origination. Column (3) adds controls for whether the property is in a CBD and the share of the city's employment that can be done at home (Dingel and Neiman, 2020). Column (4) adds controls for the occupancy and an indicator for whether the debt yield is under 8% (both as of a year previously). Columns (5)–(8) repeat the same analysis but restrict the sample to office properties. Standards errors, in parentheses, are clustered by bank-origination year for bank loans and CMBS deal for CMBS loans. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

bank loans were about 5 percentage points more likely to receive extensions compared to CMBS loans. Without a counterfactual saying what would have happened to these loans if they did not receive an extension, it is difficult to say precisely how banks' willingness to extend loans affected

performance differences. However, if some of these extended loans would have otherwise gone delinquent, such accommodation could contribute to the comparative strength of bank loans.

Columns (5)–(8) repeat the same analysis but restrict the sample to office properties. Column (5), which only controls for loan maturity, shows that CMBS' underperformance is even more pronounced for office loans, with CMBS loans having a delinquency rate that is about 4 percentage points higher than for bank loans. Additionally, defaults at maturity are even more prevalent for office loans, with a 2023 maturity raising the probability of delinquency by 18 percentage points.

Column (6) shows that the underperformance of CMBS office loans can be entirely attributed to differences in loan sizes, LTVs, and the use of recourse. Office loans have delinquency rates that are 3.9 percentage points lower when they have recourse, 1.4 percentage points higher when the LTV is 10 percentage points higher, and about 1.9 percentage points higher for properties with an at-origination property value that is 10% larger. Once these factors are controlled for, CMBS loans are found to have delinquency rates that are slightly *lower* than bank loans, though the difference is statistically insignificant. Put differently, CMBS office loans perform similarly to nonrecourse bank loans of similar size and LTV. However, CMBS have higher delinquency rates overall due to differences in these three characteristics.

Column (7) adds in geographic controls, which have a much larger effect on office loans than for CRE loans in general. The effects of being in a CBD are about doubled, and the effects of telework exposure about tripled, for office loans relative to the overall CRE loan pool. These controls reduce the coefficient on ln(Value at Orig) somewhat, but most of the effect of size is not driven by these geographic characteristics. Finally, column (8) adds in the controls for occupancy and debt yield. While weaker financial performance are more predictive of delinquency within the office sector, the inclusion of these controls has a relatively modest effect on the other estimates.

To recap the findings, many of the drivers of CRE delinquencies are as would be predicted given the nature of the stress. The largest driver of delinquency is loan maturity, reflecting problems

refinancing balloon payments amid tighter credit conditions, lower valuations, and higher interest rates. Additionally, delinquency is higher for properties most exposed to the decline in demand for space, namely, office properties, and properties in CBDs and markets with a greater shift to remote work.

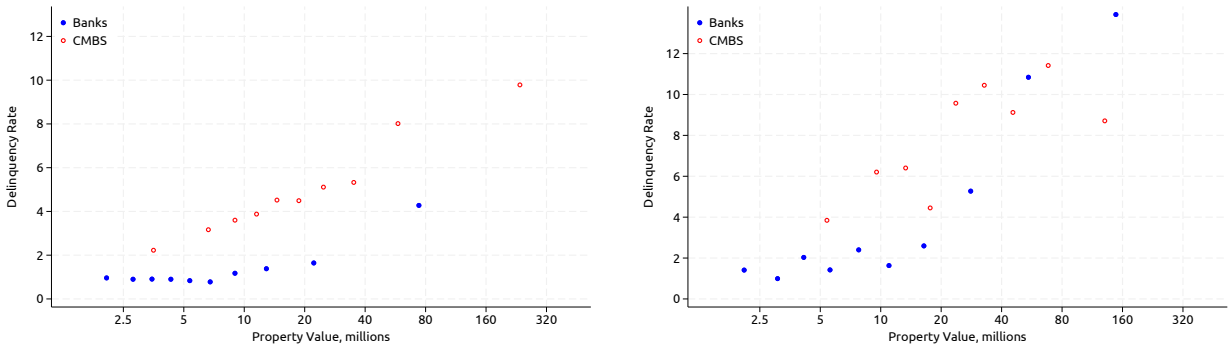
Finally, the analysis points to a couple of proximate causes of delinquency that are potentially important for understanding the credit outlook for banks. First, large banks' CRE loans outperform CMBS loans with similar terms, financial performance, and geographic characteristics. This result suggests that unobserved characteristics of banks loans—such as a greater ability to modify loan terms, or borrowers' concerns about damaging existing bank relationships—are supporting overall loan performance.

