Determinants of Pandemic-Era CRE Distress: Implications for the Banking Sector

David Glancy[1] Robert Kurtzman[1]

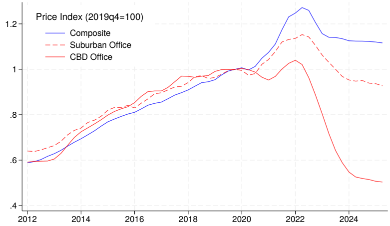
[1]Federal Reserve Board

Motivation: Concern about Small Banks' CRE Exposure

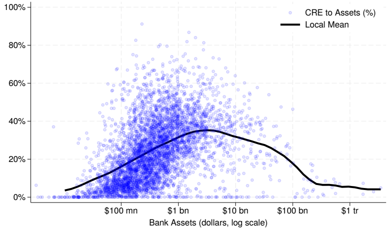
1. Changes in work patterns and interest rates straining CRE values
2. Small banks are highly exposed to CRE loans

$\Longrightarrow$ Concern about spillovers to banking sector

CRE Prices

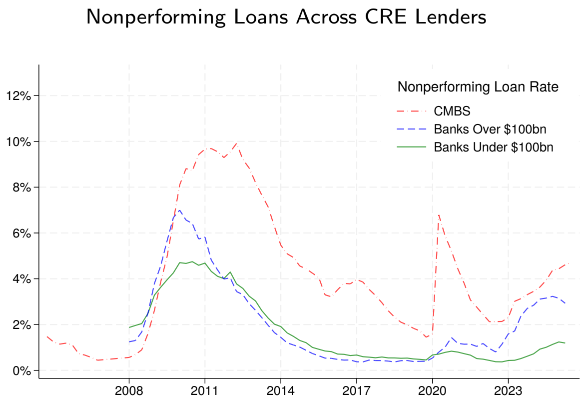


CRE Loans as Share of Asset



Notes: RCA Commercial Property Price Index

Small Banks' CRE Loan Delinquencies Still Modest



Notes: For non-owner-occupied, income-producing properties (MF & NFNR). Rise in NPLs for CLD and owner-occupied CRE are comparatively modest.
Sources: Call Reports, Trepp.

▸ Driven mostly by NFNR, in particular Office

Question: What Explains Small Bank Resilience

Possible Reasons:

1. **Loan Composition**: Small banks' loans less affected by recent stresses
2. **Loan Servicing**: Stress translates less to delinquency
    - Modifications to avert delinquency (Black et al., 2020)
    - Small banks delay loss recognition since they can't absorb losses (Peek and Rosengren, 2005; Crosignani and Prazad, 2024)

Complication: Small banks' CRE loans holdings are opaque

- Limited loan-level data on transactions, basically none on performance

Performance Decomposition

Oaxaca decomposition for delinquency differentials

$$\underbrace{\delta_{\mathrm{Lg}} - \delta_{\mathrm{Sm}}}_{\text{Diff in Delinquency Rates}} = \underbrace{\hat{\beta}'_{\mathrm{Lg}}(\bar{X}_{\mathrm{Lg}} - \bar{X}_{\mathrm{Sm}})}_{\text{Composition Effect}} + \underbrace{\bar{X}'_{\mathrm{Sm}}(\hat{\beta}_{\mathrm{Lg}} - \hat{\beta}_{\mathrm{Sm}})}_{\text{Unexplained}}$$

- δ_j: average delinquency rate
- $\hat{\beta}_j$: coefficients from LPM predicting delinquency
- $\bar{X}_j$: average portfolio characteristics

Performance Decomposition

Oaxaca decomposition for delinquency differentials

$$\underbrace{\delta_{\text{Lg}} - \delta_{\text{Sm}}}_{\text{Diff in Delinquency Rates}} = \underbrace{\hat{\beta}'_{\text{Lg}}(\bar{X}_{\text{Lg}} - \bar{X}_{\text{Sm}})}_{\text{Composition Effect}} + \underbrace{\bar{X}'_{\text{Sm}}(\hat{\beta}_{\text{Lg}} - \hat{\beta}_{\text{Sm}})}_{\text{Unexplained}}$$

- δ_j: average delinquency rate
- $\hat{\beta}_j$: coefficients from LPM predicting delinquency
- $\bar{X}_j$: average portfolio characteristics

Two Challenges:

- Limited microdata on small bank CRE loans

  $\Longrightarrow$ Compile data from different sources to estimate δ_j, $\bar{X}_j$ & $\hat{\beta}_{\text{Lg}}$
- Specification selection in face of interactions and nonlinearities

