Small Banks and the Recovery Advantage in Commercial Real Estate

Job Market Paper
This version: November 8, 2023
Click here for most recent version

Ernesto Aldana[a]

[a]*Kenan-Flagler Business School, The University of North Carolina at Chapel Hill*

Abstract

Small banks play a large role in commercial real estate (CRE) lending. In this paper, I show that small banks with a CRE lending focus achieve higher loan recovery rates than other banks through sales of foreclosed properties. I argue that this advantage in handling distressed assets leads to a competitive edge for loans with high default probability. I back this claim by showing that small banks originate a large share of hotel and construction loans, with historically high default rates, and a relatively low share of apartment loans, which are broadly considered safer. Furthermore, among banks with a CRE lending focus, small banks experience higher early delinquency rates than their larger peers. However, this pattern reverses when considering loans in later stages of delinquency and charge-off rates, suggesting that small banks are able to prevent loan defaults from becoming permanent. With this paper, I contribute to the literature on the role of small banks by providing compelling evidence for their relative advantage in CRE, an asset class in which they play an outsized role.

Keywords: Commercial Real Estate, Banking, Small Banks, Commercial Mortgages
JEL-codes: G21, R30, R33

---

*I thank Jacob Sagi for his guidance throughout every stage of this research project and, importantly, for his support and patience. I am immensely thankful to Alex van de Minne, Simon Buechler, and David Geltner for inviting me to visit the Center for Real Estate at MIT and providing me with valuable access to data. I am also grateful to Paige Ouimet, Yunzhi Hu, and Anil Shivdasani for their support and insightful advice.

1. Introduction

Small banks play a dominant role in commercial real estate (CRE). At the end of 2020, loans secured by CRE amounted to more than a quarter of the total assets held by banks with under \$5 billion in assets. Moreover, while these banks' share of the industry's assets was a mere 11.4%, they held over 27% of total CRE bank loans. This relative preponderance of smaller banks in CRE lending is not a recent phenomenon. In fact, CRE has historically been the most relevant lending category for small commercial banks as shown in Figure 1, which plots the share of loans of different categories held by banks with assets under 5 billion US dollars.

What, then, makes small banks competitive in CRE? The answer I provide in this paper is that small banks' comparative advantage in CRE comes from their ability to handle distressed loans. Small banks that specialize in CRE have higher loan recovery rates than their larger competitors. While this advantage enhances their ability to offer better terms to their prospective borrowers, the gap in market share is particularly large for loans that are more likely to default, which leads to an equilibrium situation in which small CRE specialists have relatively high default rates, particularly in the early stages of delinquency. However, they compensate their higher risk exposure by effectively handling distressed loans to minimize losses.

In the first part of my analysis, I use data on sales of foreclosed properties and find that small banks that specialize in CRE obtain higher loan recovery rates conditional on foreclosure. This advantage in recovery given default exists even after controlling for the property's type and location, the bank's financial situation, and the type of buyers and borrowers involved in the transaction. The gap in recovery rates is also robust to the property's size, as well as temporal trends in CRE specific to the property's type or its location.

I then link this recovery advantage to the composition of the CRE portfolios of banks. In particular, I explore the share of total originations devoted to each property type and find that that small CRE banks originate relatively large shares of CRE loans in which the underlying property's type is among those generally considered risky by investors, like hotel and construction loans. In contrast, the loans originated by large banks correspond mostly to apartment properties, which are historically less likely to default than the rest of CRE. Put together, these facts suggest that the recovery advantage of small banks with a CRE focus makes them particularly competitive in relatively high-risk loan sectors.

To complement the analysis of the risk profiles of banks' CRE portfolios, I compare their realized performance using regulatory data from call reports. I find that the share of CRE loans delinquent between 30 and 89 days is higher for small banks than for larger institutions, both during stable economic periods and during the great financial crisis (GFC). This indicates that the CRE loans held by small CRE specialists are ex post riskier than those held by larger banks, in line with the risk profile implied by their portfolio mix. Interestingly, however, the portfolios of large banks seem riskier when comparing the fraction of CRE loans delinquent for more than 90 days or their charge-off rate. The fact that loans by small bank default more often than those of large banks, but late-stage delinquencies and charge-offs are higher for large banks supports the claim that small banks have a comparative advantage in handling distressed loans.

I discuss different potential explanations for the recovery advantage of small CRE-focused banks. First, I study whether the differences in recovery rate could originate from a bank's ability to screen potential borrowers based on the expected recovery rate of the collateral. By analyzing properties sold by banks that acquired CRE-focused banks, I find that recovery rates for loans originated by small CRE specialists are significantly lower when the property is sold by a different bank. This result is not consistent with small CRE banks having a superior ability to identify loans that will yield high recovery rates in the event of default.

Other potential mechanisms I analyze are client networks and geographic proximity to the property. Specifically, I explore whether banks use their client networks to minimize losses given default by either selling the properties to one of their clients or financing the purchase by originating a loan to the new owner. The results show that, while the use of client networks are associated with higher loan recovery rates on average, they do not explain the different outcomes of small and large CRE-focused banks. Regarding geographic proximity, I find that recovery rates are higher for properties located in counties where CRE-focused banks have branches, but the comparative advantage of small CRE specialists prevails even after controlling for the physical proximity to the foreclosed properties.

In the last section of the paper, I formalize the link between an advantage in handling distressed loans and the lender's portfolio-level risk profile. I present a model of banking competition between two banks in which one of them has a comparative advantage in minimizing losses from loan defaults. This built-in advantage increases the bank's market shares across all loan types. However, since the advantage is realized when a loan defaults, the competitive edge of the bank is greater for loans that have a higher default probability. In turn, the portfolio of the bank with the advantage is riskier in the sense that its overall default rate is higher, although the risk is compensated by the bank's ability to recover funds from loan defaults. I show that, in contrast, a comparative advantage related to the bank's information about a project's default probability leads to relatively low portfolio-level default rates.

The academic literature explains the comparative advantage of small banks in certain lending sectors, like small business lending, emphasizing their ability to collect and process *soft* information (Stein, 2002; Brickley et al., 2003). While soft information might indeed play a role in commercial mortgages, it is not clear that this sort of informational advantage fully explains small banks' strengths in CRE. *Hard* information in the form of detailed records on past and projected income generated by the property are usually available to potential lenders during the underwriting process.[1] Construction loans, for which historical records are not available, arguably have more similarities with small business lending because the developers' reputation and their relationship with the lender might play an important role in lending decisions. In 2020, however, construction loans amounted to only 17% of the aggregate CRE portfolio of banks with less than $5 billion in assets, implying that for most of CRE loans, each property's transaction and appraisal histories, along with information about occupancy and income, are likely available to the lender, thus diminishing the role of soft information.

[1] See, for example, Berger and Black (2011). For a description of the CRE underwriting process, see, Furfine (2020).

As mentioned above, researchers that have studied the lending behavior of small banks have mainly focused on their role as lenders to small business. For example, Berger et al. (2005) show that small banks generally lend to small firms and have longer and more exclusive with relationships with their clients. These findings are complemented by Berger et al. (2017), who document that small banks alleviate the financial constraints of small firms, and Deyoung et al. (2015), who show that a subset of small banks, those specializing in business lending, provide credit to small firms during periods of economic distress. These papers attribute the relative strength of small banks to their ability to collect and process *soft* information (Stein, 2002; Brickley et al., 2003).

This paper adds to this literature by focusing on a different loan category, CRE, which notably constitutes the largest fraction of the aggregate portfolios of small banks. Furthermore, I argue that the nature of the comparative advantage supported by the existing literature does not fully explain their prevalence in the CRE market. By focusing on the advantage in recovery from defaults, I provide evidence on a distinctive aspect of small bank's behavior which interacts with other well-documented traits like relationship lending and information generation.

A couple of articles study the relationship between the financial condition of banks and the outcomes they obtain from the sales of distressed real estate. Ramcharan (2020) finds that banks with declining liquidity get lower liquidation values for residential properties, while Chu (2016) finds a similar relationship between liquidity and liquidation values for CRE properties. Motivated by this research, I include bank liquidity as a control variable in my empirical analsyis. My paper contributes to this line of study by focusing on bank size as a key determinant of realized CRE loan recovery outcomes.

The present article also contributes to the literature on CRE lending. Recent contributions to these literature analyze the characteristics of CRE loans held by different types of financial institutions. An et al. (2011) study the effects of adverse selection in the pricing of commercial mortgage backed securities (CMBS). Ghent and Valkanov (2016) use data for loans backed by office buildings in four US cities to compare the characteristics of balance sheet and securitized loans. They conclude that the most salient difference between loans that back CMBS and portfolio loans is their size. Relatedly, Black et al. (2020) adapt the theoretical predictions in Chemmanur and Fulghieri (1994) to compare the loans in CMBS to those held by large US banks. They conclude that securitized loans have a lower probability of distress because the banks' ability to renegotiate or liquidate loans. More recently, Glancy et al. (2022) study market segmentation across banks, CMBS lenders, and life insurance companies. My paper adds to this literature by focusing exclusively on bank loans and, crucially, emphasizing the role of small lenders in the CRE loan market.

The rest of the article proceeds as follows. In Section 2, I describe the data. Section 3 contains my empirical analysis of sales of foreclosed properties by banks, in which I document that small CRE specialists have a recovery advantage. I explore ex ante and ex post difference in CRE loan portfolios in Section 4. The discussion of potential mechanisms is presented in Section 5. Section 6 contains the theoretical model linking the recovery advantage to portfolio composition, and Section 7 concludes the paper with a summary of findings.

2. Data and variable description

In this section I describe the different samples I use throughout each paper section, as well as the variables I construct to perform the analysis. I use data on commercial mortgage originations and CRE property transactions from Real Capital Analytics (RCA).[2] The data set is comprehensive for transactions regarding property's in the US with a price above $2.5 million dollars, and contains information on loan characteristics for both property sales and refinances. However, its coverage of lending information increases along my period of study.[3]

The loan and transaction data set contains information about the transaction, the physical characteristics of the property, and a handful of attributes of the associated commercial mortgages. I observe the transaction type (conventional sale, refinance,

[2] In 2021, RCA was acquired by MSCI.

[3] Below I discuss the variation in the number of loans available per year (Table C.12).

or construction), the date of the transaction, the associated price of the property (or most recent appraised value in the case of refinances), and the type and identities of buyers, borrowers, and sellers involved. Regarding the physical characteristics of the property, the data set contains its location (address, geolocation, and an indicator variable of whether the property is situated within an urban central business district), and, for a limited number of transactions, the year in which the property was built. For residential and hotel properties, the data includes the number of units in the property, whereas for the rest of property types, the data set contains the size of the property in square feet. For each loan origination, I observe the loan amount, the origination date, and, crucially, the name of the lender and its type (e.g., CMBS, bank, or insurance company). To limit the influence of non-arms-length or otherwise anomalous property prices or loan amounts, I restrict the sample to properties priced over $500 thousand at both sale and loan origination, and mortgages with an loan-to-value (LTV) ratio of at least 5%.

2.1. Matching CRE loans to bank financial information

The data provider classifies lenders into several categories according to their size and industry, e.g., CMBS, regional bank, national bank. I focus on all loans corresponding to properties in the US that were originated by a bank. Instead of using the size categories generated by the data provider, I rely on the financial statements of commercial banks contained in regulatory Reports of Condition and Income, commonly known as Call Reports, which I observe quarterly for the period 2001-2021.[4] To merge the banks in the CRE loan and transaction data set to Call Reports, I develop an algorithm that uses a bank's name, range of loan origination dates, and the states where the loans' underlying CRE is located to find the correct FDIC Certificate Number in Call Reports. I use standard text matching techniques to find match candidates for each bank's name among the available name history of commercial banks in Call Reports. I differentiate amongst lenders with the same name in Call Reports using two criteria: consistency

[4] I do not observe information for banks that were regulated by the Office of Thrift Supervision (OTS) before 2011. Starting in 2012, Call Reports are available for banks previously overseen by the OTS.

between the range of CRE loan origination dates and the available Call Reports for each of the potential name matches, and proximity between a bank's head quarters and the location of the properties underlying its CRE loans. I complement the results from this matching process by manually browsing the list of names or web addresses that a candidate bank has had historically via the FDIC's BankFind Suite. Finally, I perform manual checks on the resulting matches to verify accuracy.[5]

After matching lenders in the CRE data set to their corresponding Call Report IDs, I collect lender information from the Call Reports corresponding to the quarter immediately preceding the loan origination. For example, a loan originated in July, 2016 is linked to lender information as of June 30th, 2016.[6] I use the following bank balance-sheet items:

- *Size*: Bank assets in thousands of dollars. I use the implicit gross domestic product (GDP) deflator and express bank assets in real 2020 US dollars.
- *CREloans*: Ratio of CRE loans to total assets. CRE loans are defined as the sum of loans secured by multifamily residential properties, nonfarm nonresidential properties, construction, and unsecured CRE loans.
- *Liquidity*: Ratio of the sum of cash and securities available for sale to total assets.
- *T1ratio*: Tier 1 capital divided by risk-weighted assets.
- *REO*: Ratio of other real estate owned to total assets.

For the analysis of CRE portfolio performance in Section 4, I construct the following measures using year-end Call Reports:

[5]For some lenders, the commercial mortgage data includes the lender's website, useful to distinguish among institutions with the same name. I manually verified web addresses using both the FDIC's BankFind Suite tool and the internet archive (wayback machine). The BankFind Suite's website is https://banks.data.fdic.gov/bankfind-suite/bankfind.

[6]I match loans originated in 2000 to the first available Call Report in my data set: 2001Q1. For loans made by banks supervised by the OTS before 2012, I use their first available Call Report, 2012Q1.

- *Earlydelinq*: CRE loans past due between 30 and 89 days that are still accruing, divided by the total of CRE loans held by the bank, *CREloans*.

- *Delinq*: Sum of CRE loans past due 90 days or more and still accruing and nonaccrual CRE loans, divided by *CREloans*.

- *Chargeoff*: Charge-offs of CRE loans throughout the year, divided by *CREloans*.

To control for the degree of local competition faced by the banks in my sample, I construct county-level yearly Herfindahl-Hirschman indices (*HHI*) for CRE loan competition, based on CRE loans originated up to the corresponding year. I create the variable *loancomp* by aggregating these indices at the bank level using the fraction of the banks' branches located in each county as weights. The location of every bank brach comes from the Summary of Deposits (SOD), which is published on a yearly basis.

In my empirical analysis, I use relative measures of $Size$ and $CREloans$ to simplify the interpretation of the results. In the case of $Size$, I rank all commercial banks in the correspondent in ascending order and normalize by the number of banks in each quarter. The resulting variable is called $Size_r$. For example, Size_r is 1 for the largest bank during a particular quarter, and .5 for a bank of median size during that same quarter. I identify CRE-focused banks with the dummy variable $crebank$, which indicates whether the bank belongs to the top quintile in the distribution of $CREloans$ during the corresponding quarter.

2.2. Sample of foreclosed properties

In my analysis of loan recovery rates in Section 3, I use the CRE loan and transaction information described above to construct a data set of foreclosed property sales. The CRE transaction data set includes the seller's names and types, which I use to identify properties sold by banks. I then flag as sales of foreclosed properties all transactions in which a bank that had originated a mortgage backed by the property is listed as a seller. The resulting sample consists of over three thousand sales.

For the loans that appear sample of foreclosed property sales, I observe all variables described above measured at the time when the original loan was made. In addition, I observe the following information about the sale: the buyer's identity and type (institutional, private, or public), the date of the transaction, and the price paid by the buyer. Using these measures, I construct the loan recovery rate, *recov*, defined as the ratio of sale price to original loan amount.[7]

The columns labeled Loan originations in Table 1 present summary statistics for originated mortgages backed by properties in the United States between 2000 and 2021. The bottom panel shows the corresponding statistics for the bank variables that are linked to loan originations. In Appendix Table C.12, I show the number of loans in the sample for each year. Notably, the number of bank loans in the RCA data increases substantially in 2015.[8]

The summary statistics for the sample of foreclosed property sales are shown in the columns labeled Bank sales in Table 1. Compared to the full sample of loan originations, sales of foreclosed properties involve a lower share of apartment properties, and notably higher shares of hotels, offices, and construction sites. Furthermore, unconditionally, loans that ended in foreclosure have higher LTV ratios at origination and are less frequently collateralized by properties in urban downtowns. Figure 2 shows that the loans in the foreclosure sample were mostly originated between 2005 and 2008, while most sales of foreclosed properties took place during the period 2010-2015, which is consistent with the increase in loan distress related to the Great Financial Crisis (GFC). The geographic distribution of the loans appears in Appendix Table C.13. Summary statistics for foreclosed property sales by bank size are shown in Appendix Table C.14.

2.2.1. Additional variables

In my exploration of mechanisms, I control for the effect of a bank's network of clients in its performance regarding foreclosed properties, I construct a couple of variables

[7]A more precise measure of loan recovery would involve the outstanding balance of the loan at foreclosure, as well as fixed costs related to the foreclosure process and interest losses. Unfortunately, I do not observe such information.