Second, loans securing large properties have higher delinquency rates, suggesting that they have unobserved risk characteristics—for example, a worse income outlook, more difficulty making up operating shortfalls, or sponsors more willing to strategically default—that are weighing on loan performance. The magnitude of this effect can be most clearly seen in Figure 3, which presents bin-scatter estimates of how loan delinquency varies by property size and lender type. The delinquency rate for bank CRE loans is modest for properties with an at-origination value under $20 million, even for office loans. Delinquency is instead concentrated in large CMBS-funded properties, or large bank-funded offices. As small and regional banks predominantly fund smaller properties, this pattern may be a key contributor to their stronger loan performance, as we demonstrate next section.

4. IMPLICATIONS FOR SMALL BANKS

This section explores the implications of these findings for the performance of small banks. To the extent that small banks lend against even smaller and less urban properties, the patterns documented in Section 3 may contribute to the comparatively strong loan performance of small banks. To test this, we estimate a model of loan performance using only loan characteristics that are

Figure 3: CRE Delinquency by Loan Size



(a) Full Sample (b) Office Loans

Notes: Each figure plots binscatter estimates of 2023 CRE loan delinquency rates by the logarithm of the property value at origination. Red and blue dots give the delinquency rates for CMBS and Y-14 bank loans at different deciles of their respective property size distribution. The left panel presents delinquency rates pooling across property types, while the right restricts the sample to office properties.
Sources: Y-14Q, and authors' calculations.

observable for small banks' CRE loans. We then examine the fitted delinquency rates to assess whether those factors can account for small banks' lower delinquency rates.

4.1. Methodology

This analysis proceeds in three steps. First, we use data from RCA to compile data on the composition of loan characteristics for three lender types, indexed by j: large banks, small banks, and CMBS. Whether loans are held by banks or CMBS is directly reported in RCA data. To identify whether a bank lender is a small bank or a large bank, we match lender names in the Y-14 data to lender names in RCA to identify large banks (those with over $100 million dollars in assets). Small banks are identified as bank lenders that are not identified as being a large domestic bank or foreign bank.[14] Since we are interested in portfolio holdings, we drop loans in RCA that appear to be extinguished by a subsequent transaction, are over 10 years old, or have a maturity date before 2023. We restrict the sample to loans that finance an already-build investment property to remove types of loans not typically done by CMBS (i.e., we exclude owner-occupied properties

[14]Loans from foreign banks that have an intermediate holding company subject to stress tests are identified as belonging to a large bank (e.g., loans marked as provided by RBC are attributed to RBC US and counted under the large bank category). Loans from other foreign banks are excluded from the analysis.

or properties purchased for construction or renovation). As the rise in bank non-performing loan rates was driven loans financing by non-owner-occupied commercial properties instead of owner-occupied or construction loans, this focuses the analysis on the areas where stress has already materialized. (See Figure A.2 for evidence that the rise in NPLs in 2023 predominantly reflects this segment.)

For each of these loans i from one of the three lender types j, we have a set of observable loan or property characteristics $X_{i,j}$ that includes the loan size, transaction price, property type, and property location. While this set of variables does not include all of the factors studied in Section 3, it includes most of the major variables affecting performance that are likely to differ notably across lenders.

