Specialization and Bank Exit: The Case of Minority Depository Institutions*

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Draft date: November 15, 2021

Abstract

I study the effect of market segment specialization on the probability of bank exit while focusing on Minority Depository Institutions (MDIs). I propose market-segment focus measures that capture the geography and socioeconomic status of MDIs' targeted market segment. I estimate the effect of market segment focus on a bank's likelihood of exit through failure or acquisition using a competing risks duration model and bank-level data for 2001–2019. The results suggest that MDIs with a greater focus on market segments with (i) higher shares of low-income communities or (ii) higher housing vacancy rates are less likely to fail. The empirical results are consistent with theoretical predictions that banks particularly vulnerable to economic downturns are better off concentrating their operations in regions of their expertise, given the scale and scope of effort required to manage risk. I also find that MDIs focusing on markets with higher housing vacancy rates are less likely to be acquired, indicating that banks specializing in market segments susceptible to economic shocks are not attractive acquisition targets.

Keywords: Diversification, Focus, Bank risk, Bank failures, Bank acquisitions
JEL Codes: D22, G11, G21, G28, L20, L25

*I am grateful to Paul W. Wilson for helpful comments, suggestions, and guidance throughout this project. I have also received helpful comments from (listed alphabetically) Babur De los Santos, Devon Gorry, Andy Hanssen, Matthew S. Lewis, as well as the participants of Clemson Industrial Organization and Clemson Public Economics workshops. Finally, I acknowledge Ellie Masoomkhah and the Clemson Center for Geospatial Technologies for their help in working with GIS data. Any remaining errors are my own.

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1 Introduction

Policymakers and scholars recognize the beneficial effects of increased access to financial services on the economic outcomes of individuals and firms in the community: it improves the ability of an individual or a firm to cope with economic shocks, borrow for education, purchase a house, and engage in revenue-generating projects. Reducing barriers to credit is particularly important in low- and moderate-income (LMI) communities, where individuals are more likely to benefit from increased access to credit.[1,2] Since early history, many mission-oriented financial institutions have endeavored to enhance the prosperity of the impoverished U.S. neighborhoods by locating in them and directing their services to the credit-constrained poor and minority individuals in those neighborhoods.[3] However, the poor economic condition of these communities makes households and businesses, including banks, residing in them vulnerable to economic shocks. As a result, there is an inherent trade-off between the mission to expand banking services to the poor and the viability of the mission-oriented banks. To examine this trade-off, I study the relationship between specializing in serving market segments susceptible to economic downturns and bank performance in the context of Minority Depository Institutions (MDIs) that specialize in serving businesses and individuals in LMI communities.[4]

[1] Terms "LMI communities" and "LMI neighborhoods" are used interchangeably to refer to low- and moderate-income census tracts in which the tract median family income is less than 50 percent or is between 50 percent and 80 percent of the Metropolitan Statistical Area median income, respectively. These definitions of LMI neighborhoods are consistent with the Community Reinvestment Act (CRA).

[2] For example, Tewari (2014) shows that increased access to credit due to removal of interstate branching restrictions is pronounced for low- and middle-income groups, young, and black households. Burgess and Pande (2005), and Burgess et al. (2005) discover that increased number of bank branches in previously unbanked rural areas of India lead to reduced poverty. Other studies showing benefits of increased access to financial services include Karlan and Zinman (2010), Suri and Jack (2016), and Bachas et al. (2018).

[3] Rosenthal (2018) describes the emergence of the community development finance. Harris (1968) describes the establishment of first banks for and by African Americans as well as their struggles. Jappelli (1990) finds that young, single, and non-white households are likely to be rationed out of the lending market. Stiglitz and Weiss (1981) discuss circumstances and reasons for the occurrence of credit-rationing in lending markets in the equilibrium.

[4] Section 308 of the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989 defines an MDI based on the following criteria: (i) 51 percent of the voting stock (or 51 percent of the privately-owned institution) is owned by socially and economically disadvantaged individuals or (ii) a majority of the board of directors *and* the community that the institution serves are predominantly minority. Given the ambiguity of the phrase "socially and economically disadvantaged individuals", regulators use the