[8]The variation in the number of loans in each year might be related to RCA's coverage of portfolio loans. The second and third columns of Table C.12 in the Appendix show that the ratio of bank loans to number of transactions and number of loans is considerably higher in the second half of the sample.

based on the bank's historical lending activity. The first, *network* is an indicator of whether the buyer of the property has received a CRE loan from the selling bank at some point prior to the current transaction. This variable captures situations in which the property *remains* within the bank's client network: the selling bank markets the property to firms or individuals that have previous CRE experience and an existing or past business relationship with the bank. The second variable, called *samelend*, is a dummy that equals one if the selling bank also acts as lender in the sale transaction. This dichotomous variable flags cases in which the property remains directly related to the bank's assets: it transitions from backing a CRE loan, to a delinquent loan, to REO, and finally back to a different CRE loan. The variable *samelend* is also related to a bank's client network in the sense that the buyer becomes a client because of the newly issued mortgage.

I also explore the potential influence of physical proximity on recovery rates by identifying cases in which banks have a branch in the county where the property is located. I use data on branch locations from the SOD to construct two variables. The indicator variable *branchorig* flags cases in which the bank had a branch in the property's county at the time of loan origination, whereas *branchsale* indicates that the bank had a branch in the same county as the property when the sale took place.

To analyze whether the difference in recovery rates comes from screening at origination or from the bank's actions given foreclosure, I augment the sample with properties sold by banks that acquired other banks at some point between the origination of the loan and the property's sale given foreclosure. If the difference in recovery rates stems from the bank's ability to screen properties before making the loan, the identity of the property's seller would be irrelevant. To test for this possibility, I construct the dummy variable *acqlen*, which indicates cases where the loan originator was acquired by the selling bank.

3. Sales of foreclosed properties

3.1. Empirical methodology

In this section, I use the data on sales of foreclosed properties to study how outcomes from these transaction differ across two dimensions of lender characteristics: bank size and CRE concentration. My analysis involves regressing recovery rates on a set of bank and property characteristics. In particular, I am interested in how small banks that specialize in commercial real estate fare in handling distressed assets. I estimate the following linear models using ordinary least squares (OLS):

$$\begin{aligned} recov_{i,b,t,\tau} =& \beta_1 + \beta_2 * crebank_{b,\tau} + \beta_3 * Size_{r,b,\tau} + \beta_4 * crebank_{b,\tau} * Size_{r,b,\tau} + \\ & \beta_5 * X_{i,t} + \beta_6 * \Gamma_{i,b,\tau} + \varepsilon_{i,b,t,\tau}. \end{aligned} \tag{1}$$

In equation 1, $recov_{i,b,t,\tau}$ denotes the recovery rate or the price change related to transaction i, which took place in year t, and involved a loan made by bank b in quarter τ. $crebank_{b,\tau}$ and $Size_{r,b,\tau}$ correspond to measures of CRE portfolio share and size, respectively. The variable *crebank* denotes banks that specialize in CRE and indicates whether bank b ranks among the top quintile of the distribution of $CREloans$ in quarter τ. My measure for bank size is $Size_{r,b,\tau}$, the ranking of bank b in the distribution of $Size$ across all commercial banks during quarter τ.

The vector $X_{i,t}$ contains transaction specific controls, which, depending on the specification, consist of year-of-sale fixed effects, a set of dummies indicating the property's type, state fixed effects, an indicator of whether the property is within a city's CBD. The vector $\Gamma_{i,b,\tau}$ includes loan and bank controls measured at the time of origination τ. Loan-related controls are the LTV ratio at origination, the type of loan transaction (refinance or sale), and the type of borrower (institutional, public, private). I use *Liquidity*, *T1ratio*, and *REO* as measures of a lender's financial condition during quarter τ.

In the estimations I present in this section, I cluster standard errors at the lender and quarter levels. The number of different banks, and of corresponding clusters, in the estimation sample is 806 lenders, whereas property sales take place in 69 different quarters. To alleviate the influence of outliers in recovery rates, I winsorize the dependent variable at the 2.5 and 97.5 percentiles in the main specifications. In robustness tests, I use different versions of winsorizing and show that the results are qualitatively equivalent.

3.2. Results

I present the results from estimating equation 1 using different sets of controls in Table 2. Since my analysis focuses on the relations between lender size and CRE holdings, the interpretation of the results must take into account all coefficients associated with these variables, i.e., $crebank$, $Size_r$, and the interaction term $crebank : Size_r$. For example, the coefficient for $crebank$ corresponds to the smallest CRE specialists, whereas the coefficient on $Size_r$ can be interpreted as referring to the largest non-specialists in the sample, i.e., those for which $Size_r = 1$ and $crebank = 0$. Under this framework, the difference in recovery rate between the smallest and the largest CRE-focused banks is given by the sum of the coefficients for $Size_r$ and $crebank : Size_r$, the interaction term.[9]

The estimates in column (1) corresponds to a restricted version of equation 1 in which I omit the interaction term between bank size and CRE focus. The set of controls includes the property's location, the year of sale, and the types of property, buyer, borrower, and transaction. Interestingly, banks that specialize in CRE as a group obtain significantly lower recovery rates than non specialists, around 8.5 percentage points on average. The estimated coefficient for $Size_r$, on the other hand, is statistically insignificant.

The rest of the columns in Table 2, however, highlight the importance of accounting for the interaction of CRE specialization and bank size. In other words, among CRE specialists, recovery rates conditional on property characteristics differ widely depending on the size of the selling bank. The specification in column (2) includes the same set of control variables as the first column, but incorporates the interaction term from equation 1. The results show that, among small banks, CRE specialists obtain higher recovery rates, with the average difference being as high as 41 percentage points at the

[9]This results from comparing the relevant coefficients for small CRE specialists ($crebank$) and large CRE banks ($crebank + Size_r + crebank : Size_r$).

left tail of the size distribution, as indicated by the estimated coefficient for *crebank*. Among larger banks, however, this is not true. Importantly, the recovery rates of small CRE specialists are significantly larger than the outcomes of large CRE banks, as denoted by the negative and significant estimated coefficient for the interaction term $crebank : Size_r$. This particular result is robust to the inclusion of additional controls, as shown by the results in columns (3) to (5).

In column (3), I control for the original loan's LTV ratio, broadly considered as a measure of lending risk in the sense that lenders alleviate their exposure to a particular property's default risk by limiting the size of the loan (as a proportion of the property's value). Once a property is foreclosed, recovery rates would be expected to be negatively associated with the LTV ratio.[10] The results confirm this expectation: the coefficient on the original loan's LTV is negative and significant. Furthermore, the estimated coefficients for *crebank*, $Size_r$, and their interaction barely change with respect to column (2), and remain statistically significant, indicating that the differences in recovery rates do not stem from selection with regard to LTV ratios.

In column (4) I incorporate three variables related to the lender's financial condition at the time of loan origination. The addition of these controls have little impact on the relationships found in the previous columns. The estimated coefficient for *crebank* does not change substantially, and, importantly, the difference between large and small CRE specialists, given by the sum of the coefficients for $Size_r$ and the interaction term, is economically and statistically significant, around $\frac{1}{2}$ the difference in $Size_r$.

So far, I have discussed the differences in average recovery rates using all available transactions and property types, including development sites. However, construction loans, i.e., those related to development sites, involve substantially higher uncertainty about financial outcomes in general, and proceeds given foreclosure in particular. In the

[10]To see this, notice that there is a mechanical relationship between recovery rate and LTV. Consider, for example, two hypothetical loans backed by a property whose value dropped by 40%, causing a default. The loans are identical except for their LTV ratios, which are 70% and 95%. If the property is sold at market value, the recovery rate for the 70% LTV loan will be 86%, whereas the lender of the 95% LTV will only recover 63%.

last column of Table 2, I replicate the analysis in Column (4) excluding development sites. The results show that the higher recovery rates obtained by small CRE specialists are not driven by their performance on distressed construction loans. Construction loans are similar to small business loans in the sense that information, and particularly soft information, plays a significant role in lending decisions due to the uncertainty about investment outcomes. Furthermore, the collateral backing construction loans is much less valuable, since it consists of land or a property that is scheduled for demolition. Given the comparative advantage of small banks in loans that involve soft information, it would be reasonable to expect their advantage in CRE to be related to construction loans. However, Column (5) shows that the relative outperformance of small, specialized lenders transcends development loans.

3.2.1. Robustness tests

In this subsection, I discuss the results of estimating additional specifications of equation 1. I use the specification in column (4) of table 2 as a reference point: all regression specifications in Table 3 include controls for loan and transaction variables, property types, and the banks' financial condition. In column (1) of Table 3, I incorporate fixed effects for the interaction of the state where the property is located and the year of the sale. This interacted fixed effects allow me to control for trends in CRE recovery rates that are specific to each state. The estimated coefficients show that the difference in recovery rates between large and small CRE specialists is similar to that estimated in the baseline specification. On a similar note, column (2) shows the estimation results after controlling for temporal trends in recovery rates specific to each property type. Interestingly, this yields a slightly higher estimated recovery advantage for small CRE banks.

I add the size of the property to the set of controls in the third column of Table 3. In my data set, consistent with CRE industry practices, the size of the property is reported differently depending on the property's type. For apartments, hotels, and similar properties, I observe the number of units. For other property types in which the concept of space unit is not well defined, like industrial or retail properties, the size of the property is reported in terms of square feet. Column (3) shows the results after controlling for the interaction of the property's type and the variable *units*, which may consistent of the number of apartments, rooms, or square feet according to the property's type. The results are similar to those obtained in the baseline specification.

In column (4), I estimate equation 1 winsorizing the dependent variable $recov_{i,b,t,\tau}$ at the percentiles 1 and 99 and obtain estimates consistent with those of Table 2, although the magnitudes of the coefficients related to bank size and CRE holdings are larger. Finally, column (5) shows the results of using a different definition for *crebank*. In this column *crebank* identifies banks above the 70th percentile of the distribution of $CREloans$ in the pertinent quarter. Results are similar to those obtained in the basline specification, although the difference in recovery rates between large and small CRE specialists is smaller, suggesting that the recovery advantage is weaker for banks that are less concentrated in CRE, i.e., those between the 70th and 80th percentile.

To sum up, the results in this section indicate that small CRE specialists have a comparative advantage in recovering funds from defaulted loans through the sale of foreclosed properties. The advantage is statistically significant across a wide range of different specifications that control for a property's location, the bank's financial situation, the original borrower's type, the loan's LTV ratio at the time of origination. Intuitively, a lender with an advantage in handling distressed loans would, in equilibrium, tend to originate loans that are more likely to suffer distress. In the following section, I explore this possibility by analyzing the type of properties that small CRE specialists lend to, as well as the ex post performance of their portfolios.

4. Differences in loan characteristics

In this section, I study whether the CRE portfolios of small CRE specialists differ from those of other banks in terms of their overall riskiness. First, I compare the *ex post* performance of the CRE loan portfolios of small CRE specialists and assess their overall riskiness. In the final part of the section, I compare the differences in the relative share of each property types in the mortgage originations of distinct groups of banks and discuss how the property type mix of a bank's CRE loan portfolio relates to its risk profile. The findings indicate that small CRE specialists hold riskier CRE portfolios.

11

4.1. Portfolio performance

As argued above, if the comparative advantage of small lenders with a CRE focus comes from their ability to handle distressed loans, then small CRE banks would be particularly competitive in the market for loans that have a high probability of default. In other words, while a recovery advantage allows banks to offer better loan terms than their competitors for all loans, this is particularly true for loans that are particularly likely to experience distress. This would lead banks with this type of advantage to hold CRE loan portfolios that are relatively more exposed to default risk. In this subsection, I study the ex post performance of the CRE portfolios of commercial banks. Specifically, I use bank-level information from Call Reports on CRE loan delinquencies and charge-offs to analyze how the realized performance of small CRE specialists compares to that of other bank groups.

Call reports distinguish between loans in the *early* stage of delinquency (between 30 and 90 days), and those in later phases of distress (past due 90 days or more and nonaccrual loans). There might be idiosyncrasies in the way different banks handle loans once a borrower starts missing payments. For example, certain lenders might start workout or loan renegotiation processes as soon as a borrower skips a payment. The actions involved might range from an informal phone call to the borrower to the deployment of a complete plan for loan renegotiation. Heterogeneity could also exist in the way banks decide to charge delinquent loans off.[12] For instance, depending on the borrower or loan type, a bank may decide to charge the loan off after 6 months of delinquency, while others may decide to hold it for longer if they expect that payments might resume shortly. The fact that loan amounts in CRE are generally higher than in

[11]My data allows me to calculate LTV ratios at origination, which constitutes a risk measure broadly used for CRE loan underwriting. However, without other loan-level information, like interest rates, the relationship between LTV ratio and default probability is ambiguous (Grovenstein et al., 2005). For the sake of completeness, I compare the LTV ratios of loans originated by different groups of banks in In Appendix B.

[12]When a lender charges a loan off, it recognizes it as a permanent loss in its financial statements.

other loan sectors exacerbates the importance of these decisions for banks, particularly smaller lenders for which a single loan might represent a relatively large part of the CRE portfolio. For these reasons, loan performance measures in general comprise two factors: the default probability of the loan portfolio and the bank's handling of troubled loans. To minimize the influence of the latter, I focus on the proportion of CRE loans delinquent between 30 and 89 days. Because this *early delinquency* rate presumably captures loan distress as soon as a scheduled payment is missed, it speaks more to the loans' probability of default than to the particular way a lender handles loans once they become delinquent. I document differences in *early delinquency* rates for different groups of banks by estimating the following equation:

$$\begin{aligned} Earlydelinq_{b,t} = {} & \beta_1 + \beta_2 * crebank_{b,t-1} + \beta_3 * \overline{Size}_{r,b,t-(1:2)} + \beta_4 * crebank_{b,t-1} * \overline{Size}_{r,b,t-(1:2)} \\ & + \beta_5 * GFC_t + \beta_6 * GFC_t * crebank_{b,t-1} + \beta_7 GFC_t * \overline{Size}_{r,b,t-(1:2)} \\ & + \beta_8 * GFC_t * crebank_{b,t-1} * \overline{Size}_{r,b,t-(1:2)} + \beta_9 * X_{b,t} + \varepsilon_{b,t}, \quad (2) \end{aligned}$$

where $Earlydelinq_{b,t}$ stands for bank b's *early delinquency* rate at the end of year t, and $\overline{Size}_{r,b,t-(1:2)}$ denotes the average of $Size_{r,b}$ over the previous two years. The variable $crebank$, as in Section 3, indicates banks in the top quintile of the distribution of CRE loan holdings, and is lagged one period. To isolate the effect of outstandingly higher delinquency rates during the period around the GFC, I explicitly incorporate the indicator variable GFC_t, which takes the value of 1 whenever an observation lies within the period 2007-2011.[13] Interacting GFC_t with bank characteristics also allows me to compare the relative performance of CRE portfolios during times of widespread financial distress against how they fare in normal times. Finally, the vector $X_{b,t}$ includes fixed effects for the state where the bank's headquarters are located, indicator variables identifying *community banks* as defined by the FDIC as well as banks that eventually failed, the average CRE-loan-market competition faced by the bank as measured by a weighted average of county HHIs with the weights given by the fraction of the bank's branches located in each county, and additional bank controls, which are averaged over

[13] I include 2007 because real estate prices started dropping even before the widespread banking and financial crisis.

the previous two years. I winsorize the top and bottom .5% of the dependent variable for each year and cluster standard errors at the bank level. $Earlydelinq_{b,t}$ is then standardized to have mean 0 and unit variance. The estimation results are shown in the first column of Table 4.

To interpret the differences in early delinquency rates among different bank groups and during different economic environments, I use the coefficients involving bank size and the indicators for GFC and CRE holdings to calculate the *delinquency gap* between a bank-period category and a baseline category. The baseline category corresponds to the performance of small, non-CRE banks during normal times. These quantities, along with their 95% confidence intervals are plotted in Figure 3. The bars in Figure 3 represent estimates for the extreme values (i.e., 0 or 1) of $Size_r$. For example, the bar corresponding to small CRE banks during the GFC is constructed as the sum of the coefficients for GFC, $crebank$ and $GFC : crebank$, while the bar denoting the delinquency gap between large CRE banks during non-crisis periods is calculated as the sum of the coefficients for $Size_r$, $crebank$, and $crebank : Size_r$.

The results show that the CRE portfolios of small banks are riskier, i.e., they have a higher probability of missed payments as measured by the relative value of loans delinquent between 30 and 90 days. This is true in both normal economic environments and during periods of economic distress, here denoted by the GFC dummy. Interestingly, among small banks, the delinquency gap between CRE specialists and other small banks is negative and significant during normal times, indicating that the portfolios of small CRE specialists perform better than those of small non specialists. During the GFC, however, while the delinquency rates of both groups of small banks rose significantly, the growth in 30-89 day delinquencies was substantially larger for small CRE specialists than for non-specialists, suggesting procyclical realized defaults in their CRE portfolios. In other words, Figure 3 shows that 1) small banks have riskier portfolios than large banks in terms of early delinquency rates, 2) the delinquency rates of small CRE specialists fluctuate more than those of other small banks, suggesting that larger exposure to systematic risk, and, importantly, 3) small CRE specialists hold riskier CRE portfolios than large CRE banks.