The second step is to estimate the probability that a loan becomes delinquent at the end of 2023 based on the observable characteristics available in RCA. We use the Y-14 data to estimate a delinquency function $\hat{D}(X_{i,j}) = \mathbb{E}(\text{Delinquent}_{i,\text{Large Bank}}|X_{i,\text{Large Bank}})$. We take two approaches to estimating $D(\cdot)$. First, we estimate regressions along the lines of those Table 1, but restricted to the variables available from RCA. These predicted delinquency rates have the advantage of being easily interpreted, with little uncertainty as to what drives the predictions. Second, we estimate $D(\cdot)$ using K-Nearest Neighbors (KNN). The predicted delinquency using KNN is the average delinquency rate of the 25 most similar Y-14 loans (weighted inversely by euclidean distance to those loans' characteristics). This estimate is more flexible, but the relative importance of different features is less discernible.

Finally, once we have loan portfolios by lender type and an estimate of the probability of delinquency as a function of these characteristics, we can estimate the delinquency rate that would prevail for different lenders if performance responds similarly to those factors as in the portfolio of Y-14 bank loans. The object of interest is the expected delinquency rate: $\text{Fitted Delinquency}_j = \sum_{i|j} \omega_{i,j}\hat{D}(X_{i,j})$, where $\omega_{i,j}$ is the share of j's loan portfolio accounted for by loan i. This estimate shows the extent to which differences in the performance of loans across lenders can be attributed

to broad differences in the composition of their CRE portfolios.

4.2. Bank Delinquency Model

Table 2 presents the OLS estimates that underlie the regression-based fitted delinquency rate. We include in X the primary variables that are available from RCA and were shown to be important in the previous analysis: property size, loan LTV, whether the property is in a CBD, and the share of jobs that can be done remotely. Since most of the risk factors were found to be more important for office properties, we also include interactions of these variables with the office indicator. Indicators for other property types are included, but not interacted with the other risk factors. Variables pertaining to property size, leverage, and telework ability are demeaned, so the coefficient on office shows the higher delinquency rate for an office property outside of a CBD, with an average level for other risk factors.

Since we are interested in whether differences in the composition of CRE portfolios at small banks can account for their better performance, in our main specification we use a more narrow definition for delinquency than before to better align with Call Reports reporting. Namely, we only count a loan as delinquent if it is reported as past due (not if it is performing past its maturity date) and we only include loans in the sample if they are still outstanding as of the end of 2023 (we no longer include loans that were liquidated or paid off earlier in the year).[15]

The primary estimates predicting this narrower form of delinquency are in column (1). Overall, the results offer few surprises relative given what was found previously: Loans with lower LTVS, that fund properties that are smaller in size or in areas less affected by the shift to remote work perform better. These differences are all even more stark for office loans. Column (2) presents estimates from the same specification, but with the broader sample and definition of delinquency used in the previous analysis. The main findings generally hold, but the property-specific intercepts are a bit higher. Namely, the predicted delinquency rates are somewhat higher since they account better for

[15]Those observations were previously of interest as they were relevant to the study of maturity defaults.

Table 2: Bank Delinquency Model

	100×Delinquent (Narrow)	100×Delinquent (Broad)	Year-ahead PD (%)	Expected Loss (%)
	(1)	(2)	(3)	(4)
ln(Value at Orig.)	0.08	0.08	0.34**	0.09**
	(0.06)	(0.08)	(0.08)	(0.02)
LTV at Orig.	2.77**	3.46**	4.87**	1.47**
	(0.75)	(0.85)	(0.81)	(0.23)
CBD	1.26**	1.53**	2.60**	0.75**
	(0.42)	(0.48)	(0.65)	(0.16)
Teleworkable Share	2.88	1.44	8.54**	2.08**
	(1.79)	(2.00)	(2.34)	(0.60)
Office	2.11**	2.36**	2.39**	0.99**
	(0.36)	(0.36)	(0.42)	(0.18)
× ln(Value at Orig.)	2.72**	2.77**	3.68**	1.65**
	(0.48)	(0.45)	(0.53)	(0.23)
× LTV at Orig.	7.71**	7.72**	10.66**	5.63**
	(2.20)	(2.07)	(2.55)	(1.07)
× CBD	1.25	1.78	2.23^{+}	1.07*
	(1.09)	(1.17)	(1.20)	(0.53)
×Teleworkable Share	28.21**	20.88**	33.44**	14.87**
	(6.81)	(6.40)	(8.03)	(3.93)
Retail	0.69**	1.22**	0.72**	0.26**
	(0.22)	(0.27)	(0.26)	(0.07)
Industrial	0.12	0.59*	-0.23	-0.04
	(0.16)	(0.25)	(0.19)	(0.05)
Hotel	2.33**	3.56**	3.42**	1.18**
	(0.62)	(0.73)	(0.82)	(0.24)
Intercept	0.33**	0.45**	1.33**	0.34**
	(0.09)	(0.12)	(0.18)	(0.04)
R^2_a	0.036	0.032	0.087	0.106
Observations	36,580	40,832	32,786	32,786

