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

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Abstract

We study the role of community banks in commercial real estate (CRE) lending during the Covid-19 pandemic, a period of heightened uncertainty in a market characterized by informational frictions. Using bank-level Call Reports, property-level loan data from MSCI, and leasing outcomes from Compstak, we compare lending decisions and associated outcomes of community and large banks during this period. We show that community banks increased CRE lending during the pandemic, primarily within their local markets, and in large part by financing properties previously funded by large banks. Community banks also experienced lower foreclosure rates on loans issued during this period and stronger operating performance of the properties financed. These findings are consistent with a model of banking competition in which community banks can leverage superior local information against the lower cost of capital of large banks when uncertainty is high.

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1 Introduction

The fragmented structure of the U.S. banking system comprising thousands of small community banks alongside large national institutions raises enduring questions about the role of different types of lenders in credit markets. Why does such a decentralized system persist, and under what conditions do community banks provide unique value? These questions are especially salient in commercial real estate (CRE) lending, a sector where assets are illiquid, heterogeneous, and deeply tied to local market conditions. In other words, CRE lending is a setting where informational frictions are likely to be first-order, and where any advantages in local knowledge should be most apparent.

Recent concerns about banks' exposure to the CRE market have renewed interest in how different institutions manage risk and allocate credit in this sector (see, e.g., Aldana, 2023; Crosignani and Prazad, 2024; Glancy and Kurtzman, 2024; Anenberg et al., 2025; Hinzen et al., 2025). Figure 1 illustrates the disproportionately large and growing role community banks play in CRE lending. Panel A shows that community banks overall represent a small segment of the U.S. banking system, consistently accounting for approximately 12% of aggregate assets between 2016 and 2024. By contrast, Panel B shows that community bank holdings of CRE loans have grown to approximately 30% by 2024, almost equal to the share of CRE loans held by large banks in that year. Indeed, the FDIC (2020) emphasizes CRE lending as one of the notable lending strengths of community banks. Yet, we are not aware of any formal analyses of community bank lending decisions and associated outcomes in the CRE market to date.

[Figure 1 about here.]

The Covid-19 pandemic introduced a large, unanticipated shock to economic conditions and heightened uncertainty in the CRE market (see, e.g., Gupta et al., 2022a,b). This setting provides a useful opportunity to test whether community banks by virtue of their geographic proximity and focus are better equipped to issue and manage loans when uncertainty is high. Thus, we use the Covid-19 pandemic and the subsequent period of elevated uncertainty in the CRE market, which arguably extends to the present day, as a quasi-experimental setting in which to study the lending decisions and outcomes of community banks. For brevity, we refer to the period from Q2 of 2020 onward as the "pandemic", since the World Health Organization declared Covid-19 a global pandemic in March of 2020. We use this setting to present novel insights into the competitive advantages of community banks, beyond the commonly cited benefits stemming from specialization and long-term pre-existing lending relationships (see, e.g., Berger et al., 2017; Paravisini et al., 2023).

Using bank-level data from the FFIEC Call Reports and property-level loan data from MSCI, we analyze the dynamics of CRE lending before versus during the pandemic (i.e., over the 2010–2020Q1 period versus the 2020Q2–2024 period). We focus most of our main analyses on community banks, defined by the FDIC as small, local relationship lenders, and compare their lending behavior and loan performance to that of large banks.[1] Specifically, we examine changes in market shares, lending geography, borrower and property characteristics, and post-issuance loan performance outcomes.

We document three key findings. First, CRE lending by community banks increased substantially during the pandemic period, reversing a pre-existing downward trend, while large bank lending declined. This reversal is significantly different from the steady expansion of regional banks, whose inception predates the pandemic, as has been documented elsewhere (Hinzen et al., 2025). Second, the growth in community bank lending was not primarily driven by geographic expansion, a concern previously raised in the context of regional banks. Rather, our results suggest that community banks intensified CRE lending within their existing local markets, consistent with leveraging their locally focused business model. Third, and most notably, a significant share of community bank lending during pandemic targeted properties previously financed by large banks, suggesting a reallocation of lending activity to smaller, local banks in this period of elevated economic uncertainty. Additional analyses partitioning the sample into refinancing versus new loans and examining loan denial rates (based on HMDA data for multi-family loans) suggest that this reallocation was not primarily driven by a wholesale withdrawal of large banks from CRE lending during this period.

To assess the degree to which the observed reallocation reflects superior local information of community banks, we exploit spatial variation in the proximity of lenders and the properties they finance. We find that community banks were more likely to issue loans on properties previously financed by large banks when the community bank's headquarter was located in the same MSA as the property, consistent with a local information advantage. We do not find strong evidence of community banks issuing more loans against properties located in the same MSA as a branch of the community bank, reflecting the importance of soft information that is difficult to transmit within an organization.

We then evaluate loan outcomes. Call Report data show that community banks had lower ratios of non-performing, modified, and real estate owned (REO) loans during the pandemic, but these out-

[1]For the purposes of this paper, we classify banks into three categories, namely, community banks, large banks, and regional banks. Our definition of community banks follows the FDIC (2020). In addition to the asset-size threshold of $1.65 billion, this definition incorporates a bank's business plan, geographic footprint, and branch network. Large banks are defined as those with at least $100 billion in assets at any point during 2016–2024. All other banks are classified as regional banks. See Appendix A.1 for details.

comes may partly reflect pre-pandemic loan issuance decisions. Thus, we analyze MSCI data on foreclosures for loans issued during the pandemic. We find that community bank-issued loans had lower foreclosure rates than those of large banks. However, since foreclosure decisions may be influenced by pre-existing borrower relationships, we examine asset performance more directly. Given the importance of property-level cash flows for servicing loan obligations, we analyze leasing data from Compstak. These analyses suggest that properties financed by community banks during the pandemic exhibit more intensive leasing activity, more new leases signed, and lower concession rates while maintaining comparable starting rents relative to properties financed by large banks during this period.

These findings are consistent with a framework of banking competition where large banks benefit from a lower cost of capital, while small banks more efficiently gather and process local credit risk information. During benign economic times, the informational advantage of small banks is insufficient to offset their higher capital costs. Thus, small banks lose market share to large banks during these times. However, during periods of high economic uncertainty, like the pandemic, large banks struggle to effectively screen CRE borrowers. This dynamic allows small banks to gain market share at the expense of large banks without concurrent declines in loan quality.

Our study contributes to several strands of the literature on bank organizational form, relationship lending, and commercial real estate (CRE) finance. First, we provide the first systematic evidence on how community banks intermediate credit in the CRE market during a large, unanticipated shock. Work following Stein's (2002) theory of decentralized organizations emphasizes that small banks are naturally suited to producing soft information, and a large empirical literature documents that small banks lend closer, build stronger relationships, and are more informationally sensitive than large banks (e.g., Berger et al., 2005; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Beck et al., 2018; Herpfer et al., 2023). Yet virtually all of this evidence comes from small-business or consumer lending. We instead focus on CRE, an inherently information-sensitive sector with heterogeneous, illiquid assets and strong local demand and supply conditions. Using Call Reports, MSCI loan data, and Compstak leasing outcomes, we document that community banks expanded CRE lending during the Covid-19 pandemic, while large banks contracted, and that this expansion occurred without a broadening of community banks' geographic scope. In doing so, we extend the soft-information and distance literature into a market where informational frictions should be first-order but have been largely unstudied at the bank-type level.

Second, we speak directly to the literature on competition, risk-taking, and relationship banking over the cycle. Models of bank competition with moral hazard typically predict a non-monotone

relation between competition and failure and emphasize that downturns with illiquid assets and tight external finance should induce broad credit contractions (Allen, 2000; Boyd and De Nicolo, 2005; Martinez-Miera and Repullo, 2010; Froot et al., 1993; Froot and Stein, 1998; Hauswald and Marquez, 2006). In contrast, empirical work finds that a subset of small or relationship banks maintains credit supply in crises and can alleviate financing constraints (DeYoung et al., 2015; Berger et al., 2017; Liberti and Sturgess, 2018; Li and Strahan, 2021; Balyuk et al., 2021). We show that, in CRE, community banks not only sustain but increase lending during the Covid shock and subsequent period of heightened uncertainty, and that this increase reflects an intensification of local lending rather than nationwide expansion. This pattern is consistent with a framework in which local information advantages become particularly valuable when aggregate uncertainty is high and helps rationalize why a fragmented banking system with many small institutions can persist.

Third, we shed new light on competition between large and small banks and on the quality of small-bank lending in downturns. The literature has limited theoretical guidance on how small and large banks compete when one has a lower cost of capital and the other a local information advantage (Boot and Thakor, 2000; Stein, 2002), and evidence on whether small banks "lend smart" or engage in zombie lending in crises remains mixed (Caballero et al., 2008; DeYoung et al., 2015; Beck et al., 2018). We document a substantial reallocation of new CRE originations from large banks to community banks during the pandemic, concentrated in loans financing property sales rather than refinancings and in properties located in the lender's headquarter market rather than near a branch. This pattern is difficult to reconcile with a simple retreat of large banks from CRE and instead points to community banks selectively deploying superior local information when it is most valuable. We then show that loans originated by community banks during this period are associated with lower foreclosure rates and with properties that exhibit more intensive leasing and lower concessions at comparable rents, after controlling for property, borrower, bank, and local conditions and for pre-existing relationships. These results provide rare asset-level evidence that small-bank credit expansions in a downturn are consistent with prudent screening rather than zombie lending.

