

Smaller Banks, Smarter Lending? Evidence from the Commercial Real Estate Market*

EVA STEINER[†]
Penn State

ALEXEI TCHISTYI[‡]
Cornell

ATLAS WU[§]
Cornell

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Abstract

Community banks significantly expanded CRE loan issuance during and after the Covid-19 shock while large banks lost market share. We explain this pattern with a model in which large banks have a lower cost of capital, while community banks have a local information advantage that becomes more valuable in risky lending environments. Consistent with the model, community banks expanded CRE lending, within their local footprint, and gained market share share from large banks, especially in informationally sensitive property types and acquisition loans near their headquarters, and after accounting for measures of CRE specialization as well as relationship lending. Their CRE loans had lower distress and foreclosure rates, and the properties they financed performed at least as well if not better than those of large banks across major property types. Our findings underscore the importance of community banks in supporting creditworthy borrowers during crises.

KEYWORDS: COMMERCIAL REAL ESTATE, BANK LENDING, COMMUNITY BANKS.

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[†]Penn State Smeal College of Business. Email: ems6770@psu.edu.

[‡]Cornell SC Johnson College of Business. Email: avt33@cornell.edu.

[§]Cornell SC Johnson College of Business. Email: jw2486@cornell.edu.

1 Introduction

Community banks are known to represent a small part of the U.S. banking system while holding an outsized share of commercial real estate (CRE) loans outstanding (FDIC, 2020). Figure 1, based on MSCI loan-level data, documents a separate trend that has received less attention: new CRE loan issuance by community banks increased beginning in 2020 with community banks becoming the largest issuer type by loan count in 2024, ahead of regional and large banks (Panel A). Their recent growth extends to new loan issuance volumes where it contrasts with the decline of large banks since 2020 and the steady expansion of regional banks, which predates both (Panel B). The lending activity of community banks in this period is noteworthy because the CRE market was severely disrupted by the Covid-19 pandemic (Gupta et al., 2022a,b) and the subsequent monetary tightening (Jiang et al., 2025), raising concerns about banks’ exposure to this segment (IMF, 2021; Hinzen et al., 2025).

[Figure 1 about here.]

To guide our empirical analysis of these lending patterns, we develop a model of banking competition in which large banks benefit from a lower cost of capital, while community banks possess a local informational advantage. This advantage allows community banks to process soft credit risk information more efficiently due to their physical proximity to the financed properties and closer relationships with real estate owners. We study how market equilibrium in the CRE mortgage market varies with the riskiness of the borrower pool. During benign economic times, community banks capture a smaller market share, as most borrowers appear safe and can qualify for cheaper loans from large banks. However, during periods of high economic uncertainty, identifying creditworthy borrowers becomes significantly more difficult. Under these circumstances, large banks struggle to screen borrowers effectively, allowing community banks to gain market share without a concurrent decline in loan quality. Furthermore, across a broad range of realistic parameters, our model demonstrates that community banks become more profitable in riskier lending environments due to the increased demand for their screening capabilities.

The CRE market fits the scope of our model well. Characterized by heterogeneous, illiquid assets and the importance of local demand and supply factors, it is a setting where information asymmetries are first-order (Garmaise and Moskowitz, 2004; Kurlat and Stroebe, 2015). Our CRE data combine bank-level Call Reports, loan-level data from MSCI, and asset-level performance data for five major property types from 2016 to 2024. Within this time span, we focus on the Covid-19 pandemic and

its aftermath, as fundamental risk and valuation uncertainty increased from 2020 (Gupta et al., 2022a,b) and these effects were amplified by the 2022–23 monetary tightening (Jiang et al., 2025), which raised financial stability concerns through 2024 (Board of Governors of the Federal Reserve System, 2025). We date the onset of the pandemic to Q2 of 2020, following the WHO declaration in March, and refer to the period from then through the end of our sample as a risky lending environment in the sense of our model. Our estimating equations build on the covariate and fixed-effects specifications in recent work on relationship lending during this period (Berger et al., 2024).

We document three findings consistent with the core predictions of our model. First, we confirm the descriptive evidence that new CRE loan issuance by community banks increased substantially during the pandemic while large bank lending declined, suggesting that the elevated uncertainty during this time benefited community banks at the expense of large banks—consistent with the state-contingent information advantage in our model. Second, this growth was not driven by expansion into previously unknown markets, a concern raised for regional banks (Hinzen et al., 2025); rather, community banks intensified CRE lending within their existing geographic footprint, consistent with the locally focused business model that gives rise to their information advantage in our model. Third, community bank lending expanded across all property types, but most significantly in hotel and retail, two sectors severely disrupted especially early in the pandemic (Ling et al., 2020; Steiner and Tchisty, 2024). Viewing property type as a proxy for the perceived riskiness of CRE loans at this time, this is consistent with community banks leveraging their information advantage to expand into segments that appear too risky to large banks, who are less able to identify safe borrowers amid high uncertainty—the key mechanism through which community banks compete in our model.

To further corroborate the competition channel posited in our model, we show that a significant share of community banks’ new CRE loan issuance during the pandemic targeted properties previously financed by large banks, even though we do not find evidence for a wholesale withdrawal of large banks from the CRE market during this time, an issue to which we return below. These findings suggest a substitution of new CRE lending activity from large banks to community banks in this period of elevated uncertainty, consistent with the competition mechanism emphasized in our model.

To assess the degree to which this substitution of lending activity reflects superior information of community banks, the main driver of their competitive advantage in our model, we exploit variation in the types of CRE loans issued. When partitioning our sample into refinancing versus new acquisition loans, which are arguably more informationally sensitive than refinancing previously known assets, we find that the substitution of lending activity to community banks is concentrated in acquisi-

tion loans. In contrast, we find that large banks continue to refinance previously known assets, inconsistent with a wholesale withdrawal from the CRE market (though possibly related to extend-and-pretend strategies documented, e.g., in Crosignani and Prazad (2024); Cole and Huberdeau-Reid (2026)). Our findings hold after accounting for CRE specialization of banks and pre-existing CRE lending relationships, and are thus more aligned with the information channel posited in our model.

We hone in further on the local information channel by leveraging variation in the proximity of CRE lenders to the acquisitions they finance. Partitioning our sample of new acquisition loans by the physical distance between properties and lenders, we find that community banks were more likely to finance acquisitions of properties previously financed by large banks when the community bank headquarters was in the same MSA as the property. We find little evidence of such effects for branch proximity, suggesting centralized CRE lending decisions in community banks. Our results imply that community banks expanded CRE lending at the expense of large banks by leveraging local information advantages in settings where these advantages are most critical.

If the lending patterns we document reflect the hypothesized local information advantage of community banks, this should be reflected in ex-post loan performance. Call Report data show that community banks had lower ratios of nonperforming, modified, and real estate owned loans than large banks during the pandemic, but these outcomes may reflect pre-pandemic choices that led to lower exposure to large office loans (Glancy and Kurtzman, 2024) and work-from-home trends (Anenberg et al., 2025). We therefore use MSCI data on loans issued during the pandemic and find that community bank loans had lower foreclosure rates than large bank loans by the end of our sample. Because banks may avoid costly foreclosures by extending poorly performing loans (Crosignani and Prazad, 2024; Cole and Huberdeau-Reid, 2026), we also examine the underlying properties directly. Industrial, office, and retail properties financed by community banks during the pandemic signed more new leases without greater concessions or lower rents; apartments showed comparable occupancy and rents; and hotels had higher occupancy with comparable pricing, revenue, and operating margins. In sum, properties financed by community banks during the pandemic performed strongly ex-post, consistent with these banks using their local information advantage to identify creditworthy borrowers.

Related Literature. Our study contributes to the recently emerging literature on CRE lending and bank exposure to CRE risk. Jiang et al. (2025) analyze how declining property values and monetary tightening in the aftermath of the Covid-19 pandemic reduce CRE loan values and find that CRE distress could expose many smaller banks to solvency runs. Crosignani and Prazad

(2024) and Cole and Huberdeau-Reid (2026) show that some banks respond to CRE distress by granting maturity extensions and payment relief on impaired loans, leading to a misallocation of credit. Anenberg et al. (2025) and Glancy and Kurtzman (2024) show how banks’ exposure to pandemic-induced CRE credit risk reduced credit supply and loan performance. In contrast to this prior work, our findings draw attention to local information advantages of community banks, which not only allow these institutions to expand new CRE lending in a risky market environment but also avoid misallocation of credit as far as our ex-post performance analyses can detect.

Literature on CRE finance is often focused on bank versus securitized (CMBS) lending. Black et al. (2020) characterize banks as more informed creditors than CMBS investors, leading to safer CRE assets being financed through arm’s-length CMBS debt. Ghent and Valkanov (2016) show that larger, less monitoring-intensive assets are more likely to be securitized. Glancy et al. (2022) study intermediary segmentation between banks, insurers, and CMBS lenders, estimating to what degree substitution between lender types can cushion supply shocks. Glancy et al. (2025) document how renegotiation frictions drive underwriting and performance outcomes across bank and CMBS lenders. We expand this literature by analyzing competition between different bank types, highlighting community banks’ local information advantage in screening borrowers as a driver of substitution patterns and differential loan performance outcomes between them and large banks.

Our study also contributes to the broader literature on credit provision during downturns. While credit generally dries up during crises (see, e.g., Ivashina and Scharfstein, 2010), small banks have been shown to provide liquidity and ease financial constraints for borrowers (Berger et al., 2017; Li and Strahan, 2021), a pattern often associated with relationship lending (Deyoung et al., 2015; Bolton et al., 2016; Beck et al., 2018). We highlight community banks’ local information advantages as a driver of their ability to extend credit in risky lending environments after accounting for pre-existing lending relationships. We also show that the quality of CRE credit extended by community banks did not seem to suffer, a serious concern in the face of prior evidence for zombie lending during crises (Peek and Rosengren, 2005; Caballero et al., 2008). Our results thus speak to the importance of community banks in supporting creditworthy borrowers during crises, when the cost of capital advantage of large banks is eroded relative to the local information advantage of community banks.

Our theoretical framework is built upon two foundational assumptions widely established in the banking literature: large banks enjoy a lower cost of capital, and community banks are better equipped to screen risky borrowers. Regarding funding differentials, Kroszner (2016) reviews the historical cost advantages of large institutions, while d’Avernas et al. (2023) provide recent evi-

dence that large banks systematically pay lower rates on deposits. Regarding screening capabilities, we build on Stein (2002), who theorizes that small, single-manager firms have a competitive edge in processing “soft”, hard-to-transmit information—a framework empirically supported by Berger et al. (2005). More broadly, our work connects to the theoretical literature on financial services competition under asymmetric information (e.g., Hauswald and Marquez, 2006; Hu and Zryumov, 2026). To the best of our knowledge, however, ours is the first theoretical framework to synthesize these dynamics to show that community banks can simultaneously increase both market share and profitability in a riskier economic environment.

2 Model of Banking Competition

In this section, we develop a simple model of banking competition. We also propose testable hypotheses that we take to the data in the following sections.

There is a unit mass continuum of agents who are seeking to obtain a loan at time $t = 0$ that will require repayment of \$1 at time $t = 1$. An agent of type θ fully repays the loan with probability θ at time 1, and defaults on the loan with probability $1 - \theta$. We normalize payoffs to lenders on defaulted loans to \$0. Each agent’s type is common knowledge, and θ is distributed according to CDF $F(\theta)$, and PDF $f(\theta)$, with $\theta \in [0, 1]$, across the population. For analytical tractability we assume the Power Function Distribution:

$$F(\theta, n) = \theta^n, \tag{1}$$

$$f(\theta, n) = n\theta^{n-1}. \tag{2}$$

where $\theta \in [0, 1]$, and $n > 0$. Parameter n represents the state of the economy, with a higher n corresponding to a safer lending environment. Indeed, an increase in n results in an increase in the number of high quality (high θ) borrowers and a decrease in the number of low quality (low θ) borrowers. Thus, when n increases (decreases), we say that the lending environment becomes less (more) risky.

One way to visualize how the credit risk in the economy changes with n is to compute the unconditional default rate $\delta(n)$, assuming all agents receive loans.

$$\delta(n) = \int_0^1 (1 - \theta)n\theta^{n-1}d\theta = \frac{1}{n+1}.$$

One can see that $\delta(n)$ steadily decreases from 1 when $n = 0$ to 0 as $n \rightarrow \infty$. Thus, the parameter n captures all possible levels of credit risk in the economy.

All agents live in an area where there is one small local bank. In addition to the small bank, each agent can apply for a loan at many large out-of-area banks. We assume that large banks underwrite loans based on the publicly available information θ . In particular, large banks set interest charges $r_L(\theta)$ on their loans that reflect the credit risk associated with a type- θ agent. The borrowed amount at time $t = 0$ is set to $1 - r_L(\theta)$, while the repayment is set to \$1 at time $t = 1$. We interpret $r_L(\theta)$ as the loan interest rate¹. We normalize the cost of capital for large banks to zero. Assuming perfect competition among large banks, the bank must break even and the interest rate must be equal to the default probability:

$$r_L(\theta) = 1 - \theta. \quad (3)$$

Hence, agents borrowing from large banks obtain θ dollars in cash at time 0, with a promise to repay \$1, resulting in the expected payment of θ to the bank at time 1.

The small bank differs from large banks in two important ways. First, the small bank faces a higher cost of capital. This penalty can arise because the small bank is less diversified than large banks and does not benefit from implicit too-big-to-fail guarantees. Second, due to its proximity to local agents, the small bank can screen local loan applicants. Screening generates a private signal on each local borrower, either good g or bad b . For simplicity, we assume a perfect signal, i.e., the small bank knows with certainty whether the agent will repay a loan. As a result, the small bank gives loans only to the agents who will not default. One interpretation of our setup is that θ represents hard information—such as the historical and current performance of the property - that is publicly available to all lenders. Conversely, the signal solicited by the small bank relies on local soft information that is not easily accessible to out-of-area large banks. This soft information may include local socioeconomic trends, expectations regarding future demand for a specific property type in that location, and localized leasing dynamics, such as the likelihood of current tenants renewing or the availability of replacement tenants. Additionally, it can capture the physical condition of the property and its upcoming capital expenditure needs, as well as the reputation, willingness, and capacity of the property owners to service the loan during economic downturns. Finally, while large

¹Strictly speaking, the loan interest rate is equal to $r_L(\theta)/(1 - r_L(\theta))$. The differences between $r_L(\theta)/(1 - r_L(\theta))$ and $r_L(\theta)$ have no material implications for our model. For convenience, we will refer to $r_L(\theta)$ as the loan interest rate.

banks may operate local branches, we follow Stein (2002) in assuming that this soft information cannot be credibly transmitted upward through a large corporate hierarchy.

Let r_S be the interest rate on the small bank loans and $\rho \in (0, 1)$ the cost of capital for the small bank. On each loan, the small bank makes $r_S - \rho$ in profit. The small banks serves the segment of the market in which $r_L(\theta) > r_S$, or $\theta < 1 - r_S$. This segment is perceived as high-risk by large banks. However, due to its screening advantage, the small bank extends loans to fraction θ of type θ borrowers in this segment. The small bank total profit is given by

$$\pi(r_S) = \int_0^{1-r_S} (r_S - \rho)\theta f(\theta, n) d\theta. \quad (4)$$

Plugging (2) into (4) and integrating with respect to θ yields

$$\pi(r_S) = \frac{n}{n+1} (r_S - \rho) (1 - r_S)^{(n+1)}. \quad (5)$$

The small bank chooses the interest rate that maximizes its profit. The optimal interest rate r^* must satisfy the first order condition $\pi'(r^*) = 0$. Differentiating (5) and solving for r^* yields

$$r^*(n) = \frac{1 + (n+1)\rho}{n+2}, \quad (6)$$

with the corresponding profit of

$$\pi^*(n) = \frac{n}{n+1} (r^*(n) - \rho) (1 - r^*(n))^{(n+1)}. \quad (7)$$

By setting its interest rate at $r^*(n)$, the small bank splits the population of potential borrowers into two segments. In equilibrium, the large banks originate loans for all agents with $\theta \geq \theta^*(n)$, while the small bank selectively approves loans for agents with $\theta < \theta^*(n)$, where

$$\theta^*(n) \equiv 1 - r^*(n) = \frac{(n+1)(1-\rho)}{n+2}. \quad (8)$$

The total number of loans originated by large banks is given by

$$V_L(n) = 1 - F(\theta^*(n), n) = 1 - (\theta^*(n))^n.$$

Similarly, the total number of loans originated by the small bank is given by

$$V_S(n) = \int_0^{\theta^*(n)} \theta f(\theta, n) d\theta = \frac{n}{n+1} (\theta^*(n))^{n+1}.$$

Then, the market share of the small bank's loans is equal to

$$S(n) \equiv \frac{V_S(n)}{V_S(n) + V_L(n)}.$$

We show in Appendix that $S(n)$ is strictly decreasing in n . We summarize the above discussion in the following proposition.

Proposition 1. *In equilibrium, the large banks originate loans for all agents with $\theta \geq \theta^*(n)$, while the small bank screens the agents with $\theta < \theta^*(n)$ and grants loans conditional on obtaining a good signal.*

The market share of small bank loans $S(n)$ is a decreasing function of n . In other words, as the lending environment becomes more risky (n declines), the small bank's market share $S(n)$ increases.