Notes: This table presents estimates from the equation:

$$100 \times \text{Delinquent}_{i,23} = \alpha_{p(i)} + \beta'(\text{Office}_i \times X_i) + \gamma' X_i + \varepsilon_i$$

where $\text{Delinquent}_{i,23}$ is a delinquency measure as of 2023:Q4, $\alpha_{p(i)}$ is a fixed effect for i's property type, and X_i is a set of risk factors that are observable both in Y-14 and RCA data: the logarithm of the value of the property at origination, the loan's LTV, the share of properties in i's ZIP code identified as being in a CBD in RCA, and the share of jobs in i's MSA that are identified as being able to be done at home by Dingel and Neiman (2020). Column (1) predicts delinquency for the sample of loans that on the balance sheet as of the end of 2023, column (2) presents estimates using the measure of delinquency from Section 3 (which includes performing balloon loans and liquidated loans as delinquent and paid-off loans as performing), and columns (3) and (4) present equivalent analysis predicting the reported year-ahead Probability of Default and Expected Loss (Probability of Default time Loss Given Default). Standards errors, in parentheses, are clustered by bank-origination year. $^{+}$,*,** indicate significance at 10%, 5% and 1%, respectively.

maturity-defaults, but the drivers of differences in delinquency aren't meaningfully different.

Columns (3) and (4) supplement the predictions of delinquency with forward-looking measures for the year-ahead probability of default and expected loss (probability of default times loss given default) based on banks' internal risk ratings. If small banks are only outperforming larger banks because they have loans that are expected to deteriorate later (e.g., if stress were to start in CBDs before spreading to other markets) these forward looking measures would allow us to pick up whether smaller banks have characteristics associated with an expected *future* deterioration in performance. For the most part, the factors associated with delinquency tend to be associated with expected future delinquency rates with a broadly similar intensity. If anything, estimated effects in column (3) tend to be a bit higher than estimates in columns (1) and (2), indicating that banks expect the risk factors associated with delinquency so far to be associated with somewhat further deterioration in performance going forward. The estimates of expected loss in column (4) follow similar cross-sectional patterns, but coefficients are smaller in magnitude, reflecting the fact that expected losses given default are typically well below 1.

4.3. Cross-bank Differences in Fitted NPLs

What do these estimates mean for differences in loan performance across lenders? Figure 4 plots observed NPLs by lender type based on Call Report and Morningstar data (the first set of bars), the fitted NPLs based on the KNN and OLS estimates (the second and third set of bars), and the OLS fitted year-ahead probability of default (the fourth set of bars). For the types of loans included in the previous analysis (multifamily and non-owner-occupied, nonfarm nonresidential loans), small banks have nonperforming loan rates of about 0.6 percent whereas large banks have rates around 2.6 percent. The second and third set of bars shows that this 2 percentage point differential is well explained by differences in the observable loan and property characteristics included in the model of loan performance. The KNN-fitted NPL rate for small banks is about 1.6 percentage points below that of large banks, while the OLS-fitted NPL rates are about 1.4 percentage points below that of large banks. These results suggest that loans at small banks are performing comparably

to loans at larger banks with similar characteristics, and the differences across banks sizes mostly reflect composition effects. Finally, the last set of bars show that the fitted predicted year-ahead probability of default is a bit over 2 percentage points higher for large banks than for small banks, indicating that differences in performance are expected persist.