Fourth, we contribute to the emerging literature on CRE lending and bank exposure to CRE risk. Existing work has documented intermediary segmentation between banks and CMBS and has highlighted the role of CRE in banks' risk profiles, especially around the global financial crisis and in the run-up to recent CRE stress (Garmaise and Moskowitz, 2004; Black et al., 2020; Glancy et al., 2022; Aldana, 2023; Glancy and Kurtzman, 2024; Crosignani and Prazad, 2024; Anenberg et al.,

2025; Hinzen et al., 2025). Much of this work, however, focuses on delinquency and modification outcomes in specific segments, often with limited coverage of small-bank balance-sheet lending. Building on the literature review's call for richer data and joint analysis of credit supply, loan performance, and real-asset outcomes in CRE, we integrate regulatory filings, loan-level transactions, and lease-level performance measures to provide a unified view of how community and large banks differentially allocate and manage CRE risk during a systemic shock. Our evidence suggests that the decentralized U.S. banking structure, with its large community-bank segment, can help sustain and reallocate credit to informationally opaque CRE assets without a deterioration in loan quality when aggregate uncertainty is high.

2 Data and Sample Construction

The principal data sources used in this study are the Federal Deposit Insurance Corporation, the Federal Financial Institutions Examination Council, MSCI, and Compstak. Here, we describe each of these data sources in turn and outline how we construct the sample for our empirical analyses.

2.1 Data Sources

The Federal Deposit Insurance Corporation (FDIC) maintains a database of all FDIC-insured institutions in the U.S. First, we obtain the full register of current and historical institutions from this database, identified by FDIC certificate number. This register includes data on institution characteristics, such as charter type (commercial bank or savings institution), charter agent (state or federal), and current status (active or historical), as well as location coordinates for each institution's headquarter. Importantly, this register contains a community bank indicator, based on measures of bank size, traditional relationship banking, and limited geographic scope, as defined in the FDIC Community Banking Study (2020). This indicator allows us to identify the community banks at the center of our analyses. Second, we obtain annual data sets on the branch networks of all FDIC-insured institutions from the Summary of Deposits (SOD) for the 2010–2024 period. Each annual SOD provides a snapshot of the branches associated with a given bank's headquarter, including the location coordinates of all branches in the network. Branches are identified by the FDIC unique number for holding companies, banks, branches and non-deposit subsidiaries, and headquarters by the FDIC certificate number. We merge the data sets on bank headquarters and branch networks by FDIC certificate number. The merged data set allows us to capture the insti-

tutional characteristics, headquarter locations, and point-in-time branch networks of FDIC-insured banks over the 2010–2024 period.

The Federal Financial Institutions Examination Council (FFIEC) collects and standardizes the Call Reports, formally known as Reports of Condition and Income. The Call Reports are quarterly regulatory filings submitted by all FDIC-insured commercial banks and savings institutions in the U.S. Each filing provides detailed information on 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 over the 2010–2024 period. From these reports, we extract the information related to current CRE lending, including (non) owner-occupied CRE loans and multi-family loans, along with modified CRE loans, non-performing CRE loans, and real estate owned CRE loans.

We also extract the information required to compute several bank-level financial characteristics, including total assets, the capital ratio, liquidity ratio, earnings ratio, and loan ratio. We merge the FDIC bank register data with the CRE lending and financial characteristics data in the Call Reports based on the FDIC certificate number included in both data sets. The merged data set tracks institutional characteristics and quarterly financial metrics on the bank-level for 6,567 FDIC-insured banks over the 2010–2024 period. We refer to this data set as the FDIC Call Report panel.

MSCI is the leading provider of proprietary CRE transactions and financing data in the U.S. Coverage is comprehensive, relying on county-level records as the primary source of transaction information.[2] From the MSCI database, we obtain transaction-level records of CRE deals completed in the U.S. between 2000 and 2024. Each record contains unique transaction and property identifiers, a wide range of transaction and property characteristics, as well as detailed information about the parties involved in the transaction. Key transaction characteristics include transaction type (sale, refinancing, transfer), completion date, and property value. Records on transfers additionally feature a comments field allowing us to identify foreclosures. Relevant property characteristics include property type, address, and exact location coordinates. For the parties involved in sales transactions, we observe buyer and seller identities. For the parties involved in refinancing transactions (and for mortgages issued in the context of CRE sales), we additionally observe the identity and type of the borrower (coinciding with the buyer in sales transactions financed using mortgages), the identity of the lender, the loan issuance and maturity dates, as well as the loan amount. We

[2]MSCI gathers data on all real estate transactions worth $2.5 million or more. Given this restriction, the MSCI data may exclude smaller-scale deals more likely to be financed by community banks and thus capture a lower bound on the CRE lending activity of community banks in the U.S.

supplement the MSCI transaction records with additional information on the buyers and borrowers represented in these records. Specifically, we use the MSCI investor module to identify the exact geographic location, including location coordinates, for the headquarters of the buyers and borrowers observed in the MSCI transaction records.

Within the initial sample of CRE sales and refinancing transactions, we focus on those completed over the 2016–2024 period and involving mortgages issued by bank lenders.[3] We identify mortgages issued by bank lenders by examining the lender names listed 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 the 2016–2024 period in the context of both sales and refinancing transactions, associated with 3,632 unique banks.

Compstak is the leading provider of CRE leasing information in the U.S. Compstak collects and rigorously verifies contract-level data on CRE lease terms sourced from an extensive network of CRE leasing brokers and other intermediaries. From Compstak, we obtain data on CRE leases signed in the U.S. between 2016 and 2024 to match the sample period of the MSCI loan data set. Each lease record contains detailed lease terms, notably, asking rent, net effective rent, lease start and end dates, lease type (new lease or renewal), concessions (e.g., rent-free periods, tenant improvement allowances), and property characteristics including location coordinates. The initial Compstak data set we obtain contains 613,160 leases signed over the 2016–2024 period across 241,902 unique properties. We will use this data set to track leasing activity on the property-level as a measure of operating performance later in our analyses.

We obtain quarterly county-level data on unemployment rates from the U.S. Bureau of Labor Statistics and on house price indices (HPI) from Zillow. These data cover unemployment rates for 3,222 counties and HPI values for 3,073 counties over the 2010–2024 period.

2.2 Sample Construction

We construct our main estimation sample by merging the MSCI loan data set with the FDIC data set on bank branch networks and the FDIC Call Report panel. We supplement this sample with property leasing data merged in from Compstak. Since there exist no shared identifiers between these data sets, we implement several different matching procedures, depending on the information available in each data set. We outline these procedures below.

[3]While MSCI data on CRE transactions are comprehensive going back to 2000, the loan records in the MSCI data set are focused on CMBS loans prior to 2016, when bank loans were added to the data collection.

To match the MSCI loan data set with the FDIC branch network data set, we proceed as follows. First, we pre-process the data. Notably, we standardize bank names across both data sets by capitalizing them and harmonizing acronyms (e.g., using National Association for "N.A."). We then apply a fuzzy matching algorithm based on vector decomposition of the standardized bank names, where these names are tokenized into sequences of two consecutive characters and compared across data sets. We summarize the outcomes of these comparisons in a Jaccard similarity index ranging from 0 to 1, where an index value of 1 indicates a perfect match. We consider matches with index values of 0.9 or higher to be successful.[4] Of the 3,632 unique banks in the MSCI loan data set, 2,975 are successfully matched by this measure. We review the remaining unmatched banks in the MSCI data set manually. As a result of this procedure, we successfully match over 98% of banks from the MSCI data set. For more details on the MSCI–FDIC matching procedure, see Appendix A.2.

The matching procedure outlined above allows us to locate the FDIC certificate number for the bank listed as lender for each loan in the MSCI data set. We use this number to look up the bank's headquarter location in the FDIC data and compute the physical distance between this location and the location of the property financed by a given loan. We also compute the distance to the specific branch in the bank's network that is located in closest proximity to the property financed in the year in which the loan was issued. To do so, we compute the physical distance between the property and each of the branches in the bank's network in that year and retain the closest one. This step allows us to capture, for each loan in the MSCI data set, the FDIC identifier for the lending bank, the distance between the property financed and the bank's headquarter location, as well as the distance between that property and the nearest branch in the bank's network when the loan is issued.

Next, we merge the Call Report data on bank financial characteristics into the MSCI loan data set using the FDIC certificate number. Specifically, we merge the quarterly bank financial measures into the MSCI loan data set as of Q4 of the year before a loan is issued. This is important because the Call Reports record key financial variables on a cumulative basis, where the Q4 values represent annual totals. The resulting data set represents our main estimation sample, containing the complete MSCI loan records, supplemented with information on the distance between a given property and the lending bank's headquarter, respectively, the nearest branch in the lending bank's network, and a set of (financial) characteristics for the lending bank in the year prior to loan issuance.

[4] An example of a non-exact match with an index value above 0.9 is "First Secure Community Bank" in the FDIC data, which appears as "1st Secure Community Bank" in the MSCI data.

Lastly, we match data on CRE leases from Compstak with the MSCI loan data set. Again, there exists no shared property identifier between the MSCI and Compstak data sets. Although both data sets include address information, relying on addresses for matching can be problematic due to inconsistencies in formatting and discrepancies in building numbers. To mitigate these issues, we rely instead on the property location coordinates contained in both data sets. Specifically, we compute pairwise geographic distances between all properties in the two data sets and retain the pair with the shortest distance as the best potential match. We discard potential matches where the shortest distance exceeds 100 meters. To further improve the accuracy of matches, we discard any pairs with mismatched property types and retain only matches where the lease start date falls within the corresponding loan's issuance and maturity dates observed in MSCI. The resulting data set contains 73,580 leases signed over the 2016–2024 period for 21,583 unique properties associated with 23,765 loans from the MSCI data set. In other words, we identify matching lease observations for CRE properties associated with approximately 14% of the loans in the MSCI data set.