4.1.1. From early delinquencies to permanent delinquencies

Above I argued that early delinquencies, i.e., the fraction of loans 30-89 days delinquent, constitute a measure of the missed-payment probability involved in a portfolio of loans that is less affected by a specific lender's strategies of dealing with loan default. Following that same logic, what happens to loans after being in the early delinquency stage can provide insights into a bank's *success* rate in dealing with distressed loan. In simple terms, a loan that is delinquent between 30 and 89 days could remain delinquent or the borrower could resume payments. In the first case, the loan would be classified as over-90-day delinquent and, eventually, non-accruing, which would lead to foreclosure. If, on the other hand, the borrower resumes payments, the loan leaves the delinquent pool entirely.

In the second column of Table 4 I show the results of estimating a version of equation 2 in which the dependent variable measures more permanent stages of delinquency. Specifically, I regress the ratio of loans over 90 days delinquent and non-accruals to total CRE loans, called *Delinq*, on the same set of bank characteristics. I display point estimates and 95% confidence intervals for the relevant combinations of coefficients for each group of banks in Figure 4. The results show that small CRE banks have comparable delinquency rates to large CRE specialists during normal times. During the GFC, however, large CRE specialists were the worst-performing group.

The results in Figures 3 and 4 highlight the contrast in the relative performance of bank groups depending on which delinquency measure is used. On one hand, small CRE banks perform worse than larger institutions in terms of early delinquencies. On the other hand, large banks that specialize in CRE constitute the worst-performing category during the GFC regarding later stage delinquencies.

The contrast between the two figures provides additional evidence supporting the hypothesis that small banks have a competitive advantage in CRE because of how they handle loans once they default. These findings complement the analysis of recovery rates given foreclosure by shedding light on the behavior of commercial banks during earlier stages of loan distress. Besides minimizing losses conditional on foreclosure, small CRE banks also prevent loan defaults from becoming loan chargeoffs. The reasons behind this outcomes might involve the interaction of bank officers with borrowers in the early stages of default, with the objective of working out ways to get the loan back on track early on.[14] Alternatively, although perhaps less plausibly, small CRE banks may motivate their clients to find a buyer willing to assume the existing loan. If, however, foreclosure becomes necessary, small CRE banks can still minimize losses due to their ability to get relatively high recovery rates from property sales.

A third alternative, also related to the strategies triggered by loan delinquency followed by each bank, relates to the probability of foreclosure. If, for example, certain banks tend to *wait things away* before foreclosing the mortgage, they might have more loans in the later stages of delinquency than banks that, for example, automatically foreclose any loan that has been delinquent for more than 90 days. This could be of particular importance in the case of small CRE specialists that, as per 3, have higher recovery rates on a per-loan basis. For example, given their ability to realize high recovery rates through property sales, small CRE banks might expedite the foreclosure process once a loan stays delinquent for more than 90 days, leading to higher charge-off rates. This, however, is not backed by charge-off data contained in call reports. Figure 5 repeats the analysis in Figures 3 and 4 using the banks' CRE charge-off rate as dependent variable. The pattern in the plot is similar to the one observed for delinquency rates, with large CRE-focused lenders experiencing the worst performance. Since the charge-off rates line-up with delinquencies, but not with early delinquencies, it is unlikely that the differences between early delinquencies and delinquencies are explained by the banks' propensity to foreclose given default.

The results in this subsection provide evidence supporting that 1) the CRE loans in the portfolios of small banks are riskier than those held by large banks in terms of their probability of becoming delinquent; and 2) large banks perform worse in the sense that they have larger amounts of CRE loans in later, more permanent stages of delinquency and, higher losses due to loan performance, as measured by their charge-off rates. Put together, these facts support the hypothesis that small banks, particularly

[14]Berger et al. (2005), for example, show that small banks have more frequent interactions with their borrowers than larger institutions.

those specializing in CRE, have a comparative advantage in the sector because of their ability to manage distressed loans.

4.2. Property types

The academic literature has documented stable differences in CRE default probability depending on a loan's underlying property type.[15] In this subsection, I explore differences in property type composition in the loan originations of different groups of banks and discuss how they relate to portfolio risk. I categorize lenders into different groups according to their CRE portfolio share and their size. To classify banks according to their CRE holdings, I use the variable *crebank*, which identifies banks that ranked within the top quintile of commercial bank CRE portfolio shares during the quarter corresponding to the loan origination. Throughout this subsection, I consider a bank *small* if its size lies below $5 billion in real 2020 USD. I label all banks with assets above $5 billion in real 2020 USD as *large*.

After classifying the banks according to size and CRE holdings, I calculate the share of originated loans by each bank group that corresponds to each property type. In other words, for a given size-CRE group, I sum the loan amounts devoted to each property type and divide them by the sum of all loans made by the group. I call the resulting quantities loan origination portfolio shares, and plot them in Figure 6, bucketing all banks without a high CRE concentration into a single group.

Figure 6 shows that the mortgages originated by small banks with a CRE focus are different from other banks with respect to the relative shares of each property type. Notably, the share of apartment loans in total originations is lower for small CRE specialists than for other lenders. The relative underinvestment in apartment properties by itself might increase the risk exposure of small CRE banks, as indicated by several metrics of volatility. One example from the academic literature is Downing et al. (2008), who estimate implied volatilities for office, multifamily, retail, and industrial properties using loans pooled into CMBS and conclude that multifamily loans are the least volatile among the four property types they analyze.

[15] See, for example, Downing et al. (2008).

Small CRE specialists also invest relatively more than other banks in loans backed by hotels and development projects. The latter have generally considered a particularly risky type of lending. Balla et al. (2019), for example, study the determinants of bank failures during two different crises and find that CRE and, particularly, construction and land development lending (CLD), are positively associated with a bank's probability of failure. CLD loans have also been identified by regulators as especially risky. In 2006, federal regulatory agencies issued a joint guidance encouraging banks with high concentrations of CRE, and CLD loans in particular, to follow minimum underwriting standards.[16] Furthermore, construction loans, with some exceptions, are considered High Volatility Commercial Real Estate (HVCRE) and receive a higher risk weight under the Basel III framework.[17] Hotel loans are also widely considered amongst the riskiest real estate loans. deRoos et al. (2014) document that the risk premium for hotel loans has been historically higher than for office loans, which according to the estimates in Downing et al. (2008), rank higher in implied volatility than multifamily and retail properties.

The distinction is not as clear considering the relative share of originations corresponding to retail, industrial, and office properties. Of the four major analyzed by Downing et al. (2008), office and industrial loans have the highest implied volatilities. Figure 6 shows that, the office share of loan originations is higher for small CRE specialists than for large CRE banks. However, banks without a CRE focus have a considerably larger share of office originations. This is similar to the case of CRE loans backed by industrial properties: among CRE-focused banks, small institutions rank first in terms of the share of industrial loans in total originations; however, the origination share of industrial properties for non specialists is as high as it is for small CRE banks. Interestingly, small CRE lenders originate relatively more retail loans, a property type with a relatively low volatility according to (Downing et al., 2008). However, recent trends in retail real estate, such as competition from e-commerce, might have made retail loans riskier in recent years.

[16]Bassett and Marsh (2017) study the impact of the guidance on bank outcomes and find that banks with high concentrations experienced slower growth in CRE and CLD lending after the guidance.

[17]See Glancy and Kurtzman (2022) for a description of the category.

In sum, the relative weight of apartments, development projects, and hotels in the origination portfolio of CRE specialists suggest a CRE portfolio that is overall riskier ex ante than that of other lenders in terms of property type mix. This, together with the fact that small CRE banks have higher realized defaults (Figure 3), supports the hypothesis that the advantage of small CRE banks in handling distressed loans makes them particularly competitive in the types of loans that are more likely to experience distress.

5. Potential mechanisms

5.1. Screening for recovery potential

In this subsection, I present evidence suggesting that the recovery advantage of small CRE-focused banks does not rely crucially on their ability to screen loans based on their potential for high recovery rates given default. I attempt to discern whether the difference in recovery rates between small and large CRE specialists stems from screening at origination or from the bank's ability to handle its assets once they become troubled. Recovery rates could, on one hand, be determined by the lender's ability to screen based on the recovery potential of the collateral. For example, a lender might be more inclined to originate a loan if they know the underlying property is unlikely to produce large losses even in the event of loan default. On the other hand, recovery rates could vary according to the bank's ability to deal with distressed loans, including, in the case of foreclosed properties, its associates' ability to market and sell CRE.

Bank acquisitions provide an opportunity to observe cases in which loan originations and property sales are performed by two different institutions. If the recovery advantage of small CRE-specialized banks comes mainly from their ability to identify properties that minimize losses in the event of default, then the loan recovery rates associated with those properties should be relatively high regardless of whether the bank that is forced to sell the collateral is the originator or a different institution. I augment the sample of foreclosed property sales by adding transactions in which the seller of the property is a bank that acquired the loan originator. I create the variable *acqlen*, which equals one if the property is sold by a bank that acquired the loan originator and add it as a regressor in equation 1.

Before discussing the results in Table 5, it is important to consider that these specifications might suffer from power issues because transactions involving properties sold by banks that acquired the loan originators are relatively rare. This problem is exacerbated if the objective is to compare the outcomes of loans originated by small CRE banks to the recovery rates corresponding to large CRE banks. I am able to identify 236 foreclosed property sales that involve loans made by acquired banks, of which only 110 were originated by CRE specialists.

The statistical insignificance of *acqlen* in column (1) of Table 5 suggests that the loan recovery rates realized through sales of properties sold by banks that acquired the loan originators do not differ from other cases. A similar conclusion applies to the loans originated by subsequently absorbed CRE specialists: according to the estimates in column (2), the recovery rates of these loans were not different from the rest. I break down this coefficient by the size of the originator in column (3). Strikingly, the results of interacting *crebank*, *acqlen*, and lender size suggest that loans originated by small CRE specialists had significantly lower recovery rates than those associated with other transactions, given the negative and significant coefficient of $crebank : acqlen$. To guarantee that these results are not the product of acquisitions of distressed banks, I replicate the exercise controlling for whether the acquisition involved government assistance and show the results in Appendix Table C.15. The main takeaway remains: loans originated by small CRE banks had significantly lower loan recovery rates in cases where a different bank, the acquirer, sold the foreclosed property. This is contrary to what would be expected if the recovery advantage of small CRE banks stemmed from their ability to screen loans based on the collateral's ex ante potential for recovery.

5.2. The role of client networks

A different mechanism that could lead to higher recovery rates involves a bank's relationship with its clients. Banks with access to a pool of potential CRE investors might achieve better outcomes for the properties they are forced to sell after foreclosure. In this subsection, I investigate the association between recovery rates and property buyers by exploring whether the buyer's *relationship* with the selling bank is connected to the seller's ability to obtain higher recovery rates. My findings show that recovery rates are higher for transactions that involve buyers with a relationship with the bank. In Appendix A, I complement this analysis and find that 1) CRE specialists are more likely than other lenders to sell foreclosed properties to their former and existing clients, and 2) small banks are more likely to finance the acquisition of a foreclosed property that they are selling. However, as I discuss below, these practices do not fully explain the differences in recovery rates.

I first explore whether recovery rates are higher for transactions in which the buyer had at some point received a commercial mortgage from the selling bank. In other words, my intention is to examine potential differences in recovery rates for transactions that involve a buyer that belongs to the bank's network of CRE borrowers. Columns (1) and (2) of Table 6 present the results of estimating versions of equation 1 in which $X_{i,t}$ includes the variable *network*, which indicates if the buyer had previously received a CRE loan from the bank according to my data set. The results in the first column indicate that when the a bank sells the property to one of its existing or former clients, the recovery rate is higher by 19 percentage points on average. This finding speaks to an interesting aspect of relationship lending. Besides the standard up- and cross-selling of financial products, a bank might use its relationships with clients to sell assets, such as previously foreclosed properties. The apparent premium paid by existing clients in these type of transactions could be related to diminished search costs.

However, column (2) of Table 6 shows that this relationship differs across bank types: selling a property to existing clients favors mostly banks that do not specialize in CRE, as indicated by the relatively high coefficient of *network*. CRE specialists, on the other hand, do not seem to rely on their former clients to boost their recovery rate advantage, as implied by the sum of the coefficient for *network* and the significantly negative coefficient of the interaction term $crebank : network$. Interestingly, however, the inclusion of existing client relationships in the regression model does not alter the magnitude or significance of the estimated coefficients for CRE concentration and bank size. This indicates that small banks that specialize in CRE lending do not obtain their recovery advantage through this particular channel.

Alternatively, a lender may facilitate the sale of a foreclosed property by providing the buyer with a mortgage. Because the financial constraints of prospective buyers might, in other circumstances, delay the sale and reduce the transaction price, a bank might benefit from providing funds to new buyers in the form of a loan backed by the previously foreclosed property. I study this possibility by including the variable *samelend* in 1, and present the results in columns (3) and (4) of Table 6. While the estimates suggest that recovery rates are indeed higher for transactions in which the selling bank provides the buyer with a new commercial mortgage backed by the property, a few caveats are warranted. Lender information is available for just 40% of the transactions; for the rest of the observations, two alternatives might cause the absence of lender information: the lack of a loan, in the case of an all-cash transaction, or difficulties in the data collection process for transactions involving a foreclosed assets. This kind of selection both biases the results and reduces statistical power, thus making the estimation less reliable.

The estimated coefficients in column (3) indicate that recovery rates are indeed higher if the bank finances the foreclosed property sale by offering a new loan to the buyer. However, the difference in recovery rates between small and large CRE specialists, given by the sum of the coefficients for $Size_r$ and $crebank : Size_r$, retains its economic and statistical significance, indicating that small CRE specialists have an advantage over large CRE-focused banks even in cases that do not involve making a loan to the buyer of the property. Adding the interaction term $crebank : samelend$ in column (4) yields interesting results for the rest of the coefficients. Most notably, the interaction term has a large positive and significant coefficient, indicating that CRE specialized lenders that finance the property's purchase get recovery rates that are close to 30pp higher. Moreover, the recovery advantage of small CRE-focused banks after controlling for this interaction decreases, particularly with respect to other small lenders. This suggests that the ability or willingness to lend to the property's new owner might, indeed, be amongst the reasons why CRE specialization matters among small banks. On the other hand, the advantage with respect to large CRE specialists remains significant at the 10% level, although lower than in the case of column (3), is larger than in the baseline specifications shown in Section 3.[18]

While data limitations limit the to focus to foreclosed properties, lenders could also use their network of clients to eschew fire sales even before foreclosure becomes necessary. For example, a struggling property owner could communicate her concerns to the lender, who knows other CRE investors who could be interested in buying the property and making the required changes to get the property back on a stable path. Provided that all parties reach an agreement, the original owner sells the property to another client of the bank without further damaging her credit status or her relationship with the lender; the bank eschews a potentially costly renegotiation or foreclosure process; and the buyer adds a new property to her portfolio. In this hypothetical case, the bank essentially acts as a broker who facilitates the sale of a property, while simultaneously preventing the losses associated with a non-performing loan.

5.3. Geographic proximity

The academic literature has documented that the geographic distance between banks and borrowers can shape credit outcomes due to its impact on information acquisition.[19] In this subsection, I analyze whether the geographic proximity between a bank and the property is related to loan recovery rates. Specifically, I use data on branch locations from the Summary of Deposits (SODs) and look for cases in which the bank had a branch in the same county as the property. I then construct the variables *branchorig* and *branchsale*, indicating whether the bank had a full-service branch in the property's county at the time of loan origination and property sale, respectively.

In Table 7, I show the estimation results of estimating equation 1 adding *branchorig* and *branchsale* as regressors. Columns (1) and (3) of Table 7 show that having a branch close to the property does not have an impact on banks' recovery rates on average. However, columns (2) and (4) show that, while there relationship between distance to the property and recovery rate is negligible for non specialists, CRE focused banks got

[18]The sum of the estimated coefficients for $Size_r$ and $crebank : Size_r$ is -0.56 and its standard error is 0.29.

[19]See, for example, Agarwal and Hauswald (2010), Petersen and Rajan (2002), or Nguyen (2019).

significantly higher recovery rates for properties located in the same county as one of their branches. In column (5), I include both variables simultaneously to explore their relative importance and find that the only statistically significant coefficient corresponds to *crebank* : *branchsale*, suggesting, unsurprisingly, that physical proximity during the recovery process is more important for recovery rates than distance at origination.

A key aspect of the results in Table 7 is that adding the proximity indicators as regressors does not impact the estimated recovery advantage of small CRE banks. The coefficient for *crebank* is only marginally lower —3 percentage points at most — than in the baseline specifications in Table 2. More importantly, the sum of $Size_r$ and its interaction with *crebank* is at least 47 percentage points across all specifications, indicating that small CRE-focused banks have a large advantage in recovery rates with respect to large CRE specialists even in cases in which they don't have a branch in the property's county. In other words, being geographically close to the properties is in fact relevant for both small and large CRE-focused lenders.

6. Model

In this section, I theoretically formalize the connection between a comparative advantage in handling loan defaults and portfolio-level risk profile. In broad terms, my objective is to facilitate the intuition that a bank that has developed the ability to minimize losses from loan defaults will, in equilibrium, lend relatively more to riskier projects. The reason for this is that the bank's skill at recovery is more useful in a portfolio where default risk is higher. Since diversification alleviates the idiosyncratic default risk at the CRE portfolio level, the recovery advantage makes banks more competitive in the market for loans that have a greater exposure to systematic risk. This, in turn, leads specialized lenders with a recovery advantage to hold portfolios that experience higher delinquency rates. I show that this outcome contrasts with the case in which the lender's comparative advantage stems from its ability to screen loans based on private information about the probability of default. Linking the model to the empirical results in this paper, I conclude that the nature of the comparative advantage of small CRE-focused banks is related to recovery.