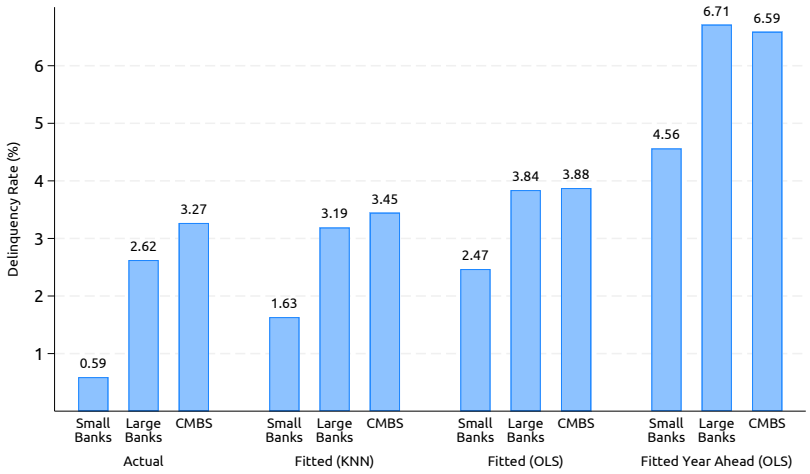
Though the gaps in performance between large and small banks is similar for observed and fitted delinquency rates, the levels of delinquency are about a percentage point higher for the fitted bank delinquency rates. One explanation for this effect is that RCA does not include the universe of bank loans; they only cover properties above $2.5 million in value and likely are better able to gather information for loans in major markets. Namely, the loans that are more exposed to losses are likely overly represented in the RCA sample, resulting in higher fitted delinquency rates. One piece of evidence favoring this explanation is that the observed and fitted delinquency rates for CMBS loans are very similar. CMBS almost exclusively fund properties above the RCA reported threshold, and have disclosure requirements such that transaction data should be readily available. Thus, the fact that fitted delinquency rates are not inflated for CMBS is consistent with sampling issues driving the differences for bank loans.[16]

Although the RCA data is not a representative sample of bank loans, there is little reason to think that the upward bias in estimated delinquency rates would be worse for small banks. Indeed, since smaller banks make smaller loans, the bias should be more pronounced for such banks. Considering this fact, the finding that the difference in delinquency rates between small and large banks can be mostly attributed to a relatively small number of factors (LTV, property size, property type, and the geographic exposure to remote work) is still notable.

What drives these differences? While the OLS estimates perform slightly worse in terms of lining up with observed NPL rates, they have the benefit of being able to be decomposed into the different variables entering the regression. The difference attributable to each variable is the product of the regression coefficient in Table 2 and the difference in the (loan weighted) average of the particular

[16]We are in the process of pulling data from public data on mortgage liens to fill information on loans below the RCA reporting threshold, so this sampling bias should be better accounted for in future versions of the paper.