2.3 Variable Definitions

We construct the following bank-level variables in the quarterly FDIC Call Report panel. *CRE Growth* is the quarterly 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 difference between the current year and the establishment year of the bank. *CRE Spec.* is an indicator that takes the value of one if the bank is classified as specializing in CRE 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. For more details on bank-level variable definitions, see Appendix A.3.

We construct the following variables in the MSCI loan data set. *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 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. We construct indicators for property type (apartment, hotel, industrial, office, retail) as well as investor objectives and investor types. Specifically, *Investment*, *Development*, and *Occupancy* are indicators that take the value of one if the objective of buyer (respectively, borrower) in a sales (refinancing) transaction is investment, development, or occupancy, respectively. *Private*, *Institutional*, and *User/Other* are indicators that take the value of one if the buyer (respectively, borrower) in a sales (refinancing) transaction is a private, institutional, or user/other type of investor. *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.[5]

A key part of our empirical analyses requires measures of proximity between (community) banks and the properties they finance. Specifically, *HQ Distance* and *Branch Distance* are the physical distance (in miles) between the property and, respectively, the headquarter or the nearest branch of the lending 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. We construct analogous indicators based on the headquarter location of the investor owning a property and the headquarter or the nearest branch of the bank issuing the loan backed by that property.

We construct the following variables based on the information in the Compstak lease data set. *All* is the total number of leases signed for a property during the loan term. *Renewals* (respectively, *New*) is the number of renewals (new leases) signed during the loan term. *Free Rent* is 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. *Start. Rent* is the average monthly starting rent per sq.ft. across the leases signed during the loan term. *Eff. Rent* is the average monthly effective rent, after concessions such as tenant improvement allowances and rent-free periods, across the leases signed during the loan term.

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.

[5]Although our estimation sample spans the 2016–2024 period, *Prev. Relation* is measured using data from the 2000–2024 period to ensure maximum coverage. However, because the MSCI dataset includes transactions worth $2.5 million or more, this variable likely reflects a lower bound of previous lending relationships, as smaller transactions may not be fully captured.

2.4 Descriptive Statistics

Table 1 presents summary statistics for the FDIC Call Report panel over the 2010–2024 period by bank type. On average, community banks are significantly smaller, older, and less well capitalized (by equity-to-assets ratio) than are non-community banks. A specialization on CRE lending is common in both bank types (55% of community banks and 69% of non-community banks are classified as CRE specialists according to the FDIC). By contrast, the statistics reported indicate no significant differences in average CRE loan growth, the share of non-performing loans, as well as liquidity, earnings, and loan ratios by bank type. The reported differences in average modified and REO loan shares are statistically significant but numerically small.

[Table 1 about here.]

Table 2 presents summary statistics for the MSCI loan data set over the 2016–2024 period by bank type.[6] On average, properties financed by community banks are smaller and have lower values (per sq.ft.) than those financed by non-community banks. The statistics reported further indicate statistically significant, but economically minor, differences in age, renovated status, CBD location, and LTV between properties financed by community versus non-community banks. We observe significant shares of pre-existing lending relationships between the borrowers and the banks in the MSCI loan data set across community and non-community banks.

[Table 2 about here.]

The statistics in Table 2 also show that properties financed by community banks are significantly more likely to be located in the same MSA as the lending bank's headquarter than are those financed by non-community banks, while we observe the opposite pattern for the MSA location of the property relative to that of the nearest bank branch. These observations are consistent with the community bank business model of limited geographic scope (FDIC, 2020). They likely also reflect the density of the branch networks maintained by large, nationally operating banks in major locations across the U.S. The statistics reported in Table 2 indicate similar patterns for the alternative indicators based an investor's headquarter location and the (headquarter or branch) location of the lending bank. This finding likely reflects that the CRE market is dominated by (small-scale) private investors, who mainly acquire properties locally.

[6] Figure B.1 shows the distribution of the properties in this data set across U.S. counties.

Figure 2 depicts the distribution of the distance between a given property and the lending bank in the MSCI loan data set. The patterns in Panel A show that in nearly 50% of loans made by community banks the distance between the property and the lending bank's headquarter is within 50 miles, while only 20% of loans made by non-community banks fall into this distance band. By contrast, the patterns in Panel B show that in approximately 80% of loans made by non-community banks the distance between the property and the nearest branch of the lending bank is within 50 miles, while 60% of community bank loans fall into that band. The patterns shown in Figure 2 are consistent with the statistics reported in Table 2.

[Figure 2 about here.]

Figure 3 presents the breakdown of the MSCI loan data set by bank type across property type, investor type, and investor objective. The patterns depicted in this figure indicate that property type composition is similar across community and non-community banks, with the former financing slightly more hotel properties and fewer apartment properties than the latter. Across both bank types, private investors and those seeking financing to fund investments dominate the sample over private or other investor types and development or owner-occupancy objectives.

[Figure 3 about here.]

Table 3 presents summary statistics for the Compstak lease data. Specifically, these statistics are for the property leases signed 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 statistics reported indicate that there is no difference in the average number of leases signed per quarter across properties financed by community banks versus those financed by non-community banks (1.10 and 1.09, respectively). However, we see that the share of new leases relative to renewals is higher in properties financed by community banks than it is in those financed by non-community banks (0.68 versus 0.62). Further, the statistics reported indicate that leases in properties financed by community banks feature shorter rent-free periods (3.58 months versus 4.14 months). We also see that these leases feature lower starting rents and lower effective rents than do the leases in properties financed by non-community banks. The unconditional summary statistics presented here suggest significant differences in leasing activity and lease terms across properties financed by community versus non-community banks. We will later analyze

these differences more formally as an indicator of operating performance across properties financed by community banks versus those financed by non-community banks during the pandemic.[7]

[Table 3 about here.]

3 CRE Lending Activity of Community Banks

Figure 4 presents annual trends for market shares in CRE loan issuance based on the MSCI loan data set over the 2016–2024 period by bank type. Panel A shows aggregate shares of CRE loan issuance by loan count. The patterns depicted indicate that community banks exhibit a sharp increase in loan issuance beginning in 2020, becoming the largest contributor to aggregate issuance in 2024. Panel B shows aggregate shares of CRE loan issuance by loan amount. The patterns shown here again indicate a strong increase in loan issuance by community banks beginning in 2020, reversing the downward trajectory observed prior to the pandemic. This trend contrasts with that of large banks, whose CRE loan issuance (by loan count as well as loan amount) has declined consistently starting in 2020. In sum, the patterns displayed in Figure 4 indicate strong growth in the CRE loan issuance of community banks starting at the time of the Covid-19 pandemic, primarily at the expense of large banks in this market.

[Figure 4 about here.]

We begin our empirical analyses by examining the growth in CRE lending by community banks during the Covid-19 pandemic. First, we assess whether community banks increased their CRE lending activity during this period and to what degree they did so by expanding in geographic scope. Further, we study the competition between community banks and large banks. The estimating equations used in our study build on the econometric specifications in the recent analyses of relationship banking in Berger et al. (2024). Complementing these analyses, our results provide novel insight into the role of community banks as CRE lenders during times of heightened economic uncertainty.

[7] Tables B.1, B.2, and B.3 present summary statistics of key bank, property, and local economic characteristics across the FDIC Call Report panel, the MSCI loan data set, and the Compstak lease data set. The characteristics of the banks, properties, and counties represented in these data sets are generally comparable, except: (i) the community banks in the FDIC Call Report panel are, on average, numerically smaller and older than those represented in the MSCI and Compstak data sets, (ii) the properties in the MSCI loan data set are, on average, numerically smaller and less valuable per sq.ft. than are those in the Compstak lease data set, and (iii) in contrast to MSCI, Compstak does not cover apartment or hotel properties.

3.1 Increase in CRE Lending Activity

The time-series patterns depicted in Figure 4 suggest significant growth in the CRE lending activity of community banks during the Covid-19 pandemic. We corroborate the unconditional trends shown in this figure by estimating the quarterly growth rate in the balance of CRE loans outstanding as a function of bank type in the FDIC Call Report panel over the 2010–2024 period. Specifically, we estimate linear OLS regressions of the following form:

$$CRE\ Growth_{b,t} = \alpha_b + \beta_t + \gamma Comm.\ Bank_b \times Covid_t + \sum_{m \in M} \delta_m Z^{m \in M} + \epsilon_{b,t} \tag{1}$$

where $CRE\ Growth_{b,t}$ is the growth rate in the balance of CRE loans outstanding for bank b in year-quarter t. α_b are bank fixed effects, accounting for time-invariant bank characteristics such as institution class, headquarter location, year of establishment, and an indicator that takes the value of one if the bank is classified as specializing in CRE lending by the FDIC. β_t are year-quarter fixed effects, accounting for variation in broad macro-economic trends. $Comm.\ Bank_b$ is an indicator that takes the value of one if bank b is classified by the FDIC as a community bank. $Covid_t$ 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. α_b absorbs the main effect of $Comm.\ Bank_b$. β_t absorbs the main effect of $Covid_t$. $Z^{m \in M}$ represents $M = 2$ different sets of covariates. These covariates include time-varying bank financial characteristics, namely, an indicator that takes the value of one if the bank is classified as a CRE specialist by the FDIC, as well as ratios for bank capital, liquidity, earnings, and loans to assets, all measured for bank b at time $t = mr$, that is, Q4 of the most recent year. We also account for time-varying local economic characteristics, namely, the unemployment rate, the level of the house price index, and the quarterly growth rate in this index, all measured for the county of a given bank's headquarter c at time $t-1$, that is, with a one-quarter lag. $\epsilon_{b,t}$ is the residual. Standard errors are clustered by bank. The coefficient of interest γ captures the differential growth rate in the balance of CRE loans outstanding at community banks during the pandemic.