I start from a spatial model of competition between two lenders in the style of

Hotelling (1929), which I combine with the loan portfolio model in Vasicek (2002) to analyze the composition and performance of each lender's portfolio in equilibrium.[20] In particular, I allow for the existence of two types of projects (or borrowers) that differ in their failure probability. Riskier projects have a higher unconditional probability of default p_i. In each case, I solve for the equilibrium market shares of each lender for the two types of loans, which, in turn, determine the composition of each lender's portfolio in equilibrium. As I show below, the model's predictions about delinquency rates and portfolio composition depend crucially on the specific nature of the specialist's advantage: since the recovery advantage is more relevant for loans that are more likely to default, the lender's portfolio becomes *tilted* towards riskier loans. Under a similar framework, a bank with a screening advantage that enables the selection of good projects, for example, would hold a safer portfolio than its competitors, i.e. would have lower delinquency rates unconditionally.

6.1. Basic framework

6.1.1. Borrowers

A unit mass of entrepreneurs is uniformly distributed along a unit-length line. Each entrepreneur has access to an investment opportunity that costs \$1, but lacks the funds to finance it and needs to borrow them from a bank. Each successful project produces \$R, and unsuccessful projects yield \$0. Projects have a maturity of 1 period: entrepreneurs borrow money and invest at the beginning of the period, and at the end of the period they receive their proceeds and pay the corresponding debt service to their lender. There are two types of projects: G and B, each equally likely to occur. Entrepreneurs observe the type of their project and make borrowing decisions accordingly. A project's type characterizes its unconditional probability of default. Building upon Vasicek (2002), project i defaults if

[20]Several papers have used spatial models of this kind to model loan market competition. See, for example Besanko and Thakor (1992) and Heddergott and Laitenberger (2017). Relatedly, Martinez-Miera and Repullo (2010) use the Vasicek (2002) framework of loan default in a model about the relationship between banking competition and failure. My model, however, links a bank's comparative advantage to a bank's performance in terms of loan defaults.

$$-\Phi^{-1}(p_i) + \sqrt{\rho}z + \sqrt{1-\rho}\varepsilon_i < 0. \tag{3}$$

In the expression above, $\Phi(\cdot)$ denotes the CDF of the standard normal distribution, and $(z, \varepsilon_1, \varepsilon_2, ...)$ are mutually independent standard normal random variables.[21] The random variable z can be interpreted as a common risk factor that influences all projects according to their degree of exposure ρ. The projects differ in their riskiness, which in the model is determined by their unconditional probability of default p_i. Type-G projects default with probability p_G, which I assume to be lower than the probability of failure for type-B projects, p_B. Given this parameterization, projects of type B are riskier than type-G projects.

6.1.2. Banks

Entrepreneurs are penniless and, therefore, need to borrow funds from a bank to finance their investment projects. There are two banks, Bank S and Bank L, each located at opposite ends of the unit-length line. I assume that banks have enough funding capacity to make as many loans as the borrowers demand from them, i.e., they don't have capital constraints. Furthermore, I assume that every project is fully funded by one of the two banks. Banks may observe the borrowers' types, but not their location within the unit-length line. Using their information about the borrower's type, banks quote an interest rate to each borrower.

6.1.3. Choice of lender

Borrowers must pay a transportation cost to meet their lender and obtain the loan, which is proportional to the distance between them and the banks. The cost per unit of distance that borrowers pay may be different across banks. This flexibility allows me to capture situations in which one bank may find it more difficult to attract customers. One such situation could be related to banking regulations that favor specific types of competitors (e.g., shadow banks). The transportation cost could also be interpreted as

[21] Notice that the probability of default is given by $\Pr\left[-\Phi^{-1}(p_i) + \sqrt{\rho}z + \sqrt{1-\rho}\varepsilon_i < 0\right] = \Phi\left(\Phi^{-1}(p_i)\right) = p_i$.

a reduced-form parameter for the local competitive environment.[22]

Borrowers get quotes from both banks and choose a lender based on the most favorable combination of loan terms and transportation cost. Formally, a type-G entrepreneur located at a distance δ from Bank S must pay $t_S\delta$ to borrow from Bank S. Alternatively, she could get financing from Bank L by paying transportation cost $t_L(1-\delta)$. Denoting γ_k the amount (interest and principal) that must be paid to bank k at maturity, the entrepreneur will take a loan from Bank S if and only if

$$(1-p_G)(R-\gamma_S)-t_S\delta \geq (1-p_G)(R-\gamma_L)-t_L(1-\delta). \tag{4}$$

From the above expression, it follows that all type-G entrepreneurs separated from Bank S by a distance lower or equal than δ will choose Bank S to finance their projects. Because entrepreneurs are uniformly distributed along the unit-length line, the fraction of type-G entrepreneurs that borrow from Bank S is given by

$$S_G(\gamma_L,\gamma_S)=\frac{(1-p_G)(\gamma_L-\gamma_S)+t_L}{t_S+t_L} \tag{5}$$

Similarly, a type-B entrepreneur chooses Bank S when $(1-p_B)(R-\beta_S)-t_S\delta \geq (1-p_B)(R-\beta_S)-t_L(1-\delta)$, and the share of type-$B$ borrowers serviced by Bank S is

$$S_B(\beta_L,\beta_S)=\frac{(1-p_B)(\beta_L-\beta_S)+t_L}{t_S+t_L}, \tag{6}$$

with β_k denoting the amount payable to bank k once the loan matures.

Expressions 5 and 6 represent the market share of bank S as a function of the loan terms offered by each lender to the corresponding borrower type. Given the assumption that every project is funded by one of the two banks, the market shares of bank L are simply $1-S_G$ and $1-S_B$. Furthermore, because all borrowers receive a loan, the key element determining the market share —other than transportation costs and default probabilities, which are model parameters— is the difference in loan terms $\gamma_L-\gamma_S$

[22]To see this, consider that a higher transportation cost essentially makes it harder for a bank to attract borrowers. In other words, the bank will attract fewer borrowers by offering the same loan terms, which would also happen under increased loan market competition.

and $\beta_L - \beta_S$. In the following subsections, I'll describe the bank's problem and obtain closed-form expressions for the equilibrium loan terms and market shares.

6.1.4. Distribution of portfolio losses

Vasicek (2002) derives the distribution of portfolio losses when individual loan defaults behave according to equation 3. I use his results to obtain the distribution of portfolio losses for each type of loan. Start by defining $L_{\theta i}$ as the random variable that takes a value of 1 if loan i of type θ defaults, and 0 otherwise. Then, for the case of n loans of a given type, the fraction of type-θ loans that default is given by $L_\theta \equiv \frac{1}{n}\sum_i^n L_{\theta i}$. Conditional on z, the probability that a single loan of type θ defaults is given by

$$\Psi_\theta(z) \equiv \Phi\left(\frac{\Phi^{-1}(p_\theta) - \sqrt{\rho}z}{\sqrt{1-\rho}}\right). \tag{7}$$

Because z captures the unique common factor among the L_i random variables, they are conditionally i.i.d. Then, by the law of large numbers, for a large-enough number of loans ($n \to \infty$), L_θ converges to $E[L_{\theta i}] = \Psi_\theta(z)$. In other words, the fraction of loans of type θ that default conditional on the realization of the common risk factor coincides with the conditional probability of default of a single type-θ loan.

The distribution of portfolio losses from type-θ loans $\Pr[L_\theta \leq x]$ when the number of loans is sufficiently high is given by

$$\Pr[L_\theta \leq x] = \Pr[\Psi_\theta(z) \leq x] = \Phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(x) - \Phi^{-1}(p_\theta)}{\sqrt{\rho}}\right) \tag{8}$$

As in Vasicek (2002), the mean of this distribution is p_θ, and the corresponding density function is

$$f(x; p_\theta, \rho) = \sqrt{\frac{1-\rho}{\rho}}\frac{\phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(x)-\Phi^{-1}(p_\theta)}{\sqrt{\rho}}\right)}{\phi\left(\Phi^{-1}(x)\right)}. \tag{9}$$

6.2. Recovery advantage

To illustrate the portfolio implications of a bank's ability to gain a larger recovery rate, I assume that one of the banks, Bank S, is able to recover a certain fraction κ from each failed loan. For simplicity, I will assume that Bank L's recovery rate is zero. In practice, this higher recovery rate could come from obtaining higher prices when selling foreclosed collateral from delinquent mortgages. Because I'm interested particularly in the implications of a different recovery rate, I will assume, for now, that the banks are identical in their ability to perfectly observe the type of each entrepreneur.

The bank with the recovery advantage, Bank S, maximizes its expected payoff by choosing loan terms, i.e., repayment amounts (γ_S, β_S). The objective function is given by

$$E\left\{\frac{1}{2}S_G\left[(1-L_G)\gamma_S + L_G\kappa - 1\right] + \frac{1}{2}S_B\left[(1-L_B)\beta_S + L_B\kappa - 1\right]\right\}. \tag{10}$$

To interpret expression 10, recall that the demand for loans is split equally between the two types for borrowers, that the bank always finds it profitable to make a loan to either type of borrower, and that all borrowers receive a loan, leading automatically to market clearing. The probability that a borrower's type is G is one half, and the share of type-G borrowers Bank S is able to attract is given by S_G, which is itself a function of γ_S per equation 5. Bank S receives γ_S from the fraction $1 - L_G$ of succesful type-G entrepreneurs. The remaining fraction L_G of loans defaults, yielding a recovery rate of κ to Bank S. Since equation 10 corresponds to Bank S's net payoffs, I subtract the loan amount disbursed by the lender at the beginning of the period. The rest of the elements in the objective function correspond analogously to loans to borrowers of type B.

As stated above, other than the costs paid by the entrepreneur, the only difference between the two lenders lies in the amount that Bank S is able to recover from each loan. Consequently, the expected net payoff of Bank L is similar to equation 10 with a recovery rate of zero:

$$E\left\{\frac{1}{2}(1-S_G)\left[(1-L_G)\gamma_L - 1\right] + \frac{1}{2}(1-S_B)\left[(1-L_B)\beta_L - 1\right]\right\}. \tag{11}$$

6.2.1. Recovery advantage: equilibrium loan terms

In the previous section, I argue that, for a number of loans that is large enough, the fraction of loans of each type that default L_θ converges to its expectation, which coincides with $\Psi_\theta(z)$ in equation 7. This implies that, provided that the banks lend to enough borrowers of each type, the only random variables inside the expectations in equations 10 and 11 are $\Psi_G(z)$ and $\Psi_B(z)$, which are in turn functions of a single random variable z, the common risk factor. Relying on the result in Vasicek (2002) that $E\left[\Psi_\theta(z)\right] = p_\theta$, it is straightforward to find the repayment amounts $\left(\left(\gamma_S, \beta_S\right), \left(\gamma_L, \beta_L\right)\right)$ that maximize both banks' expected net payoffs:

$$\gamma_S = \frac{ts + 2t_L + 3 - 2p_G\kappa}{3(1-p_G)} \qquad \beta_S = \frac{ts + 2t_L + 3 - 2p_B\kappa}{3(1-p_B)} \tag{12}$$

$$\gamma_L = \frac{2ts + t_L + 3 - p_G\kappa}{3(1-p_G)} \qquad \beta_L = \frac{2ts + t_L + 3 - p_B\kappa}{3(1-p_B)}. \tag{13}$$

The quantities above have two properties worth discussing. First, when comparing the terms offered to borrowers of different type by the same lender, the amount charged to type-G entrepreneurs is lower than what type-B borrowers must repay at maturity. In other words, the difference in unconditional default probabilities make both lenders offer more favorable terms to type-G borrowers. Second, for the case of symmetric transportation costs, the repayment amounts required by Bank S are lower those charged by Bank L because the recovery advantage of Bank S allows it to offer more attractive loan terms than its competitors.

6.2.2. Recovery advantage: Equilibrium market shares

The quantities in equations 12 and 13, along with the transportation costs and unconditional default probabilities, determine the lenders' shares of the market for each loan type. Substituting the equilibrium repayment amounts in the expressions for the market shares of Bank S (eqs. 5 and 6) yields:

$$S_G = \frac{t_S + 2t_L + p_G\kappa}{3(t_S + t_L)} \quad ; \quad S_B = \frac{t_S + 2t_L + p_B\kappa}{3(t_S + t_L)}. \tag{14}$$

It is worth highlighting a few properties of the market shares in equation 14. First, the recovery advantage of Bank S has an intuitively positive impact in its market share for both types of loans. Second, in the case of symmetric transportation costs, Bank S's advantage allows it to serve a larger portion of both markets than its competitor.[23] Third, because type-B borrowers are more likely to default unconditionally than type-G entrepreneurs, the market share of Bank S is larger for type-B loans than for type-G loans. This, in turn, implies that Bank S effectively tilts its portfolio holdings towards type-B loans. An interpretation for this outcome is that, because type-B loans are less likely to succeed, the recovery advantage of Bank S becomes more relevant in the market for type-B loans. For this reason, the competitive edge of Bank S is larger for type-B loans, leading to a larger market share for the riskier loans.

6.3. Screening advantage

I model an informational advantage that leads to better screening prior to loan origination as differences in the lender's ability to properly identify the borrower's type. In particular, the bank with the screening advantage, Bank S, perfectly observes whether it faces a borrower of type G or B. Bank L, on the other hand, cannot distinguish across entrepreneur types and offers identical loan terms to all potential borrowers. That is, $\gamma_L = \beta_L \equiv \alpha_L$. In this scenario, Bank S faces a similar problem to the one stated in equation 10, with $\kappa = 0$. Bank L, on the other hand, chooses the repayment amount that maximizes the problem in 11 with the additional constraint $\gamma_L = \beta_L \equiv \alpha_L$. Bank L knows that its competitor can identify each borrower's riskiness, and internalizes it via the *residual* market shares $1 - S_G$ and $1 - S_B$.

6.3.1. Screening advantage: equilibrium loan terms

Simultaneously solving the problems for both lenders yields the following equilibrium loan terms:

$$\alpha_L = \frac{1 - p_G + 1 - p_B}{(1 - p_G)^2 + (1 - p_B)^2} \left(\frac{2}{3} t_S + \frac{1}{3} t_L + 1 \right) \tag{15}$$

[23]Note that, under symmetric transportation costs, the market shares become $S_G = \frac{1}{2} + \frac{p_G \kappa}{6t}$.

$$\gamma_S = \frac{1}{2}\left\{\alpha_L + \frac{t_L + 1}{1 - p_G}\right\} \quad ; \quad \beta_S = \frac{1}{2}\left\{\alpha_L + \frac{t_L + 1}{1 - p_B}\right\}. \tag{16}$$

Intuitively, since borrowers of type G are less likely to default than type-B entrepreneurs, Bank S requires a lower repayment amount to its type-G clients in equilibrium, i.e., $\gamma_S < \beta_S$. Comparing the equilibrium loan terms of Bank S to the repayment amount required by Bank L is not as straightforward, mainly because it depends on the relative values of transportation costs t_S and t_L. However, it is useful to point out that in the case of symmetric transportation costs, Bank S charges less than Bank L to type-G borrowers, but the opposite is true for type-B clients, i.e., $\gamma_S < \alpha_L < \beta_S$.

6.3.2. Screening advantage: equilibrium market shares

The equilibrium market shares when Bank S has a screening advantage are:

$$S_G = \frac{(1 - p_G)\alpha_L - 1 + t_L}{2(t_S + t_L)} \quad ; \quad S_B = \frac{(1 - p_B)\alpha_L - 1 + t_L}{2(t_S + t_L)}. \tag{17}$$

Clearly, because $p_G < p_B$, the market share of Bank S is larger for type-G loans.

6.4. Differences in portfolio-level default rates

The market shares and failure rates in the model allow for the calculation of portfolio-level loan default rates for each bank, defined as the fraction of the *total* loans made by each bank that fails. Formally, the default rate of Bank S, λ_S, is given by a weighted sum of the failure rates L_G and L_B:

$$\lambda_S = \frac{S_G}{S_G + S_B} L_G + \frac{S_B}{S_G + S_B} L_B. \tag{18}$$

Similarly, the expression for Bank L's default rate is

$$\lambda_L = \frac{1 - S_G}{1 - S_G + 1 - S_B} L_G + \frac{1 - S_B}{1 - S_G + 1 - S_B} L_B. \tag{19}$$

To facilitate the comparison between both quantities, I denote the difference in default rates $\Delta_\lambda \equiv \lambda_S - \lambda_L$. The resulting expression is:

$$\Delta_\lambda(z) = \frac{(S_G - S_B)(\Psi_G(z) - \Psi_B(z))}{(2 - S_G - S_B)(S_G + S_B)}. \tag{20}$$

To compare the default rates of Bank S against Bank L, it suffices to determine the sign of the expression in equation 20. Since the denominator is the product of the total loans held by both banks, its sign is strictly positive. This implies that the sign of $\lambda_S - \lambda_L$ is fully determined by the quantities in the numerator. The sign of $\Psi_G(z) - \Psi_B(z)$ is negative.[24] On the other hand, the sign of $S_G - S_B$ varies depending on the nature of the comparative advantage of Bank S.