  $\Longrightarrow$ Machine learning approach to estimate delinquency function

This paper: Approach to decompose performance differences

$$\underbrace{\delta_{\text{Lg}} - \delta_{\text{Sm}}}_{\text{Diff in Delinquency Rates}} = \underbrace{\hat{\beta}'_{\text{Lg}}(\bar{X}_{\text{Lg}} - \bar{X}_{\text{Sm}})}_{\text{Composition Effect}} + \underbrace{\bar{X}'_{\text{Sm}}(\hat{\beta}_{\text{Lg}} - \hat{\beta}_{\text{Sm}})}_{\text{unexplained}}$$

1. Detailed micro data on performance at large banks (Y-14) to analyze drivers of delinquency $\Longrightarrow \hat{\beta}_{\text{Lg}}$
2. Transaction data on CRE loan holdings across different lenders (RCA & CoreLogic) $\Longrightarrow \bar{X}_{\text{Lg}}, \bar{X}_{\text{Sm}}$
3. Compute share of difference in delinquency rates (in Call Reports) attributable to origination characteristics:

$$\text{Composition Effect (\%)} = \frac{\hat{\beta}'_{\text{Lg}}(\bar{X}_{\text{Lg}} - \bar{X}_{\text{Sm}})}{\delta_{\text{Lg}} - \delta_{\text{Sm}}}$$

Findings: Preview

1. Loan-level drivers of delinquency ($\hat{\beta}_{\text{Lg}}$):
    - Delinquency at large banks concentrated in office loans with other risk factors (large sizes, CBD locations, telework exposure)
2. Portfolio composition ($\bar{X}_{\text{Lg}}, \bar{X}_{\text{Sm}}$):
    - Large and small banks have similar office exposure, but small banks have better-performing types of office loans
3. Portfolio-level drivers of delinquency:
    - Small banks have 2pp lower CRE delinquency rates
    - $\approx$ 75% attributable to observed factors (mostly small banks' low exposure to large office loans)
4. Extension to include nonbanks
    - Stronger loan performance at large banks relative to CMBS attributable to banks making smaller loans where borrowers have more skin in the game (low LTVs/recourse)

Related Literature

Risks to banking sector post-SVB: Jiang et al. (2023); Acharya et al. (2023); Crosignani and Prazad (2024)

- Though small banks more vulnerable to CRE losses, they have minimal holdings of the most at-risk loans
- Low delinquency attributable to origination characteristics, leaving less room for "extend and pretend"

Effects of remote work: Ramani and Bloom (2021); Gupta et al. (2022); Rosenthal et al. (2022); Ghosh et al. (2022); Monte et al. (2023)

- Document the (highly uneven) effects on CRE loan performance

Role of CRE in Banking Crises: Browne and Case (1992); Fenn and Cole (2008); Cole and White (2012); Herring and Wachter (1999); Gan (2007)

- Method to analyze small bank risk exposures in absence of detailed performance data

Loan-level Panel Data for Delinquency Model (to estimate $\hat{\beta}_{\mathrm{Lg}}$)

Large bank data from stress test reporting (Y-14Q H.2 schedule)

- Data includes non-owner-occupied CRE loans with committed values over \$1 million from banks with over \$100 billion in assets
- Focus on already-constructed properties since that is where performance deteriorated

Key variables:

- $\mathrm{Delinquent}_{i,23}$: Indicator if delinquent at end of 2023
- Explanatory variables: At-origination characteristics that are available in public records data (so $\bar{X}_{\mathrm{Sm}}$ can be constructed)
  - Loan size, property type, property location
  - Expand to other variables (e.g. LTV and recourse) in CMBS analysis

Location matched to geographic remote work exposure measures:

- Central Business District identifiers (CBRE)
- Share of jobs in city that can be done at home (Dingel and Neiman, 2020)

Loan Origination Data ($\bar{X}_{\text{Lg}}, \bar{X}_{\text{Sm}}$)

MSCI Real Capital Analytics (RCA): Data on large (>$2.5 million) CRE transactions

- Data from public filings, news reports and industry contacts yields fairly complete loan information
- Cleaned lender names and lender-type identifiers allows us to distinguish CMBS, large bank, and small bank CRE loans
- Exclude loans likely to no longer be outstanding (based on maturity date or the presence of future transactions that would extinguish the loan)

CoreLogic CRE Voluntary Liens: Supplementary data we use for small loans

- Public records data on outstanding CRE loans
- Messier, so only used for the small transactions that RCA would miss
- Identify lenders by fuzzy name matching

Combined data approximates origination characteristics (loan size, property type, and property location) for outstanding loans across CRE lenders.