Table 4 presents the results from estimating Eq. (1) in the FDIC Call Report panel over the 2010–2024 period. The coefficient estimates reported in column 1 indicate that, accounting for bank fixed effects and year-quarter fixed effects, community banks experience significantly higher growth rates in their balances of CRE loans outstanding during the pandemic period than did other bank types. This result holds after accounting for time-varying bank-level financial covariates (see column 2) and after additionally accounting for time-varying local economic covariates (column 3).

The results reported in column 3 represent our most saturated model specification. The magnitude of the coefficient estimate γ of 0.053 in this column indicates that the quarterly growth rate in CRE loans outstanding increased more than 50% for community banks during the pandemic, relative to the unconditional mean of 0.035. In sum, the evidence presented in Table 4 is consistent with the observation that community banks significantly expanded their aggregate CRE loan balances during the Covid-19 pandemic relative to other bank types.

[Table 4 about here.]

To characterize the lending activity of community banks in the CRE market during the pandemic more fully, we analyze the lender classifications in the MSCI loan data set over the 2016–2024 period. These analyses allow us to corroborate the trends depicted in Figure 4 by capturing key drivers of the marginal CRE lending decisions made by community banks on the level of individual loans. Specifically, we estimate linear probability models of the following form:

$$Comm.\ Bank_{i,p,t} = \alpha Covid_t + \sum_{m \in M} \delta_m Z^{m \in M} + \epsilon_{i,p,t} \tag{2}$$

where $Comm.\ Bank_{i,p,t}$ is an indicator that takes the value of one if the bank providing loan i against property p issued at time t is classified by the FDIC as a community bank. $Covid_t$ 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. $Z^{m \in M}$ represents $M = 4$ different sets of control variables, namely, on the level of the property financed, the loan issued, the borrower (investor) obtaining the loan, and the bank providing the loan. Specifically, property-level covariates include the natural logarithm of property size (in '000 sq.ft.), the natural logarithm of property value per sq.ft., indicators for property type (hotel, industrial, office, or retail, with apartment being the omitted category), property age, an indicator that takes the value of one if the property has been renovated since its construction, and an indicator that takes the value of one if the property is located in a central business district. Loan-level covariates include the loan-to-value ratio at the time of loan issuance. Borrower-level covariates include investor type (institutional or user/other, with private investors being the omitted category) , investor objective (re-development or occupancy, with investment being the omitted category), and an indicator that takes the value of one if the borrower in a given loan previously financed another property with the same bank. All of the characteristics outlined above are measured as of the time when a given loan is issued. Bank-level covariates include ratios for

bank capital, liquidity, earnings, and loans to assets, all measured as of Q4 of the most recent year prior to loan issuance. Standard errors are clustered by bank. The coefficient of interest α captures the differential likelihood that a CRE loan is issued by a community bank during the pandemic.

In alternative specifications, we include, in turn, county fixed effects, property fixed effects, and county-level covariates to account for key confounding factors that could affect our inferences. County-level fixed effects allow us to account for the possibility that we observe more CRE loans issued in counties where community banks have a greater market share. Property-level fixed effects allow us to limit our inferences to the same properties serving as collateral across loans issued before versus during the pandemic. County-level covariates include the unemployment rate, the level of the house price index, and the quarterly growth rate in this index, all measured for the county where a given property is located as of the quarter prior to loan issuance. These covariates allow us to account for the possibility that the counties we observe are differentially affected by economic fluctuations during the pandemic, which could influence local demand for CRE loans.

Table 5 presents the results from estimating Eq. (2) in the MSCI loan data set over the 2016–2024 period. The coefficient estimates reported in column 1 indicate 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 they are before the pandemic. This result holds after accounting for county fixed effects (column 2) and property fixed effects (column 3). The results tabulated in column 4 represent our preferred specification, accounting for property, loan, investor, and bank covariates, local economic characteristics, and property fixed effects. The coefficient estimate α of 0.036 in this column indicates that, accounting for all of the covariates outlined above, the same property is 3.6 percentage points more likely to be financed by a community bank during the pandemic than it is before the pandemic. Relative to the unconditional mean likelihood of community bank financing in this sample of 0.322, this coefficient implies an over 10% increase in the likelihood of community bank financing during the pandemic. In sum, the evidence presented in Table 5 corroborates the observation that community banks significantly expanded their CRE lending activity during the Covid-19 pandemic as compared to other bank types.

[Table 5 about here.]

We augment Eq. (2), including property, loan, investor, and bank covariates, local economic characteristics, and property fixed effects, to examine the evolution of community bank lending in event time around the onset of the Covid-19 pandemic in Q2 of 2020. To that end, we replace the

Covid indicator in Eq. (2) with 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 Q2 of 2020 (event time 1). We summarize the results of this event study analysis in Figure 5.

[Figure 5 about here.]

The patterns depicted in Figure 5 indicate that, after accounting for the saturated set of covariates and fixed effects in the expanded version of Eq. (2) outlined above, the differential likelihood of a property being financed by a community bank prior to the onset of the Covid-19 pandemic was numerically close to zero and statistically indistinguishable from zero. In other words, our analyses reveal no evidence of any significant pre-trends in the likelihood of community bank financing leading up to the pandemic. In stark contrast, we estimate a higher likelihood of community bank financing starting in quarter 2 after the onset of the pandemic and stabilizing in quarters 6 through 8. The coefficient values of approximately 0.05 estimated during this period are statistically significant and economically meaningful, representing a more than 15% increase in the likelihood of community bank financing relative to the unconditional mean of this variable in the underlying estimation sample of approximately 0.33. The evidence presented in Figure 5 reinforces our inference that community banks significantly increased their CRE lending activity during the Covid-19 pandemic.

3.2 Expansion of Geographic Scope

One of the key features of community banks is their limited geographic scope of operations (FDIC, 2020). Evidence of a significant increase in the CRE lending activity of community banks during the Covid-19 pandemic thus raises the question whether these banks expanded their geographic scope, as recently documented for regional banks (Hinzen et al., 2025). To test whether community banks extended CRE loans on properties further afield during this period, we leverage our granular, time-varying data on bank locations and branch networks. Using these data, we measure the geographic scope of banks' CRE lending activity based on the physical distance between a given property and the lending bank's location. We consider the lending bank's location on the level of the headquarter and, alternatively, on the level of the nearest branch in the bank's network. We then examine variation in these distance measures by bank type in the MSCI loan data set over the 2016–2024 period. Specifically, we estimate linear OLS regressions of the following form:

$$Distance_{b,i,p,t} = \alpha_b + \beta_t + \gamma Comm.\ Bank_b \times Covid_t + \sum_{c \in C} \delta_c Z^{c \in C} + \epsilon_{b,i,p,t} \tag{3}$$

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 in year-quarter t. In alternative specifications, we replace the dependent variable with an indicator that takes the value of one if the bank's headquarter location is in the same Metropolitan Statistical Area (MSA) as the property, the natural logarithm of the physical distance between the nearest branch of the lending bank and the property, and an indicator that takes the value of one if the bank's nearest branch is in the same MSA as the property.

As in Eq. (1), α_b are bank fixed effects, accounting for time-invariant bank characteristics. β_t are year-quarter fixed effects, accounting for variation in broad macro-economic trends. $Comm.\ Bank_b$ is an indicator that takes the value of one if bank b is classified by the FDIC as a community bank. $Covid_t$ is an indicator that takes the value of one in any year-quarter t starting in Q2 of 2020. Similar to Eq. (2), $Z^{c \in C}$ represents $C = 5$ different sets of control variables, namely, on the level of the property financed, the loan issued, the borrower (investor) obtaining the loan, the bank providing the loan, and the county of the property. $\epsilon_{b,i,p,t}$ is the residual. Standard errors are clustered by bank. The coefficient of interest γ captures the differential change in the physical distance between community bank locations and the properties financed by these banks during the Covid-19 pandemic.

Table 6 reports the results from estimating Eq. (3) in the MSCI loan data set over the 2016–2024 period. 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 99^{th} 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 a large 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. In sum, the evidence presented thus far suggests that community banks increased their CRE lending activity during the Covid-19 pandemic without deviating from their traditional business model of maintaining a limited geographic scope of operations.

[Table 6 about here.]

3.3 Competition with Large Banks

In this section, we examine the degree to which the increase in CRE loan issuance by community banks during the Covid-19 pandemic represents a reallocation of lending activity away from large banks. We assess the evidence for this dynamic by augmenting Eq. (2). Specifically, we estimate linear probability models of the following form:

$$\begin{aligned} \textit{Comm. Bank}_{i,p,t} = \alpha\, \textit{Covid}_t + \beta\, \textit{Prev. Large Bank}_p + \gamma\, \textit{Covid}_t \times \textit{Prev. Large Bank}_p \\ + \sum_{c \in C} \delta_c Z^{c \in C} + \epsilon_{i,p,t} \end{aligned} \tag{4}$$

where $\textit{Comm. Bank}_{i,p,t}$ is an indicator that takes the value of one if the bank providing loan i against property p issued at time t is classified by the FDIC as a community bank. $\textit{Covid}_t$ is an indicator that takes the value of one at any time t starting in Q2 of 2020. $\textit{Prev. Large Bank}_{i,p,t}$ 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. Similar to Eq. (2), $Z^{c \in C}$ represents $C = 5$ different sets of control variables, namely, property, loan, investor, bank, and local economic controls. Standard errors are clustered by bank. The coefficient of interest γ captures the differential likelihood that a CRE loan is issued by a community bank during the pandemic if the property was previously financed by a large bank.