In the case of a recovery advantage, a higher unconditional probability of default for type-B loans allows Bank S to achieve a higher market share for this type of loans. Consequently, type-B loans take up the majority of Bank S's loan portfolio, i.e. $S_G - S_B < 0$. Thus, the portfolio-level default rate is higher for Bank S than for Bank B. In the model, Bank S compensates the effect of higher default rates by recovering a fraction of loan defaults. This is consistent with the empirical evidence shown in Section 4: among banks that specialize in CRE lending, early delinquency rates are higher for small institutions relative to large banks. However, small CRE banks make up for the higher default rates by preventing early delinquencies from becoming permanent.

The case of a screening advantage has different implications. Bank S discriminates between different types of borrowers and minimizes losses from loan defaults by offering more competitive terms to type-G borrowers. This leads to a higher share of the type-G loan market for Bank S. In turn, Bank S tends to have a lower portfolio default rate than Bank L, contrary to the evidence shown in Figure 3.

In summary, a recovery advantage in the event of default allows a bank to become more competitive across all types of loans. However, the gain in competitivenes and, consequently, market share, is higher for loans that are particularly likely to experience distress. Put differently, the ability to alleviate losses from delinquent loans encourages Bank S to offer relatively more aggressive loan terms to type-B borrowers, allowing

[24]Notice that $\Psi_G(z) < \Psi_B(z)$ because $\frac{\Phi^{-1}(p_G) - \sqrt{\rho}z}{\sqrt{1-\rho}} < \frac{\Phi^{-1}(p_B) - \sqrt{\rho}z}{\sqrt{1-\rho}}$ given the assumption that that $p_G < p_B$.

it to obtain a larger market share. Since the recovery advantage is more valuable for high-risk loans, the bank holds more of them in equilibrium, leading to a relatively high portfolio-level default rate that is compensated by the high recovery rate achievable by the bank. An informational advantage that allows banks to identify safe projects would lead to opposite outcomes in terms of default rates and would not explain the difference in recovery rates given foreclosure.

7. Conclusion

In this paper, I document that small banks that specialize in CRE lending have an advantage in handling distressed loans. Analyzing the outcomes obtained by banks through the sales of foreclosed properties, I document that small CRE specialists obtain higher average recovery rates than any other bank groups, and that this advantages decreases with size. The recovery advantage is robust to property and bank characteristics. Beyond that, the higher average recovery rates persist even after controlling for the nature of the relationship between the foreclosed property's buyer and the selling bank and the geographic proximity between the property and the bank's offices. Moreover, outcomes from loans of acquired banks suggest that the recovery advantage is unlikely to stem from the ability of small CRE banks to screen loans prior to origination.

I argue that an advantage of this nature gives small banks with a CRE focus a competitive edge particularly in those type of loans that are more likely to experience default. I back this claim empirically by showing that small CRE specialist experience higher CRE early default rates than large banks, both during normal economic times and during economic crises. Interestingly, small CRE specialists perform better than their large competitors in terms of more permanent measures of default (charge-offs and over-90 day delinquencies), which suggests that small CRE banks are succesful in handling distressed loans even before the foreclosure stage. I also show that small CRE specialists have a mix of property types that exposes to a high level of default risk. Specifically, they originate relatively fewer apartment loans and more construction and hotel loans than large CRE-focused banks.

Finally, I formalize the argument through a model of banking competition that allows me to compare the implications of different types of comparative advantage in banking. Using this framework, I show that an advantage in recovery leads lenders to hold loan portfolios with higher default rates in equilibrium. This contrasts with the case of a screening advantage, which allows the lender to identify the risk profile of potential borrowers. By offering attractive terms to borrowers with a low probability of default, lenders gain a relatively large market share for those type of loans that have higher default probability.

References

Agarwal, S. and Hauswald, R. (2010). Distance and private information in lending. *The Review of Financial Studies*, 23(7):2757–2788.

An, X., Deng, Y., and Gabriel, S. A. (2011). Asymmetric information, adverse selection, and the pricing of cmbs. *Journal of Financial Economics*, 100(2):304–325.

Balla, E., Mazur, L. C., Prescott, E. S., and Walter, J. R. (2019). A comparison of community bank failures and fdic losses in the 1986–92 and 2007–13 banking crises. *Journal of Banking & Finance*, 106:1–15.

Bassett, W. F. and Marsh, W. B. (2017). Assessing targeted macroprudential financial regulation: the case of the 2006 commercial real estate guidance for banks. *Journal of Financial Stability*, 30:209–228.

Berger, A. N. and Black, L. K. (2011). Bank size, lending technologies, and small business finance. *Journal of Banking & Finance*, 35(3):724–735.

Berger, A. N., Bouwman, C. H., and Kim, D. (2017). Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time. *The Review of Financial Studies*, 30(10):3416–3454.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., and Stein, J. C. (2005). Does function follow organizational form? evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76(2):237–269.

Besanko, D. and Thakor, A. V. (1992). Banking deregulation: Allocational consequences of relaxing entry barriers. *Journal of Banking & Finance*, 16(5):909–932.

Black, L. K., Krainer, J. R., and Nichols, J. B. (2020). Safe collateral, arm's-length credit: Evidence from the commercial real estate market. *The Review of Financial Studies*, 33(11):5173–5211.

Brickley, J. A., Linck, J. S., and Smith Jr, C. W. (2003). Boundaries of the firm: evidence from the banking industry. *Journal of Financial Economics*, 70(3):351–383.

Chemmanur, T. J. and Fulghieri, P. (1994). Reputation, renegotiation, and the choice between bank loans and publicly traded debt. *Review of financial Studies*, 7(3):475–506.

Chu, Y. (2016). Asset fire sales by banks: evidence from commercial reo sales. *The Review of Corporate Finance Studies*, 5(1):76–101.

deRoos, J., Liu, C., Quan, D., and Ukhov, A. (2014). The dynamics of credit spreads in hotel mortgages and signaling implications. *Journal of Real Estate Research*, 36(2):137–168.

Deyoung, R., Gron, A., Torna, G., and Winton, A. (2015). Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis. *The Journal of Finance*, 70(6):2451–2488.

Downing, C., Stanton, R., and Wallace, N. (2008). Volatility, mortgage default, and cmbs subordination. *Working Paper, University of California, Berkeley.*

Furfine, C. (2020). *Practical finance for property investment.* Routledge, Abingdon.

Ghent, A. and Valkanov, R. (2016). Comparing securitized and balance sheet loans: Size matters. *Management Science*, 62(10):2784–2803.

Glancy, D., Krainer, J. R., Kurtzman, R. J., and Nichols, J. B. (2022). Intermediary segmentation in the commercial real estate market. *Journal of Money, Credit and Banking*, 54(7):2029–2080.

Glancy, D. and Kurtzman, R. (2022). How do capital requirements affect loan rates? evidence from high volatility commercial real estate. *The Review of Corporate Finance Studies*, 11(1):88–127.

Grovenstein, R. A., Harding, J. P., Sirmans, C., Thebpanya, S., and Turnbull, G. K. (2005). Commercial mortgage underwriting: How well do lenders manage the risks? *Journal of Housing Economics*, 14(4):355–383.

Heddergott, D. and Laitenberger, J. (2017). A simple model of banking competition with bank size heterogeneity and lending spillovers. *Economic Notes: Review of Banking, Finance and Monetary Economics*, 46(2):381–404.

Hotelling, H. (1929). Stability in competition. *The Economic Journal*, 39(153):41–57.

Martinez-Miera, D. and Repullo, R. (2010). Does competition reduce the risk of bank failure? *The Review of Financial Studies*, 23(10):3638–3664.

Nguyen, H.-L. Q. (2019). Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics*, 11(1):1–32.

Petersen, M. A. and Rajan, R. G. (2002). Does distance still matter? the information revolution in small business lending. *The journal of Finance*, 57(6):2533–2570.

Ramcharan, R. (2020). Banks' balance sheets and liquidation values: Evidence from real estate collateral. *The Review of Financial Studies*, 33(2):504–535.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The journal of finance*, 57(5):1891–1921.

Vasicek, O. (2002). The distribution of loan portfolio value. *Risk*, 15(12):160–162.

Figure 1: **Share of small banks by loan category**. For each loan category, the graph shows the ratio of loans held by small banks to total bank loans in the corresponding category at the end of each year between 2001 and 2020. Small banks are defined as those with under \$5 billion in assets, measured in real 2020 USD using the implicit GDP deflator.

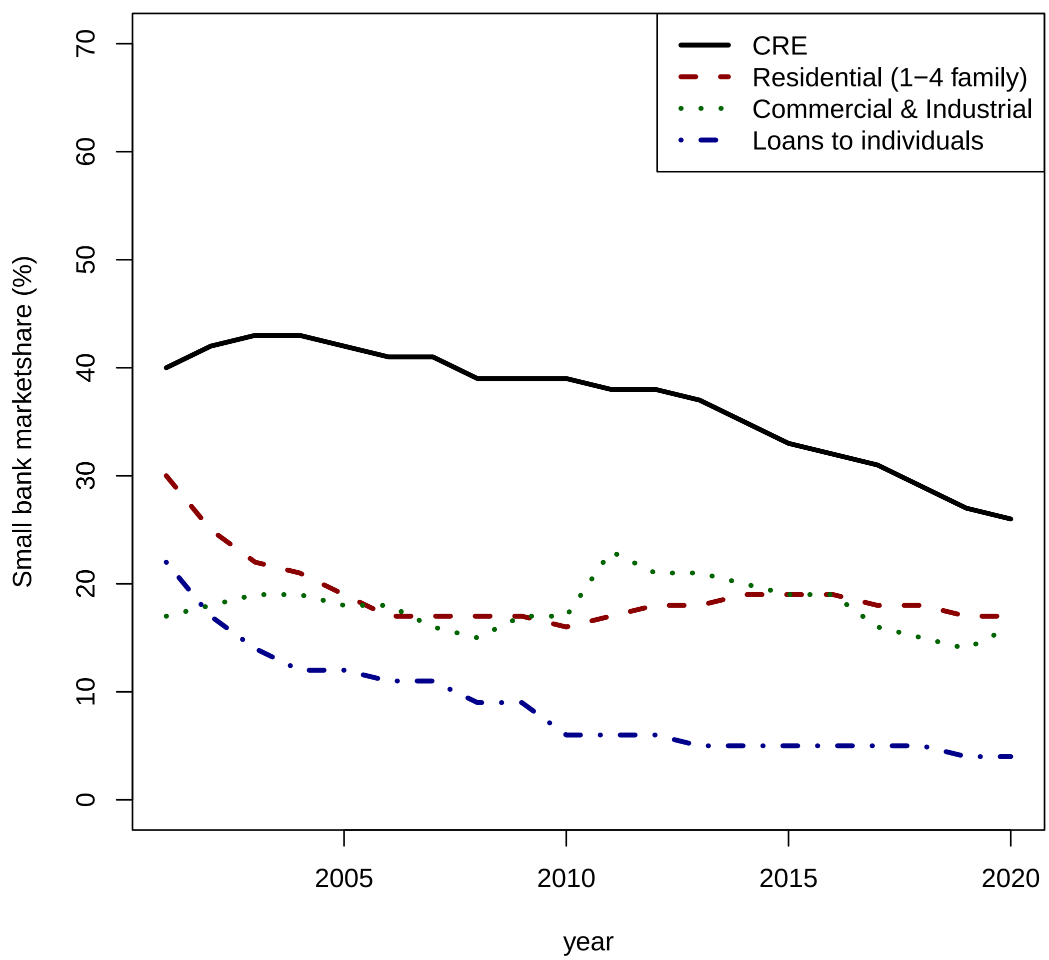

Figure 2: **Number of observations per year**. The graph shows the yearly number of observations in the sample of bank sales of foreclosed properties. The bars in light gray represent sales of foreclosed properties, whereas the darker bars correspond to their associated loans.

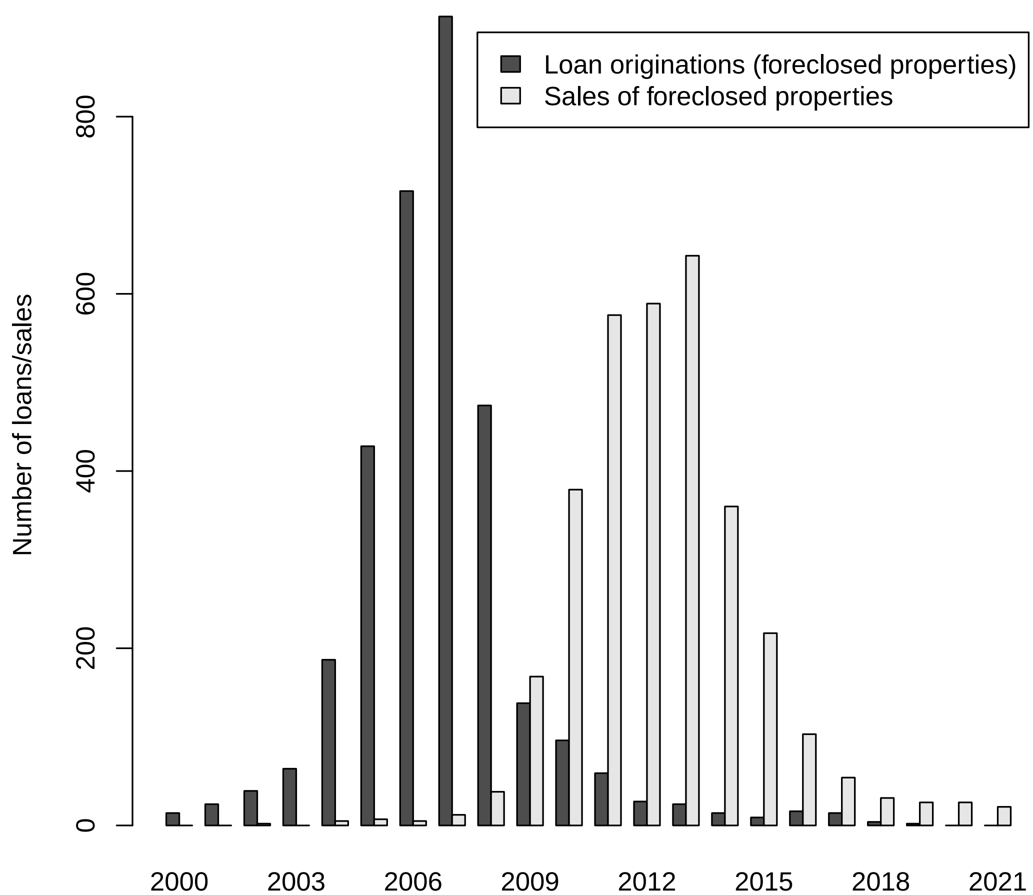

Figure 3: **Differences in *early* delinquency rates**. The graph shows the linear combinations of the coefficients for $crebank$, $Size_r$, and GFC in equation 2, along with their corresponding interactions according to each lender group and economic period. Each bar shows average differences in the standardized dependent variable with respect to the baseline category: small non-specialists ("Small other") during normal times. Results for small and large banks are calculated using values of 0 and 1 for $Size_r$, respectively.

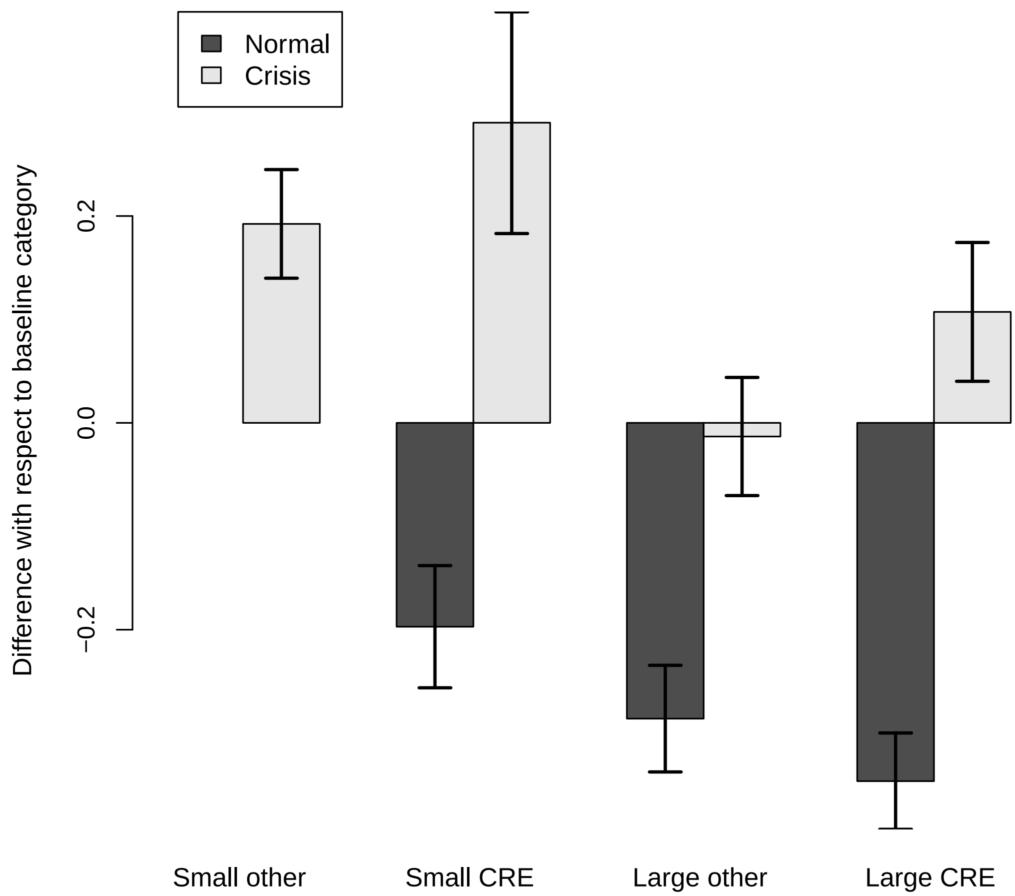

Figure 4: **Differences in delinquency rates**. The graph shows the linear combinations of the coefficients for *crebank*, $Size_r$, and *GFC* in equation 2 using *Delinq* as dependent variable, along with their corresponding interactions according to each lender group and economic period. Each bar shows average differences in the standardized dependent variable with respect to the baseline category: small non-specialists ("Small other") during normal times. Results for small and large banks are calculated using values of 0 and 1 for $Size_r$, respectively.