Delinquency Function Estimation

Use Y-14 data to estimate a delinquency function $\hat{D}(X_{i,j})$

More Interpretable

More Flexible

1. **OLS:** Regressions interacting office indicator with other characteristics
2. **Shallow Decision Tree:** Successively partitions feature space to achieve best improvement with each split
3. **K-nearest neighbors:** Weighted average for K most similar loans, weighting by similarity of X vector
4. **Random forest:** Averages decision trees across bootstrapped samples

Transactions data to predict portfolio-level NPL by lender type j with model m:

$$\widehat{\text{NPL}}_{j,m} = \sum_{i|j} \omega_{i,j} \hat{D}_m(X_{i,j}) \ \ (= \hat{\beta}'_{\text{Lg}} \bar{X}_{\text{j}} \text{ w. linear model})$$

$$\text{Composition Effect } (\%)_m = (\widehat{\text{NPL}}_{\text{Lg},m} - \widehat{\text{NPL}}_{\text{Sm},m})/(\delta_{\text{Lg}} - \delta_{\text{Sm}})$$

OLS Estimates

	100×Delinquent		Year-ahead
	30+ days	+ Ballooned	PD (%)
	(1)	(2)	(3)
ln(Balance at Orig.)	0.16**	0.25**	0.37**
	(0.04)	(0.07)	(0.06)
CBD	0.34	0.37	1.30**
	(0.22)	(0.25)	(0.38)
Teleworkable Share	4.17*	2.83	11.16**
	(1.78)	(2.11)	(2.43)
Office	1.21**	1.28**	1.71**
	(0.23)	(0.24)	(0.28)
× ln(Balance at Orig.)	2.19**	2.36**	2.90**
	(0.40)	(0.42)	(0.45)
× CBD	2.55*	3.35**	2.58*
	(1.12)	(1.23)	(1.20)
×Teleworkable Share	17.11**	15.19**	18.04**
	(5.36)	(5.82)	(6.28)
R^2_a	0.027	0.026	0.063
Observations	46,925	46,925	39,419
Other Prop Type FE?	✓	✓	✓

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

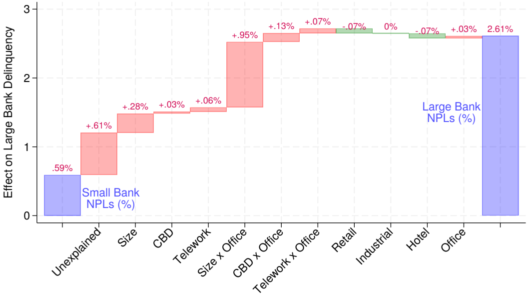
ln(Balance at Orig.) and Teleworkable Share are demeaned.

$^{+}, ^{*}, ^{**}$ indicate significance at 10%, 5%, and 1%, respectively.

Sources: Authors' calculations using the Y-14Q H.2 Schedule.

- Delinquency higher for larger loans and loans located in CBDs or areas with high telework potential
- Risk factors greatly amplified for office loans
- Similar risk characteristics identified when delinquency measure includes loans current on interest but past maturity date (column 2) or when using the forward looking probability of default (column 3).

OLS Model: Composition explains ≈70% of NPL gap



OLS decomposition of differences delinquency rates:

- 1.4pp of 2pp gap explained by portfolio composition, mostly reflecting small banks having few large office loans
- Small banks also benefit from smaller loans in general, and fewer CBD office loans

Decision Tree: Composition explains ≈60% of NPL Gap

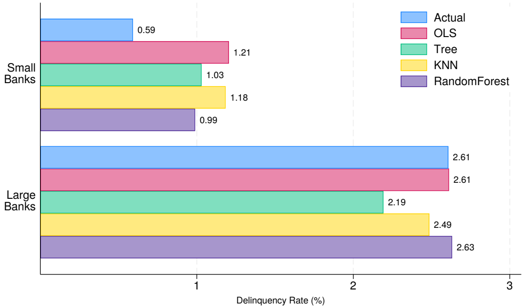
Large and small banks both have about 20% office exposure, but large banks have more large office loans, especially in the most adversely affected markets.

	(1) Pr(Delinquent)	(2) Large Bank Share (%)	(3) Small Bank Share (%)
Non-office	0.54%	79.73	82.53
Small Office	1.39%	5.62	13.58
Large Office, Low Telework	8.41%	11.54	3.42
Large Office, High Telework	22.89%	3.11	0.46
Weighted average delinquency		2.19%	1.03%

Notes: Small/Large office loans defined by an at-origination loan balance above/below $23.3 million. Low/High Telework cities have a telework eligible share of employment below/above 44.4%.