Proof. See Appendix. □

The intuition behind Proposition 1 is as follows. In an economic environment dominated by safe borrowers, large banks capture a larger market share because their lower funding costs allow them to offer low-interest loans. Conversely, when the population of potential borrowers becomes riskier, large banks lose ground to the local small bank, which possesses a superior ability to screen high-risk borrowers.

We now turn our attention to how a change in the risk of the economic environment affects the profitability of the small bank. We note that:

$$\frac{\partial r^*(n)}{\partial n} = -\frac{1-\rho}{(n+2)^2} < 0. \tag{9}$$

Equation (9) implies that as the economy becomes safer (n goes up), the small bank lowers its interest rate in order to compete for safer borrowers against large banks. Conversely, in a riskier economy (n decreases), the small bank maximizes its profit by raising its interest rate, leveraging its information advantage over the growing population of risky borrowers.

Taking the derivative of the small bank's profit $\pi^*(n)$ with respect to n yields the following proposition.

Proposition 2. *The small bank’s profit $\pi^*(n)$ decreases in n if either $n > 1.212$ or $\rho > 1 - \frac{n+2}{n+1}e^{-\frac{1}{n(n+1)}}$. In other words, under these conditions, the small bank’s profitability increases as the lending environment becomes riskier (n decreases).*

Proof. See Appendix. □

Proposition 2 demonstrates that across a broad range of realistic parameters, the small bank becomes more profitable in a riskier economic environment. While this result may initially appear counterintuitive—given that the overall pool of creditworthy borrowers shrinks as n decreases - the underlying mechanism is driven by the information advantage of the small bank. Specifically, as the segment of risky borrowers expands, so does the demand for the small bank’s loans, which translates into higher profits for the small bank.

In what follows, we use the predictions and logic of the model developed here to explain recent patterns in community bank lending in CRE markets. Community banks fit the scope of the model well as they are characterized not only by their relatively small size but also by their distinctly local business model (FDIC, 2020), which plausibly allows them to develop their information advantage over large, non-local banks. The CRE market is a useful setting in which to study the lending activity of community banks as CRE assets are illiquid, heterogeneous, and their financial performance is strongly tied to local market conditions. In other words, CRE lending is a setting where any advantages in local information should be especially apparent (Garmaise and Moskowitz, 2004; Kurlat and Stroebl, 2015). Moreover, the Covid-19 pandemic introduced a large, unanticipated shock to economic conditions and elevated uncertainty in the CRE market (see, e.g., Gupta et al., 2022a,b). This period thus offers an opportunity to test the predictions of our model that community banks by virtue of their geographic proximity and focus are better equipped to issue informationally sensitive loans when uncertainty is high.

3 Data and Sample Construction

The primary data sources for this study are the Federal Deposit Insurance Corporation, the Federal Financial Institutions Examination Council, and MSCI, complemented with three specialist sources on CRE operating performance data by property type (Compstak, Yardi Matrix, and CBRE). Here, we describe each of these data sources in turn and outline the construction of our main sample.

3.1 Data Sources

The Federal Deposit Insurance Corporation (FDIC) maintains a database of all FDIC-insured institutions in the U.S. We obtain from it the full register of current and historical institutions, identified by FDIC certificate number. This register includes institution characteristics such as charter type (commercial bank or savings institution), charter agent (state or federal), and headquarter location coordinates. Importantly, it also contains an indicator for community banks based on measures of bank size, local scope, and focus on traditional intermediation through loans and deposits, as defined in the FDIC Community Banking Study (2020). Community banks are often misidentified or overlooked in the banking literature as prior research tends to focus on small banks defined solely by total assets (Petropoulou et al., 2025). In contrast, the FDIC definition incorporates key features of community banks’ local business model. This definition thus captures the characteristics that distinguish small banks from large banks in our model more fully (see Section 2).²

We obtain annual branch-network data for all FDIC-insured institutions from the Summary of Deposits (SOD), for 2010–2024. Each SOD snapshot lists a bank’s branches, including their location coordinates. Branches are assigned to bank headquarters by the FDIC certificate number, on which we merge the FDIC institution and branch-network data sets. The merged data captures institutional characteristics, headquarter locations, and point-in-time branch networks of FDIC-insured commercial banks and savings institutions over the 2010–2024 period.

The Federal Financial Institutions Examination Council (FFIEC) collects and standardizes the Call Reports, quarterly regulatory filings submitted by all FDIC-insured commercial banks and savings institutions in the U.S. Each filing details bank balance sheets, income statements, loan portfolio composition, asset quality, capital adequacy, and other key financial metrics. We obtain the quarterly Call Reports for FDIC-insured banks for 2010–2024. From these, we extract current CRE lending (non-/owner-occupied CRE and multi-family loans), along with modified, non-performing, and real estate owned CRE loans, and the inputs needed to compute bank-level financial metrics: total assets, capital ratio, liquidity ratio, earnings ratio, and loan ratio. We merge the FDIC

²For the purposes of this paper, we classify banks into three categories: community banks, large banks, and regional banks. In addition to the asset-size threshold of \$1.65 billion, the FDIC (2020) community bank definition incorporates a bank’s business plan, geographic footprint, and branch network. Large banks are those with at least \$100 billion in assets at any point during 2016–2024. All other banks are classified as regional banks. The 2020 Community Banking Study updates the FDIC’s first community banking study, published in 2012, and covers year-end 2011 through year-end 2019, retaining the definition of community banks established in the earlier edition. Between 2016 and 2024, only 195 of the 5,763 community banks (about 3%) lost their community bank status for at least a year under the official definition. We therefore treat the community bank identifier as time-invariant throughout our analysis. See Appendix B.1 for details.

bank register with the Call Report data based on the FDIC certificate number common to both. The merged data set tracks institutional characteristics and quarterly bank-level financial metrics for 6,567 FDIC-insured banks over 2010–2024. We refer to this as the FDIC–Call Report panel.

MSCI is a leading provider of CRE transactions and financing data in the U.S., relying on county-level deed records as the primary source.³ We obtain MSCI’s transaction-level records of CRE deals completed in the U.S. over 2000–2024. Each record contains unique transaction and property identifiers, numerous deal and property characteristics, and detailed information on the parties involved. Transaction characteristics include type (sale, refinancing, transfer), completion date, and property value; transfer records feature a comments field that lets us identify foreclosures. Property characteristics include type, address, and exact location coordinates. For acquisitions, we observe buyer and seller identities. For refinancings (and for mortgages used in CRE acquisitions), we observe the borrower’s identity and type (coinciding with the buyer in mortgage-financed acquisitions), the lender identity, loan issuance and maturity dates, and loan amount. We supplement these records using the MSCI investor module to identify the exact geographic location, including coordinates, of the headquarters of the buyers and borrowers observed.

We focus on CRE acquisition and refinancing transactions completed over 2016–2024 and involving mortgages issued by banks.⁴ We identify bank-issued mortgages by examining the lender names in the MSCI transactions data and validating them against the FDIC register of U.S. financial institutions. The resulting MSCI loan data set comprises 202,143 CRE loans issued by banks in the U.S. over 2016–2024 across both sales and refinancing transactions, associated with 3,632 unique banks.

We complement the bank- and loan-level data sets outlined above with different measures of property-level operating performance of CRE assets by property type.

Compstak is the leading provider of CRE leasing information in the U.S., covering office, industrial, and retail leases. Compstak sources contract-level lease terms from an extensive network of CRE brokers and other intermediaries. We obtain data on U.S. CRE leases signed between 2016 and 2024 to match the MSCI loan sample period. Each record contains detailed lease terms—asking rent, net effective rent, start and end dates, lease type (new or renewal), concessions (rent-free peri-

³As Anenberg et al. (2025) note, MSCI records CRE transactions of \$2.5 million or more. Community banks may be under-represented in MSCI as they tend to finance smaller deals. The MSCI data nonetheless suit our setting as we focus on the competition between community and large banks, and the market segment where large banks traditionally operate, and where that competition takes place, is well covered by MSCI.

⁴While MSCI CRE transaction data are comprehensive back to 2000, the loan records focus on CMBS loans prior to 2016, when bank loans were added to the data collection.

ods, tenant improvement allowances)—and property characteristics including location coordinates. The full data set contains 613,160 leases signed over 2016–2024 across 241,902 unique properties.

Yardi Matrix provides transaction-level records for U.S. multi-family properties, including transaction prices and dates, as well as ongoing monthly operating performance metrics and detailed property attributes such as location coordinates. We focus on multi-family properties transacted between 2016 and 2024 to match the MSCI loan data set, and extract data on monthly occupancy rates and annual rent per square foot for these properties. The full data set comprises 73,977 properties with complete monthly occupancy and rent information over 2016–2024.

CBRE provides hotel operating performance data collected annually through voluntary surveys of hotel financial statements across the U.S. The survey covers roughly 6,500 hotels—about 10% of U.S. hotel inventory—with a focus on larger, institutional-grade assets. The CBRE financial statements span 2017–2024 and contain annual operating performance metrics, including occupancy, average daily rate (ADR), revenue per available room (RevPAR), and gross operating profit (GOP).

Macroeconomic indicators including quarterly county-level unemployment rates are obtained from the U.S. Bureau of Labor Statistics, and house price indices (HPI) from Zillow. These cover unemployment rates for 3,222 counties and HPI values for 3,073 counties over 2010–2024.

3.2 Sample Construction

We construct our main estimation sample by merging the MSCI loan data set with the FDIC–Call Report panel containing data institutional characteristics, bank branch networks, and quarterly financial metrics. We supplement this sample with the operating performance data from Compstak, Yardi Matrix, and CBRE. Since there are no property identifiers common to all of these data sets, we implement several different matching procedures, depending on the information available in each. We outline these procedures below.

To match the MSCI loan and FDIC bank register, we first pre-process the data, standardizing bank names across both sets by capitalizing them and harmonizing acronyms (e.g., “National Association” for “N.A.”). We then apply a fuzzy matching algorithm based on vector decomposition of the standardized names, tokenizing them into sequences of two consecutive characters and comparing across data sets. We summarize each comparison in a Jaccard similarity index ranging from 0 to 1, where 1 indicates a perfect match, and consider matches of 0.9 or higher successful. Of the 3,632 unique banks in the MSCI loan data set, 2,975 are matched by this measure; we review the

remainder manually, successfully matching over 98% of MSCI banks. See Appendix B.2 for details. This procedure locates the FDIC certificate number for each bank in the MSCI data. We use this number to look up the bank’s headquarters location and compute its distance to the property financed by each loan, as well as the distance to the nearest branch in the bank’s network in the year the loan was issued.

Next, we merge bank financial characteristics from the Call Report data into the MSCI loan data set by FDIC certificate number, as of Q4 of the year before a loan is issued. This matters because the Call Reports record key financial variables cumulatively, with Q4 values representing annual totals. The resulting data set represents our main estimation sample: the MSCI loan records supplemented with the distances between a property and the lending bank’s headquarter and nearest branch, and a set of (financial) characteristics for the lending bank in the year prior to issuance.

We match leasing data from Compstak as well as occupancy and rent data from Yardi Matrix with the MSCI loan data using the property coordinates provided in each data set. On this basis, we compute pairwise geographic distances between all properties in MSCI and each of the two other data sets, retaining the shortest-distance pairs of the same property type as best matches and discarding those with distance exceeding 100 meters. The resulting data set captures 73,580 leases signed over 2016–2024 for 21,583 Compstak properties associated with 23,765 MSCI loans—roughly 20% of the industrial, retail, and office loans in MSCI (we retain only leases whose start date falls within the corresponding loan’s issuance and maturity dates). It also captures occupancy and rent information for 30,952 multi-family properties associated with 44,009 MSCI loans, or 84% of the apartment loans. We link CBRE hotel operating data to MSCI loan records using hotel address and shared property identifier. The matched sample captures operating data for 198 hotels over 2017–2024 associated with 210 hotel loans in MSCI (the CBRE hotel performance data are limited to a relatively small sample of larger, institutional-grade hotels).

3.3 Variable Definitions

In the FDIC–Call Report panel, *CRE Growth* is the quarterly growth rate of CRE loans outstanding. *NPL Share*, *Mod. Share*, and *REO Share* are non-performing, modified, and real estate owned CRE loans, respectively, as shares of total CRE loans outstanding. *Size* is total assets (\$ billion). *Age* is the current year minus the bank’s establishment year. *Capital Ratio* (total equity), *Liquidity Ratio* (cash, available-for-sale debt securities, and four times the quarterly average of federal funds

sold and securities purchased under agreements to resell), and *Loan Ratio* (four times the quarterly average of total loans) are scaled by total assets; *Earnings Ratio* is net income (loss) scaled by total equity. *CRE Spec.* equals one if the FDIC classifies the bank as a CRE specialist; specialization (see, e.g., Aldana, 2023; Paravisini et al., 2023) is a potential confounder for the local information advantage of community banks posited in our model (Section 2). See Appendix B.3 for details.

In the MSCI loan data, *Size* is property area ('000 sq.ft.), *Value* is property value per square foot at issuance (\$ '000), and *Age* is the issuance year minus the property's construction year. *Renovated (CBD)* equals one if the property was renovated after construction (is in the central business district). *LTV* is loan amount divided by property value. We also construct indicators for property type (apartment, hotel, industrial, office, retail), investor objective, and investor type: *Investment*, *Development*, and *Occupancy* equal one if the buyer's (borrower's) objective in an acquisition (refinancing) transaction is investment, development, or occupancy, respectively; *Private*, *Institutional*, and *User/Other* equal one if that buyer (borrower) is a private, institutional, or user/other investor, respectively. *Prev. Relation* equals one if the borrower previously financed a property with the lending bank; pre-existing lending relationships (see, e.g., Bolton et al., 2016; Berger et al., 2017; Beck et al., 2018) are another potential confounder for community banks' local information advantage.⁵

In our model, the information advantage with which community banks compete against large banks stems from proximity to the properties and borrowers they finance, a common proxy for such advantages in prior literature (see, e.g., Agarwal and Hauswald, 2010; Huang et al., 2026; Jiang et al., 2026). We therefore define *HQ Distance* and *Branch Distance* as the distance (in miles) between the property and the lending bank's headquarters or nearest branch, respectively. *HQ in MSA (Branch in MSA)* equals one if the bank's headquarters (nearest branch) is in the property's Metropolitan Statistical Area (MSA). We construct analogous indicators based on the headquarters locations of the investor owning the property and the lending bank.

In the Compstak lease data, *All* is the total number of leases signed for a property during the loan term. *Renewals (New)* is the number of renewals (new leases) signed during the loan term. *Free Rent* is the average number of rent-free months, scaled by total lease term, across leases signed during the loan term. *Start. Rent* is the average monthly starting rent per sq.ft. across those leases. *Eff. Rent* is the average monthly effective rent, after concessions such as tenant improvement allowances and rent-free periods, across those leases. In the Yardi Matrix multi-family data, *Occ.*

⁵Although our main sample spans 2016–2024, we measure *Prev. Relation* from 2000 for maximum coverage. Because MSCI bank loan coverage expanded in 2016, this variable likely reflects a lower bound.

is the average monthly occupancy rate during the loan term. *Rent* is the average annual rent per square foot during the loan term. *Occ. Growth* and *Rent Growth* are the average monthly occupancy and rental growth rates during the loan term. In the CBRE hotel data, *Occ.* is the average annual occupancy rate during the loan term. *ADR* is the average daily rate during the loan term. *RevPAR* is the average annual revenue per available room during the loan term. *GOP Margin* is the average annual gross operating profit, scaled by total revenue, during the loan term. We use these measures to track ex-post operating performance of CRE loans issued by community versus large banks.

Unemployment is the county-level unemployment rate. *HPI Level* is the level of the county-level Zillow house price indices, scaled to a base period of 2010 Q1. *HPI Growth* is the quarterly growth rate in these indices. These variables are measured for the county of a given bank headquarter location in the FDIC–Call Report panel and a given property location in the MSCI loan data set.

3.4 Descriptive Statistics

Table 1 presents summary statistics for the FDIC–Call Report panel over 2010–2024 by bank type. Average growth in CRE loans outstanding does not differ significantly across bank types; however, this measure captures net changes in outstanding CRE loan balances, whereas our analyses focus on new loan issuance at the loan level. Community banks are significantly smaller than both regional and large banks, older than regional but younger than large banks, and less well capitalized than regional banks. Compared to large banks, they have lower earnings ratios and higher loan ratios, while liquidity ratios are similar across bank types. These differences highlight the importance of accounting for time-varying bank financial characteristics in our estimations. CRE specialization is common across bank types (55% of community, 72% of regional, and 35% of large banks are FDIC-classified CRE specialists) and is a potential confounder for community banks’ local information advantage, which we will also account for in our empirical analyses.

[Table 1 about here.]

Table 2 presents summary statistics for the MSCI loan data set over 2016–2024 by bank type.⁶ Community banks lend on significantly smaller and less valuable properties that are less likely to be located in a CBD than those financed by regional and large banks, and on younger properties with slightly higher LTVs than those financed by large banks. We account for these differences in

⁶Figure C.1 shows the distribution of properties across U.S. counties. Figure C.2 breaks down the sample by bank type across property type, investor type, and investor objective.

property and loan characteristics in our analyses. We see that 38% of community bank loans are on properties in the same MSA as the lending bank’s headquarters, compared to 24% and 9% for regional and large banks, whereas the ordering reverses for the nearest branch (54%, 67%, and 87%).⁷ This pattern is consistent with community banks’ limited geographic scope (FDIC, 2020) and denser branch networks of larger banks. Indicators based on the investor’s headquarters location instead of the property location show similar patterns, consistent with the CRE market being dominated by small-scale, local investors. Finally, we see that pre-existing CRE lending relationships are common across bank types. Because such relationships are a potential confounder for community banks’ local information advantage, we account for them in our analyses.