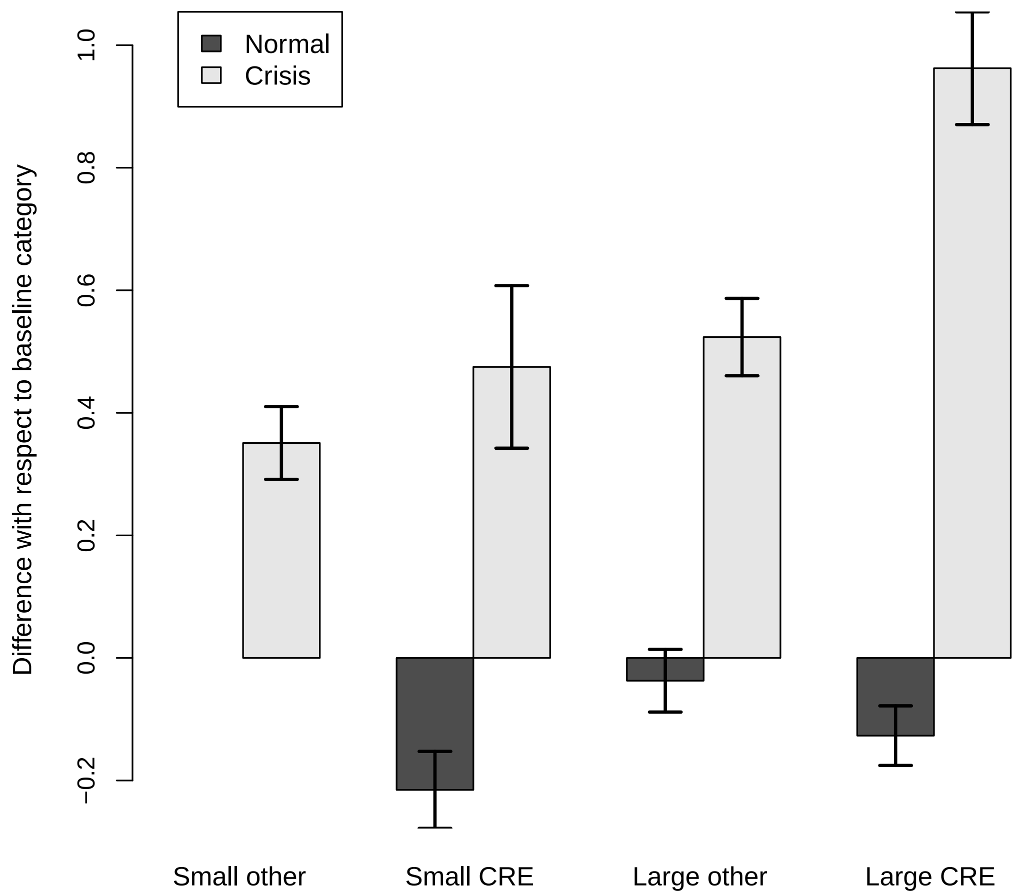

Figure 5: **Differences in charge-off rates**. The graph shows the linear combinations of the coefficients for $crebank$, $Size_r$, and GFC in equation 2 using $Chargeoff$ as dependent variable, along with their corresponding interactions according to each lender group and economic period. Each bar shows average differences in the standardized dependent variable with respect to the baseline category: small non-specialists ("Small other") during normal times. Results for small and large banks are calculated using values of 0 and 1 for $Size_r$, respectively.

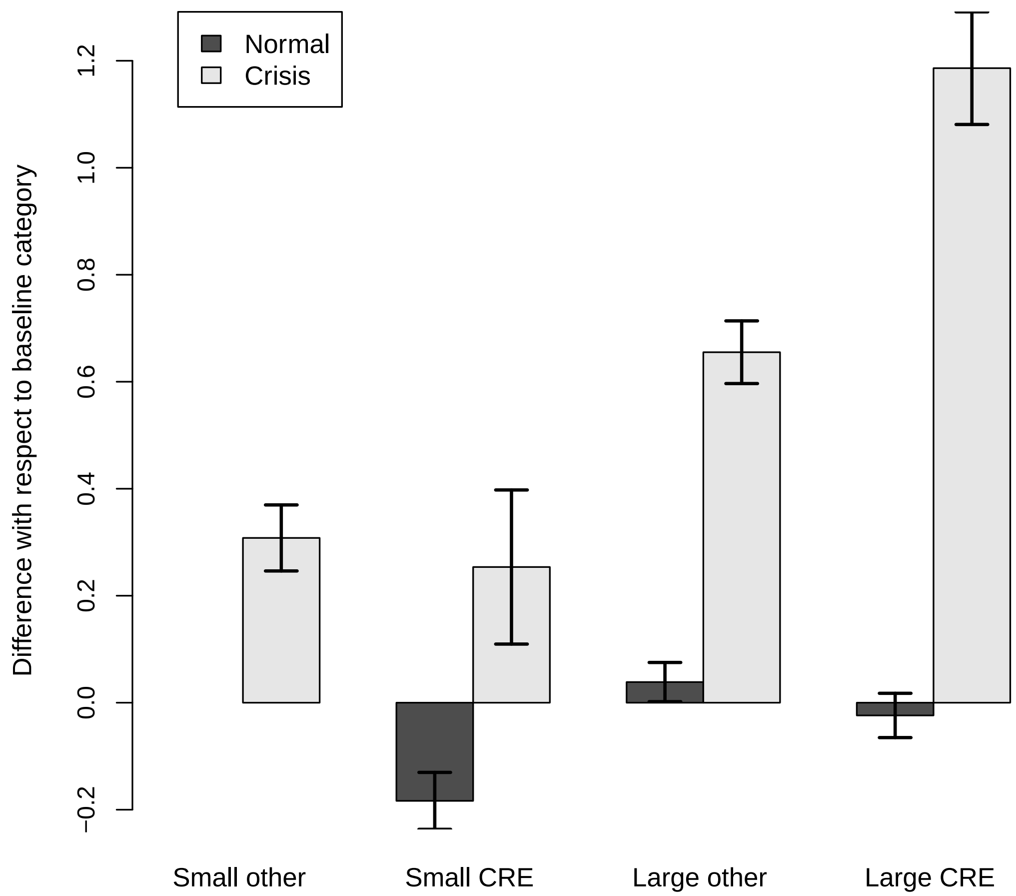

Figure 6: **Loan origination portfolio**. The figure shows, for each group of banks, the share of loan originations that correspond to each property type. Small banks are defined as having \$5 billion or less in assets measured in real 2020 USD.

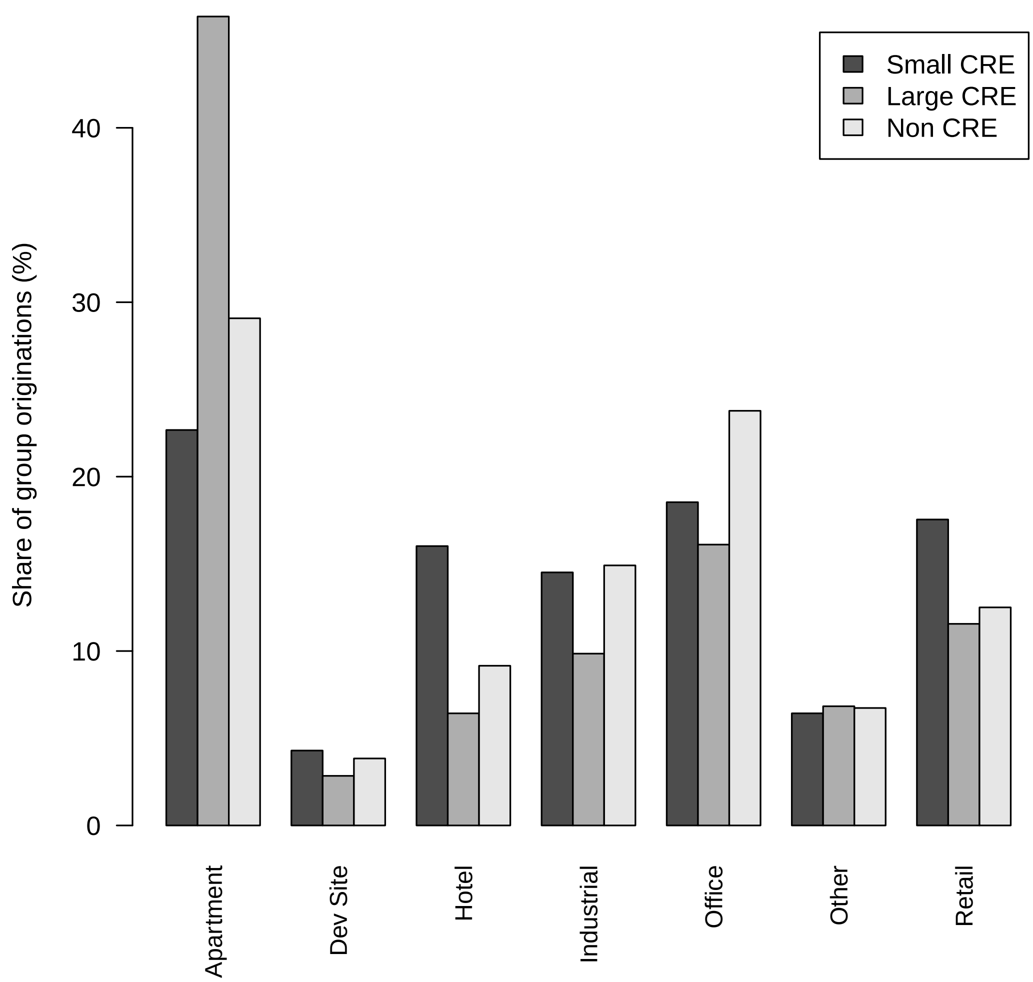

Table 1: **Summary statistics**. The table shows summary statistics for property, loan and transaction characteristics (upper panel), and bank characteristics (lower panel). $Price_o$ and $Loanamt_o$ and denote the price of the property and the loan amount at the time of loan origination, respectively. LTV_o corresponds to the loan-to-value ratio at origination. $Price_s$ denotes the transaction price of the property sold by the bank, and $recov_s$ represents the loan recovery rate, measured as the ratio of $Price_s$ to $Loanamt_o$. The dummy CBD indicates properties located in the Central Business District (CBD) of a metropolitan area. All variables in the Bank characteristics panel are measured at the time of loan origination. $Size$ denotes bank assets in thousands of real USD, $CREloans$ is the ratio of CRE loans to $Size$. $Liquidity$ denotes the sum of cash and available-for-sale securities, REO represents the bank's REO assets divided by $Size$, and $T1ratio$ corresponds to the ratio of Tier 1 capital to risk-weighted assets.

	Bank sales						Loan originations					
Variable	Mean	SD	p.25.	p.50.	p.75.	N	Mean.1	SD.1	p.25..1	p.50..1	p.75..1	N.1
Property and loan characteristics												
.												
$Price_o$	11,507,272	38,976,029	3,059,229	5,000,000	8,988,750	3,262	14,901,363	51,040,560	3,700,000	6,000,000	12,142,857	269,497
$Loanamt_o$	9,399,512	28,484,753	2,430,000	4,000,000	7,822,426	3,262	9,530,002	25,813,234	2,500,000	4,000,000	8,125,462	269,497
LTV_o	0.9695	1.027	0.7019	0.7538	0.9001	3,262	0.7568	1.097	0.5928	0.7	0.795	269,497
$Price_s$	8,373,034	46,446,438	1,785,938	2,850,000	5,000,000	3,262	-	-	-	-	-	-
$recov_s$	1.07	1.805	0.4732	0.6957	1.012	3,262	-	-	-	-	-	-
CBD	0.07669	0.2661	0	0	0	3,260	0.1611	0.3676	0	0	0	269,424
Property type												
$Apartment$	0.1781	0.3827	0	0	0	3,262	0.2768	0.4474	0	0	1	269,497
$DevSite$	0.08829	0.2838	0	0	0	3,262	0.02848	0.1663	0	0	0	269,497
$Hotel$	0.1193	0.3241	0	0	0	3,262	0.08975	0.2858	0	0	0	269,497
$Industrial$	0.1766	0.3814	0	0	0	3,262	0.2006	0.4005	0	0	0	269,497
$Office$	0.2186	0.4133	0	0	0	3,262	0.1724	0.3777	0	0	0	269,497
$Retail$	0.183	0.3867	0	0	0	3,262	0.1756	0.3805	0	0	0	269,497
Borrower type												
$Institutional$	0.04249	0.2017	0	0	0	3,248	0.0705	0.256	0	0	0	269,232
$Private$	0.8608	0.3462	1	1	1	3,248	0.8315	0.3743	1	1	1	269,232
$Public$	0.02617	0.1597	0	0	0	3,248	0.01768	0.1318	0	0	0	269,232
Transaction type												
$Refinance$	0.4341	0.4957	0	0	1	3,262	0.4562	0.4981	0	0	1	269,497
$Sale$	0.5607	0.4964	0	1	1	3,262	0.4777	0.4995	0	0	1	269,497
Buyer type												
$Institutional$	0.08241	0.275	0	0	0	3,240	-	-	-	-	-	-
$Private$	0.8071	0.3946	1	1	1	3,240	-	-	-	-	-	-
$Public$	0.0142	0.1183	0	0	0	3,240	-	-	-	-	-	-
Bank characteristics												
.												
$Size$	107,076,551	308,077,097	748,353	4,275,569	30,755,275	3,136	359,821,325	734,145,710	2,094,679	16,073,050	129,184,470	269,497
$CREloans$	0.3444	0.2118	0.158	0.3162	0.5059	3,136	0.2917	0.1906	0.117	0.2857	0.4216	269,497
$Liquidity$	0.1761	0.1094	0.09791	0.169	0.2259	3,136	0.2495	0.1375	0.1453	0.2243	0.356	269,497
REO	0.003114	0.008871	0	0.0003528	0.001893	3,136	0.001552	0.0058	0.00004255	0.0002716	0.001086	269,497
$T1ratio$	0.127	0.1505	0.09092	0.1022	0.1222	3,126	0.134	0.09273	0.1094	0.1231	0.1382	255,205

Table 2: **Differences in recovery rates**. The table presents the results of regressions of recovery rates on banks' size, CRE holdings, and different sets of control variables. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. Transaction/borrower controls include the type of buyer, seller, and transaction. The dependent variable is winsorized at the 2.5 and 97.5 percentiles. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	Recovery rate				
	(1)	(2)	(3)	(4)	(5)
$crebank$	-0.0843^{***}	0.4175^{**}	0.4045^{**}	0.3871^{**}	0.3732^{*}
	(0.0312)	(0.1815)	(0.1813)	(0.1804)	(0.1940)
$Size_r$	-0.0995	0.1076	0.1229	0.0647	0.0875
	(0.1007)	(0.1016)	(0.0997)	(0.1306)	(0.1347)
$crebank : Size_r$		-0.5681^{***}	-0.5536^{***}	-0.5407^{***}	-0.5555^{**}
		(0.1975)	(0.1974)	(0.1977)	(0.2141)
CBD	0.1135	0.1120	0.1279	0.1302	0.1306
	(0.0840)	(0.0836)	(0.0820)	(0.0811)	(0.0913)
LTV			-0.1489^{***}	-0.1470^{***}	-0.1876^{***}
			(0.0382)	(0.0380)	(0.0415)
$Liquidity$				0.0536	0.0187
				(0.1659)	(0.1714)
REO				-2.8215^{**}	-2.8991^{**}
				(1.1622)	(1.3793)
$T1ratio$				-0.0924	-0.0735
				(0.1024)	(0.1086)
Transaction/Borrower	Yes	Yes	Yes	Yes	Yes
Property Type	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes
Includes Dev. Site	Yes	Yes	Yes	Yes	No
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	3099	3099	3099	3089	2808
Adj. R^2	0.4249	0.4264	0.4451	0.4509	0.4703