Origination Characteristics Can Account for Performance Differences

Figure: Realized vs. Expected Nonperforming Loan Rates



- CRE delinquency 2pp higher at large banks: 2.61% vs. 0.59%
- Expected delinquency rates w. random forest: 2.63% and 0.99%
- Origination characteristics account for ≈60%-80% of gap depending on model

Limitations of previous analysis

Analysis restricted to origination characteristics in public records data

- Factors such as LTV, recourse, maturity also affect performance

Developments common to large and small banks differenced out

- Servicing differences might be more pronounced between banks and nonbanks than between large and small banks (Glancy et al., 2022)

For last part of paper, we use micro data on securitized CRE loans (CMBS loans) to examine delinquency drivers in more detail and how patterns extrapolate outside the banking sector.

Bank vs. CMBS performance: Summary of results

Drivers of loan performance:

- Delinq. rates 12pp higher for maturing loans & 3pp higher for office loans
- Delinquency also higher for larger properties, with less skin-in-the-game (high LTV or nonrecourse), or more pandemic affected areas (CBDs or high telework eligible regions)
  - Risk factors appear for full sample, but amplified for office loans
- CMBS loans ≈1.6pp more likely to go delinquent
  - Mostly reflect CMBS' higher LTVs, less recourse, & larger properties
  - Those variables account for entire office performance differential

▸ Specification ▸ Full Sample Results ▸ Office Results

Conclusion

Using a combination of data sources, we shed light on the factors affecting loan performance across different types of lenders

- Recent CRE delinquency concentrated in large-sized office loans
- Low delinquency at small banks mostly accounted for by composition of office loan portfolio rather than, for example, "extend and pretend"
- Small loan sizes and more skin-in-the-game support bank performance relative to CMBS

Caveat: Though small banks are serving a less-adversely-affected segment of the market so far, stress may still spread to other parts of the market.

- Small bank loans not inherently safer, just less-exposed to office segments affected by pandemic

Bibliography

Acharya, V. V., A. Savov, and P. Schnabl (2023): "Chapter 3: Banks, Interest Rate Risk and Systemic Risk–Theoretical and Historical Perspectives," in *SVB and Beyond: The Banking Stress of 2023*, ed. by M. P. Richardson, K. L. Schoenholtz, and B. Tuckman, Volatility and Research Institute of New York University Stern School of Business, 35–72.

Black, L., J. Krainer, and J. Nichols (2020): "Safe Collateral, Arm's-Length Credit: Evidence from the Commercial Real Estate Mortgage Market," *The Review of Financial Studies*, 33, 5173–211.

Browne, L. E. and K. E. Case (1992): "How the commercial real estate boom undid the banks," in *Conference Series;[Proceedings]*, Federal Reserve Bank of Boston, vol. 36, 57–113.

Cole, R. A. and L. J. White (2012): "Déjà vu all over again: The causes of US commercial bank failures this time around," *Journal of financial services Research*, 42, 5–29.

Crosignani, M. and S. Prazad (2024): "Extend-and-Pretend in the U.S. CRE Market," *Federal Reserve Bank of New York Staff Reports*, 1130.

Dingel, J. I. and B. Neiman (2020): "How Many Jobs can be Done at Home?" *Journal of Public Economics*, 189, 104235.

Fenn, G. W. and R. A. Cole (2008): "The Role of Commercial Real Estate Investments in the Banking Crisis of 1985-92," *Available at SSRN 1293473*.

Gan, J. (2007): "The real effects of asset market bubbles: Loan-and firm-level evidence of a lending channel," *The Review of Financial Studies*, 20, 1941–1973.

Ghosh, C., L. Rolheiser, A. Van de Minne, and X. Wang (2022): "The Price of Work-from-Home: Commercial Real Estate in the City and the Suburbs," *Working Paper*.

Glancy, D. P., R. J. Kurtzman, and L. Loewenstein (2022): "Loan Modifications and the Commercial Real Estate Market," *FEDS Working Paper 2022-050*.

Gupta, A., V. Mittal, and S. Van Nieuwerburgh (2022): "Work from Home and the Office Real Estate Apocalypse," *NBER Working Paper No. 30526*.

Herring, R. J. and S. M. Wachter (1999): "Real estate booms and banking busts: An international perspective," *The Wharton School Research Paper*.

Jiang, E. X., G. Matvos, T. Piskorski, and A. Seru (2023): "Monetary Tightening, Commercial Real Estate Distress, and US Bank Fragility," *NBER Working Paper No. 31970*.