Table 7 and Table 8 present the results from estimating Eq. (4) in the MSCI loan data set over the 2016–2024 period. By construction, the estimation sample is limited to properties for which we observe more than one loan. We also exclude loans issued by regional banks from these estimations so the results capture the competition between large banks and community banks. Table 7 shows the results by transaction type (i.e., all transactions, sales, and refinancing deals) and including all property locations. The coefficient estimates of the *Covid* indicator reported across all the columns in this table suggest that CRE loans were more likely to be issued by a community bank during this period. This finding is consistent with the significant growth we document in the CRE lending activity of community banks during the pandemic (see Tables 4 and 5). The negative signs on the coefficient estimates of the *Prev. Large Bank* indicator suggest that community banks and large banks typically issue loans in different segments of the CRE market. This finding is consistent with the unconditional lending patterns reported in Table 2 and prior evidence on intermediary segmentation in the CRE market (Glancy et al., 2022).

[Table 7 about here.]

The main coefficient of interest reported in Table 7 is that of the interaction term between the *Covid* indicator and the *Prev. Large Bank* indicator. In column 1, this coefficient is significantly negative, suggesting that during the pandemic, community banks were less likely to extend loans on properties previously financed by large banks than they were prior to the pandemic. This finding implies a growing segmentation in the CRE lending market during the Covid-19 pandemic. However, we see starkly contrasting results when examining CRE loans issued in the context of sales versus refinancing transactions separately. Notably, the estimates in column 2 suggest that during the pandemic, community banks were more likely to issue loans on CRE properties previously financed by large banks if these loans were used to finance the sale of the property. By contrast, the estimates in column 3 suggest that the reduced likelihood of obtaining a community bank loan during the pandemic for a property previously financed by a large bank is concentrated in the sub-sample of loans used for refinancing purposes. The results suggest that large banks did not withdraw from the CRE lending market during the COVID-19 pandemic, as they continued to refinance existing properties. However, when it came to financing new properties where informational frictions are likely more pronounced a reallocation of CRE lending activity from large banks to community banks becomes evident. In summary, our findings indicate a shift in CRE lending from large banks to community banks, particularly for CRE assets whose investors sought new sources of financing during this period of heightened economic uncertainty. Importantly, the continuing activity of large banks in refinancing loans suggests that this reallocation was not primarily driven by a wholesale withdrawal of large banks from CRE lending during this period.

Table 8 shows results for the sub-sample of loans issued for sales transactions, where we observe evidence for a reallocation of CRE lending activity towards community banks during the pandemic. Within this set of loans, we now focus on sample splits based on the location of the property relative to the location of the bank providing the loan.[8] The results reported in Table 6 indicate that community banks increased their CRE lending activity during the pandemic without abandoning their traditional business model of maintaining limited geographic scope. Here, we assess the role of geographic proximity between banks and the assets they finance in modulating the reallocation of CRE lending activity from large banks to community banks during this period.

[Table 8 about here.]

[8]Table B.4 presents the results from replicating these analyses based on the headquarter location of the investor owning the property relative to the location of the bank. Our inferences remain unchanged.

The results in columns 1 and 2 of Table 8 indicate that properties previously financed by large banks were more likely to obtain financing from community banks during the pandemic if they were located in the same MSA as the headquarter of the bank providing the loan. If we view the proximity between properties and banks as a proxy for the cost of acquiring local information about the performance of the property (Agarwal and Hauswald, 2010), our results suggest that community banks are more likely to finance properties for which they can access this information more easily. Large banks, whose headquarters are typically far from the properties they finance (see Table 2) are unlikely to enjoy the same access. In other words, these results imply that during times of heightened economic uncertainty, community banks can compete with large banks based on a local information advantage. This finding is consistent with asymmetric information concerns between local and more distant agents being first-order in real estate markets (Garmaise and Moskowitz, 2004; Kurlat and Stroebel, 2015). By contrast, our estimations reveal little evidence that greater proximity between a property and a branch location of the bank providing the loan modulates the likelihood of obtaining community bank financing during the pandemic (see columns 3 and 4). This finding is consistent with CRE finance involving soft information that is difficult to transmit within organizations, e.g., from a branch location to the bank's headquarter where key decisions are made (Liberti and Petersen, 2019).

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 during the pandemic, we analyze mortgage application outcomes over the 2018–2024 period using the Home Mortgage Disclosure Act (HMDA) database. Table B.5 reports the results from estimating Eq. (3) 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.

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 B.2. 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 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.

4 CRE Loan Performance by Bank Type

The growth we document in CRE lending by community banks at least in part at the expense of large banks may be associated with a decline in lending standards, possibly resulting in poor loan performance outcomes. To assess the evidence for this conjecture, we examine measures of loan performance on the bank-, loan-, and property-level.

4.1 Non-Performing, Modified, and REO Loans

We begin by examining CRE loan performance based on the shares of non-performing, modified, and REO loans on the bank-level. Non-performing loans comprise all CRE loans that are 90+ days past due and those placed on non-accrual status. Modified loans comprise all CRE loans restructured in troubled debt restructurings. REO loans are CRE loans for which the underlying collateral has been repossessed by the bank but has not yet been sold at auction. We scale non-performing, modified, and REO loans by total CRE loans outstanding. The data for these analyses are from the FFIEC Call Reports, summarized in Table 1.

Figure 6 depicts annual trends in the shares of non-performing, modified, and REO loans outstanding in the FDIC Call Report panel over the 2016–2024 period by bank type. The patterns shown in Panel A indicate that non-performing loan shares hover around 0.5% of total CRE loans across all bank types in the years leading up to the pandemic. Then, we observe a significant increase in the non-performing loan shares of large banks starting with the pandemic and reaching 2.5% in 2024. At the same time, the corresponding shares at regional and community banks remain low, barely exceeding 0.5%. The patterns shown in Panel B suggest similar trends for modified loan shares, which decline across bank types prior to the pandemic, dropping to approximately 0.1% in 2019. Again, we see a sharp increase in loan modifications at large banks starting with the pandemic, reaching 0.5% in 2024, while the corresponding shares remain low for regional and community banks. Moreover, the patterns shown in Panel C reveal similar trends in REO loan shares. Community banks experienced a sharp decline from about 0.4% to 0.1% between 2016 and 2024, whereas regional banks exhibited a more moderate decrease from 0.2% to 0.1%. Large banks, by contrast, remained below 0.1% from 2016 through 2019, with a slight uptick starting in 2020.

[Figure 6 about here.]

We formalize the analyses of non-performing, modified, and REO loan shares by bank type using the regression framework from Eq. (1). Specifically, we replicate the estimation of Eq. (1) but replace the dependent variable with *NPL Share*$_{b,t}$, the share of non-performing CRE loans outstanding at bank b in quarter t. In alternative specifications, we replace the dependent variable with *Mod. Share*$_{b,t}$ (respectively, *REO Share*$_{b,t}$), the share of modified (real estate owned) CRE loans outstanding at bank b in quarter t. We estimate these regressions in the FDIC Call Report panel over the 2016–2024 period. However, we exclude regional banks from these analyses so the results capture loan performance trends across community banks and large banks. Table 9 presents the results.

[Table 9 about here.]

The coefficient estimates reported in columns 1 and 2 of Table 9 indicate that community banks experienced significantly lower shares of non-performing loans during the Covid-19 pandemic than did large banks. These results hold in the presence of bank and year-quarter fixed effects (column 1) and after accounting for time-varying bank financial characteristics and local economic controls (column 2). Considering the coefficient estimate of -0.013 on the interaction term between the community bank and pandemic indicators in the fully specified model (column 2), the estimated effect is also economically significant. Relative to the unconditional mean of 0.009, this coefficient estimate represents a marginal reduction in the non-performing loan share of over 100% for community banks relative to large banks during the pandemic. The coefficient estimates reported in columns 3 and 4 of Table 9 indicate that community banks also experienced significantly lower shares of modified loans during the Covid-19 pandemic than did large banks. Again, the relevant coefficient estimates are statistically and economically significant on a scale comparable to that observed for non-performing loan shares. The coefficients reported in columns 5 and 6 of Table 9 indicate that community banks held significantly lower shares of REO loans during the pandemic compared with large banks, suggesting that community banks were less likely to experience foreclosures during this period. Relative to the unconditional mean foreclosure rate of 0.4%, the coefficient in the fully specified model (column 6) implies a 75% marginal reduction in foreclosure rates for community banks compared with large banks during the pandemic. In sum, the evidence presented in Table 9 indicates that community banks experienced superior CRE loan performance, in terms of non-performing loans, modified loans, and repossessed loans, relative to large banks during the Covid-19 pandemic.

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 exposure to local characteristics such as remote work tendencies. The estimates presented in Table 9 are derived from specifications including county-level fixed effects and time-varying county-level economic controls that at least partly capture such tendencies. Thus, our findings are more consistent with smarter CRE lending decisions of community banks. That said, the outcomes examined here 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.

4.2 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 2, 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. (3) 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 exclude regional banks from these analyses so the results capture loan performance trends across community banks and large banks. To avoid mis-classifying loan performance outcomes, we also exclude all loans for which we cannot observe a final outcome (sale, refinance, or foreclosure). Table 10 presents the results.