Table 3: **Robustness tests: Differences in recovery rates**. The table presents the results of regressions of recovery rates on banks' size, CRE holdings, and different sets of control variables. In columns (1) - (4), *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. In column (5), the threshold for *crebank* is the 70th percentile. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. Transaction/borrower controls include the type of buyer, seller, and transaction. The dependent variable is winsorized at the 2.5 and 97.5 percentiles in columns (1) - (3) and (5), and at the 1 and 99 percentiles in column (4). Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	Recovery rate				
	(1)	(2)	(3)	(4)	(5)
$crebank$	0.4027^{*}	0.4614^{**}	0.3611^{**}	0.4978^{**}	0.3728^{*}
	(0.2200)	(0.1801)	(0.1698)	(0.2270)	(0.1927)
$Size_r$	0.0402	0.1022	0.0425	0.1271	0.1189
	(0.1406)	(0.1423)	(0.1270)	(0.1588)	(0.1684)
$crebank : Size_r$	-0.5277^{**}	-0.6090^{***}	-0.5119^{***}	-0.6894^{***}	-0.4844^{**}
	(0.2403)	(0.2023)	(0.1884)	(0.2473)	(0.2177)
CBD	0.0638	0.1327^{*}	0.0962	0.1960^{*}	0.1320
	(0.0678)	(0.0724)	(0.0816)	(0.1061)	(0.0824)
LTV	-0.1192^{***}	-0.1427^{***}	-0.1476^{***}	-0.1687^{***}	-0.1478^{***}
	(0.0315)	(0.0365)	(0.0389)	(0.0474)	(0.0383)
$Liquidity$	0.0750	0.0653	0.0715	-0.0969	0.0808
	(0.1397)	(0.1595)	(0.1748)	(0.2326)	(0.1685)
REO	-3.3348^{**}	-2.2586^{*}	-3.0760^{**}	-2.9478^{**}	-2.8524^{**}
	(1.3513)	(1.2532)	(1.2390)	(1.2802)	(1.1673)
$T1ratio$	-0.1367	-0.0571	-0.0885	-0.0520	-0.0664
	(0.1217)	(0.1272)	(0.1015)	(0.1186)	(0.1105)
Transaction/Loan	Yes	Yes	Yes	Yes	Yes
Property Type	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	No	Yes	Yes	Yes
State F.E.	No	Yes	Yes	Yes	Yes
Year-State F.E.	Yes	No	No	No	No
Year-P.Type F.E.	No	Yes	No	No	No
Includes Dev. Site	Yes	Yes	Yes	Yes	Yes
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	3089	3089	3071	3089	3089
Adj. R^2	0.5269	0.4715	0.4567	0.4053	0.4499

Table 4: **Ex post portfolio performance**. The table presents the results of regressions of distinct CRE loan portfolio perfomance measures on bank size and CRE holdings. Control variables include HQ-state fixed effects, REO ratio, T1 capital ratio, liquidity, the FDIC's indicator for comunity banks, and *loancomp*, a weighted average of the county-level CRE loan market competition faced by the bank. Continuous regressors are averaged over their first two lags. Dichotomous regressors are lagged 1 period. The dependent variables are winsorized yearly at the .5 and 99.5 percentiles and then standardized to have mean zero and unit variance across the sample period. Standard errors are clustered by lender. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	$Earlydelinq$	$Delinq$	$Chargeoff$
GFC	0.1924^{***}	0.3508^{***}	0.3080^{***}
	(0.0268)	(0.0303)	(0.0315)
$crebank$	-0.1971^{***}	-0.2154^{***}	-0.1835^{***}
	(0.0301)	(0.0321)	(0.0271)
$Size_r$	-0.2860^{***}	-0.0372	0.0386^{**}
	(0.0263)	(0.0261)	(0.0187)
$failed$	0.5211^{***}	0.7682^{***}	0.4591^{***}
	(0.0383)	(0.0419)	(0.0389)
$community$	-0.0044	-0.0377^{*}	-0.1377^{***}
	(0.0144)	(0.0204)	(0.0225)
$loancomp$	0.1265^{***}	0.0154	-0.0295^{*}
	(0.0200)	(0.0226)	(0.0178)
$Liquidity$	-0.0356	0.1507^{***}	0.0394
	(0.0424)	(0.0443)	(0.0350)
$T1ratio$	0.0934	-0.0142	-0.1989^{***}
	(0.0682)	(0.0680)	(0.0736)
REO	6.6330^{***}	25.5777^{***}	20.0863^{***}
	(0.6180)	(1.3076)	(1.2071)
$GFC : crebank$	0.2949^{***}	0.3395^{***}	0.1291
	(0.0591)	(0.0744)	(0.0813)
$GFC : Size_r$	0.0804^{**}	0.2100^{***}	0.3086^{***}
	(0.0385)	(0.0464)	(0.0511)
$crebank : Size_r$	0.1366^{***}	0.1257^{***}	0.1211^{***}
	(0.0399)	(0.0440)	(0.0368)
$GFC : crebank : Size_r$	-0.1140	0.1890^{*}	0.4643^{***}
	(0.0813)	(0.1094)	(0.1273)
State Fixed Effects	Yes	Yes	Yes
Num. obs.	80710	80710	80710
Adj. R^2	0.0622	0.1885	0.1510

Table 5: **Acquired banks**. The table presents the results of regressions of recovery rates on banks' size, CRE holdings, a bank acquisition indicator, and additional control variables. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. The dummy variable *acqlen* equals one if the property was sold by a bank that acquired the loan originator. Transaction/borrower controls include the type of buyer, borrower, and transaction. Bank controls include liquidity, REO ratio, and Tier 1 capital ratio. Property controls comprise property type dummies and the CBD flag. The dependent variable is winsorized at the 2.5 and 97.5 percentiles. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	Recovery rate		
	(1)	(2)	(3)
$crebank$	0.3145^{*}	0.3190^{*}	0.3774^{**}
	(0.1737)	(0.1722)	(0.1782)
$Size_r$	0.0352	0.0329	0.0757
	(0.1285)	(0.1276)	(0.1305)
$crebank : Size_r$	-0.4421^{**}	-0.4525^{**}	-0.5260^{***}
	(0.1898)	(0.1878)	(0.1945)
$acqlen$	-0.0784		
	(0.0519)		
$crebank : acqlen$		0.0513	-0.6270^{*}
		(0.0709)	(0.3578)
$crebank : Size\_r : acqlen$			0.7325
			(0.4562)
Transaction/Loan	Yes	Yes	Yes
Property Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes
Includes Dev. Site	Yes	Yes	Yes
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	3284	3284	3284
Adj. R^2	0.4421	0.4419	0.4265

Table 6: **Client networks.** The table presents the results of regressions of recovery rates on banks' size, CRE holdings, variables describing the banks' relationship with the buyers, and additional controls. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. The dummy variable *network* equals one if the property was sold to a buyer that had received a CRE loan from the selling bank before the transaction. *samelend* indicates transactions in which the selling bank financed the sale by providing a mortgage to the property's buyer. Transaction/borrower controls include the type of buyer, borrower, and transaction. Bank controls include liquidity, REO ratio, and Tier 1 capital ratio. Property controls comprise property type dummies and the CBD flag. The dependent variable is winsorized at the 2.5 and 97.5 percentiles. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	Recovery rate			
	(1)	(2)	(3)	(4)
crebank	0.3732**	0.3881**	0.3292	0.1578
	(0.1783)	(0.1800)	(0.3354)	(0.3674)
$Size_r$	0.0595	0.0552	−0.0037	−0.0480
	(0.1306)	(0.1316)	(0.2454)	(0.2549)
$crebank : Size_r$	−0.5298***	−0.5221***	−0.6173*	−0.5138
	(0.1957)	(0.1945)	(0.3678)	(0.3814)
network	0.1922***	0.2990***		
	(0.0550)	(0.1006)		
crebank : *network*		−0.2416*		
		(0.1291)		
samelend			0.1029*	−0.0556
			(0.0584)	(0.0990)
crebank : *samelend*				0.2901**
				(0.1191)
Transaction/Loan	Yes	Yes	Yes	Yes
Property Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes
Includes Dev. Site	Yes	Yes	Yes	Yes
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	3089	3089	1259	1259
Adj. R^2	0.4533	0.4541	0.5751	0.5767

Table 7: **Geographic proximity**. The table presents the results of regressions of recovery rates on banks' size, CRE holdings, proximity of bank offices to the property, and additional controls. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. The dummy variable *branchorig* equals one if the bank had a full-service office in the property's county at the time of loan origination. The variable *branchsale* indicates cases in which the selling bank had a full-service office in the property's county at the time of the sale. Transaction/borrower controls include the type of buyer, borrower, and transaction. Bank controls include liquidity, REO ratio, and Tier 1 capital ratio. Property controls comprise property type dummies and the CBD flag. The dependent variable is winsorized at the 2.5 and 97.5 percentiles. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	Recovery rate				
	(1)	(2)	(3)	(4)	(5)
crebank	0.3827^{**}	0.3479^{*}	0.3819^{**}	0.3613^{*}	0.3507^{*}
	(0.1814)	(0.1857)	(0.1805)	(0.1824)	(0.1853)
$Size_r$	0.0592	0.0848	0.0546	0.0952	0.0959
	(0.1298)	(0.1317)	(0.1316)	(0.1371)	(0.1368)
$crebank : Size_r$	-0.5365^{***}	-0.5730^{***}	-0.5340^{***}	-0.5926^{***}	-0.5939^{***}
	(0.1984)	(0.1966)	(0.1980)	(0.1970)	(0.1972)
branchorig	0.0143	−0.0530			−0.0210
	(0.0305)	(0.0499)			(0.0510)
crebank : branchorig		0.1540^{**}			0.0616
		(0.0597)			(0.0531)
branchsale			0.0181	−0.0614	−0.0471
			(0.0334)	(0.0553)	(0.0593)
crebank : branchsale				0.1885^{**}	0.1483^{*}
				(0.0817)	(0.0879)
Transaction/Loan	Yes	Yes	Yes	Yes	Yes
Property Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes
Includes Dev. Site	Yes	Yes	Yes	Yes	Yes
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	3089	3089	3089	3089	3089
Adj. R^2	0.4508	0.4517	0.4508	0.4523	0.4520

Appendix A. The use of client networks

In this appendix, I explore the characteristics of lenders that frequently recur to their clients to sell foreclosed real estate. The results show that small banks are particularly likely to provide a loan to the buyer of the property. To analyze the type of banks that are more likely to sell foreclosed properties to their loan recipients, I estimate the following linear probability model (LPM):

$$nw_{i,b,t,\tau} = \beta_1 + \beta_2 * crebank_{b,\tau} + \beta_3 * Size_{r,b,\tau} + \beta_4 * crebank_{b,\tau} * Size_{r,b,\tau} + \beta_5 * X_{i,t} + \beta_6 * \Gamma_{i,b,\tau} + \varepsilon_{i,b,t,\tau}. \tag{A.1}$$

In equation A.1 above, $nw_{i,b,t,\tau}$ corresponds to *network* or *samelend*, depending on the specification. The vector of controls $X_{i,t}$ includes fixed effects for year of sale and state, property type dummies, the type of buyer, and the CBD indicator. Bank controls in $\Gamma_{i,b,\tau}$ are liquidity, REO ratio, and T1 capital ratio, whereas the loan characteristics are the LTV ratio and indicator variables for transa and borrower type.

The first two columns of Table A.8 show the estimation output for the LPM using *network* as dependent variable. In column (1), I omit the interaction term between bank size and CRE specialization. The results point out that banks with a high concentration of CRE have a higher probability of selling to one of their clients. I analyze the difference between CRE specialists of different sizes in column (2). Although the point estimate for *crebank* is positive in column (2), neither the coefficients related to bank size nor those that regard CRE holdings are significant from a statistical standpoint. This results suggest that small and large CRE-focused banks are as likely to sell the property to their former clients.

Columns (3)-(4) of Table A.8 show the estimation results for the LPM in equation A.1 using *samelend* as the dependent variable. Notably, the coefficients for the the variables indicating the degree of CRE specialization are positive and significant. In the model that does not explicitly incorporate interactions of lender size and CRE holdings (column (3)), the estimated coefficients indicate that the probability that specialized lenders provide a commercial mortgage to the new buyer of the property is larger by over 14 percentage points. Interestingly, larger banks tend not to make a new loan backed by the property as per the estimated coefficient for $Size_r$. I investigate the differences among CRE specialists of different size in column (4). The estimation results indicate that small CRE specialists are remarkably likely to fund the purchase of the foreclosed property.

The differences in results between both dependent variables warrant further discussion. In the case of *network*, while banks that specialize in CRE are generally more likely to sell foreclosed properties to their clients, the size of the lender does not seem as important. One potential explanation is that the crucial element enabling a bank to sell a CRE property to one of its clients is not the size of its client network, but rather the quantity or proportion of their clients that usually invest in CRE. Since investing in and operating commercial properties requires significant expertise , and acquisitions generally involve debt, commercial mortgagors are likely to be CRE investors.[25]. Thus, a large non-specialist bank will need to find a buyer amongst the general public, even if it sustains relationships with a high number of firms and individuals. On the other hand, banks for which CRE constitutes a major portion of their portfolio may have a relatively broad network of clients that, crucially, might be interested in growing their CRE holdings.

In contrast, the coefficients for $Size_r$ in the last two columns of Table A.8 show that smaller lenders are much more likely to originate a new mortgage backed by the property than larger banks. In fact, the point estimates of the interaction terms in column (4) suggest that this difference in likelihood is even larger among CRE specialists of different size, although their standard errors are too large to justify proper inference. A potential explanation for the higher propensity of small banks to keep making loans backed by the same property is that a single CRE loan might represent a large portion not only of the bank's CRE loan holdings, but also of their overall assets. Hence, a small bank that recently needed to foreclose a property might be highly pressed to compensate the asset loss, in both principal and receivable interest, caused by the foreclosure. If a bank

[25]This contrasts, for example, with the case of residential real estate, in which most borrowers would not be in a position to acquire a second property

provides a mortgage backed by the property, it immediately converts the REO holding into an income-generating asset, thus providing at least partial relief to their formerly shrunk balance sheet. Larger institutions, on the other hand, might not be as pressed to compensate the asset losses caused by the foreclosure of a single property, simply because the relative reduction in their loan portfolio is minor compared to the case of a small bank.

Table A.8: **Use of client networks**. The table presents the estimation results for the linear probability model in equation A.1. The dependent variable in the first two columns is *network*, an indicator of whether the property's buyer had received a CRE loan from the selling bank before the transaction. The dependent variable in the third and fourth columns is *samelend*, which equals 1 if the bank financed the sale by providing a loan to the property's buyer. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. Transaction/loan controls include the type of buyer, borrower, and transaction, as well as the LTV ratio. Bank controls include liquidity, REO ratio, and Tier 1 capital ratio. Property controls comprise property type dummies and the CBD flag. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	network		*samelend*	
	(1)	(2)	(3)	(4)
crebank	0.0217^{*}	0.0727	0.1461^{***}	0.2918^{*}
	(0.0125)	(0.0531)	(0.0425)	(0.1595)
$Size_r$	0.0012	0.0274	-0.4026^{***}	-0.3165^{**}
	(0.0371)	(0.0371)	(0.1237)	(0.1470)
crebank : *samelend*		-0.0568		-0.1619
		(0.0561)		(0.1673)
Transaction/Loan	Yes	Yes	Yes	Yes
Property Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes
Includes Dev. Site	Yes	Yes	Yes	Yes
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	3089	3089	1259	1259
Adj. R^2	0.1737	0.1736	0.1279	0.1279

Appendix B. LTV ratio at origination

Banks can adjust the *magnitude* of their exposure by manipulating certain loan terms. In particular, a lender might control its exposure to shocks that affect a particular property by fine-tuning the LTV ratio of the loan. With the purpose of illustrating, consider, hypothetically, a bank that faces the underwriting process for a mortgage backed by an industrial property and deciding whether to offer the borrower a 90% or a 70% LTV ratio. A shock to local industrial RE prices would affect the loan's performance differently, since the price of the property would need to drop by at least 30% for the 70%-LTV loan to be *underwater*, making strategic default relatively unlikely. In contrast, with the 90%-LTV mortgage, the borrower's default option would be valuable whenever the property's price dropped by more than 10%. From the lender's perspective, the loan with the higher LTV ratio is clearly riskier, even if backed by the same real estate as the alternative.

I analyze potential differents in LTV ratios at origination that may impact the risk exposure of lenders by regressing LTV on a set of property and lender characteristics. Specifically, I estimate the coefficients in the following equation:

$$LTV_{i,b,t} = \beta_1 + \beta_2 * crebank_{b,t} + \beta_3 * Size_{r,b,t} + \beta_4 * crebank_{b,t} * Size_{r,b,t} + \beta_5 * X_{i,t} + \beta_6 * \Gamma_{b,t} + \varepsilon_{i,b,t}. \tag{B.1}$$

In equation B.1, $LTV_{i,b,t}$ corresponds to the LTV ratio at origination of loan i, originated by bank b at time t. As before, $CRE_{b,t}$ and $Size_{r,b,t}$ denote relative measures of bank b's CRE holdings and size at time t, respectively. The transaction-level controls in $X_{i,t}$ are year-of-origination and state fixed effects, the property's type, the CBD indicator, and indicator variables for the type of borrower and transaction. I also include measures of liquidity, foreclosed real estate, and regulatory capital as bank-level controls in $\Gamma_{b,t}$. For the estimation, I winsorize the dependent variable at the 1 and 99 percentiles and display the results in Table B.9.