[Table 2 about here.]

Table 3 presents summary statistics for operating performance metrics by property type. Properties financed by community banks on average generate lower rents than those financed by regional and large banks, in terms of asking and net effective rents for retail, office, and industrial properties (Panel A), multi-family rents (Panel B), and average daily rates and revenue per available room for hotels (Panel C). Properties financed by community banks also see a higher share of new leases relative to renewals and a lower free rent share. We will study pandemic-period operating performance across properties financed by community versus large banks as an indicator for community banks’ ability to identify creditworthy borrowers in risky lending environments as posited in our model.⁸

[Table 3 about here.]

4 CRE Lending Activity of Community Banks

Proposition 1 of our model implies that the market share of community banks should increase as the lending environment becomes riskier. This result is predicated on community banks’ local information advantage becoming more valuable in risky lending environments because it allows them to

⁷Figure C.3 shows the distribution of property–bank distances. Nearly 50% of community bank loans are on properties within 50 miles of the lending bank’s headquarters, versus 20% of non-community bank loans (Panel A), whereas approximately 80% of non-community bank loans are within 50 miles of the nearest branch, versus 60% of community bank loans (Panel B).

⁸Tables C.1, C.2, and C.3 compare key bank, property, and local economic characteristics across the FDIC–Call Report panel, the MSCI loan data set, and the Compstak lease data set. These characteristics are generally comparable, except that: (i) community banks in the FDIC–Call Report panel are, on average, smaller and older than those in the MSCI and Compstak data sets; (ii) properties in the MSCI loan data set are, on average, smaller and less valuable per sq.ft. than those in the Compstak lease data set; and (iii) unlike MSCI, Compstak does not cover apartment or hotel properties.

identify creditworthy borrowers that appear too risky to large banks. As a consequence, we expect community banks to expand in such environments, at the expense of large banks, and especially in informationally sensitive lending segments.

Throughout our analyses, we treat the period from the onset of the Covid-19 pandemic through the end of our sample in 2024 as a risky lending environment in the sense of our model: the pandemic beginning in 2020 introduced a persistent increase in fundamental risk and valuation uncertainty in CRE (Gupta et al., 2022a,b), which was amplified by the 2022–23 monetary tightening cycle (Jiang et al., 2025), raising financial stability concerns through 2024 (Board of Governors of the Federal Reserve System, 2025). For brevity, we refer to this entire period as the Covid-19 pandemic. Our estimating equations build on the rich covariate and fixed-effects specifications in closely related recent work on consumer and small business lending during that time (Berger et al., 2024).

4.1 Increase in Lending Activity

We begin to evaluate the evidence for Proposition 1 by assessing the differential likelihood that a CRE loan is issued by a community bank during the Covid-19 pandemic versus before. We estimate the following linear probability model in the MSCI loan data set over the 2016–2024 period:

$$Comm. Bank_{i,p,t} = \alpha Covid_t + \sum_{m \in M} \delta_m Z^{m \in M} + \epsilon_{i,p,t} \quad (10)$$

where $Comm. Bank_{i,p,t}$ indicates whether the bank providing loan i against property p at time t is classified by the FDIC as a community bank, and $Covid_t$ indicates any time t from Q2 2020 onward, following the World Health Organization’s March 2020 pandemic declaration. $Z^{m \in M}$ represents $M = 4$ sets of controls—on the property, loan, borrower, and bank level—measured as of loan issuance unless otherwise stated. Property covariates include the natural logarithms of property size (in ’000 sq.ft.) and value per sq.ft., property type indicators (hotel, industrial, office, or retail, with apartment omitted), property age, and indicators for post-construction renovation and central-business-district location. Loan covariates include the loan-to-value ratio at issuance. Borrower covariates include investor type (institutional or user/other, with private omitted), investor objective (re-development or occupancy, with investment omitted), and an indicator for a prior CRE financing relationship with the same bank. Bank covariates include capital, liquidity, earnings, and loans-to-assets ratios, measured as of Q4 of the most recent year prior to issuance. Standard errors are clustered by bank. The coefficient α captures the differential likelihood that a CRE loan is

issued by a community bank during the pandemic. In alternative specifications, we add county fixed effects, property fixed effects, and county-level covariates to capture potential confounders.

Table 4 presents estimates of Eq. (10). Column 1 indicates that, accounting for observable property, loan, investor, and bank covariates, new CRE loans are significantly more likely to be issued by a community bank during the pandemic than before it. This result holds under county fixed effects (column 2) and property fixed effects (column 3). Column 4, our preferred specification, adds local economic characteristics to the property fixed effects and full covariate set. The coefficient α of 0.033 indicates that the same property is 3.3 percentage points more likely to be financed by a community bank during the pandemic than before it—an over 10% increase relative to the unconditional mean likelihood of community bank financing in this sample of 0.321. These results suggest the elevated economic uncertainty during the pandemic benefited the growth in market share of community banks, consistent with the state-contingent local information advantage formalized in our model.⁹ In the following sections we provide additional tests focused on the components and mechanisms of our theoretical model to corroborate this interpretation.

[Table 4 about here.]

4.2 Persistence of Geographic Scope

The community bank attribute that gives rise to their local information advantage in our model is their characteristically small geographic scope of operations (FDIC, 2020); indeed, nearly 40% of community bank CRE loans are for properties in the same MSA as the bank’s headquarters (see Section 3.4). If the expansion in community bank CRE lending we document above reflects this advantage becoming more valuable in risky lending environments, that growth should occur within community banks’ existing geographic footprint rather than further afield.

To test whether community banks extended CRE loans on properties further afield during the pandemic, we examine variation in the physical distance between a property and the lending bank’s location in the MSCI loan data set over 2016–2024, estimating OLS regressions of the following form:

$$Distance_{b,i,p,t} = \alpha_b + \beta_t + \gamma Comm. Bank_b \times Covid_t + \sum_{c \in C} \delta_c Z^{c \in C} + \epsilon_{b,i,p,t} \quad (11)$$

⁹These inferences are corroborated in bank-level analyses estimating the quarterly growth rate in CRE loans outstanding as a function of bank type in the FDIC–Call Report panel over 2010–2024; see Table C.4. Figure C.4 provides supporting event-time evidence on the increase of community bank CRE lending around the onset of the pandemic in Q2 of 2020. Reassuringly for our empirical design, the figure shows no significant effects or differential pre-trends in the likelihood of community bank CRE financing prior to the pandemic.

where $\text{Distance}_{b,i,p,t}$ is the natural logarithm of the distance (in miles) between the headquarter location of bank b issuing loan i for property p at time t . In alternative specifications, we replace the dependent variable with an indicator for the bank’s headquarters being in the same MSA as the property, the natural logarithm of the distance between the lending bank’s nearest branch and the property, and an indicator for that nearest branch being in the same MSA as the property. α_b are bank fixed effects, accounting for time-invariant bank characteristics, and β_t are year-quarter fixed effects, accounting for broad macroeconomic trends. *Comm. Bank_b* indicates whether bank b is classified by the FDIC as a community bank, and *Covid_t* indicates any year-quarter t from Q2 2020 onward. As in Eq. (10), $Z^{c \in C}$ represents $C = 5$ sets of controls—on the level of the property, loan, borrower, bank, and county. $\epsilon_{b,i,p,t}$ is the residual, and standard errors are clustered by bank. The coefficient γ captures the differential change in physical distance between community vs. large bank locations and the properties they finance during the pandemic.

Table 5 estimates of Eq. (11). Panel A (Panel B) presents results based on the physical distance between a given property and the lending bank’s headquarter location (the lending bank’s nearest branch location). To mitigate the influence of outliers and extreme values, we winsorize and, alternatively, trim the physical distance measure at the 99th percentile. The estimates reported reveal little evidence of significant changes in the physical distance between community bank locations and the properties financed by these banks during the Covid-19 pandemic. These results hold after accounting for the full set of control variables, in the presence of bank and year-quarter fixed effects, for different outlier treatments, and across various measures of distance between a given bank and the properties financed. The evidence presented suggests that community banks increased their CRE lending activity during the Covid-19 pandemic (as shown in Section 4.1) within their existing geographic scope of operations, rather than expanding into new markets further afield. These findings are consistent with the premise of our model that community banks leverage the information advantage they possess in their local markets to compete with large banks in risky lending environments.

[Table 5 about here.]

4.3 Expansion in Risky Property Types

The framework in Section 2 implies that community banks, by virtue of their local information advantage, screen borrowers more effectively than large banks in risky lending environments, allowing them to grow their market share by identifying creditworthy borrowers that appear too risky to large

banks. A plausible determinant of the perceived risk of a CRE loan during the pandemic was the type of property financed. CRE performance varied substantially across property types, where hotels and retail experienced sever disruption from early shut-down orders and social distancing mandates (Ling et al., 2020; Steiner and Tchisty, 2024), while office properties were adversely affected by the shift to remote work (Gupta et al., 2022b). To test whether community banks expanded into segments that appeared high-risk at the time, we augment Eq. (10) with interactions between the Covid indicator and property-type dummies, controlling for the full set of property, loan, investor, and bank characteristics, local economic conditions, and county fixed effects. Figure 2 summarizes these interaction estimates. The hotel and retail interactions are statistically significant at the 10% level, indicating that community banks were more likely to finance these property types during the pandemic. Our findings suggest that community banks expanded their CRE lending overall during the pandemic (as shown in Section 4.1), but more so in high-risk property types where borrower screening is particularly important. This finding is consistent with the proposed mechanism in our model, whereby community banks possess a superior ability to identify creditworthy borrowers when the share of risky borrowers in the market increases, expanding their market share at the expense of large banks.

[Figure 2 about here.]

4.4 Competition with Large Banks

To assess the degree to which the pandemic-era increase in community bank CRE loan issuance documented above represents substitution away from large banks—consistent with the competition mechanism emphasized in our model—we trace switches in lender type for properties with more than one observed loan, using an augmented version of Eq. (10):

$$\begin{aligned} \text{Comm. Bank}_{i,p,t} = & \alpha \text{Covid}_t + \beta \text{Prev. Large Bank}_p + \gamma \text{Covid}_t \times \text{Prev. Large Bank}_p \\ & + \sum_{c \in C} \delta_c Z^{c \in C} + \epsilon_{i,p,t} \end{aligned} \quad (12)$$

where $\text{Comm. Bank}_{i,p,t}$ indicates whether the bank providing loan i against property p at time t is classified by the FDIC as a community bank, and Covid_t indicates any time t from Q2 2020 onward. $\text{Prev. Large Bank}_{i,p,t}$ indicates whether the previous loan against property p was provided by a large bank, defined as one with at least \$100 billion in assets at any point over 2016–2024. As in Eq. (10), $Z^{c \in C}$ represents $C = 5$ sets of controls—on the level of the property, loan, investor,

bank, and local economic fundamentals. Standard errors are clustered by bank. The coefficient γ captures the differential likelihood that a CRE loan is issued by a community bank during the pandemic when the same property was previously financed by a large bank.

We estimate Eq. (12) in the full MSCI loan data set and split by transaction type (acquisition versus refinancing loans). Refinancing deals by the incumbent lender require less new information production than acquisition financing, because the relevant asset- and borrower-level information has already been observed. Acquisition financing, in contrast, requires the lender to evaluate a property under a new owner and asset management plan. Its future cash flows depend on local demand, tenant quality, and the new owner’s execution. Greater proximity to the property and its local market should help lenders assess these factors. If community banks’ competitive advantage stems from local information, as posited in our model, we would therefore expect the substitution of CRE lending activity to be more pronounced in acquisition loans relative to refinancing loans.

Table 6 presents estimates of Eq. (12) in the MSCI loan data set over 2016–2024, split by transaction type (all transactions, sales, and refinancing deals). The *Covid* coefficients across all columns suggest that CRE loans were more likely to be issued by a community bank during this period, consistent with the growth we document in community bank CRE lending during the pandemic (see Tables 4 and C.4). The negative coefficients on *Prev. Large Bank* suggest that community banks and large banks typically lend in different segments of the CRE market, consistent with the unconditional patterns in Table 2 and prior evidence on intermediary segmentation (Glancy et al., 2022).¹⁰

[Table 6 about here.]

The main coefficient of interest in Table 6 is the interaction between the *Covid* and *Prev. Large Bank* indicators. In column 1, this coefficient is significantly negative, indicating that community banks were less likely to lend on properties previously financed by large banks during the pandemic than before it—implying growing segmentation in the CRE lending market. However, the results contrast sharply across sales and refinancing transactions. Column 2 indicates that during the pandemic community banks were *more* likely to issue loans on properties previously financed by large

¹⁰As noted, we exclude regional banks from our competition analysis. By definition, regional banks may exhibit characteristics of both community and large banks, making their underlying business models difficult to categorize. In addition, Maingi (2026) documents substantial deposit reallocation within the regional banking sector during the 2023 regional bank panic, highlighting the intensity of competition among regional banks themselves during periods of uncertainty, at least in the deposit market. Our results echo Maingi (2026), but in the CRE lending market, where we find little evidence of meaningful competition between community and regional banks. Table C.5 presents these results, employing the specification in Eq. (12) but replacing *Prev. Large* with *Prev. Regional*. We find no significant evidence that community banks compete with, or gain market share from, regional banks in CRE lending amid uncertainty.

banks when those loans financed a sale. In contrast, column 3 shows that the reduced likelihood of a community bank loan for a property previously financed by a large bank is concentrated among refinancing loans (which large banks seem to continue to provide). Importantly, these estimations all account for pre-existing CRE financing relationships between borrowers and lending banks.

Viewing new acquisition loans as more informationally sensitive than refinancing previously known CRE assets, the findings reported in Table 6 are consistent with community banks competing on their ability to identify creditworthy borrowers in risky lending environments, the core mechanism in our model. Additional testing reveals that the substitution of CRE lending activity to community banks we document is unlikely to be driven by large banks’ wholesale withdrawal from CRE lending during the pandemic, for which we find little evidence.¹¹ Nevertheless, part of large banks’ continued refinancing activity could be related to extend-and-pretend strategies documented for some lenders during the pandemic (see, e.g., Crosignani and Prazad, 2024; Cole and Huberdeau-Reid, 2026)

To corroborate community banks’ local information advantage as the driver of the superior screening ability allowing them to expand at the expense of large banks, we test whether the substitution of CRE acquisition financing to community banks during the pandemic was stronger in those banks’ local markets. We assess the evidence for this conjecture by re-estimating Eq. (12) in our sample of sales loans over the 2016–2024 period, split by whether the property financed is located in the same MSA as the headquarters of the lending bank (respectively, the nearest branch of the lending bank). This test again relies on closer distance between lenders and borrowers—here, the properties financed—as a proxy for information advantages, as established in prior literature (see, e.g., Agarwal and Hauswald, 2010; Huang et al., 2026; Jiang et al., 2026). Table 7 presents the results.

[Table 7 about here.]

Columns 1 and 2 of Table 7 indicate that properties previously financed by large banks were more likely to obtain community bank financing during the pandemic when located in the same MSA as the lending bank’s headquarters. Viewing property-bank proximity as a proxy for the cost of acquiring local soft information about property performance, this finding suggests that community banks are more likely to finance properties for which such information is more readily accessible—an advantage that large banks, whose headquarters are typically distant from the properties they finance (see Table 2), are less likely to possess. By contrast, columns 3 and 4 provide little evidence

¹¹Appendix D provides further evidence against a wholesale withdrawal of large banks from CRE lending during the pandemic using data on mortgage approval rates for multi-family properties and drawing on the Federal Reserve Board’s Senior Loan Officer Opinion Survey on Bank Lending Practices.

that proximity between a property and the lending bank’s nearest *branch* affects the likelihood of community bank financing during the pandemic. These findings suggest that CRE lending decisions, while involving local soft information that cannot be easily transmitted within an organization (Liberti and Petersen, 2019), may require centralized approvals rather than being fully delegated to branches (for a discussion of decentralized lending organizations, see, e.g., Stein, 2002; Berger et al., 2005; Canales and Nanda, 2012; Lim et al., 2025).¹² In sum, our results imply that community banks increase their market share relative to large banks in risky lending environments notably through informationally sensitive loans where they can leverage a local information advantage, consistent with the competition mechanism emphasized in our model.

5 CRE Loan Performance of Community Banks

In Section 4, we provide evidence consistent with Proposition 1 of our model and its underlying premises: community banks increased their CRE lending during the pandemic, at the expense of large banks, by leveraging their local scope, and expanding into informationally sensitive lending segments, notably property types severely hit by the pandemic and new acquisition loans. We now turn to Proposition 2, which implies that community banks should become more profitable in risky lending environments. This result is driven by two factors. First, if community banks can indeed identify creditworthy borrowers in risky environments, their loans should perform better. Second, because large banks screen borrowers less effectively, they must raise interest rates to compensate, which in equilibrium allows community banks to charge somewhat higher rates as well. While interest rates are not sufficiently well populated in the MSCI loan data to permit formal analyses, our final set of tests is focused on bank-, loan-, and property-level performance outcomes during the pandemic.