[Table 10 about here.]

The coefficient estimates reported in Table 10 indicate that loans issued by community banks during the Covid-19 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). Considering the coefficient estimate of -0.028 on the interaction term between the community bank and pandemic indicators in the fully specified model (column 3), the estimated effect is also economically significant.[9] Relative to the unconditional mean of 0.076,

[9]Note that the sample mean of foreclosures is scaled by the total number of loans for which we observe a final resolution in the form of a subsequent sale, refinancing, or transfer. This rate is therefore not directly comparable to bank-level measures like the share of REO loans as reported in Table 9.

this coefficient estimate represents a marginal reduction in the likelihood of foreclosure of over 35% for CRE loans issued by community banks during the pandemic. In sum, the loan-level evidence presented in Table 10 corroborates the bank-level evidence from Table 9 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 typically 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), allows banks to defer loss recognition in hopes of improved future conditions, potentially masking the true extent of distress. While we lack comprehensive loan performance data, property-level leasing metrics can provide insight into property operating performance and thus, to a degree, also credit quality. We examine a set of such metrics in the next section.

4.3 Property Leasing Activity

We assess property-level leasing activity based on data from Compstak, which we merge into the MSCI loan data set over the 2016–2024 period using the procedure outlined in Section 2.2. For each loan in the merged MSCI-Compstak data set, we compute the total number of leases signed in the property backing this loan during the loan term, broken down by lease type (renewal or new lease). We also compute 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. (3) 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 the rent variables. Again, we exclude regional banks from these analyses. Table 11 presents the results.

[Table 11 about here.]

The estimates reported in column 1 indicate that loans issued by community banks during the pandemic were backed by properties experiencing significantly higher leasing activity during the loan term. To assess the economic magnitude of the estimated effects in the Poisson count model, we need to compute $e^{(\text{coef.})} - 1$. Thus, the coefficient estimate of 0.125 in column 1 implies an over 13% increase in the number of leases signed during the loan term. The coefficient estimates in

columns 2 and 3 indicate that this increase is mainly driven by new leases, rather than renewals. The coefficient estimate of interest for renewals in column 2 is numerically positive, but statistically insignificant. The estimates reported in columns 4, 5, and 6 indicate no statistically or numerically significant differences in rent-free periods, starting rents, or effective rents for leases signed in properties financed by community banks during the pandemic. In sum, our estimations show that loans issued by community banks during the pandemic were backed by properties attracting more tenants but not at the expense of greater concessions or lower rents. These results suggest that properties financed by community banks during the pandemic experienced superior operating performance, which constitutes an important prerequisite for better loan performance.

5 Conclusion

This paper examines the role of community banks in commercial real estate lending during the Covid-19 pandemic, a period of elevated uncertainty in a market characterized by informational frictions. Using regulatory filings from Call Reports, loan-level data from MSCI, and leasing outcomes from Compstak, we analyze lending patterns, loan performance, and property operating outcomes across bank types.

The evidence indicates that community banks increased their CRE lending activity during the pandemic, in contrast to large banks, and that this increase was concentrated within existing local markets rather than a product of geographic expansion. A notable share of community bank lending during the pandemic replaced financing previously provided by large banks, predominantly in the locations of the community bank headquarters. Our estimation results indicate a reallocation of CRE lending activity from large, nationally operating banks to smaller, locally focused institutions during this period of elevated uncertainty. Loans originated by community banks during this period were subsequently associated with lower foreclosure rates and were extended against properties exhibiting stronger leasing performance. Notably, all of our findings hold in the presence of extensive property, loan, investor, bank, and local economic controls. Importantly, these controls include indicators capturing bank specialization in CRE lending and pre-existing lending relationships that could produce observationally equivalent patterns in the data. Our choice of control variables thus allows us to interpret our estimations in terms of the importance of local information after accounting for these potentially confounding drivers.

These results are consistent with a framework in which community banks leverage local information advantages that become more valuable in times of heightened uncertainty, offsetting the lower cost of capital typically enjoyed by large banks. Our findings contribute to the literature on bank heterogeneity in credit markets and suggest that the decentralized structure of the U.S. banking system may help sustain credit supply to informationally opaque sectors such as CRE during systemic shocks.

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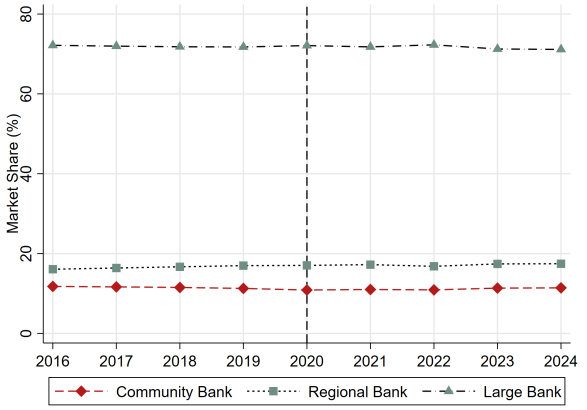
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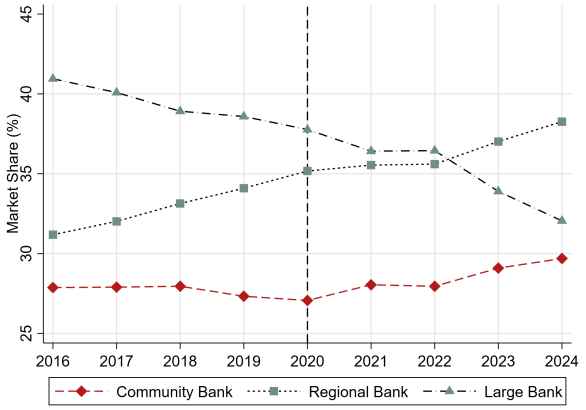
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Figure 1. Market Shares in the U.S. Banking Sector

This figure depicts annual trends for market shares in the U.S. banking sector over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification. 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. Panel A shows market shares of total assets. Panel B shows market shares of total CRE loans outstanding. The data used to produce this figure are from the FFIEC Call Reports.



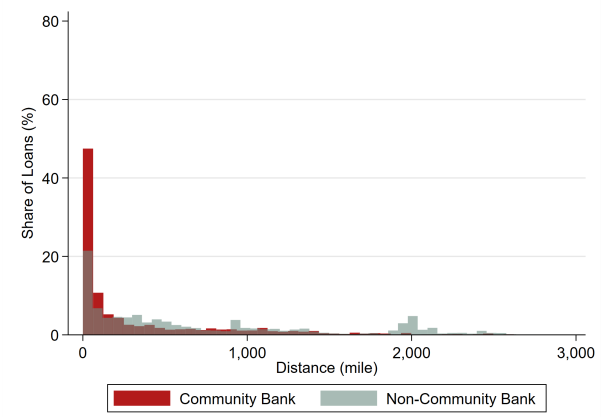
(A) Total Assets



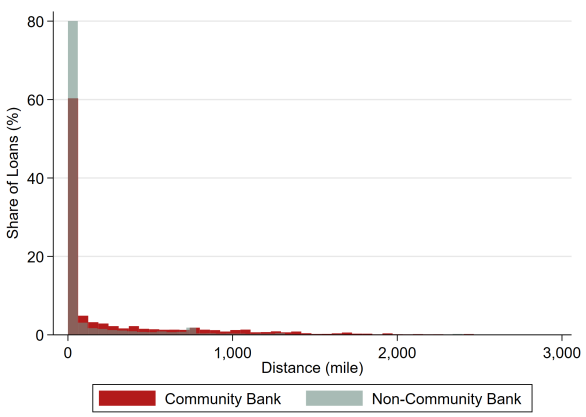
(B) CRE Loans

Figure 2. 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.



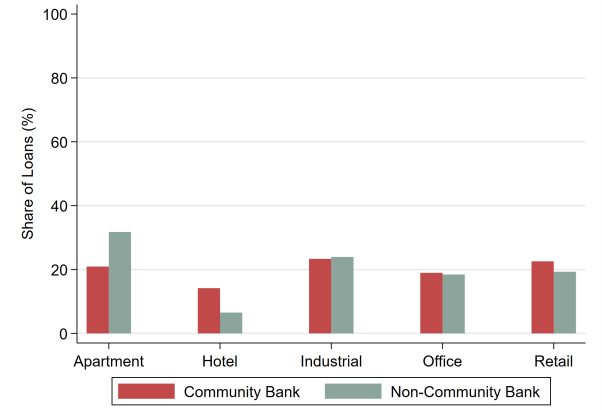
(A) Headquarter



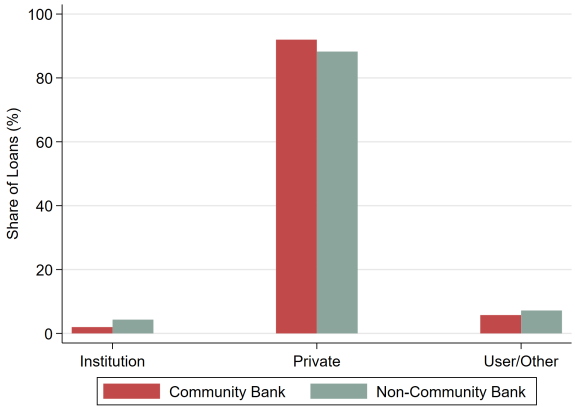
(B) Nearest Branch

Figure 3. Sample Composition

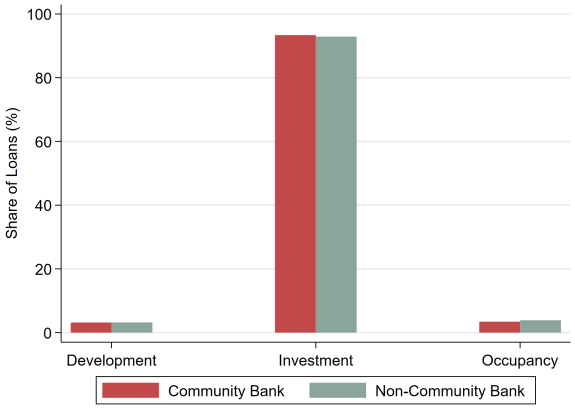
This figure depicts the composition of the MSCI loan data set over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification. Panel A shows the sample distribution of property types. Panel B shows the sample distribution of investor types. Panel C shows the sample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