In the first three columns of Table B.9, I explore whether CRE specialists originate loans with different LTV ratios regardless of their size. In column (1), I restrict controls to year and state fixed effects, as well as a set of variables indicating the type of the underlying property. The estimation results suggest that CRE specialists, on average, originate loans with slightly higher LTV ratios. In the specifications that account for transaction and property characteristics (second column), and lender attributes (third column), the coefficient for *crebank* is considerably smaller in magnitude and statistically insignificant.

Columns (4)-(6) break down the results in the first three columns by allowing for the interaction between *crebank* and lender size. The coefficient for *crebank* is negative and significant at the 10% level across the three specifications. Interestingly, the coefficient for the interaction of *crebank* and $Size_r$ is positive and statistically significant. Taken together, these estimated coefficients imply that large banks with a high CRE concentration tend to originate loans with higher LTV ratios than other lender groups, and that, in fact, the lowest average LTV ratios correspond to small CRE specialists.

One takeaway from the analysis in Table B.9 is that small CRE specialists generally do not augment their exposure to CRE risk by offering high LTV ratios to their borrowers. In fact, the opposite is true: loans made by large CRE specialists had higher LTV ratios on average after controlling for property and borrower's characteristics. Interpreting these findings in the light of the evidence in Figure 6, it seems plausible that small, CRE-oriented banks use LTV to manage their exposure to the high risk implied in their mix of property types. To explore this possibility, I analyze differences in LTV ratios for each of the main property types separately in Table B.10.[26]

In the estimation results by property type, the coefficient for *crebank* is significantly different from zero only in the case of loans backed by hotels. This indicates that, among small banks, CRE specialists offer lower LTV ratios than non-specialists, up to 10 percentage points lower at the bottom of the size distribution. On the other hand, the estimated coefficients for bank size indicate that, among non-specialists, larger banks tend to make larger loans for office and industrial properties. The interaction term is

[26] Performing the analysis separately for each property type allows me to add $Prop.Size$ to the vector of controls $X_{i,t}$. The reason for this is that $Prop.Size$ is a measure that corresponds to the number of units in apartments and hotels, but to the number of square feet for other property types.

statistically significant for only two property types: apartments and hotels.

To facilitate the comparison of LTV ratios corresponding to CRE specialists of different size, I use the results from Table B.10 to obtain t statistics for the sum of the estimated coefficients for $Size_r$ and the interaction term $crebank : Size_r$, which I show in Table B.11. This sum can be interpreted as the average difference in LTV between the extremes of the size distribution of CRE specialists after controlling for property and transaction attributes. The table shows that large CRE specialists originate loans with higher LTV for all the major property types. Notably, the difference in LTV is statistically significant for all property types except loans backed by hotels.

The potential implications for portfolio risk of the results described above are worth discussing. Multifamily loans by large CRE specialists have higher LTVs, which, combined with the large share of apartment loans in their portfolios (Figure 6), suggests that shocks affecting multifamily properties could be particularly impactful for large, CRE-oriented commercial banks. However, as noted in the previous subsection, apartments have historically experienced lower default rates than other property types. Small CRE banks offer loans with lower LTV ratios across most major property types, which, as illustrated above, diminishes their exposure to default risk. In the case of hotels, the LTV ratios are similar across the size distribution of CRE-focused banks. This, on top of the relatively large share of hotels in the portfolios of small CRE specialists offers additional evidence that, at least in some respects, the portfolios of small banks that specialize in CRE are riskier than those of larger institutions.

Another interpretation of the relatively low LTV ratios offered by small CRE specialists, particularly for hotels and apartments, is the inherent risk in the underlying properties, as perceived by the lender. In other words, the LTV ratios of loans by small CRE specialists could be low precisely because the underlying property is riskier, constituting the reason for the lender to reduce their exposure via the size of the loan relative to the value of the property. Within a similar line of reasoning, apartment properties financed by large CRE specialists might be relatively safe, leading banks to agree to finance a larger portion of the asset's value. This endogeneity of LTV during underwriting has led to mixed results in studies on the relationship between LTV and default probability.[27] Additional credit measures, like credit spreads, can help clarify whether the differences in LTV are driven by risk factors inherent to the property. Unfortunately, my data set does not include information regarding loan interest rates.

[27] See, for example, Grovenstein et al. (2005), and the discussion in Ghent and Valkanov (2016).

Table B.9: **Differences in LTV ratio**. The table presents the results of regressions of LTV ratio on banks' size, CRE holdings, and different sets of control variables using the full sample of CRE loan originations. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. Transaction/borrower controls include the type of buyer, seller, and transaction. The dependent variable is winsorized at the 1 and 99 percentiles. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	LTV ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$crebank$	0.0147^{**}	0.0073	0.0075	-0.0356^{*}	-0.0293^{*}	-0.0552^{***}
	(0.0073)	(0.0058)	(0.0055)	(0.0197)	(0.0167)	(0.0170)
$Size_r$	−0.0066	0.0211	0.0103	−0.0317	0.0027	−0.0226
	(0.0226)	(0.0171)	(0.0157)	(0.0330)	(0.0250)	(0.0232)
$crebank : Size_r$				0.0548^{**}	0.0399^{*}	0.0685^{***}
				(0.0270)	(0.0225)	(0.0217)
CBD		−0.0067	−0.0063		−0.0068	−0.0064
		(0.0062)	(0.0064)		(0.0062)	(0.0064)
$Liquidity$			0.0022			0.0060
			(0.0284)			(0.0279)
REO			0.1288			0.1300
			(0.1728)			(0.1758)
$T1ratio$			-0.0653^{***}			-0.0722^{***}
			(0.0229)			(0.0222)
Transaction/Borrower	No	Yes	Yes	No	Yes	Yes
Property Type	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Includes Dev. Site	No	No	No	No	No	No
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	261783	261494	247827	261783	261494	247827
Adj. R^2	0.0403	0.0554	0.0554	0.0404	0.0554	0.0555

Table B.10: **Differences in LTV ratio**. The table presents the results of regressions of LTV ratio on banks' size, CRE holdings, and different sets of control variables using the full sample of CRE loan originations. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. Transaction/borrower controls include the type of buyer, seller, and transaction. Bank controls comprise liquidity, REO ratio, and T1 capital ratio. The dependent variable is winsorized at the 1 and 99 percentiles. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	LTV ratio				
	Apartment	Office	Hotel	Retail	Industrial
crebank	-0.0354	-0.0270	-0.1219^{***}	-0.0403^{*}	-0.0387
	(0.0272)	(0.0235)	(0.0359)	(0.0234)	(0.0293)
$Size_r$	0.0007	0.0306	-0.1011^{*}	0.0084	0.0058
	(0.0262)	(0.0236)	(0.0534)	(0.0234)	(0.0284)
$crebank : Size_r$	0.0666^{*}	0.0382	0.1263^{**}	0.0370	0.0385
	(0.0347)	(0.0270)	(0.0520)	(0.0258)	(0.0329)
Transaction/Borrower	Yes	Yes	Yes	Yes	Yes
Property Controls	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes
Includes Dev. Site	No	No	No	No	No
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	70865	43936	22846	44381	51409
Adj. R^2	0.0647	0.0476	0.2267	0.0462	0.0867

Table B.11: **Differences in LTV ratio among CRE-focused banks**. The first two rows of the table shows values and standard errors for the sum of the coefficients for $Size_r$ and $crebank : Size_r$ from Table B.10. The third row shows the t-stat for a test of the null hypothesis that $Size_r + crebank : Size_r = 0$.

	Property type				
	Apartment	Office	Hotel	Retail	Industrial
$Size_r + crebank : Size_r$	0.0673	0.0688	0.0252	0.0454	0.0444
S.E.	0.0244	0.0166	0.0271	0.0174	0.0210
t-stat	2.7534	4.1537	0.9282	2.6088	2.1162

Appendix C. Additional tables and figures

Table C.12: **Bank loans in RCA data**. The table shows the number of loans originated by banks for each year that are observed in the CRE loan database. The column labeled Share of RCA loans shows the ratio of the first column to the number of loans in each year made by all types of lenders (e.g. CMBS, insurance companies, private lenders). The column labeld Share of RCA transactions shows the ratio of the first column to the number of all transactions observed in the CRE data set for each year, regardless of whether loan information is available.

Year	Number of loans	Share of RCA loans	Share of RCA transactions
2000	292	6.21	3.82
2001	517	8.64	5.23
2002	689	10.97	6.40
2003	1031	10.52	6.96
2004	2603	19.76	12.43
2005	6942	25.01	19.24
2006	7325	23.37	18.55
2007	7686	22.59	19.59
2008	5007	41.72	25.56
2009	2106	32.14	19.56
2010	3025	25.47	16.86
2011	4583	25.35	17.73
2012	8267	31.71	23.32
2013	11900	41.86	30.15
2014	12969	39.94	29.25
2015	20258	41.62	32.03
2016	26633	54.13	41.56
2017	25778	48.52	38.75
2018	26271	48.59	36.69
2019	36069	54.03	43.90
2020	33613	57.28	44.31
2021	25933	55.80	39.21

Table C.13: **Number of loans by state**. The table shows the number of loans related to properties in each different state. The column labeled Bank sales corresponds to the sample of foreclosed property sales, whereas the column named Loan originations refers to all available loan information in the CRE loan database.

State	Bank sales	Loan originations
AK	1	220
AL	19	1321
AR	10	1471
AZ	201	6747
CA	722	65850
CO	82	6552
CT	14	1685
DC	6	1349
DE	1	417
FL	526	18812
GA	184	6565
HI	9	689
IA	13	1196
ID	2	623
IL	225	11763
IN	34	3721
KS	9	958
KY	10	1371
LA	5	799
MA	20	5743
MD	12	3837
ME	1	358
MI	91	4156
MN	36	3760
MO	76	3744
MS	4	242
MT	2	406
NC	63	5814
ND	1	585
NE	5	1093
NH	0	703
NJ	39	7762
NM	17	943
NV	187	3285
NY	50	32996
OH	30	4860
OK	23	2283
OR	39	3210
PA	29	5769
RI	0	428
SC	30	2814
SD	2	28
TN	43	4261
TX	210	20638
UT	26	2135
VA	18	3664
VT	0	13
WA	73	7573
WI	62	3869
WV	0	152
WY	0	225

Table C.14: **Summary statistics by bank size**. The table shows summary statistics for property, loan and transaction characteristics (upper panel), and bank characteristics (lower panel) in the sample of foreclosed property sales. $Price_o$ and $Loanamt_o$ and denote the price of the property and the loan amount at the time of loan origination, respectively. LTV_o corresponds to the loan-to-value ratio at origination. $Price_s$ denotes the transaction price of the property sold by the bank, and $recov_s$ represents the loan recovery rate, measured as the ratio of $Price_s$ to $Loanamt_o$. The dummy CBD indicates properties located in the Central Business District (CBD) of a metropolitan area. All variables in the Bank characteristics panel are measured at the time of loan origination. $Size$ denotes bank assets in thousands of real USD, $CREloans$ is the ratio of CRE loans to $Size$. $Liquidity$ denotes the sum of cash and available-for-sale securities, REO represents the bank's REO assets divided by $Size$, and $T1ratio$ corresponds to the ratio of Tier 1 capital to risk-weighted assets.

	Small banks ($\leq$ \$5 billion)						Large banks (> \$5 billion)					
Variable	Mean	SD	p.25.	p.50.	p.75.	N	Mean.1	SD.1	p.25..1	p.50..1	p.75..1	N.1
Property and loan characteristics												
.												
$Price_o$	9,724,691	37,455,676	3,000,000	4,500,000	7,517,250	1,714	13,733,809	42,081,075	3,200,000	5,548,334	11,000,000	1,422
$Loanamt_o$	7,615,253	28,407,635	2,292,351	3,600,000	6,000,000	1,714	11,438,262	29,106,506	2,563,576	4,800,000	10,287,500	1,422
LTV_o	0.9201	0.7812	0.7	0.7536	0.9035	1,714	1.026	1.258	0.7046	0.7574	0.9012	1,422
$Price_s$	6,565,182	33,663,928	1,750,000	2,700,000	4,250,000	1,714	10,590,285	59,664,203	1,803,750	3,000,000	6,037,500	1,422
$recov_s$	1.194	2.168	0.4959	0.7089	1.038	1,714	0.9162	1.262	0.445	0.6619	0.9811	1,422
CBD	0.07297	0.2602	0	0	0	1,713	0.07811	0.2684	0	0	0	1,421
Property type												
$Apartment$	0.1505	0.3577	0	0	0	1,714	0.206	0.4046	0	0	0	1,422
$DevSite$	0.09102	0.2877	0	0	0	1,714	0.08861	0.2843	0	0	0	1,422
$Hotel$	0.1418	0.3489	0	0	0	1,714	0.0865	0.2812	0	0	0	1,422
$Industrial$	0.1925	0.3944	0	0	0	1,714	0.1639	0.3703	0	0	0	1,422
$Office$	0.2048	0.4037	0	0	0	1,714	0.2314	0.4219	0	0	0	1,422
$Retail$	0.1844	0.3879	0	0	0	1,714	0.1842	0.3878	0	0	0	1,422
Borrower type												
$Institutional$	0.01932	0.1377	0	0	0	1,708	0.07072	0.2564	0	0	0	1,414
$Private$	0.8653	0.3415	1	1	1	1,708	0.8564	0.3508	1	1	1	1,414
$Public$	0.0404	0.1969	0	0	0	1,708	0.008487	0.09176	0	0	0	1,414
Transaction type												
$Refinance$	0.4405	0.4966	0	0	1	1,714	0.4248	0.4945	0	0	1	1,422
$Sale$	0.5583	0.4967	0	1	1	1,714	0.5647	0.496	0	1	1	1,422
Buyer type												
$Institutional$	0.07231	0.2591	0	0	0	1,701	0.09477	0.293	0	0	0	1,414
$Private$	0.8272	0.3782	1	1	1	1,701	0.7786	0.4153	1	1	1	1,414
$Public$	0.01235	0.1105	0	0	0	1,701	0.01768	0.1318	0	0	0	1,414
Bank characteristics												
.												
$Size$	1,434,048	1,361,412	393,448	865,407	2,110,209	1,714	234,412,171	423,914,544	13,519,529	36,722,563	214,587,975	1,422
$CREloans$	0.4484	0.1899	0.3034	0.449	0.5865	1,714	0.2191	0.1635	0.1105	0.1699	0.2942	1,422
$Liquidity$	0.1619	0.1078	0.08706	0.1531	0.2149	1,714	0.1931	0.109	0.1181	0.1801	0.2407	1,422
REO	0.003968	0.01069	0	0.00008762	0.002895	1,714	0.002084	0.00583	0.0001466	0.0005494	0.001655	1,422
$T1ratio$	0.1455	0.1976	0.09813	0.1089	0.1338	1,706	0.1048	0.04558	0.08136	0.09381	0.1082	1,420

Table C.15: **Acquired banks and government assistance**. The table presents the results of regressions of recovery rates on banks' size, CRE holdings, and additional control variables. The variable *crebank* denotes CRE specialization and equals one if the selling bank pertained to the top quintile of CRE portfolio shares across all US commercial banks in the quarter of loan origination. $Size_r$ refers to the selling bank's ranking in the distribution of bank size during the quarter of origination; it ranges from 0 to 1, with $Size_r = 1$ for the largest bank in a given quarter. The dummy variable *acqlen* equals one if the property was sold by a bank that acquired the loan originator. The variable *govass* indicates whether the acquisiton of the bank that originated the loan involved government assistance. Transaction/borrower controls include the type of buyer, seller, and transaction. Bank controls include liquidity, REO ratio, and Tier 1 capital ratio. Property controls comprise property type dummies and the CBD flag. The dependent variable is winsorized at the 2.5 and 97.5 percentiles. Standard errors are clustered by lender and quarter. ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$)

	Recovery rate			
	(1)	(2)	(3)	(4)
crebank	0.3285*	0.3203*	0.3827**	0.3835**
	(0.1766)	(0.1745)	(0.1808)	(0.1812)
$Size_r$	0.0428	0.0412	0.0861	0.0862
	(0.1289)	(0.1273)	(0.1321)	(0.1319)
$crebank : Size_r$	−0.4646**	−0.4668**	−0.5433***	−0.5434***
	(0.1945)	(0.1922)	(0.1988)	(0.1991)
acqlen	−0.1408*	−0.2066**	0.0906	1.2265
	(0.0744)	(0.1019)	(0.3264)	(0.9310)
crebank:acqlen		0.2637*	−0.7383*	−2.8459*
		(0.1507)	(0.4337)	(1.4348)
Size_r:acqlen			−0.2811	−1.4192
			(0.3822)	(1.0150)
crebank:Size_r:acqlen			1.1157*	3.3398*
			(0.5780)	(1.6972)
govass	0.1557	−0.0088	−0.1017	−1.2655
	(0.1078)	(0.1326)	(0.1408)	(0.9774)
crebank:govass				2.5128
				(1.5635)
Size_r:govass				1.0069
				(1.0945)
crebank:Size_r:govass				−2.4826
				(1.8729)
Transaction/Loan	Yes	Yes	Yes	Yes
Property Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes
Includes Dev. Site	Yes	Yes	Yes	Yes
Standard Errors	Bank+qtr	Bank+qtr	Bank+qtr	Bank+qtr
Num. obs.	3284	3284	3284	3284
Adj. R^2	0.4422	0.4426	0.4270	0.4267