Figure 4: Realized vs. Expected Nonperforming Loan Rates

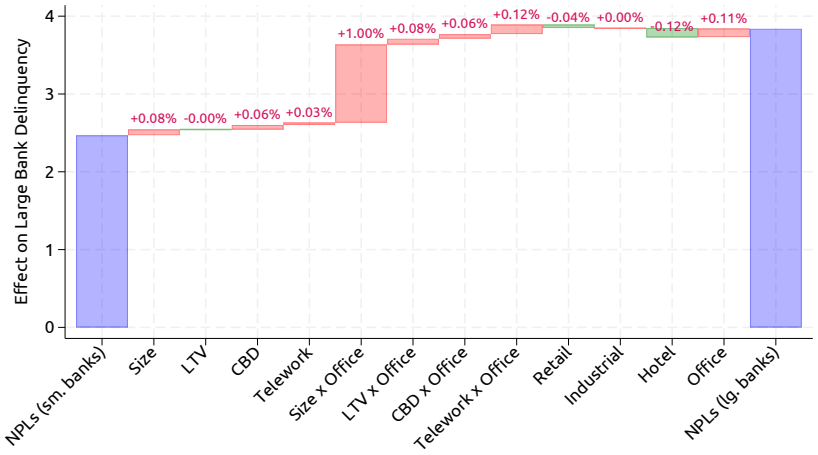


Notes: From left to right, each set of bars shows (1) the observed delinquency rate as of 2023:Q4, (2) the KNN fitted delinquency rate, (3) the OLS fitted delinquency rate, and the OLS fitted year-ahead probability of default. (1) comes from aggregate delinquency in Call Report and Morningstar data, (2) is based on KNN estimates using the same variables as in Table 2 (excluding interaction terms), and (3) and (4) come from the OLS estimates shown in columns (1) and (3) of Table 2, respectively. Fitted estimates use estimates of $\overline{X}_j$ that come from aggregating active loans in RCA by lender type, weighting by the intial loan balance.
Sources: Call Reports, Morningstar, RCA, and authors' calculations.

variable between small and large banks. Figure 5 presents a waterfall chart showing the various factors contributing to differences in expected nonperforming loan rates between large and small banks.

The results show that the greater predicted nonperforming loan rate for large banks is mostly attributable to their making more loans against large office properties. The property size-by-office interaction effect accounts for about 1 percentage point of the 1.6-percentage-point-difference in NPLs. Most other effects work in the same direction, but nothing else contributes more than 0.12 percentage points to differences in NPLs. Those other variables have either too small an effect on delinquencies or not large enough differences across bank sizes to contribute as notably to differences in predicted NPLs.

Figure 5: OLS Decomposition of Difference in Fitted NPLs at Large and Small Banks



Notes: Blue bars show the OLS-fitted delinquency rates for small (left) and large (right) banks. The bars in between show how much each variable from the regression in column (1) of Table 2 contributes to the difference.
Sources: Y-14, RCA, and authors' calculations.

5. CONCLUSION

Rising interest rates and shifts in the demand for space have impaired the performance of many CRE properties. As banks are large holders of CRE loans, these developments have generated concern about CRE exposure exacerbating other banking sector strains.

Using a combination of different sources, we shed light on the factors affecting loan performance across different types of lenders. CRE loans held by large banks were less likely to go delinquent in 2023 than those held by CMBS. For office loans, these differences can be accounted for by banks making smaller loans, where borrowers have more skin in the game (from either recourse or property equity). These factors only partially explain the differences in performance of non-office loans, suggesting that other factors, such as banks' willingness to work out stressed loans, also contribute. Lower NPLs at small banks are estimated to predominantly reflect small banks' lower exposure to at-risk office loans (i.e., loans secured by larger office properties).

While this work highlights the factors contributing to differences in loan performance so far, uncertainty remains about the outlook for performance going forward. Some features of bank

loans—modification ability, lower leverage, and lower at-risk office exposure—are likely to continue supporting performance going forward. However, the reason loans against smaller properties are performing better is less clear, so the persistence of this effect is less certain. Additionally, this analysis has focused predominantly on CRE loans secured by income-producing properties. While the delinquency rate on bank construction loans has been modest so far, difficulties leasing new space or obtaining stabilized financing could create strains in the future as more projects exit construction into a challenging environment.

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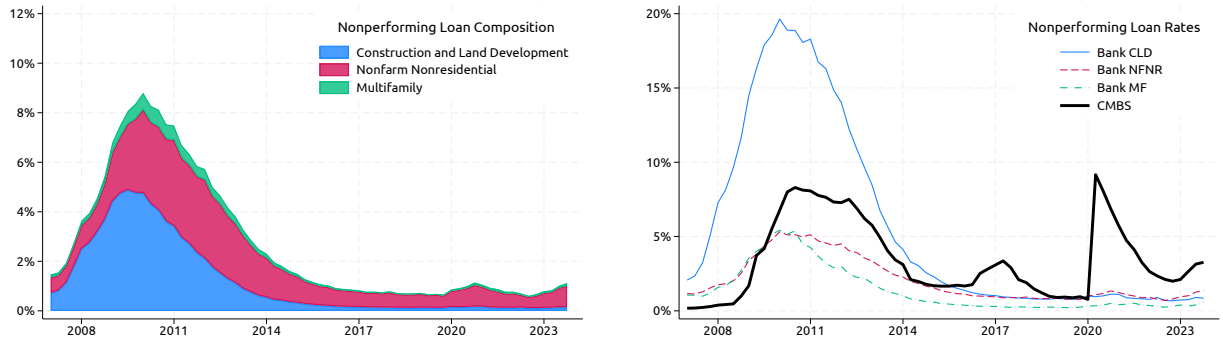
A. ADDITIONAL TABLES AND FIGURES