5.1 Non-Performing, Modified, and REO Loans

We begin by examining CRE loan performance on the bank-level. Figure 3 plots annual shares of non-performing, modified, and REO loans in the FDIC–Call Report panel from 2016 to 2024 by bank type. Panel A shows that non-performing loan shares hover between 0.5% and 1% of total CRE loans across bank types before the pandemic. From 2020, the share at large banks rises sharply, reaching 2.5% in 2024, while shares at community banks barely exceed 0.5%. Panel B shows a

¹²Table C.6 presents these analyses based on the headquarters location of the investor owning the property relative to the location of the bank; our inferences remain unchanged.

similar pattern for modified loans: shares decline across bank types to about 0.1% in 2019, then rise sharply at large banks to 0.5% in 2024 but remain low for community banks. Panel C shows that REO shares fall from about 0.4% to 0.1% at community banks and from 0.2% to 0.1% at regional banks between 2016 and 2024. At large banks, REO shares begin to tick up slightly from 2020.

[Figure 3 about here.]

We formalize the analyses of non-performing, modified, and REO loan shares across bank types by estimating OLS regressions of the following form:

$$NPL\ Share_{b,t} = \alpha_b + \beta_t + \gamma Comm. Bank_b \times Covid_t + \sum_{m \in M} \delta_m Z^{m \in M} + \epsilon_{b,t} \quad (13)$$

where $NPL\ Share_{b,t}$ is the share of non-performing CRE loans outstanding at bank b in quarter t . $Comm. Bank_b$ equals one if the FDIC classifies bank b as a community bank, and $Covid_t$ equals one from 2020Q2 onward. Bank fixed effects, α_b , absorb time-invariant bank characteristics, including the main effect of $Comm. Bank_b$; year-quarter fixed effects, β_t , absorb macroeconomic trends, including the main effect of $Covid_t$. $Z^{m \in M}$ represents $M = 2$ sets of covariates. The first contains bank characteristics measured as of Q4 of the most recent year ($t = mr$): an FDIC CRE specialist indicator and ratios of capital, liquidity, earnings, and loans to assets. The second contains local economic conditions in the county of the bank’s headquarters, c , lagged one quarter: the unemployment rate and the level and quarterly growth of the house price index. $\epsilon_{b,t}$ is the residual, and standard errors are clustered by bank. In alternative specifications, the dependent variable is $Mod. Share_{b,t}$ or $REO Share_{b,t}$, the share of modified or real estate owned CRE loans. We estimate these regressions in the FDIC–Call Report panel over 2016–2024, focusing on community banks and large banks. Table 8 presents the results.

[Table 8 about here.]

Columns 1 and 2 of Table 8 show that community banks had significantly lower non-performing loan shares during the pandemic than non-community banks. The estimate is robust to controlling for time-varying bank characteristics and local economic conditions (column 2), and it is economically large. The coefficient of -0.013 in column 2 implies that community banks’ NPL share rose by 1.3 percentage points less than that of large banks during the pandemic. Large banks’ NPL share increased by approximately two percentage points over this period (see Figure 3), so community banks

avoided roughly two thirds of this deterioration. Columns 3 and 4 (respectively, 5 and 6) show that community banks also held significantly modified loan shares and REO shares during the pandemic, consistent with stronger loan outcomes. Consistent with recent evidence (Cole and Huberdeau-Reid, 2026), Table 8 shows that community banks’ CRE loans performed better than those of large banks during the pandemic, in terms of non-performing loans, modifications, and foreclosures.

Glancy and Kurtzman (2024) report that a significant share of bank-level variation in CRE loan performance during the Covid-19 pandemic is due to differential pre-existing exposure to loans on properties that were adversely affected by pandemic-era trends such as remote work. The estimates presented in Table 8 reflect both pre-pandemic and pandemic-era lending decisions. To sharpen our inferences, we dig deeper into these headline findings and examine CRE lending outcomes on the loan-level by bank type and issuance date.

5.2 CRE Loan Foreclosures

While we cannot observe ongoing loan-level performance outcomes such as delinquency or modifications in the MSCI data set, we are able to observe foreclosures. As outlined in Section 3, the MSCI data set contains records on transfers that feature a comments field flagging such events. We thus define an indicator $Foreclosure_{i,p,t}$ that takes the value of one if the MSCI transfer records show that loan i for property p issued at time t was subsequently the subject of a foreclosure. We then replicate the estimation of Eq. (11) but replace the dependent variable with this indicator. We estimate these regressions in the MSCI loan data set over the 2016–2024 period. Again, we focus on community banks and large banks, which are at the center of our model. To avoid right-censoring and misclassifying loan performance outcomes, we also exclude all loans for which we cannot observe a final outcome (sale, refinance, or foreclosure). Table 9 presents the results for community versus large banks.

[Table 9 about here.]

The coefficient estimates reported in Table 9 indicate that loans issued by community banks during the pandemic had a significantly lower likelihood of foreclosure than did those issued by large banks during the same period. These results hold in the presence of bank and year-quarter fixed effects (column 1), after accounting for time-varying bank financial characteristics and local economic controls (column 2), and after additionally accounting for property, loan, and investor controls (column 3). In sum, the loan-level evidence presented in Table 9 corroborates the bank-level

evidence from Table 8 that community banks experienced superior CRE loan performance relative to large banks during the Covid-19 pandemic.

However, given the limited post-pandemic time horizon in the MSCI loan data set and the often protracted resolution of CRE foreclosures, observed foreclosure outcomes may understate loan distress. An alternative explanation involves variation in foreclosure practices, whereby some banks may be more likely to delay foreclosure. Such “extend-and-pretend” behavior, documented for instance in Crosignani and Prazad (2024) and Cole and Huberdeau-Reid (2026), allows banks to defer loss recognition in hopes of improved future conditions, potentially masking the true extent of distress (see also Hinzen et al., 2025). While we lack comprehensive loan performance data, property-level operating performance metrics can provide insight into ex-post credit quality (Glancy and Wang, 2023). We examine a set of such metrics in the next section for five major CRE property types.

5.3 Property Operating Performance

We first assess property-level leasing activity for industrial, retail, and office properties based on the Compstak data, merged with the MSCI loan data set over the 2016–2024 period using the procedure outlined in Section 3.2. For each loan in the merged MSCI-Compstak data set, we examine the total number of leases signed in the property backing the loan during the loan term, broken down by lease type (renewal or new lease). We also examine the average number of rent-free months included in these leases (scaled by total lease term in months), along with the average monthly starting rent and the average monthly effective rent per sq.ft. We then use the regression specification from Eq. (11) to estimate each of these loan-level outcomes as a function of bank type and loan issuance date. Specifically, we estimate this specification as a Poisson pseudo-ML model for the count variables (number of leases signed), as a linear OLS model for the free rent share, and as a log-linear OLS model for starting and effective rent. Table 10 presents the results for community versus large banks.

[Table 10 about here.]

Panel A presents results for industrial, retail, and office properties. The estimates in column 1 indicate that loans issued by community banks during the pandemic were backed by properties with significantly higher leasing activity. The PPML coefficient of 0.125 implies an over 13% increase in the number of leases signed. Columns 2 and 3 show that this increase is driven mainly by new leases rather than renewals. Columns 4 to 6 show no significant differences in rent-free periods, starting

rents, or effective rents. In sum, community bank loans during the pandemic involved properties that attracted more tenants without offering greater concessions or accepting lower rents.

Panel B in Table 10 presents the results for operating performance in apartment properties, namely, average monthly occupancy and rent per square foot, along with their growth rates, using the specification from Eq. (11). Across all metrics, we find no statistically significant differences between properties financed by community banks and those financed by large banks during the pandemic. Because apartments outperformed other property types amid strong housing demand and were widely considered a safer asset class during this period (Gamber et al., 2023; Ling et al., 2020), these results suggest that community banks financed relatively stable and resilient assets.

Lastly, we examine hotel operating performance for in the CBRE data. Given the small size of the merged data set, we replace the bank and year-quarter fixed effects in Eq. (11) with indicators for the pandemic period and community banks to preserve statistical power. Panel C in Table 10 presents the results. Column 1 shows that hotels financed by community banks during the pandemic had significantly higher occupancy rates than those financed by large banks. The effect is economically substantial: the 10.7 percentage point difference represents about 16% of the sample mean occupancy rate (65.7%). Columns 2 to 4 show no statistically significant differences in ADR, RevPAR, or GOP margin. Taken together, community banks were more likely to finance hotels that attracted more guests while maintaining comparable pricing, revenue generation, and operational efficiency. This pattern is consistent with community banks leveraging a local information advantage to identify creditworthy borrowers within the riskiest CRE segment, as hotels were among the hardest-hit property types during the pandemic (Ling et al., 2020; Steiner and Tchisty, 2024).¹³

In sum, properties financed by community banks during the pandemic exhibited operating performance at least comparable and often superior to that of properties financed by large banks—notably in riskier property types—an important prerequisite for stronger loan performance and the improved profitability of community banks implied in Proposition 2 of our model.

¹³The CBRE data cover mainly investment-grade hotels and thus excludes many economy hotels, which are often the primary target of community bank financing. Nevertheless, within the investment-grade segment, community banks were more effective at financing hotels with stronger demand during the pandemic.

6 Conclusion

We study the growing role of community banks in CRE lending during the Covid-19 pandemic and its aftermath, when concerns about banks' CRE exposure were widespread. We explain this expansion with a simple model of banking competition in which large banks have a lower cost of capital, while community banks have a local information advantage in screening borrowers. This advantage becomes more valuable as the lending environment becomes riskier, so community banks gain market share and can become more profitable.

Our empirical evidence supports these predictions in a large sample of CRE loans issued between 2016 and 2024, where the same property became significantly more likely to be financed by a community bank during the pandemic and its aftermath. This expansion occurred within community banks' existing geographic footprint and was most pronounced for hotel and retail properties, the segments hit hardest early in the pandemic. Community banks gained market share from large banks mainly in acquisition loans, which are more informationally sensitive than refinancing previously known assets. Lender substitution was also concentrated among properties in the same MSA as the lending bank's headquarters, consistent with the local information advantage at the core of our model. Ex post, community banks performed better than large banks on several measures: they had lower shares of non-performing, modified, and real estate owned CRE loans, and their pandemic-era CRE loans had lower foreclosure rates by the end of our sample. Industrial, office, and retail properties they financed signed more new leases without greater concessions or lower rents, and hotels they financed had higher occupancy with comparable pricing and profit margins.

Our study contributes to the literature on CRE lending and banks' CRE exposure, which has largely focused on distress, forbearance, and the segmentation between bank and securitized lending. We instead highlight competition between bank types, driven by community banks' local information advantage. We also add to the literature on credit provision during downturns by showing that community banks extended new credit in a risky environment without apparent deterioration in credit quality, even after accounting for relationship lending. Community banks can thus be a stabilizing source of credit when uncertainty erodes large banks' cost of capital advantage. Supervisory assessments of community banks' CRE concentration should account for their superior screening ability in local markets. Continued consolidation of the community banking sector may also erode the local information capital that supports lending to creditworthy borrowers during downturns.

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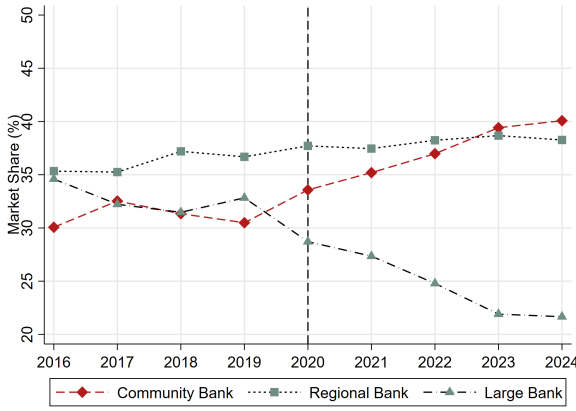
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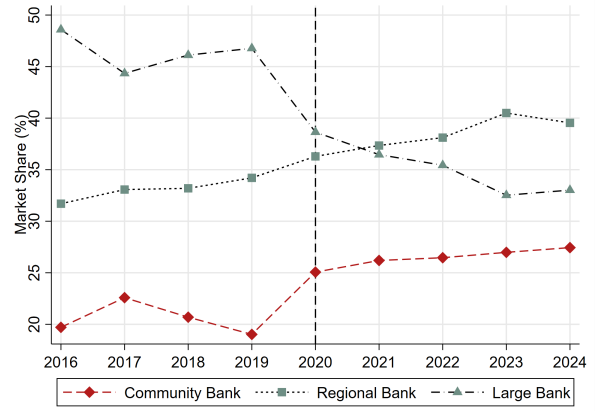
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Figure 1. Market Shares in CRE Loan Issuance

This figure depicts annual trends for market shares in CRE loan issuance by U.S. banks over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification (see Section 3.1). Large banks are those with at least \$100 billion in assets at any point during this period. All other banks are classified as regional banks. Panel A shows the aggregate shares of CRE loans issued by loan count. Panel B shows the aggregate shares of CRE loans issued by loan amount. The data used to produce this figure are from MSCI.



(A) Loan Count



(B) Loan Amount

Figure 2. CRE Loan Issuance by Community Banks by Property Type

This figure depicts the results from estimating Eq. (10) with interaction terms between a COVID-period indicator and property type dummies in the MSCI loan data set over the 2016–2024 period. Property types include apartment, hotel, industrial, office, and retail. Our estimations include property, loan, investor, and bank covariates, local economic characteristics, and county fixed effects. The markers indicate the coefficient estimates on each property type interacted with the Covid period indicator. The capped lines indicate 90% confidence intervals around the coefficient estimates. The data used to produce this figure are from the FDIC, FFIEC, MSCI, BLS, and Zillow.

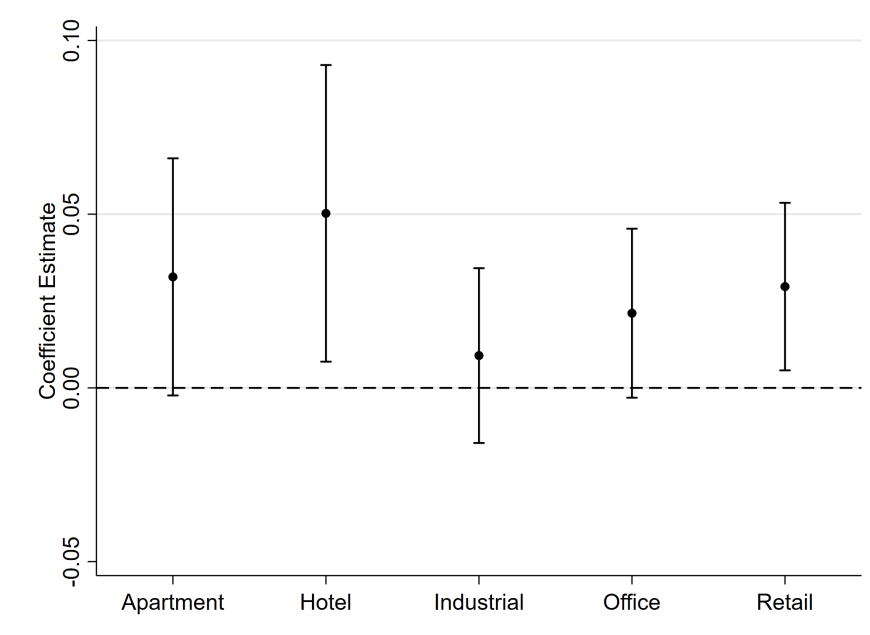
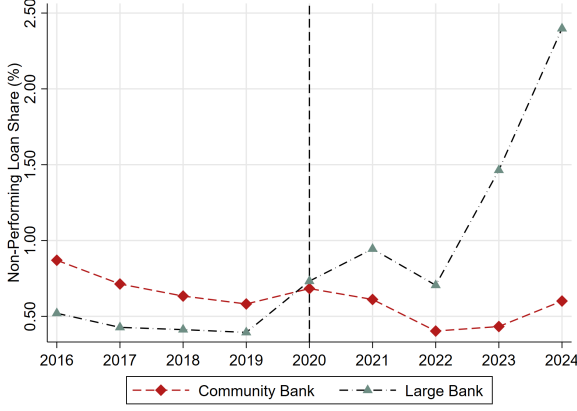
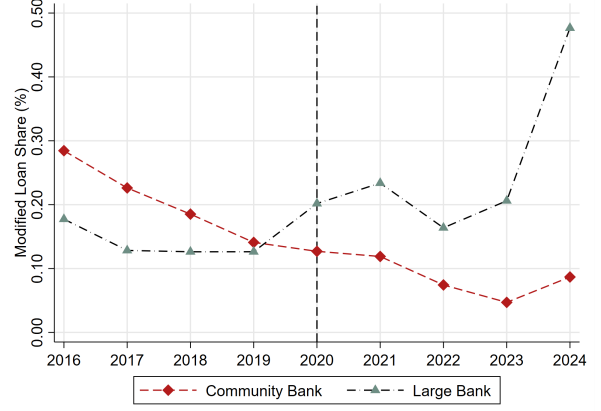


Figure 3. CRE Loan Performance

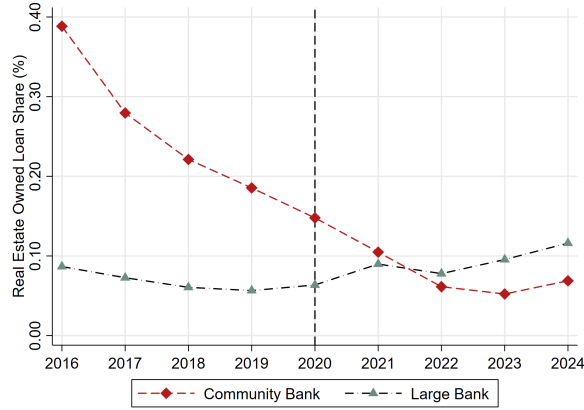
This figure depicts annual trends in the performance of CRE loans outstanding over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification (see Section 3.1). Large banks are those with at least \$100 billion in assets at any point during this period. Panel A (respectively, Panel B and Panel C) shows the share of non-performing CRE loans (modified CRE loans and real estate owned CRE loans) relative to total CRE loans. The data used to produce this figure are from the FFIEC Call Reports.