(A) Property Type



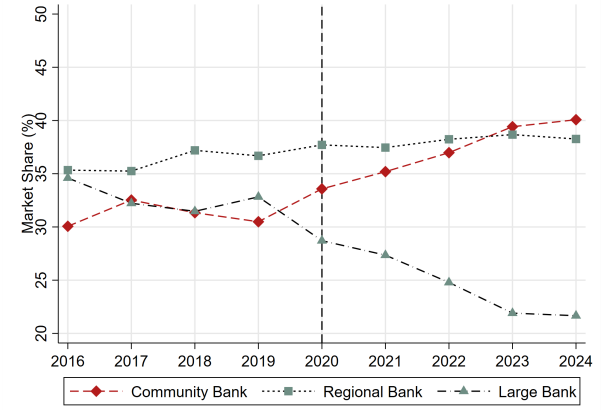
(B) Investor Type



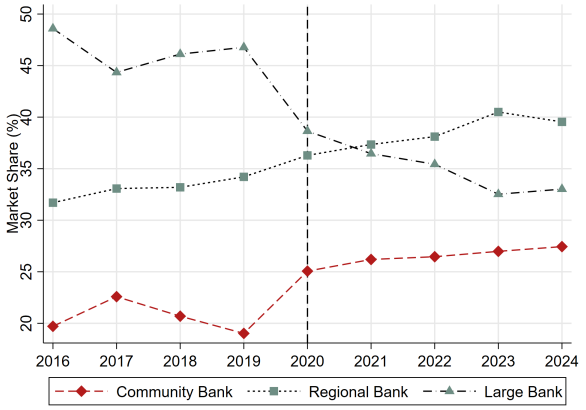
(C) Investor Objective

Figure 4. 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. 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 5. Marginal Changes in CRE Loan Issuance by Community Banks

This figure depicts the results from estimating Eq. (2) 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.

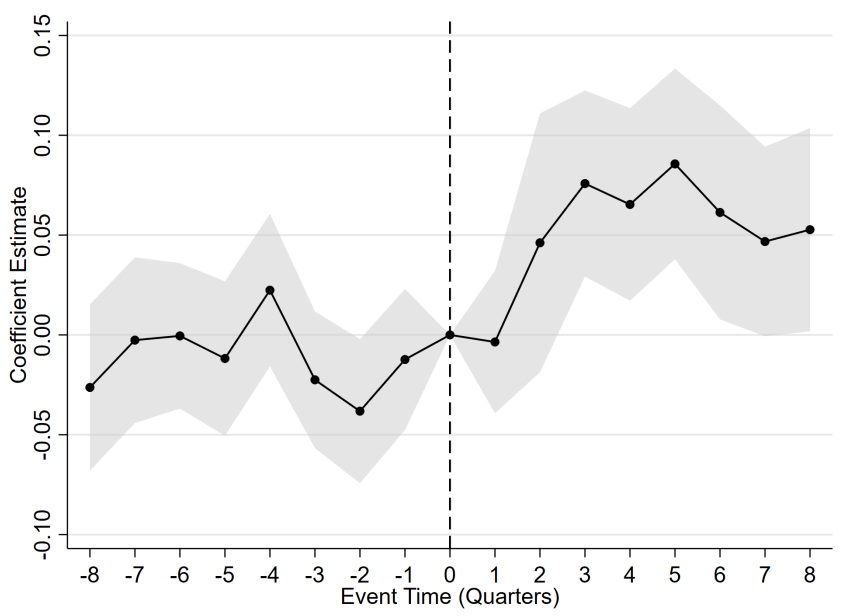
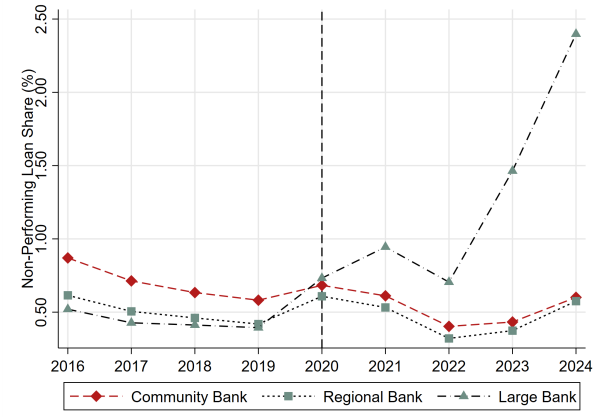
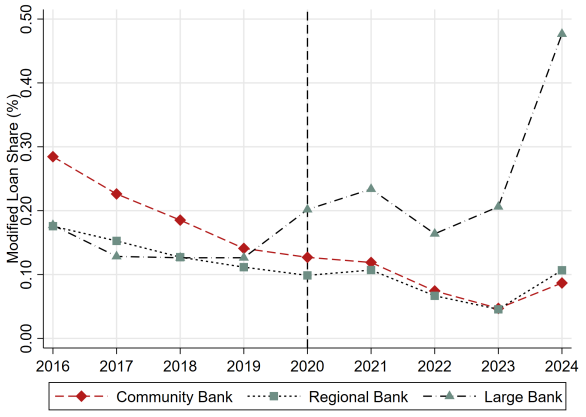


Figure 6. CRE Loan Performance

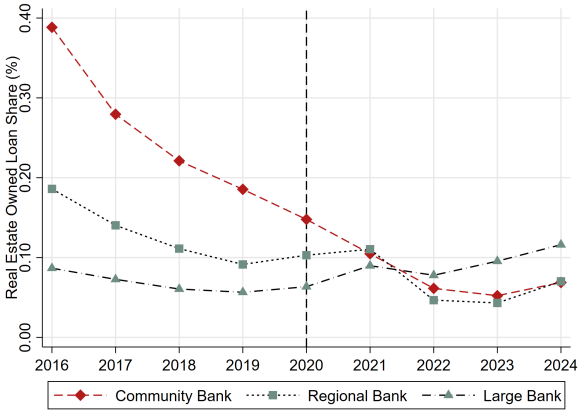
This figure depicts annual trends in the performance of CRE loans outstanding over the 2016–2024 period by bank type. Community banks are defined based on the FDIC classification. Large banks are those with at least $100 billion in assets at any point during this period. All other banks are classified as regional banks. Panel A (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. *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) NonComm. Bank			(1)–(2)
	N	Mean	SD	N	Mean	SD	Diff. in Means
CRE Growth	309,318	0.04	2.02	32,058	0.05	1.08	-0.01
NPL Share	309,977	0.02	0.04	32,106	0.02	0.05	0.00
Mod. Share	309,977	0.00	0.02	32,106	0.00	0.02	-0.00***
REO Share	309,977	0.01	0.10	32,106	0.01	0.02	0.01***
Size	312,668	0.40	0.91	36,433	26.03	159.05	-25.63***
Age	312,668	82.44	42.86	36,433	64.50	50.86	17.94***
CRE Spec.	312,668	0.55	0.50	36,433	0.69	0.46	-0.14***
Capital Ratio	307,750	0.11	0.04	35,566	0.15	0.16	-0.04***
Liquidity Ratio	307,750	0.30	0.22	35,566	0.30	0.30	-0.00
Earnings Ratio	307,750	0.06	0.94	35,566	0.07	0.87	-0.01
Loan Ratio	307,750	0.62	0.16	35,566	0.62	2.33	-0.00

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. *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 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) Non-Comm. Bank			(1)–(2)
	N	Mean	SD	N	Mean	SD	Diff. in Means
Size	55,972	57.99	79.21	111,404	72.04	128.54	-14.05***
Value	62,611	59.40	131.03	121,246	90.11	177.00	-30.71***
Age	58,344	40.63	30.93	115,085	43.39	31.62	-2.75***
Renovated	63,842	0.23	0.42	122,810	0.23	0.42	-0.01**
CBD	63,842	0.11	0.32	122,809	0.15	0.36	-0.04***
LTV	63,624	0.70	0.37	122,335	0.69	0.40	0.01***
Prev. Relation	62,580	0.72	0.45	120,551	0.76	0.43	0.04***
HQ in MSA	63,840	0.38	0.49	122,810	0.17	0.38	0.21***
Branch in MSA	63,578	0.54	0.50	122,386	0.75	0.43	-0.21***
HQ in MSA (Inv.)	35,555	0.38	0.48	80,611	0.19	0.39	0.19***
Branch in MSA (Inv.)	35,380	0.45	0.50	80,324	0.55	0.50	-0.10***