Figure A.1: Nonperforming Loan Rate Decomposition



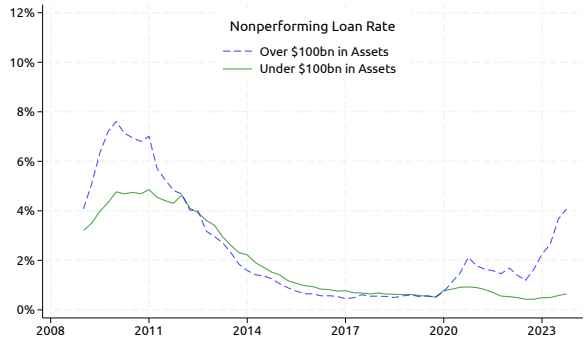
(a) Decomposition of Bank Nonperforming loans

(b) Nonperforming Loans by Loan Type

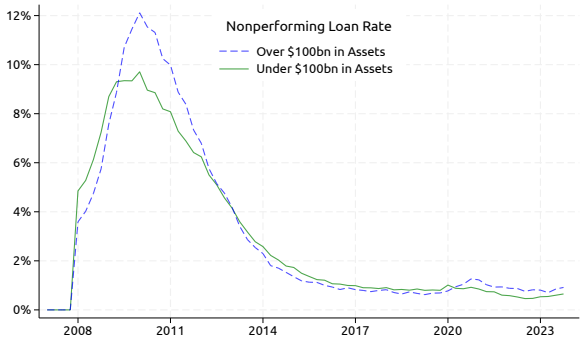
Notes: The left figure decomposes the bank nonperforming loan rate into delinquencies for construction and land development (blue), nonfarm nonresidential (red) and multifamily (green) loans. The right figure presents the equivalent nonperforming loan rates for each bank CRE loan category as well as the overall delinquency rate for CMBS loans. Nonperforming loans are loans that are 30 days or more past due or nonaccrual, plotted as a share of aggregate outstanding balances. CMBS calculations exclude defeased and REO loans.

Sources: Call Reports, Morningstar, and authors' calculations.

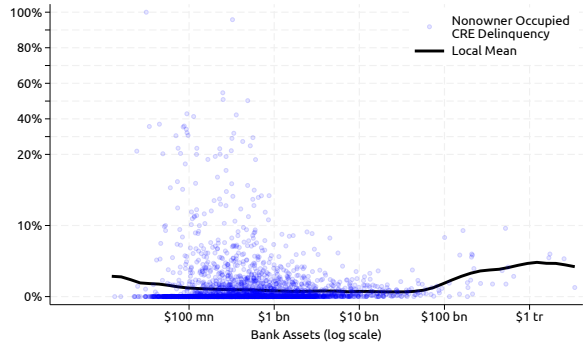
Figure A.2: Nonperforming Loan Rates by Bank Size