(A) Non-Performing Loans



(B) Modified Loans



(C) Real Estate Owned Loans

Table 1. Descriptive Statistics FDIC Call Report Panel

This table presents summary statistics for the FDIC Call Report panel over the 2010–2024 period by bank type. Community banks are defined based on the FDIC classification (see Section 3.1). Large banks are those with at least \$100 billion in assets at any point over the 2016–2024 period. All other banks are classified as regional banks. *CRE Growth* is the growth rate in the balance of CRE loans outstanding. *NPL Share* is the share of non-performing CRE loans relative to total CRE loans outstanding. *Mod. Share* is the share of modified CRE loans relative to total CRE loans outstanding. *REO Share* is the share of real estate owned CRE loans relative to total CRE loans outstanding. *Size* is total assets (in \$ billion). *Age* is the number of years since establishment. *CRE Spec.* is an indicator that takes the value of one if the bank is classified as specializing in commercial real estate lending by the FDIC. *Capital Ratio* is total equity scaled by total assets. *Liquidity Ratio* is the sum of cash, available-for-sale debt securities, and four times the quarterly average of federal funds sold and securities purchased under agreements to resell, scaled by total assets. *Earnings Ratio* is net income (or loss) scaled by total equity. *Loan Ratio* is computed as four times the quarterly average of total loans, scaled by total assets. Statistical significance from a difference-in-means test between Community Banks and Non-Community Banks is indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

	(1) Comm. Bank			(2) Regional Bank			(3) Large Bank			(1)-(2)	(1)-(3)
	N	Mean	SD	N	Mean	SD	N	Mean	SD		
<i>CRE Growth</i>	309,331	0.04	2.11	29,982	0.05	1.16	2,080	0.07	1.07	-0.01	-0.03
<i>NPL Share</i>	309,977	0.02	0.04	30,023	0.02	0.05	2,083	0.01	0.02	-0.00	0.00***
<i>Mod. Share</i>	309,977	0.00	0.02	30,023	0.00	0.02	2,083	0.00	0.00	-0.00***	0.00***
<i>REO Share</i>	309,977	0.01	0.10	30,023	0.01	0.02	2,083	0.00	0.01	0.01***	0.01***
<i>Size</i>	312,668	0.40	0.91	34,028	5.24	9.93	2,405	320.20	537.84	-4.83***	-319.79***
<i>Age</i>	312,668	82.44	42.86	34,028	62.39	48.75	2,405	94.41	67.87	20.05***	-11.96***
<i>CRE Spec.</i>	312,668	0.55	0.50	34,028	0.72	0.45	2,405	0.35	0.48	-0.16***	0.20***
<i>Capital Ratio</i>	312,668	0.11	0.04	34,027	0.16	0.17	2,405	0.11	0.03	-0.04***	-0.00***
<i>Liquidity Ratio</i>	312,668	0.25	0.16	34,027	0.27	0.20	2,405	0.26	0.14	-0.01***	-0.01*
<i>Earnings Ratio</i>	312,668	0.07	1.50	34,026	0.09	1.21	2,405	0.11	0.11	-0.02**	-0.04***
<i>Loan Ratio</i>	312,668	0.62	0.16	34,027	0.61	1.22	2,405	0.54	0.21	0.01	0.07***

Table 2. Descriptive Statistics MSCI Loan Data

This table presents summary statistics for the MSCI loan data over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification (see Section 3.1). Large banks are those with at least \$100 billion in assets at any point over the 2016–2024 period. All other banks are classified as regional banks. *Size* is total property area (in '000 sq.ft.). *Value* is property value per square foot at the time of loan issuance (in \$ '000). *Age* is difference between the current year and the construction year of the property. *Renovated* is an indicator that takes the value of one if the property has been renovated after construction. *CBD* is an indicator that takes the value of one if the property is located in the central business district. *LTV* is loan amount divided by property value. *Prev. Relation* is an indicator that takes the value of one if the borrower in a given loan previously financed another property with the same bank. *HQ in MSA (Branch in MSA, respectively)* is an indicator that takes the value of one if the bank's headquarter (nearest branch) is located in the same Metropolitan Statistical Area (MSA) as the property. *HQ in MSA (Inv.)* (*Branch in MSA (Inv.)*, respectively) is an indicator that takes the value of one if the bank's headquarter (nearest branch) is located in the same MSA as the investor's headquarter. Statistical significance from a difference-in-means test between Community Banks and Non-Community Banks is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) Comm. Bank			(2) Regional Bank			(3) Large Bank			(1)–(2)		(1)–(3)	
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Diff. in Means	Diff. in Means	Diff. in Means	Diff. in Means
<i>Size</i>	55,972	57.99	79.21	63,156	67.04	112.32	48,088	78.61	146.98	-9.05***	-20.62***		
<i>Value</i>	62,611	59.40	131.03	68,507	69.64	160.84	52,556	116.72	192.82	-10.25***	-57.32***		
<i>Age</i>	58,344	40.63	30.93	64,760	40.81	30.79	50,145	46.70	32.37	-0.18	-6.06***		
<i>Renovated</i>	63,842	0.23	0.42	69,455	0.24	0.43	53,166	0.22	0.42	-0.01***	0.00		
<i>CBD</i>	63,842	0.11	0.32	69,455	0.13	0.33	53,165	0.19	0.39	-0.01***	-0.07***		
<i>LTV</i>	63,624	0.70	0.37	69,179	0.70	0.42	52,967	0.68	0.37	0.00	0.02***		
<i>HQ in MSA</i>	63,840	0.38	0.49	69,455	0.24	0.43	53,166	0.09	0.28	0.14***	0.30***		
<i>Branch in MSA</i>	63,578	0.54	0.50	69,271	0.67	0.47	53,042	0.87	0.34	-0.13***	-0.33***		
<i>HQ in MSA (Inv.)</i>	35,555	0.38	0.48	43,601	0.26	0.44	36,885	0.10	0.30	0.11***	0.28***		
<i>Branch in MSA (Inv.)</i>	35,380	0.45	0.50	43,476	0.50	0.50	36,795	0.62	0.49	-0.05***	-0.16***		
<i>Prev. Relation</i>	62,580	0.72	0.45	68,234	0.73	0.44	52,131	0.80	0.40	-0.02	-0.08***		

Table 3. Descriptive Statistics Operating Performance Data

This table presents summary statistics on the property operating performance data in the U.S. over the 2016–2024 period that we are able to match to CRE loans in the MSCI loan data set. The variables in Panel A (Panel B and Panel C, respectively) are merged from Compstak Lease (Yardi Matrix and CBRE Hotels) Data Set. The summary statistics are presented by bank type. In Panel A, *No. of Leases* is the total number of leases signed for a property in a given quarter. *Renewals* (respectively, *New*) is an indicator that takes the value of one if the lease is a renewal of a previous lease (a new lease). *Free Rent* is the number of months in which no rent is charged. *Start. Rent* is the monthly starting rent per square foot. *Eff. Rent* is the monthly effective rent after concessions such as tenant improvement allowances and rent-free periods. In Panel B, *Occupancy* is the occupancy rate for an apartment in a given month. *Rent* is the rent price per square foot for an apartment in a given year. *Occupancy Growth* is the monthly occupancy growth rate for an apartment. *Rent Growth* is the annual rent price per square foot growth rate for an apartment. In Panel C, *Occupancy* is the occupancy rate for a hotel in a given year. *ADR* is the average daily rate for a hotel in a given year. *RevPAR* is the revenue per available room for a hotel in a given year. *GOP Margin* is the gross operating profit scaled by the total revenue for a hotel in a given year. Statistical significance from a difference-in-means test between Community Banks and Non-Community Banks is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(A) Compstak (office, industrial, and retail)

	(1) Comm. Bank			(2) Regional Bank			(3) Large Bank			(1)–(2)	(1)–(3)
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Diff. in Means	Diff. in Means
<i>No. of Leases</i>	6,282	1.10	0.54	7,938	1.09	0.40	5,752	1.09	0.42	0.01	0.00
<i>Renewal</i>	12,712	0.32	0.47	20,459	0.35	0.48	22,850	0.39	0.49	-0.03***	-0.07***
<i>New Lease</i>	12,712	0.68	0.47	20,459	0.65	0.48	22,850	0.60	0.49	0.03***	0.07***
<i>Free Rent Share</i>	8,875	3.58	4.12	14,953	3.75	3.93	19,833	4.43	4.44	-0.17**	-0.85***
<i>Asking Rent</i>	17,242	26.04	23.47	26,081	29.13	33.80	28,539	36.12	35.66	-3.09***	-10.08***
<i>Net Effective Rent</i>	16,908	25.67	23.25	25,998	28.26	32.11	28,311	34.78	31.36	-2.59***	-9.11***

Table 3. Descriptive Statistics Operating Performance Data (Continued)

(B) Yardi Matrix (multi-family)

	(1) Comm. Bank		(2) Regional Bank		(3) Large Bank		(1)-(2)	(1)-(3)
	N	Mean	SD	N	Mean	SD	Diff. in Means	Diff. in Means
<i>Occupancy</i>	191,895	0.95	0.07	241,302	0.95	0.07	0.00***	-0.01***
<i>Rent</i>	171,294	1.71	0.91	216,089	1.89	0.95	-0.18***	-0.48***
<i>Occupancy Growth</i>	191,436	0.00	0.03	240,706	0.00	0.03	-0.00	0.00***
<i>Rent Growth</i>	167,454	0.05	0.07	212,991	0.05	0.07	-0.00	0.01***

(C) CBRE (hotel)

	(1) Comm. Bank		(2) Regional Bank		(3) Large Bank		(1)-(2)	(1)-(3)
	N	Mean	SD	N	Mean	SD	Diff. in Means	Diff. in Means
<i>Occupancy</i>	213	0.67	0.14	316	0.68	0.16	-0.02	0.03*
<i>ADR</i>	213	135.75	47.04	316	162.62	60.38	-26.87***	-87.42***
<i>RevPAR</i>	213	91.63	40.42	316	111.89	48.37	-20.26***	-52.06***
<i>GOP Margin</i>	213	0.36	0.15	316	0.35	0.17	0.01	0.01

Table 4. CRE Loan Issuance by Community Banks

This table presents the results from estimating Eq. (10) in the MSCI loan data set over the 2016–2024 period. The dependent variable is *Comm. Bank*, an indicator that takes the value of one if the bank providing loan i against property p at time t is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one at any time t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. Property, loan, investor, bank, and local economic controls are included as indicated (see Section 4.1 for details). Fixed effects are included as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) Comm. Bank	(2) Comm. Bank	(3) Comm. Bank	(4) Comm. Bank
<i>Covid</i>	0.054*** (0.013)	0.039*** (0.012)	0.020** (0.009)	0.033** (0.015)
Property Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Economic Controls	No	No	No	Yes
County FE	No	Yes	No	No
Property FE	No	No	Yes	Yes
S.E. clustered by	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.328	0.328	0.324	0.321
R-squared	0.15	0.22	0.74	0.74
Observations	152,577	152,294	50,140	49,498

Table 5. Expansion in Geographic Scope of Community Banks

This table presents the results from estimating Eq. (11) in the MSCI loan data set over the 2016–2024 period. The dependent variables in Panel A (Panel B, respectively) are based on measures of the physical distance between a given property and the lending bank’s headquarter location (the lending bank’s nearest branch). In columns 1, 2, and 3, the dependent variable is the natural logarithm of the physical distance (in miles) between a property and the lending bank’s location. In columns 4 and 5, the dependent variable is an indicator that takes the value of one if the property is located in the same metropolitan statistical area (MSA) as the lending bank. Columns 1 and 4 present results using the dependent variables in their original form. Column 2 reports results with physical distance observations winsorized at the 99th percentile, while Columns 3 and 5 show results with both physical distance and indicator variables trimmed at the 99th percentile. *Comm. Bank* is an indicator that takes the value of one if bank *b* is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one in any year-quarter *t* starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. Property, loan, investor, bank, and local economic controls are included as indicated (see Section 4.2 for details). Fixed effects are included as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported as the natural logarithm of distance (in miles) in odd columns and in decimal form in even columns. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(A) Headquarter Location

	(1)	(2)	(3)	(4)	(5)
	Distance	Distance	Distance	Same MSA	Same MSA
<i>Comm. Bank # Covid</i>	0.046 (0.036)	0.046 (0.036)	0.054 (0.036)	-0.010 (0.007)	-0.012* (0.007)
Property Controls	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Outlier Treatment	None	Winsor	Trim	None	Trim
S.E. clustered by	Bank	Bank	Bank	Bank	Bank
Mean Dep. Var.	5.195	5.193	5.166	0.247	0.249
R-squared	0.54	0.54	0.55	0.49	0.49
Observations	149,531	149,531	147,930	149,531	147,930

Table 5. Expansion in Geographic Scope of Community Banks (Continued)**(B)** Nearest Branch Location

	(1) Distance	(2) Distance	(3) Distance	(4) Same MSA	(5) Same MSA
<i>Comm. Bank # Covid</i>	0.000 (0.053)	0.001 (0.053)	0.010 (0.053)	-0.008 (0.009)	-0.009 (0.009)
Property Controls	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Outlier Treatment	None	Winsor	Trim	None	Trim
S.E. clustered by	Bank	Bank	Bank	Bank	Bank
Mean Dep. Var.	2.239	2.237	2.180	0.694	0.701
R-squared	0.54	0.54	0.53	0.42	0.41
Observations	149,211	149,211	147,636	149,211	147,636

Table 6. CRE Loan Issuance by Transaction Type

This table presents the results from estimating Eq. (12) in the MSCI loan data set over the 2016–2024 period by transactions types, namely sales transactions and refinance transactions. Column 1 includes both transactions types, whereas columns 2 and 3 contain only sales and refinance transactions, respectively. The sample excludes loans issued by regional banks. The dependent variable is Comm. Bank, an indicator that takes the value of one if the bank providing loan i against property p at time t is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one at any time t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. *Prev. Large Bank* $_{i,p,t}$ is an indicator that takes the value of one if the bank providing the previous loan against property p was a large bank. Large banks are those with at least \$100 billion in assets at any point over the 2016–2024 period. Property controls, loan controls, investor controls, bank controls, and local economic controls are included as indicated (see Section 4.4 for details). Sample restrictions by transaction type are applied as indicated. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) Comm. Bank	(2) Comm. Bank	(3) Comm. Bank
<i>Covid</i>	0.080*** (0.019)	0.082*** (0.023)	0.078*** (0.020)
<i>Prev. Large Bank</i>	-0.246*** (0.058)	-0.113*** (0.030)	-0.303*** (0.070)
<i>Covid</i> # <i>Prev. Large Bank</i>	-0.034*** (0.012)	0.042* (0.024)	-0.042*** (0.014)
Property Controls	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes
Sample	All	Sale	Refinance
MSA Location	All	All	All
S.E. clustered by	Bank	Bank	Bank
Mean Dep. Var.	0.501	0.585	0.476
R-squared	0.63	0.60	0.65
Observations	27,600	6,406	21,194

Table 7. CRE Sale Loan Issuance by Property Proximity

This table presents the results from estimating Eq. (12) in the MSCI loan data set over the 2016–2024 period. The sample excludes loans issued by regional banks and refinance transactions. Columns 1 and 2 show results for sales transactions where the property is located in the same MSA (respectively, a different MSA) as the headquarter location of the bank providing the loan. Columns 3 and 4 show results for sales transactions where the property is located in the same MSA as a branch location of the bank providing the loan (respectively, a different MSA). The dependent variable is *Comm. Bank*, an indicator that takes the value of one if the bank providing loan i against property p at time t is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one at any time t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. *Prev. Large Bank* $_{i,p,t}$ is an indicator that takes the value of one if the bank providing the previous loan against property p was a large bank. Large banks are those with at least \$100 billion in assets at any point over the 2016–2024 period. Property controls, loan controls, investor controls, bank controls, and local economic controls are included as indicated (see Section 4.4 for details). Sample splits by MSA location are applied as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Property & Bank HQ		Property & Bank Branch	
	(1)	(2)	(3)	(4)
	Comm. Bank	Comm. Bank	Comm. Bank	Comm. Bank
<i>Covid</i>	0.028 (0.019)	0.094*** (0.027)	0.074*** (0.023)	0.029 (0.030)
<i>Prev. Large Bank</i>	-0.161*** (0.060)	-0.095*** (0.030)	-0.093*** (0.034)	-0.106*** (0.034)
<i>Covid</i> $\#$ <i>Prev. Large Bank</i>	0.099** (0.045)	0.016 (0.025)	0.028 (0.023)	0.070 (0.043)
Property Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes
Sample	Sale	Sale	Sale	Sale
MSA Location	Same	Diff.	Same	Diff.
S.E. clustered by	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.873	0.499	0.454	0.815
R-squared	0.49	0.59	0.68	0.40
Observations	1,470	4,936	4,074	2,312