Table 3. Descriptive Statistics Compstak Lease Data

This table presents summary statistics on the property leases signed 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 summary statistics are presented by bank type. *All* 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. 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) NonComm. Bank			(1)–(2)
	N	Mean	SD	N	Mean	SD	Diff. in Means
No. of Leases	6,282	1.10	0.54	13,805	1.09	0.41	0.01
Renewal	12,712	0.32	0.47	43,830	0.37	0.48	-0.05***
New Lease	12,712	0.68	0.47	43,830	0.63	0.48	0.05***
Free Rent Share	8,875	3.58	4.12	35,203	4.14	4.23	-0.56***
Asking Rent	17,242	26.04	23.47	55,286	32.88	35.83	-6.84***
Net Effective Rent	16,908	25.67	23.25	54,975	31.76	32.89	-6.09***

Table 4. Growth in CRE Loans Outstanding

This table presents the results from estimating Eq. (1) 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 3.1 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
Comm. Bank # Covid	0.034*	0.038**	0.053**
	(0.019)	(0.020)	(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 5. CRE Loan Issuance by Community Banks

This table presents the results from estimating Eq. (2) 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 3.1 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
Covid	0.054***	0.039***	0.020**	0.033**
	(0.013)	(0.012)	(0.009)	(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 6. Expansion in Geographic Scope of Community Banks

This table presents the results from estimating Eq. (3) 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 99^{th} percentile, while Columns 3 and 5 show results with both physical distance and indicator variables trimmed at the 99^{th} 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 3.2 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) Distance	(2) Distance	(3) Distance	(4) Same MSA	(5) Same MSA
Comm. Bank # Covid	0.046	0.046	0.054	-0.010	-0.012*
	(0.036)	(0.036)	(0.036)	(0.007)	(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 6. Expansion in Geographic Scope of Community Banks (Continued)

(B) Nearest Branch Location

	(1) Distance	(2) Distance	(3) Distance	(4) Same MSA	(5) Same MSA
Comm. Bank # Covid	0.000	0.001	0.010	-0.008	-0.009
	(0.053)	(0.053)	(0.053)	(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 7. CRE Loan Issuance by Transaction Type

This table presents the results from estimating Eq. (4) in the MSCI loan data set over the 2016–2024 period by transactions types, namely sales transactions and refinance transactions. 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 3.3 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
Covid	0.080***	0.082***	0.078***
	(0.019)	(0.023)	(0.020)
Prev. Large Bank	-0.246***	-0.113***	-0.303***
	(0.058)	(0.030)	(0.070)
Covid # Prev. Large Bank	-0.034***	0.042*	-0.043***
	(0.012)	(0.024)	(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 8. CRE Loan Issuance by Property Proximity

This table presents the results from estimating Eq. (4) 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 3.3 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
Covid	0.028	0.094***	0.074***	0.029
	(0.019)	(0.027)	(0.023)	(0.030)
Prev. Large Bank	-0.160***	-0.095***	-0.093***	-0.106***
	(0.060)	(0.030)	(0.034)	(0.034)
Covid # Prev. Large Bank	0.099**	0.016	0.028	0.070
	(0.045)	(0.025)	(0.023)	(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 9. Non-Performing, Modified, and Real Estate Owned Loan Shares by Bank Type

This table presents the results from estimating Eq. (1) 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 3.1 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
Comm. Bank # Covid	-0.014***	-0.013***	-0.004***	-0.004***	-0.003***	-0.003***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(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 10. CRE Loan Foreclosure by Bank Type

This table presents the results from estimating Eq. (3) 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 3.2 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
Comm. Bank # Covid	-0.037***	-0.037***	-0.029**
	(0.013)	(0.013)	(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 11. CRE Leasing Activity by Bank Type

This table presents regression results from Eq. (3) in the MSCI loan data set over the 2016–2024 period. The sample excludes loans issued by regional banks. The dependent variables are merged from Compstak Lease Data Set. 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. *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 3.2 for details). Fixed effects are included as indicated. Standard errors are clustered by bank. Columns 1, 2, and 3 present the results from estimating Eq. (3) as Poisson count models, whereas columns 4, 5, and 6 present the results from estimating Eq. (3) as ordinary least squares models. 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) All	(2) Renewals	(3) New	(4) Free Rent	(5) Start. Rent	(6) Eff. Rent
Comm. Bank # Covid	0.136**	0.062	0.183**	-0.002	-0.023	-0.018
	(0.068)	(0.100)	(0.078)	(0.001)	(0.020)	(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.	0.196	0.036	0.113	0.020	3.086	3.079
(Pseudo) R-squared	0.27	0.25	0.25	0.20	0.67	0.66
Observations	86,219	74,220	82,908	8,438	8,535	8,452

ONLINE APPENDIX

Appendix A Sample Construction Details & Definitions

A.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

A.2 Bank Name Matching Process

As discussed in Section 2.2, 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.

A.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".

A.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.

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.

A.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.

A.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.

A.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 accuring,
- **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 accuring,
- **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.

A.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.

A.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.

A.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 B Figures & Tables

Figure B.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.

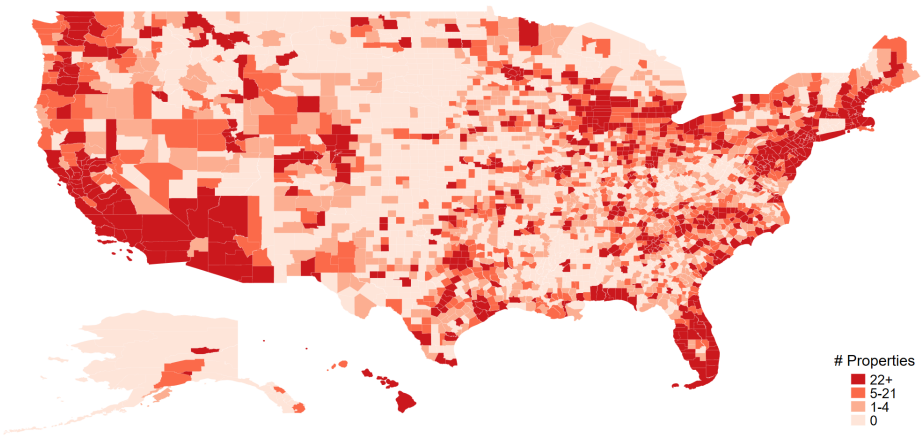
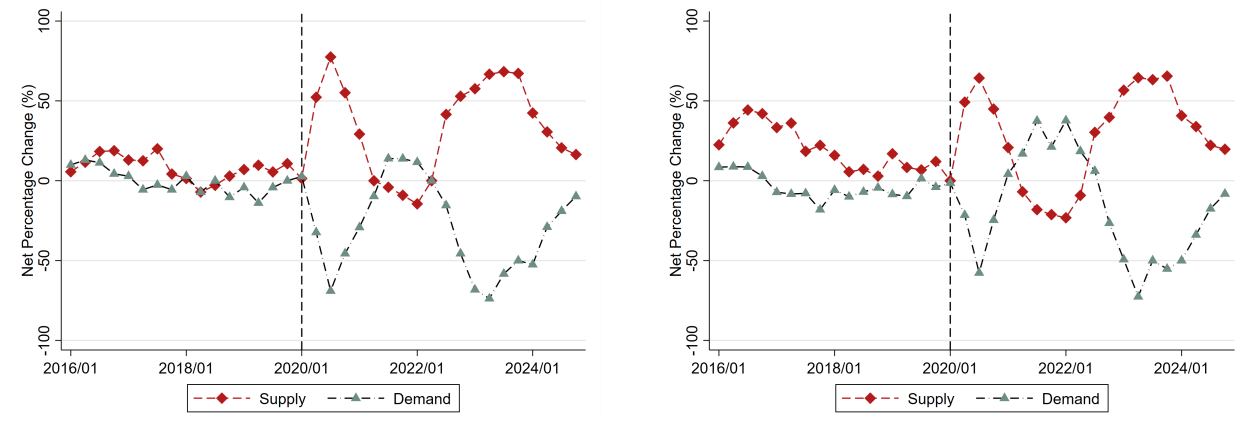


Figure B.2. CRE Loan Supply and Demand of Large Banks in U.S.

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 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.



(A) Nonresidential and Nonfarm Loans

(B) Multifamily Loans

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

Table B.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
Size	115,651	70.50	125.22	154,631	192.75	278.04
Value	115,654	0.29	0.44	154,688	0.83	22.38
Age	106,658	38.77	28.23	151,385	40.11	26.52
Renovated	117,205	0.21	0.41	155,248	0.49	0.50
Industrial	117,205	0.38	0.48	155,248	0.21	0.41
Office	117,205	0.30	0.46	155,248	0.62	0.48
Retail	117,205	0.33	0.47	155,248	0.16	0.37

Table B.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
Unemployment	185,474	0.04	0.02	185,454	0.05	0.02	154,416	0.05	0.02
HPI Level	141,491	150.26	40.17	184,128	171.24	45.11	127,050	143.33	41.54
HPI Growth	141,465	0.02	0.02	184,121	0.02	0.02	127,050	0.02	0.02

Table B.4. CRE Loan Issuance by Investor Proximity

This table presents the results from estimating Eq. (4) 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 3.3 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
Covid	0.039	0.084***	0.089***	0.069*
	(0.029)	(0.030)	(0.027)	(0.035)
Prev. Large Bank	-0.104**	-0.098***	-0.080**	-0.113***
	(0.046)	(0.032)	(0.032)	(0.030)
Covid # Prev. Large Bank	0.094**	0.030	0.028	0.079**
	(0.037)	(0.029)	(0.031)	(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

Table B.5. Application Denial of Multifamily Loans

This table presents the results from estimating Eq. (3) 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 3.1 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
Large Bank # Covid	0.025	0.009	0.002	0.002	0.002
	(0.033)	(0.017)	(0.005)	(0.005)	(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