In particular, I investigate the effect of specializing in serving poor communities on a bank's probability of exit through failure or acquisition using a competing risks duration model. The focus of this paper is federally insured commercial banks with an MDI designation. There are several elements essential for the analysis. First, I present market-segment focus measures capturing two key dimensions — geography and demographics — of MDIs' targeted market segments. I calculate banks' branch-level deposit shares in each geographic market and integrate them with important socioeconomic measures in those markets (i.e., share of LMI census tracts, share of vacant houses, and unemployment rate) to determine the extent of banks' exposure to them through their branches. The resulting branch-level information is aggregated to bank-level market-segment focus variables. The advantage of the proposed market segment-focus measures is that they internalize regional socioeconomic conditions central to the analysis. Second, I examine the differential effects of market-segment focus measures on the exit probability for MDIs and non-MDIs by estimating the effects for each group of banks separately. Third, the analysis uses several sources to construct a unique sample of banks that were in existence in 2001. The study period for these banks consists of 76 quarters from first-quarter 2001 through fourth-quarter 2019. Fourth, I construct a measure of management quality using robust, unconditional order-m efficiency estimators developed by Cazals et al. (2002) and Wilson (2011).

Brimmer (1992) and Butler (1991) are among the first scholars to explicitly characterize the trade-off between viability and the community development effort faced by minority-owned banks and firms. Similarly, Elyasiani and Mehdian (1992) and Henderson (1999) emphasize the importance of accounting for regional differences in bank performance studies among minority-owned and non-minority banks due to contrasting socioeconomic conditions among the regions.[5] More recently, Breitenstein et al. (2014), Eberley et al. (2019), and Toussaint-Comeau and Newberger (2017) show that most MDIs locate in markets with a

term "minority" instead. The FIRREA defines "minority" as any "Black American, Asian American, Hispanic American, or Native American." Appendix A outlines relevant MDI-directed policies.

[5] Brimmer (1971) and Harris (1968) suggest that poor management is another important element explaining minority-owned banks' poor performance and express skepticism about their viability.

larger share of economically distressed communities *and* provide a larger share of their credit to individuals and businesses in LMI communities in contrast to their non-MDI counterparts. They argue that the 2008 financial crisis disproportionately devastated MDIs' markets. Breitenstein et al. (2014) further conjecture that MDIs' focus on serving LMI communities may account for a higher failure rate among MDIs relative to non-MDIs. Budding on this literature, I explore the trade-off between MDIs' mission and their performance in the framework of a long-standing debate over benefits of focus (specialization) versus diversification in the financial intermediation, portfolio theory, and corporate finance literature. For example, Diamond (1984) argues that diversification reduces agency problems between the bank and its depositors. Arguments based on Markowitz (1991) contend that banks should be diversified to reduce risk due to uncertainty. Conversely, corporate finance literature views diversification as a value-reducing venture. For example, Rajan et al. (2000) argue that power struggles among divisions within a firm lead to the diversification discount, Denis et al. (1997) provide agency-cost explanation, and Scharfstein and Stein (2000) suggest that branch managers' rent-seeking behavior is a contributing factor. Finally, Winton (1999) suggests that the benefit of diversification depends on the financial institutions' loan downside risk (in terms of exposure to sectoral downturns). Acknowledging that MDIs' focus on poor communities is the mainstay of their mission to serve individuals and businesses in LMI communities, this paper complements existing studies by linking the ideas in the literature together while recognizing a nuanced relationship between diversification and bank performance. The analysis focuses on the market segment dimension of specialization and sets banks apart based on their exposure to economic downturns.

Lending to borrowers in poor communities is particularly information-intensive.[6] Consequently, information asymmetries, as modeled by Stiglitz and Weiss (1981), are likely more prevalent in LMI communities. Specialized knowledge and relationship with borrow-

[6]According to the Report on the Economic Well-Being of U.S. Households in 2018, the majority of unbanked and underbanked individuals had lower income and were in a minority group. Moreover, Barr (2004) argues that underbanked individuals are more likely to lack or have an insufficient credit history. Finally, Nguyen (2019) argues that lending to small businesses is particularly information-intensive.

ers could mitigate information asymmetry and enhance a bank's comparative advantage in serving them, but, as noted by Boot and Thakor (2000), obtaining such expertise requires a costly upfront investment. Hence, given MDIs' mission, increased specialization may improve MDIs' comparative advantage through enhanced monitoring, while excessive market segment diversification may exacerbate MDIs' survival prospects by detracting from monitoring effectiveness or overextending monitoring capacity. The results provide evidence in support of this hypothesis. I show that MDIs whose operations are focused in markets with a higher share of LMI census tracts and markets with higher housing vacancy rates are less likely to fail. The advantage of market segment focus is not detected for non-MDI banks. These findings are consistent with Winton's (1999) theoretical predictions that survival prospects of banks with relatively high downside risk are better when their banking operations are more focused. The results further demonstrate that managerial quality is an important determinant of MDIs' probability of failure. These findings are unsurprising, given the considerable monitoring effort required to manage the loan downside risk due to operating in poor communities.