Table 8. Non-Performing, Modified, and Real Estate Owned Loan Shares by Bank Type

This table presents the results from estimating Eq. (13) in the FDIC Call Report panel over the 2016–2024 period. The sample excludes regional banks. The dependent variable in columns 1 and 2 (respectively, columns 3 and 4, and columns 5 and 6) is NPL Share, the share of non-performing CRE loans relative to total CRE loans outstanding at bank b in quarter t (respectively, Mod. Share, the share of modified CRE loans relative to total CRE loans outstanding at bank b in quarter t , and REO Share, the share of real estate owned loans relative to total CRE loans outstanding at bank b in quarter t). *Comm. Bank* is an indicator that takes the value of one if bank b is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one in any year-quarter t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. Bank controls and local economic controls are included as indicated (see Section 4.1 for details). Fixed effects are included as indicated. Standard errors, clustered by bank, are reported in parentheses. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) NPL Share	(2) NPL Share	(3) Mod. Share	(4) Mod. Share	(5) REO Share	(6) REO Share
<i>Comm. Bank # Covid</i>	-0.014*** (0.002)	-0.013*** (0.002)	-0.004*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Bank Controls	No	Yes	No	Yes	No	Yes
Local Economic Controls	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by	Bank	Bank	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.010	0.009	0.002	0.002	0.005	0.004
R-squared	0.37	0.39	0.34	0.39	0.21	0.15
Observations	166,509	123,577	166,509	123,577	166,509	123,577

Table 9. CRE Loan Foreclosure by Bank Type

This table presents the results from estimating Eq. (11) in the MSCI loan data set over the 2016–2024 period. The sample excludes loans issued by regional banks. The sample also excludes loans for which we cannot observe a subsequent transaction (sale, refinance, or foreclosure). The dependent variable is Foreclosure, an indicator that takes the value of one if the MSCI transfer records show that loan i for property p issued at time t was subsequently the subject of a foreclosure. *Comm. Bank* is an indicator that takes the value of one if bank b is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one in any year-quarter t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. Property, loan, investor, bank, and local economic controls are included as indicated (see Section 4.2 for details). Fixed effects are included as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) Foreclosure	(2) Foreclosure	(3) Foreclosure
<i>Comm. Bank # Covid</i>	-0.037*** (0.013)	-0.037*** (0.013)	-0.029** (0.014)
Property Controls	No	No	Yes
Loan Controls	No	No	Yes
Investor Controls	No	No	Yes
Bank Controls	Yes	Yes	Yes
Local Economic Controls	No	Yes	Yes
Bank FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
S.E. clustered by	Bank	Bank	Bank
Mean Dep. Var.	0.073	0.072	0.081
R-squared	0.14	0.15	0.20
Observations	22,559	22,148	17,801

Table 10. CRE Operating Performance by Bank Type

This table presents regression results from Eq. (11) in the MSCI loan data set over the 2016–2024 period by property types. The sample excludes loans issued by regional banks. The dependent variables in Panel A (Panel B and Panel C, respectively) are merged from Compstak Lease (Yardi Matrix and CBRE Hotels) Data Set. In Panel A, the dependent variable in column 1 is All, the total number of leases signed during the loan term. The dependent variable in column 2 (respectively, column 3) is Renewals (New), the total number of renewals (new leases) signed during the loan term. The dependent variable in column 4 is Free Rent, the average number of months in which no rent is charged, scaled by the total lease term, across the leases signed during the loan term. The dependent variable in column 5 (respectively, column 6) is the natural logarithm of Start. Rent (Eff. Rent), the average monthly starting rent per sq.ft. (effective rent per sq.ft., after concessions such as tenant improvement allowances and rent-free periods) across the leases signed during the loan term. Columns 1, 2, and 3 present the results from estimating Eq. (11) as Poisson count models, whereas columns 4, 5, and 6 present the results from estimating Eq. (11) as ordinary least squares models. In Panel B, the dependent variable in column 1 (respectively, column 3) is Occ. (Occ. Growth), the average monthly occupancy rate (occupancy growth rate) during the loan term. The dependent variable in column 2 (respectively, column 4) is Rent (Rent Growth), the average annual rent (rent growth rate) during the loan term. In Panel C, the dependent variable in column 1 is Occ., the average annual occupancy rate during the loan term. The dependent variable in column 2 is ADR, the average annual average daily rate (ADR) during the loan term. The dependent variable in column 3 is RevPAR, the average annual revenue per available room (RevPAR) during the loan term. The dependent variable in column 4 is GOP Margin, the average annual gross operating profit (GOP), scaled by total revenue, during the loan term. *Comm. Bank* is an indicator that takes the value of one if bank b is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one in any year-quarter t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. Property, loan, investor, bank, and local economic controls are included as indicated (see Section 4.2 for details). Fixed effects are included as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(A) Industrial, Office, and Retail

	(1) All	(2) Renewals	(3) New	(4) Free Rent	(5) Start. Rent	(6) Eff. Rent
<i>Comm. Bank # Covid</i>	0.141** (0.055)	0.140 (0.105)	0.170*** (0.064)	-0.002 (0.001)	-0.023 (0.020)	-0.019 (0.020)
Property Controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered by	Bank	Bank	Bank	Bank	Bank	Bank
Model	Poisson	Poisson	Poisson	OLS	OLS	OLS
Mean Dep. Var.	2.802	0.799	1.442	0.020	3.086	3.079
(Pseudo) R-squared	0.25	0.28	0.19	0.20	0.67	0.66
Observations	8,622	7,895	8,514	8,438	8,535	8,452

Table 10. CRE Operating Performance by Bank Type (Continued)**(B)** Apartment

	(1) Occ.	(2) Rent	(3) Occ. Growth	(4) Rent Growth
<i>Comm. Bank # Covid</i>	-0.005 (0.006)	-0.046 (0.072)	-0.003 (0.002)	0.002 (0.004)
Property Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
S.E. clustered by	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.950	2.192	0.001	0.045
R-squared	0.23	0.29	0.12	0.21
Observations	5,354	4,686	5,343	4,639

(C) Hotel

	(1) Occ.	(2) ADR	(3) RevPAR	(4) GOP Margin
<i>Covid</i>	-0.048 (0.038)	28.733* (15.760)	8.346 (11.315)	0.009 (0.020)
<i>Comm. Bank</i>	-0.024 (0.043)	26.490 (38.262)	24.366 (23.451)	-0.013 (0.046)
<i>Comm. Bank # Covid</i>	0.107** (0.051)	-31.946 (27.184)	-9.627 (18.311)	-0.000 (0.037)
Property Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes
Bank FE	No	No	No	No
Year-Quarter FE	No	No	No	No
S.E. clustered by	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.657	186.843	123.345	0.357
R-squared	0.50	0.78	0.80	0.51
Observations	90	90	90	90

ONLINE APPENDIX

Appendix A Proofs

A.1 Proof of Proposition 1

The share of small bank loans can be rewritten as follows

$$\begin{aligned} S(n) &= \frac{V_S(n)}{V_S(n) + V_L(n)} \\ &= 1 - \frac{V_L(n)}{V_S(n) + V_L(n)} \\ &= 1 - \frac{1}{\frac{V_S(n)}{V_L(n)} + 1}. \end{aligned}$$

Thus, to prove that $S(n)$ is a decreasing function of n , we need to show that the ratio $Q(n) \equiv \frac{V_S(n)}{V_L(n)}$ is a decreasing function of n .

To prove the proposition, we will show that the derivatives $Q'(n) < 0$ for all $n > 0$, and $\rho \in [0, 1]$. Recall that according to equations (6), (8) and (9),

$$\begin{aligned} r^*(n) &= \frac{1 + (n+1)\rho}{n+2}, \\ \theta^*(n) &= 1 - r^*(n) = \frac{(n+1)(1-\rho)}{n+2}, \\ \frac{\partial r^*(n)}{\partial n} &= -\frac{1-\rho}{(n+2)^2}, \\ \frac{\partial \theta^*(n)}{\partial n} &= \frac{1-\rho}{(n+2)^2}. \end{aligned}$$

We can now calculate the derivatives of $V_L(n) = 1 - (\theta^*(n))^n$ and $V_S(n) = \frac{n}{n+1}(\theta^*(n))^{n+1}$.

$$\begin{aligned} V'_L(n) &= -(\theta^*(n))^n \left[\ln(\theta^*(n)) + \frac{n}{(n+1)(n+2)} \right], \\ V'_S(n) &= \frac{(\theta^*(n))^{n+1}}{n+1} \left[n \ln(\theta^*(n)) + \frac{n^2 + 2n + 2}{(n+1)(n+2)} \right]. \end{aligned}$$

Then,

$$\begin{aligned}
Q'(n) &= \frac{V'_S(n)V_L(n) - V'_L(n)V_S(n)}{(V_L(n))^2} \\
&= \frac{\frac{(\theta^*(n))^{n+1}}{n+1}(n \ln(\theta^*(n)) + \frac{n^2+2n+2}{(n+1)(n+2)})(1 - (\theta^*(n))^n) + (\theta^*(n))^n(\ln(\theta^*(n)) + \frac{n}{(n+1)(n+2)})\frac{n}{n+1}(\theta^*(n))^{n+1}}{(1 - (\theta^*(n))^n)^2} \\
&= \frac{(\theta^*(n))^{n+1} \left[(n \ln(\theta^*(n)) + \frac{n^2+2n+2}{(n+1)(n+2)})(1 - (\theta^*(n))^n) + (\theta^*(n))^n(\ln(\theta^*(n)) + \frac{n}{(n+1)(n+2)})n \right]}{(n+1)(1 - (\theta^*(n))^n)^2} \\
&= \frac{(\theta^*(n))^{n+1} \left[\frac{n^2+2n+2}{(n+1)(n+2)} + n \ln(\theta^*(n)) + (\theta^*(n))^n \left(-\frac{n^2+2n+2}{(n+1)(n+2)} + \frac{n^2}{(n+1)(n+2)} \right) \right]}{(n+1)(1 - (\theta^*(n))^n)^2} \\
&= \frac{(\theta^*(n))^{n+1} \left[\frac{n^2+2n+2}{(n+1)(n+2)} + n \ln(\theta^*(n)) - \frac{2}{n+2}(\theta^*(n))^n \right]}{(n+1)(1 - (\theta^*(n))^n)^2}.
\end{aligned}$$

To prove that $Q'(n) < 0$, we need to show that the term in the square brackets is negative for all $n > 0$, and $\rho \in [0, 1]$. Substituting $\theta^*(n)$ into the term in question yields

$$\begin{aligned}
g(n, \rho) &\equiv \frac{n^2 + 2n + 2}{(n+1)(n+2)} + n \ln(\theta^*(n)) - \frac{2}{n+2}(\theta^*(n))^n \\
&= \frac{n^2 + 2n + 2}{(n+1)(n+2)} + n \ln \left(\frac{(n+1)(1-\rho)}{n+2} \right) - \frac{2}{n+2} \left(\frac{(n+1)(1-\rho)}{n+2} \right)^n.
\end{aligned}$$

One can see that $g(n, \rho)$ is decreasing in ρ . Indeed, its derivative with respect to ρ is always negative:

$$\begin{aligned}
\frac{\partial g(n, \rho)}{\partial \rho} &= -\frac{n(n+2)}{(n+1)(1-\rho)} + \frac{2n(n+1)}{(n+2)^2} \left(\frac{(n+1)(1-\rho)}{n+2} \right)^{n-1} \\
&< -\frac{n(n+2)}{(n+1)} + \frac{2n(n+1)}{(n+2)^2} \\
&= -n \frac{(n+2)^3 - 2(n+1)^2}{(n+1)(n+2)^2} \\
&= -n \frac{n^3 + 4n^2 + 8n + 6}{(n+1)(n+2)^2} < 0.
\end{aligned}$$

Hence, $g(n, \rho)$ achieves its maximum value at the lowest possible value of ρ . Thus, we can set $\rho = 0$, and define

$$h(n) \equiv g(n, 0) = \frac{n^2 + 2n + 2}{(n+1)(n+2)} + n \ln \left(\frac{(n+1)}{n+2} \right) - \frac{2}{n+2} \left(\frac{(n+1)}{n+2} \right)^n.$$

We verify numerically that $h(n) < 0$ for all $n > 0$, which proves that $Q'(n) < 0$ for all $n > 0$, and $\rho \in [0, 1]$. **Q.E.D.**

A.2 Proof of Proposition 2

Plugging (6) into (7) yields

$$\begin{aligned}
\pi^*(n) &= \frac{n}{n+1} (r^*(n) - \rho)(1 - r^*(n))^{(n+1)} \\
&= \frac{n}{n+1} \left(\frac{1 + (n+1)\rho}{n+2} - \rho \right) \left(1 - \frac{1 + (n+1)\rho}{n+2} \right)^{(n+1)} \\
&= \frac{n}{n+1} \left(\frac{1 - \rho}{n+2} \right) \left(\frac{(n+1)(1 - \rho)}{n+2} \right)^{(n+1)} \\
&= n \frac{(n+1)^n}{(n+2)^{n+2}} (1 - \rho)^{n+2}.
\end{aligned}$$

Let's define

$$\chi(n) \equiv \ln(\pi^*(n)) = \ln(n) + n \ln(n+1) - (n+2) \ln(n+2) + (n+2) \ln(1 - \rho),$$

and take its derivative with respect to n :

$$\begin{aligned}
\chi'(n) &= \frac{1}{n} + \left[\ln(n+1) + \frac{n}{n+1} \right] - \left[\ln(n+2) + \frac{n+2}{n+2} \right] + \ln(1 - \rho) \\
&= \frac{1}{n(n+1)} + \ln \left(\frac{n+1}{n+2} (1 - \rho) \right).
\end{aligned}$$

Function $\pi^*(n)$ is decreasing in n if and only if $\chi'(n) < 0$. The derivative $\chi'(n)$ is negative when

$$\left(\frac{n+1}{n+2} \right) (1 - \rho) < e^{-\frac{1}{n(n+1)}},$$

or

$$\rho > 1 - \frac{n+2}{n+1} e^{-\frac{1}{n(n+1)}}.$$

Thus, when the above inequality holds, $\pi^*(n)$ is decreasing in n . Moreover, we note that $1 - \frac{n+2}{n+1} e^{-\frac{1}{n(n+1)}} = 0$ when $n = 1.212$, and $1 - \frac{n+2}{n+1} e^{-\frac{1}{n(n+1)}} < 0$ for $n > 1.212$. Since $\rho > 0$, the above inequality is always true for all $n > 1.212$. **Q.E.D.**

Appendix B Definitions and Sample Construction

B.1 Community Bank Definition

Community banks are designated at the level of the banking organization. The FDIC provides the following detailed definition of community banks in its [FDIC Community Banking Study \(2020\)](#).

Community banks **exclude** any organization with:

- No loans or no core deposits
- Assets held in foreign branches $\geq 10\%$ of total assets
- More than 50% of assets in certain specialty banks, including:
 - Credit card specialists
 - Consumer nonbank banks
 - Industrial loan companies
 - Trust companies
 - Bankers’ banks

Community banks **include** any organization with:

- Total assets $< \$1.65$ billion
- Total assets $\geq$ indexed size threshold, where:
 - Loan-to-assets ratio $> 33\%$
 - Core deposits-to-assets ratio $> 50\%$
 - More than 1 office but no more than 94 offices
 - Offices in no more than 2 large MSAs
 - Offices in no more than 3 states
 - No single office with deposits $> \$8.24$ billion

B.2 Bank Name Matching Process

As discussed in Section 3.2, linking loan level data from MSCI with bank level data from the Call Reports requires precise identification of the lending institution. To achieve this, we merge the two datasets using bank name information from both sources. This step is critical for the integrity of the regression analysis, as misidentification can introduce measurement error and bias the estimates. In this section, we detail the fuzzy-matching procedures implemented to ensure accurate and consistent linkage between the two data sources.

B.2.1 Identify Banks from MSCI

In addition to banks, a wide range of institutions—including mortgage companies, insurance companies, and private lenders—participate in the commercial real estate lending market. Since the primary focus of this paper is on bank lenders, the first step in our matching process is to identify transactions in the MSCI data set that involve bank lenders. To do so, we implement the following procedure:

1. We retain observations in which the lender name contains common banking-related terms, including “bank”, “b&t”, “b&t”, “nat’l bk”, “bancorp”, “banc”, “bk”, “bnk”, “sb”, “savings”, “fsb”, “s&l”, “svgs”, or “svngs”;
2. We also identify and retain lender names that follow specific naming conventions associated with banks, such as “FNB” and “American Express” to improve classification accuracy;
3. We manually verify and include banks with unconventional or abbreviated names that may not match standard patterns. These include, but are not limited to: “IndyMac”, “Jamestown”, “NewtekOne”, “Pathward NA”, “SNB Texas”, “Savanna”, “Washington First Int’l”, “Wilmington Natl Assn”, “MUFG”, “Portigon AG”, “SBM”, and “SNS Reaal”.