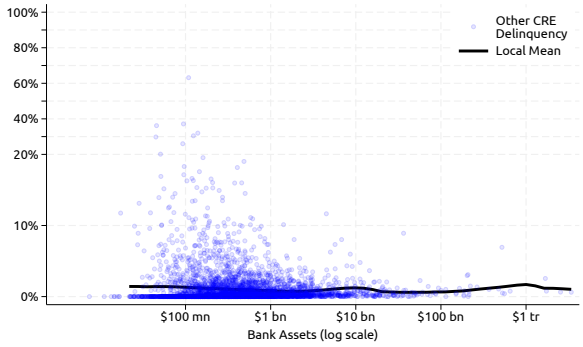
(a) Nonowner-occupied NFNR Delinquency



(b) Other CRE Delinquency



(c) Nonowner-occupied NFNR Delinquency



(d) Other CRE Delinquency

Notes: Each figure plots CRE non-performing loan rates for nonowner-occupied nonfarm nonresidential (NFNR) loans (left charts), other CRE loans (right charts). Nonperforming loans are loans that are 30 days or more past due or nonaccrual, plotted as a share of aggregate outstanding balances. Other CRE includes multifamily, construction and land development, and owner-occupied NFNR loans. The top figures plot NPLs over time for banks above (blue) and below (green) $100 billion in assets. The bottom charts plot 2023:Q4 NPLs against bank size. Blue dots report individual banks' NPLs, while the black line plots an estimate of the average for banks of that size based on a local linear regression. The scale on the y-axis expands after 20% to prevent outlier responses from obscuring variation within normal bounds.
Sources: Call Reports and authors' calculations.

Table A.1: Loan Performance By Lender Type

	$100 \times \text{Extension}_{i,23}$							
	Full Sample				Offices			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CMBS	-5.37**	-6.40**	-6.21**	-6.26**	-6.26**	-9.74**	-9.41**	-9.42**
	(0.50)	(0.55)	(0.53)	(0.53)	(0.70)	(1.12)	(1.08)	(1.08)
Maturing	33.20**	32.27**	31.87**	31.60**	37.85**	36.59**	34.85**	34.70**
	(2.18)	(2.14)	(2.15)	(2.18)	(2.32)	(2.26)	(2.26)	(2.25)
Office	3.41**	1.43**	1.40**	1.33**				
	(0.47)	(0.40)	(0.38)	(0.37)				
LTV at Orig.		4.77**	4.60**	4.21**		9.43**	10.14**	9.81**
		(0.66)	(0.68)	(0.68)		(2.15)	(2.23)	(2.24)
ln(Value at Orig.)		2.10**	1.89**	1.80**		2.58**	2.38**	2.35**
		(0.19)	(0.18)	(0.18)		(0.32)	(0.32)	(0.32)
Recourse		1.36**	1.47**	1.43**		-0.13	-0.07	0.00
		(0.26)	(0.27)	(0.26)		(1.05)	(1.02)	(1.03)
CBD			0.95**	0.91**			1.36	1.14
			(0.28)	(0.27)			(0.83)	(0.84)
Teleworkable Share			-1.94	-2.66			-3.64	-4.33
			(1.91)	(1.93)			(4.92)	(4.98)
Occupancy				-4.80**				-4.01*
				(1.03)				(1.92)
Debt Yield$<$.08				0.42^{+}				0.95
				(0.23)				(0.71)
R^2_a	0.231	0.246	0.241	0.243	0.256	0.275	0.262	0.264
Observations	59,179	59,095	54,326	53,616	7,849	7,829	7,189	7,064
Other Property Fixed Effects?	✓	✓	✓	✓				

Notes: This table presents estimates from the equation:

$$100 \times \text{Extension}_{i,23} = \beta_1 \text{CMBS}_i + \beta_2 \text{Maturing}_{i,23} + \beta_3 \text{Office}_i + \gamma' X_{i,23} + \varepsilon_i$$

where $\text{Extension}_{i,23}$ is in indicator for whether loan i received an extension (i.e., had its maturity date pushed out) in the last year. The main independent variables of interest are whether loan i is in a CMBS pool, whether the loan was scheduled to mature in 2023, and whether the loan is secured by an office property. Fixed effects for other property types are included by not displayed (multifamily is the omitted category). Column (2) adds controls for the loan's at-origination LTV, whether the loan has recourse, and for the logarithm of the property value at origination. Column (3) adds controls for whether the property is in a CBD and the share of the city's employment that can be done at home (Dingel and Neiman, 2020). Column (4) adds controls for the occupancy and an indicator for whether the debt yield is under 8% (both as of a year previously). Columns (5)–(8) repeat the same analysis but restrict the sample to office properties. Standards errors, in parentheses, are clustered by bank-origination year for bank loans and CMBS deal for CMBS loans. $^{+},^{*},^{**}$ indicate significance at 10%, 5% and 1%, respectively.