Monte, F., C. Porcher, and E. Rossi-Hansberg (2023): "Remote Work and City Structure," *American Economic Review*, 113, 939–81.

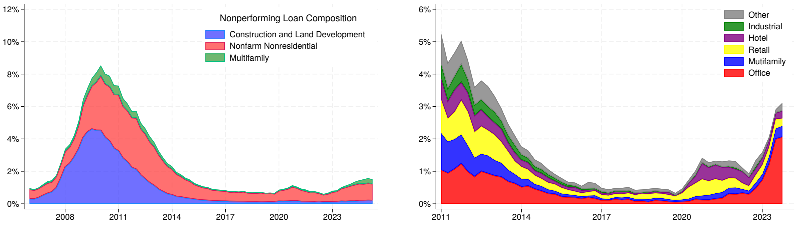
Peek, J. and E. S. Rosengren (2005): "Unnatural Selection: Perverse Incentives and the Misallocation of Credit in Japan," *American Economic Review*, 95, 1144–66.

Ramani, A. and N. Bloom (2021): "The Donut effect of COVID-19 on cities," *NBER working paper*.

Rosenthal, S. S., W. C. Strange, and J. A. Urrego (2022): "JUE Insight: Are City Centers Losing their Appeal? Commercial Real Estate, Urban Spatial Structure, and COVID-19," *Journal of Urban Economics*, 127, 103381.

NPL by Loan Type

Figure: Nonperforming Loan Rate Decomposition



(a) Decomposition of Bank Nonperforming loans (b) By property type (income producing)

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 decomposes income producing delinquency by property type for the large bank sample. *Sources:* Call Reports, Y-14.

Back

Regression Specification

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

- Sample: CRE loans in large bank or CMBS portfolios that were outstanding at 2022-end
- $\text{Delinquent}_{i,23}$: indicator for whether loan i is delinquent as of the last observation in 2023 (0 if paid-off or current)
- Explanatory variables: Indicators for whether loan is in a CMBS pool, is scheduled to mature in 2023, is secured by an office
- $X_{i,23}$: includes other property type dummies, LTV, property size, a recourse indicator, geographic characteristics

We investigate what causes bank and CMBS to differ by assessing how β_1 changes as we add controls

Back

Results: Loan Performance by Lender Type - Full Sample

	$100 \times$ Delinquent$_{i,23}$ Full Sample		
	(1)	(2)	(3)
CMBS	1.65**	0.45	0.69*
	(0.26)	(0.36)	(0.33)
Maturing	12.23**	11.82**	11.77**
	(0.96)	(0.95)	(0.95)
Office	3.37**	2.59**	2.48**
	(0.33)	(0.30)	(0.30)
LTV at Orig.		4.87**	5.53**
		(0.72)	(0.83)
ln(Value at Orig.)		0.83**	0.73**
		(0.11)	(0.10)
Recourse		-0.40	-0.26
		(0.25)	(0.23)
CBD			2.31**
			(0.46)
Teleworkable Share			7.37**
			(1.84)
R^2_a	0.056	0.061	0.064
Observations	57,799	57,799	57,799
Other Property Fixed Effects?	✓	✓	✓

Notes: Telework eligibility from Dingel and Neiman (2020). Standard 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.

- CMBS loans ≈1.6pp more likely to go delinquent
- Worse CMBS performance explained by higher leverage, nonrecourse loans against larger properties
- Delinquency rates 12pp higher for maturing loans and 3pp higher for office loans, also elevated in areas with greater remote work exposure

▸ Back

Results: Loan Performance by Lender Type - Office Loans Only

	$100 \times$ Delinquent$_{i,23}$ Offices		
	(1)	(2)	(3)
CMBS	3.36**	-2.17^{+}	-1.69
	(0.67)	(1.19)	(1.18)
Maturing	19.56**	18.45**	18.16**
	(1.88)	(1.86)	(1.85)
ln(Value at Orig.)		1.97**	1.44**
		(0.30)	(0.31)
LTV at Orig.		13.23**	15.22**
		(1.88)	(1.98)
Recourse		-3.61**	-3.24**
		(1.06)	(1.05)
CBD			5.15**
			(1.06)
Teleworkable Share			14.11**
			(5.16)
R^2_a	0.072	0.093	0.100
Observations	7,652	7,652	7,652

Notes: Standard 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.

- Underperformance of CMBS office loans can be explained entirely by differences in property sizes sizes, LTVs, and the use of recourse
- Previously discussed risk factors have larger effects on office delinquency (likely reflecting more office loans being on the boarder of defaulting)

Back