B.2.2 Matching Procedure

To maximize the accuracy of our fuzzy matching algorithm, we begin by systematically cleaning and standardizing bank names across data sets. Given the variation in naming conventions between the MSCI and Call Report data sets, this pre-processing step is critical to minimizing false negatives in name matching. Specifically, we complete the following steps:

1. Generate new bank names for matching purpose
2. Convert to all caps
3. Replace “B&T”, “BK&TR”, and “BANK & TRUST” with “BANK AND TRUST”
4. Replace “NAT’L” and “N’TL” with “NATIONAL”; “INT’L” with “INTERNATIONAL”; “FD’L” and “FED’L” with “FEDERAL”; “FIN’L” with “FINANCIAL”; “COM’L” with “COMMERCIAL”
5. Replace “ FSB” with “ FEDERAL SAVINGS BANK”; “SB ” with “SAVINGS BANK ”; “SVGS” with “SAVINGS”; “ S&L” with “ SAVINGS AND LOAN”
6. Replace “CMNTY”, “CNTY”, “SVC”, “SVCS”, “VLY”, “CTRL” with “COMMUNITY”, “COUNTY”, “SERVICE”, “SERVICES”, “VALLEY”, “CENTRAL”
7. Replace “BK ” and “BNK ” with “ BANK ”
8. Replace “CO” and “CO.” with “COMPANY” (Co in MSCI may also mean county)
9. Replace “&” with “ AND ”
10. Remove trailing “NATIONAL ASSOCIATION”, “, NATIONAL ASSOCIATION”, “N.A.”, “, N.A.”
11. Remove leading or trailing word “THE” and “, THE”
12. Remove all the punctuation marks
13. Replace state abbreviation with full name
14. Remove all the leading and trailing spaces
15. Remove all the repeated spaces

After standardizing bank names to the greatest extent possible, we perform fuzzy matching based on the cleaned names. The fuzzy matching algorithm employed in this paper is implemented using the `matchit` package in Stata. This algorithm tokenizes each string into character bigrams—two-character moving sequences—to capture local structural similarities. For example, the bank name “JP MORGAN” would be parsed into the following bigrams: “JP”, “P ”, “ M”, “MO”, “OR”, “RG”, “GA”, and “AN”.

We assume that all bigrams have equal weight in the matching process. Once tokenized, the algorithm computes a similarity score for each pair of bank names using the Jaccard index, which is defined as:

$$\text{Jaccard}(s_1, s_2) = \frac{|s_1 \cap s_2|}{|s_1 \cup s_2|}$$

where:

- s_1 and s_2 are sets, in this case, they are 2 grams from bank names,
- $|s_1 \cap s_2|$ is the number of elements shared between s_1 and s_2 ,
- $|s_1 \cup s_2|$ is the total number of unique elements in both sets.

A Jaccard similarity score of 1 indicates that the two sets are identical, while a score of 0 indicates no overlap. This similarity measure is particularly useful in capturing near matches between strings with minor differences in formatting, abbreviation, or spacing, which is the case in our bank name matching practice. We consider matches with index values of 0.9 or higher to be successful. An example of a non-exact match above 0.9 is “First Secure Community Bank” in the FDIC data, which appears as “1st Secure Community Bank” in the MSCI data.

For any remaining matches with scores below this threshold, we conduct a manual review to validate and correct any misclassifications. For each unmatched bank in the MSCI data set, we identify potential matches from the FDIC data set based on name similarity and retain banks that were active at the time a given loan was issued by the bank in question. If we find multiple potential matches, we conduct online searches to identify the bank whose geographic footprint aligns most closely with the lending activity observed for this bank in the MSCI data set. This hybrid approach—combining algorithmic precision with human oversight—ensures high-quality matching outcomes. The process yields a 98.5% matching success rate, successfully identifying bank-level counterparts for 3,632 bank institutions in the MSCI data set.

B.3 Call Report Variable Construction

We utilize regulatory bank data from the Reports of Condition and Income (commonly known as Call Reports), which are quarterly filings required by all insured U.S. depository institutions, to construct bank-level information. Maintained by the Federal Financial Institutions Examination Council (FFIEC), these reports provide comprehensive, standardized data on banks’ balance sheets, income statements, off-balance-sheet exposures, and risk-based capital.

The Call Reports are modular in structure, with core schedules such as Schedule RC (Balance Sheet), Schedule RI (Income Statement), and supplemental schedules capturing detailed information on loan portfolios (RC-C), deposit liabilities (RC-E), trading assets and liabilities (RC-D), derivatives and off-balance-sheet items (RC-L), and capital adequacy (RC-R), among others. The structure is further complicated by conditional reporting requirements—many schedules and line items vary based on a bank’s asset size, activity type, or charter status. As a result, constructing

consistent time-series panels across banks and modules requires careful harmonization and accounting for structural changes over time. Due to the modular and conditional structure of the Call Reports, certain variables may be missing from one schedule depending on a bank’s size or reporting status. To construct a consistent and complete dataset, it is often necessary to cross-reference the same item across multiple modules or reporting schedules.

In what follows, we outline the construction of key variables derived from the Call Report data. For clarity and consistency, we refer to each variable using its original Call Report line item name, accompanied by a brief explanation of its economic meaning and role in our analysis.

B.3.1 Commercial Real Estate Loan Balance

We construct the Commercial Real Estate (CRE) Loan Balance using data from the balance sheet schedule (Schedule RC) of the Call Report. Specifically, CRE loans are defined as the sum of the following three line items:

- **RCONF160**—Loans secured by owner-occupied nonfarm nonresidential properties,
- **RCONF161**—Loans secured by other nonfarm nonresidential properties, and
- **RCON1460**—Loans secured by multifamily (five or more units) residential properties.

Notably, we exclude construction and land development loans from our CRE loan measure to focus on income-producing properties that are stabilized or in operation. This definition aligns with industry standards and facilitates comparability with prior research on CRE lending.

B.3.2 Nonperforming CRE Loan Balance

We construct Nonperforming CRE Loan Balance using data from the balance sheet schedule (Schedule RC) of the Call Report. Specifically, it is defined as the sum of the following six items:

- **RCONF180**—Loans secured by owner-occupied nonfarm nonresidential properties; 90 or more days past due and still accruing,
- **RCONF182**—Loans secured by owner-occupied nonfarm nonresidential properties; nonaccrual,
- **RCONF181**—Loans secured by other nonfarm nonresidential properties; 90 or more days past due and still accruing,
- **RCONF183**—Loans secured by other nonfarm nonresidential properties; nonaccrual,
- **RCON3500**—Loans secured by real estate (in domestic offices): Secured by multifamily (5 or more) residential properties—past due 90 days or more and still accruing, and
- **RCON3501**—Loans secured by real estate (in domestic offices): Secured by multifamily (5 or more) residential properties—nonaccrual.

In brief, nonperforming loans are defined as the sum of the three components of the CRE loan balance that are either 90 days or more past due or in nonaccrual status. This definition is consistent with industry standards, which commonly use the 90-day threshold to identify nonperforming assets.

B.3.3 Modified CRE Loan Balance

We identify CRE loan modifications using the restructured loan items reported in the balance sheet schedule (Schedule RC) of the Call Reports. These items are disaggregated by the three main categories of CRE loans: (i) loans secured by owner-occupied nonfarm nonresidential properties, (ii) loans secured by other nonfarm nonresidential properties, and (iii) loans secured by multifamily (five or more units) residential properties. The corresponding nine line items used to construct this measure are detailed as follows:

- **RCONK114**—Loan restructured in troubled debt restructurings – Loans secured by owner-occupied nonfarm nonresidential properties: Past due 30 through 89 days and still accruing,
- **RCONK115**—Loan restructured in troubled debt restructurings – Loans secured by owner-occupied nonfarm nonresidential properties: Past due 90 days or more and still accruing,
- **RCONK116**—Loan restructured in troubled debt restructurings – Loans secured by owner-occupied nonfarm nonresidential properties: Past due 90 days or more and still accruing: Nonaccrual,
- **RCONK117**—Loan restructured in troubled debt restructurings – Loans secured by other nonfarm nonresidential properties: Past due 30 through 89 days and still accruing,
- **RCONK118**—Loan restructured in troubled debt restructurings – Loans secured by other nonfarm nonresidential properties: Past due 90 days or more and still accruing,
- **RCONK119**—Loan restructured in troubled debt restructurings – Loans secured by other nonfarm nonresidential properties: Nonaccrual,
- **RCONK111**—Loan restructured in troubled debt restructurings – Secured by multifamily residential properties in domestic offices: Past due 30 through 89 days and still accruing,
- **RCONK112**—Loan restructured in troubled debt restructurings – Secured by multifamily residential properties in domestic offices: Past due 90 days or more and still accruing, and
- **RCONK113**—Loan restructured in troubled debt restructurings – Secured by multifamily residential properties in domestic offices: Nonaccrual.

B.3.4 Real Estate Owned (REO) CRE Loan Balance

We identify real estate owned CRE loans using the restructured loan items reported in the balance sheet schedule (Schedule RC) of the Call Reports. These items are disaggregated by the two main categories of CRE loans: (i) loans secured by nonfarm nonresidential properties, and (ii) loans secured by multifamily (five or more units) residential properties. The corresponding two line items used to construct this measure are detailed as follows:

- **RON5511**—All other real estate owned: multifamily (5 or more) residential properties in domestic offices , and
- **RON5512**—All other real estate owned: nonfarm nonresidential properties in domestic offices.

B.3.5 Bank Financial Characteristics

To control for bank financial characteristics in our regression analysis, we construct several accounting measures using data from the Call Reports. Due to differences in reporting requirements, certain variables may appear in different schedules depending on the bank’s size, structure, and reporting scope. For example, while total assets are commonly reported under **RCON2170** in Schedule RC (Balance Sheet), some banks report **RCFD2170** instead. This distinction reflects the reporting scope: **RCON** represents the parent-only (domestic) reporting entity, whereas **RCFD** corresponds to the fully consolidated entity, including foreign offices and subsidiaries.

In what follows, we list the exact Call Report line items used to construct our bank financial characteristics to ensure transparency and reproducibility.

- **RIAD3210**–Total equity from Schedule RI (Income Statement)
- **RCON2170** or **RCFD2170**–Total assets from Schedule RC (Balance Sheet)
- **RIAD4340**–Net income (loss) from Schedule RI (Income Statement)
- **RCON0010** or **RCFD0010**–Cash and balances due from depository institutions (Schedule RC)
- **RCON1773** or **RCFD1773**–Available-for-sale debt securities (Schedule RC)
- **RCON3365** or **RCFD3365**–Quarterly average of federal funds sold and securities purchased under agreements to resell (Schedule RC)
- **RCON3306**–Quarterly average of total loans (Schedule RC)
- **RIAD4047**–Net interest income (Schedule RI)
- **RIAD4079**–Total noninterest income (Schedule RI)
- **RIAD4093**–Total noninterest expense (Schedule RI)

We construct the following bank performance measures using Call Report data to control for bank-level heterogeneity in our analysis. Each measure is defined below:

- **Capital Ratio**–Defined as total equity divided by total assets.
- **Liquidity Ratio**–Calculated as the sum of cash, available-for-sale debt securities, and four times the quarterly average of federal funds sold and securities purchased under agreements to resell, scaled by total assets.
- **Earnings Ratio**–Measured as net income (loss) scaled by total equity.
- **Loan Ratio**–Computed as the quarterly average of total loans scaled by total assets.

Appendix C Figures & Tables

Figure C.1. Locations of Sample Properties by County

This figure depicts the locations of the sample properties in the MSCI loan data set over the 2016–2024 period by county. Darker shading of areas in the map indicates a larger number of CRE properties located in a given county. The data used to produce this figure are from MSCI.

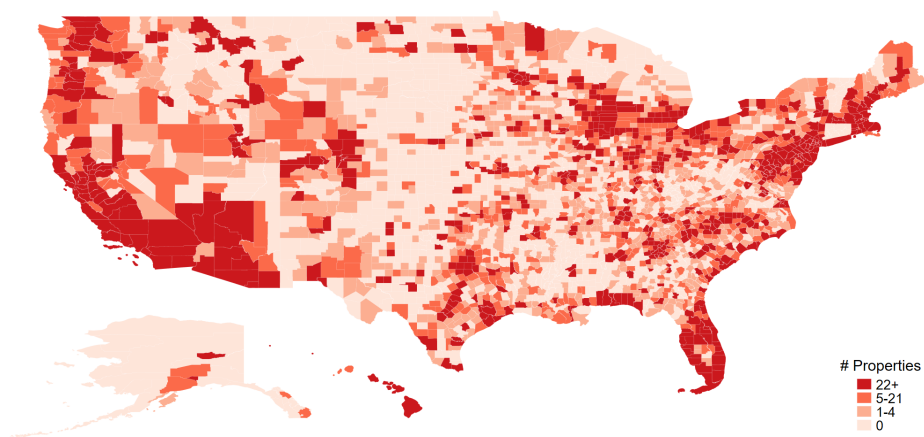
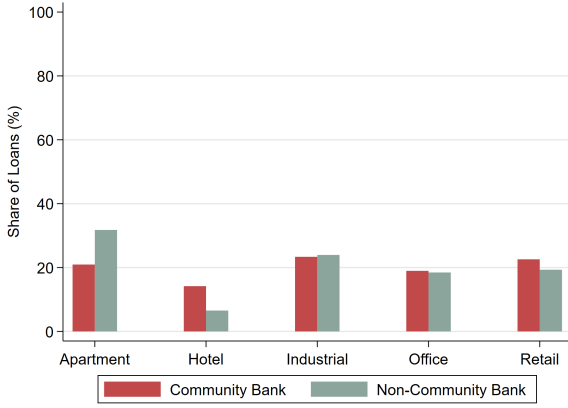
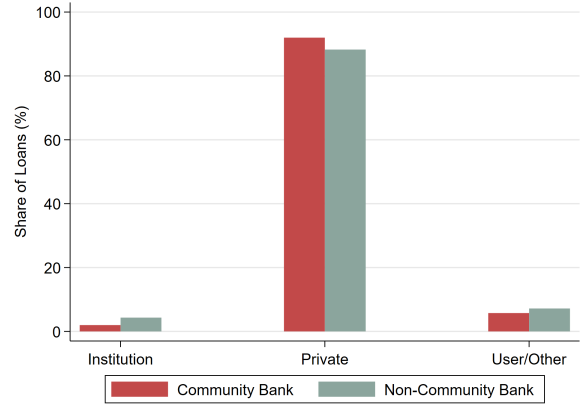


Figure C.2. Sample Composition

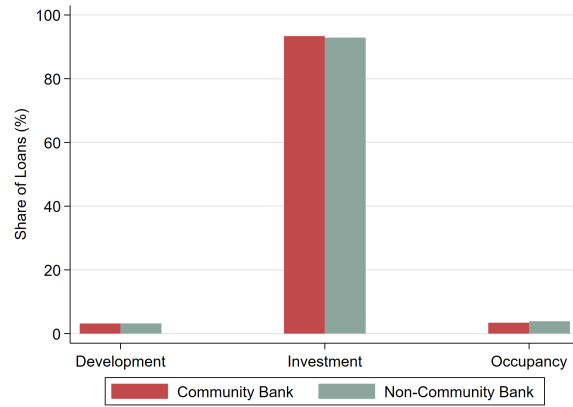
This figure depicts the composition of the MSCI loan data set over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification. Panel A shows the sample distribution of property types. Panel B shows the sample distribution of investor types. Panel C shows the sample distribution of investor objectives. The data used to produce this figure are from MSCI.



(A) Property Type



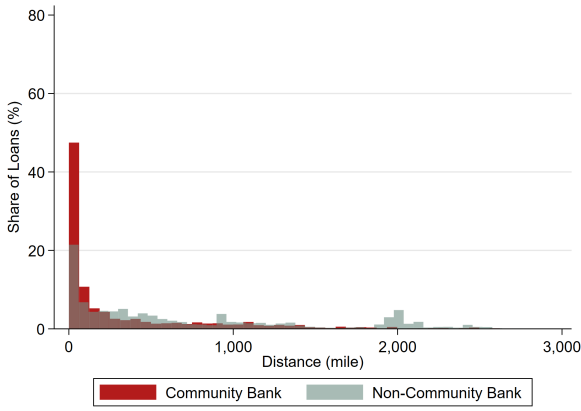
(B) Investor Type



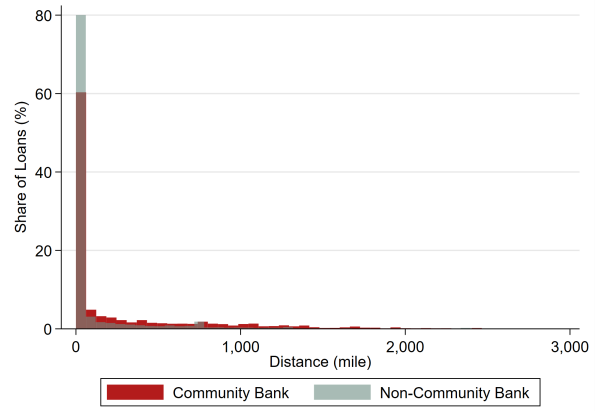
(C) Investor Objective

Figure C.3. Histogram of Distance Measures

This figure depicts the distribution of the distance between a given property and the lending bank in the MSCI loan data set over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification. Panel A shows the distribution of the physical distance (in miles) between the property and the headquarter of the lending bank. Panel B shows the distribution of the physical distance (in miles) between the property and the nearest branch of the lending bank. The data used to produce this figure are from MSCI and FDIC.



(A) Headquarter



(B) Nearest Branch

Figure C.4. Marginal Changes in CRE Loan Issuance by Community Banks

This figure depicts the results from estimating Eq. (10) in the MSCI loan data set over the 2016–2024 period. Our estimations include property, loan, investor, and bank covariates, local economic characteristics, property fixed effects, and individual indicators for each of the eight year-quarters leading up to Q1 of 2020 (event time 0) and each of the subsequent eight year-quarters starting from the onset of the pandemic in Q2 of 2020 (event time 1). The markers indicate the coefficient estimates on each of these year-quarter indicators. The shaded gray area indicates a 90% confidence interval around the coefficient estimates. The data used to produce this figure are from the FDIC, FFIEC, MSCI, BLS, and Zillow.

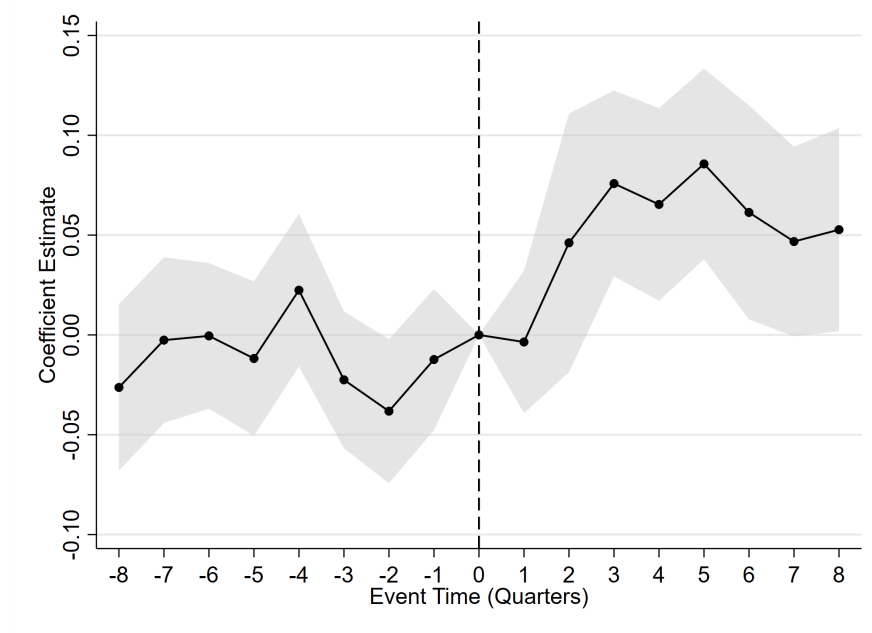


Table C.1. Key Community Bank Characteristics Across Samples

This table presents summary statistics of key community bank characteristics across the three main data sets used in this study, namely, the FDIC Call Report panel, the MSCI loan data set, and the merged MSCI-Compstak lease data set, for the 2016–2024 period. *CRE Growth* is the growth rate in the balance of CRE loans outstanding. *NPL Share* is the share of non-performing CRE loans relative to total CRE loans outstanding. *Mod. Share* is the share of modified CRE loans relative to total CRE loans outstanding. *Size* is total assets (in \$ billion). *Age* is the number of years since establishment. *Capital Ratio* is total equity scaled by total assets. *Liquidity Ratio* is the sum of cash, available-for-sale debt securities, and four times the quarterly average of federal funds sold and securities purchased under agreements to resell, scaled by total assets. *Earnings Ratio* is net income (or loss) scaled by total equity. *Loan Ratio* is computed as four times the quarterly average of total loans, scaled by total assets.

	FDIC Call Report Panel			MSCI Loan Data Set			CompStak Lease Data Set		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
<i>CRE Growth</i>	165,303	0.04	2.47	63,594	0.06	2.63	16,672	0.05	0.20
<i>NPL Share</i>	165,356	0.01	0.03	63,597	0.01	0.01	16,730	0.01	0.02
<i>Mod. Share</i>	165,356	0.00	0.01	63,597	0.00	0.00	16,730	0.00	0.01
<i>Size</i>	166,806	0.50	1.10	63,598	2.66	4.08	17,227	2.29	3.54
<i>Age</i>	166,806	87.83	41.77	63,842	73.25	47.80	17,501	65.30	46.03
<i>CRE Spec.</i>	166,806	0.54	0.50	63,842	0.90	0.29	17,501	0.88	0.33
<i>Capital Ratio</i>	164,247	0.11	0.04	62,957	0.11	0.03	16,976	0.11	0.03
<i>Liquidity Ratio</i>	164,247	0.26	0.20	62,957	0.19	0.13	16,976	0.21	0.14
<i>Earnings Ratio</i>	164,247	0.09	0.62	62,957	0.11	0.09	16,976	0.10	0.10
<i>Loan Ratio</i>	164,247	0.63	0.16	62,957	0.71	0.12	16,976	0.71	0.12

Table C.2. Key Property Characteristics Across Samples

This table presents summary statistics of key property characteristics across the MSCI loan data set and the Compstak lease data set for the 2016–2024 period. To ensure consistency for the comparison of these data sets, apartment and hotel properties are excluded from the MSCI loan data set, as Compstak does not cover these property types. *Size* is total property area (in '000 sq.ft.). *Value* is property value per square foot at the time of loan issuance (in \$ '000). *Age* is the difference between the current year and the construction year of the property. *Renovated* is an indicator that takes the value of one if the property has been renovated after construction. *Industrial* (*Office* or *Retail*, respectively) is an indicator that takes the value of one if property type is industrial (office or retail).

	MSCI Loan Data Set			CompStak Lease Data Set		
	N	Mean	SD	N	Mean	SD
<i>Size</i>	115,651	70.50	125.22	154,631	192.75	278.04
<i>Value</i>	115,654	0.29	0.44	154,688	0.83	22.38
<i>Age</i>	106,658	38.77	28.23	151,385	40.11	26.52
<i>Renovated</i>	117,205	0.21	0.41	155,248	0.49	0.50
<i>Industrial</i>	117,205	0.38	0.48	155,248	0.21	0.41
<i>Office</i>	117,205	0.30	0.46	155,248	0.62	0.48
<i>Retail</i>	117,205	0.33	0.47	155,248	0.16	0.37

Table C.3. Key Local Economic Characteristics Across Samples

This table presents summary statistics of key local economic characteristics the three main data sets used in this study, namely, the FDIC Call Report panel, the MSCI loan data set, and the merged MSCI-Compstak lease data set, for the 2016–2024 period. Local economic characteristics are measured for the county of a given bank headquarter location in the FDIC Call Report panel and a given property location in the MSCI loan data set and Compstak lease data set. *Unemployment* is the county-level unemployment rate. *HPI Level* is the level of the county-level Zillow house price indices, scaled to a base period of 2010 Q1. *HPI Growth* is the quarterly growth rate in these indices.

	FDIC Call Report Panel			MSCI Loan Data Set			CompStak Lease Data Set		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
<i>Unemployment</i>	185,474	0.04	0.02	185,454	0.05	0.02	154,416	0.05	0.02
<i>HPI Level</i>	141,491	150.26	40.17	184,128	171.24	45.11	127,050	143.33	41.54
<i>HPI Growth</i>	141,465	0.02	0.02	184,121	0.02	0.02	127,050	0.02	0.02

Table C.4. Growth in CRE Loans Outstanding

This table presents the results from estimating Eq. (13) in the FDIC Call Report panel over the 2010–2024 period. The dependent variable is CRE Growth, the growth rate in the balance of CRE loans outstanding for bank b in year-quarter t . *Comm. Bank* is an indicator that takes the value of one if bank b is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one in any year-quarter t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. Bank controls and local economic controls are included as indicated (See Section 5.1 for details). Fixed effects are included as indicated. Standard errors, clustered by bank, are reported in parentheses. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) CRE Growth	(2) CRE Growth	(3) CRE Growth
<i>Comm. Bank # Covid</i>	0.034* (0.019)	0.038** (0.020)	0.053** (0.024)
Bank Controls	No	Yes	Yes
Local Economic Controls	No	No	Yes
Bank FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
S.E. clustered by	Bank	Bank	Bank
Mean Dep. Var.	0.038	0.037	0.035
R-squared	0.02	0.02	0.02
Observations	341,265	338,922	252,799

Table C.5. CRE Loan Issuance by Property Proximity Between Community and Regional Banks

This table presents the results from estimating Eq. (12) in the MSCI loan data set over the 2016–2024 period by focusing on community bank and regional bank sample. The sample excludes loans issued by large banks and refinance transactions. Columns 1 and 2 show results for sales transactions where the property is located in the same MSA (respectively, a different MSA) as the headquarter location of the bank providing the loan. Columns 3 and 4 show results for sales transactions where the property is located in the same MSA as a branch location of the bank providing the loan (respectively, a different MSA). The dependent variable is Comm. Bank, an indicator that takes the value of one if the bank providing loan i against property p at time t is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one at any time t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. *Prev. Regional Bank* $_{i,p,t}$ is an indicator that takes the value of one if the bank providing the previous loan against property p was a regional bank. Regional banks are those not categorized as community banks and large banks over the 2016–2024 period. Property controls, loan controls, investor controls, bank controls, and local economic controls are included as indicated (see Section 4.4 for details). Sample splits by MSA location are applied as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Property & Bank HQ		Property & Bank Branch	
	(1)	(2)	(3)	(4)
	Comm. Bank	Comm. Bank	Comm. Bank	Comm. Bank
<i>Covid</i>	0.198*** (0.047)	0.168*** (0.032)	0.231*** (0.035)	0.109*** (0.039)
<i>Prev. Regional Bank</i>	-0.100*** (0.028)	-0.073*** (0.018)	-0.106*** (0.020)	-0.057** (0.026)
<i>Covid</i> # <i>Prev. Regional Bank</i>	-0.086** (0.038)	-0.032 (0.023)	-0.041 (0.027)	-0.047 (0.034)
Property Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes
Sample	Sale	Sale	Sale	Sale
MSA Location	Same	Diff.	Same	Diff.
S.E. clustered by	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.553	0.421	0.394	0.544
R-squared	0.16	0.13	0.15	0.09
Observations	2,367	5,983	4,779	3,548

Table C.6. CRE Loan Issuance by Investor Proximity

This table presents the results from estimating Eq. (12) in the MSCI loan data set over the 2016–2024 period. The sample excludes loans issued by regional banks. Columns 1 and 2 show results for sales transactions where the investor’s headquarter is located in the same MSA (respectively, a different MSA) as the headquarter location of the bank providing the loan. Columns 3 and 4 show results for sales transactions where the investor’s headquarter is located in the same MSA as a branch location of the bank providing the loan (respectively, a different MSA). The dependent variable is Comm. Bank, an indicator that takes the value of one if the bank providing loan i against property p at time t is classified by the FDIC as a community bank. *Covid* is an indicator that takes the value of one at any time t starting in Q2 of 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. *Prev. Large Bank* $_{i,p,t}$ is an indicator that takes the value of one if the bank providing the previous loan against property p was a large bank. Large banks are those with at least \$100 billion in assets at any point over the 2016–2024 period. Property controls, loan controls, investor controls, bank controls, and local economic controls are included as indicated (see Section 4.4 for details). Sample restrictions by transaction type are applied as indicated. Sample splits by MSA location are applied as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Investor HQ & Bank HQ		Investor HQ & Bank Branch	
	(1)	(2)	(3)	(4)
	Comm. Bank	Comm. Bank	Comm. Bank	Comm. Bank
<i>Covid</i>	0.039 (0.028)	0.084*** (0.030)	0.089*** (0.027)	0.069* (0.035)
<i>Prev. Large Bank</i>	-0.104** (0.046)	-0.098*** (0.032)	-0.080** (0.032)	-0.113*** (0.030)
<i>Covid</i> # <i>Prev. Large Bank</i>	0.095** (0.037)	0.030 (0.029)	0.028 (0.031)	0.080** (0.035)
Property Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Investor Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Economic Controls	Yes	Yes	Yes	Yes
County FE	No	No	No	No
Property FE	No	No	No	No
Sample	Sale	Sale	Sale	Sale
MSA Location	Same	Diff.	Same	Diff.
S.E. clustered by	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.826	0.465	0.496	0.593
R-squared	0.52	0.61	0.71	0.57
Observations	977	3,207	1,908	2,258

Appendix D Tests on Large Bank Withdrawal

To further corroborate our inference that the shift in CRE lending from large banks to community banks was not primarily driven by a wholesale withdrawal of large banks from CRE lending, for instance due to the tightened regulatory standards on CRE exposure after 2023, we analyze mortgage application outcomes over the 2018–2024 period using the Home Mortgage Disclosure Act (HMDA) database.¹⁴ Table D.1 reports the results from estimating Eq. (11) in this data set. Across all specifications, the estimates reveal no significant evidence for an increase in the probability of denial for multi-family loan applications by large banks during the pandemic. These findings suggest that, at least in the multi-family segment, large banks did not restrict credit supply or withdraw from the CRE lending during the pandemic.

Table D.1. Application Denial of Multifamily Loans

This table presents the results from estimating Eq. (11) in the Home Mortgage Disclosure Act (HMDA) Data Set over the 2018–2024 period. The dependent variable, Denial, is an indicator that takes the value of one if the loan i for property p was denied by bank b in year t . *Large Bank* is an indicator that takes the value of one if bank b is with at least \$100 billion in assets at any point during this period. *Covid* is an indicator that takes the value of one in any year- t starting in 2020, as the World Health Organization declared Covid-19 a global pandemic in March of 2020. Property controls include property value and number of units. Loan controls include combined loan-to-value ratio (CLTV), loan term, and sales loan indicator. Bank controls and local economic controls are included as indicated (see Section 4.1 for details). Fixed effects are included as indicated. Standard errors are clustered by bank. The mean of the dependent variable is reported in decimal form. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) Denial	(2) Denial	(3) Denial	(4) Denial	(5) Denial
<i>Large Bank # Covid</i>	0.025 (0.033)	0.009 (0.017)	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)
Property Controls	No	No	Yes	Yes	Yes
Loan Controls	No	No	Yes	Yes	Yes
Bank Controls	No	No	No	Yes	Yes
Local Economic Controls	No	No	No	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
S.E. clustered by	Bank	Bank	Bank	Bank	Bank
Mean Dep. Var.	0.067	0.067	0.049	0.049	0.051
R-squared	0.00	0.14	0.19	0.19	0.19
Observations	252,692	252,622	157,538	157,535	145,483

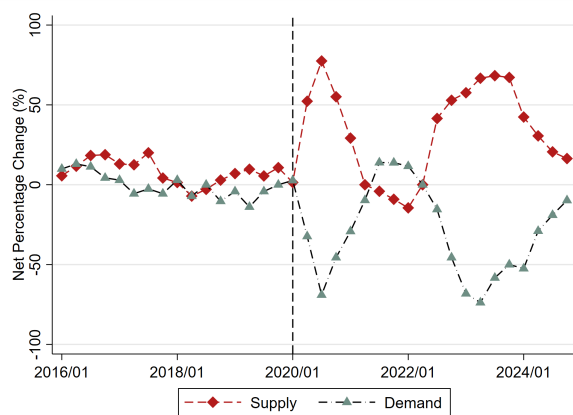
Although we do not have loan-level application data for other property types, we can draw some inferences from the Senior Loan Officer Opinion Survey (SLOOS) conducted by the Federal Reserve Board on eighty large U.S. banks, as shown in Figure D.1. The trends in both credit supply and loan demand following the onset of the pandemic exhibit similar patterns for non-residential non-farm loans (Panel A) and multi-family loans (Panel B). For multi-family loans, a larger share

¹⁴After the 2023 banking turmoil (especially the collapses of Silicon Valley Bank, Signature Bank, and First Republic Bank), U.S. regulators substantially tightened scrutiny on large banks’ CRE lending practices, intensifying their examination of CRE concentration on large banks’ balance sheets.

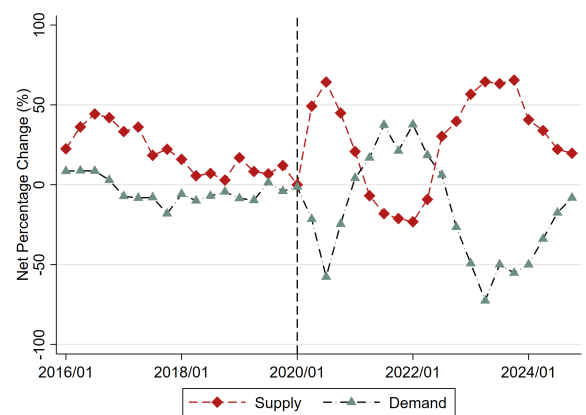
of large banks reported tightening lending standards for CRE loans during the Covid-19 pandemic. However, the regression results above show no significant increase in denial rates, suggesting that these tighter standards did not translate into an actual reduction in credit supply. These findings suggest that CRE credit supply by large banks did not fully evaporate during the pandemic.

Figure D.1. CRE Loan Supply and Demand of Large Banks in U.S.

This figure depicts trends for CRE loan supply and demand reported by up to eighty large domestic banks in U.S. from 2016 to 2024. Supply is measured as the net percentage of domestic respondents tightening standards for CRE loans whereas demand is measured as the net percentage of domestic respondents reporting stronger demand for CRE loans. Panel A shows the trends for nonresidential and nonfarm loans. Panel B shows the trends for multifamily loans. The data used to produce this figure are from Senior Loan Officer Opinion Survey on Bank Lending Practices from The Federal Reserve Board.



(A) Nonresidential and Nonfarm Loans



(B) Multifamily Loans