A bank's focus on a market segment that is vulnerable to economic downturns also has implications for its prospect of being acquired by another bank. Winton (1999) notes that a bank may be reluctant to expand into an unfamiliar sector or new geography in the presence of an experienced incumbent. Hence, expertise, e.g., due to relationship lending and specializing in servicing particular market segments, serves as an entry barrier. Alternatively, Winton argues that an expanding bank may strategically acquire its incumbent to gain expertise and suppress competition. However, the incumbent's high loan downside risk may defeat the desire to obtain expertise through a merger. Hence, MDIs' lending expertise increases their attractiveness as acquisition targets, mainly when there are cost advantages, while their market segment focus on distressed communities decreases their attractiveness as acquisition targets. What happens *de facto* is an open question. MDIs' focus on serving poor communities provides an ideal opportunity to examine this empirical question. My results reveal that despite the enticement to acquire an MDI for its expertise, MDIs' susceptibility to economic downturns offsets the desire. Particularly, the results suggest that MDIs whose operations are focused in markets with higher housing vacancy rates are less likely to be acquired, suggesting that the high downside risk of their loans repels potential acquirers. Furthermore, the analysis does not detect any dependence between the proximity to a failure and the likelihood of an MDIs' acquisition.

This paper is related to an important community development problem of access to financial services in poor neighborhoods. Nguyen (2019) shows that branch closings have long-lasting, persistent adverse effects on credit supply that concentrate in LMI communities and particularly affect small businesses. Importantly, she also finds that the entry of new banks does not alleviate the credit needs of small businesses in LMI communities since information-intensive, relationship lending requires time and cannot be readily replaced. These findings imply that the failure of an MDI or its acquisition by a non-MDI may disrupt the local economy. My findings offer important implications to regulators seeking to preserve specialized, mission-oriented financial institutions and the minority character of MDIs. Serving distressed communities requires specialized expertise in lending and considerable monitoring. I show that MDIs with a relatively higher focus on distressed communities vulnerable to economic shocks fail less often than less focused MDIs, implying that a greater focus reinforces MDIs' monitoring incentives.[7] In addition, my findings reveal that competent management is an important determinant of MDIs' failure, which provides a basis for regulatory effort to prevent MDI insolvency through the provision of technical assistance and educational programs. Finally, the results are cautionary for policies encouraging diversification and intend to highlight complexities associated with diversification. Standard regulations advocating for diversification, e.g., through capital adequacy evaluations and risk assessments, may not be adequate for small, specialized banks such as MDIs. The

[7]Winton also notes that competition exacerbates the downside risk of loans in a given market segment. Therefore, consistent with predictions in Boot and Thakor (2000), the added benefit of MDIs' increased focus on poor communities is enhanced comparative advantage and protection against intense competition.

findings demonstrate that diversification could be both beneficial and undesired, depending on the bank type, highlighting the importance of distinguishing among different banks by their downside risk and area of expertise. These insights are useful for devising effective, targeted, and less-invasive strategies to preserve mission-oriented banks. The information is also instructive to sound, strategic decisions for community development leaders with a vested interest in the viability of their institutions.

The rest of the paper is organized as follows. Section 2 presents the hypotheses investigated in the empirical analyses as well as a summary of key theoretical predictions in Winton's (1999) lending model within the scope and context of this study. I describe the empirical model and estimation strategy in Section 3. Data and variables used in the analyses are described in Section 4. Section 5 presents the results, and Section 6 concludes.

2 Hypotheses and Theory Overview

Diamond (1984) terms a deposit-taking financial intermediary as a delegated monitor because it is delegated the task of contracting with and monitoring the borrowers on behalf of their depositors. Winton (1999) extends Diamond's model by accounting for portfolio downside risk but retains the original agency problem between the bank and its depositors. The agency problem emerges when a bank acquires and holds private information about its loans and monitoring effort. Loan repayments in the model are state-dependent within a market segment such that a larger share of loans is repaid in a good state. Since loan returns are higher in a good state, monitoring is most useful in a bad state.[8] Moreover, monitoring is costly, but it helps detect problem loans before they seriously deteriorate and allows banks to invoke protective covenants in the contract, renegotiate or address deteriorating loans in other ways.[9] An expert bank is more successful in detecting problem loans in its domain

[8]Winton also assumes that the net present value of monitored loans is above zero, monitoring is more appealing to banks *ex ante* than not monitoring, and at least some probability of failure is associated with unmonitored loans.

[9]Rajan and Winton (1995) explore the link between covenants, collateral, and monitoring. They argue

market segment (segment in which a bank has expertise) than an inexpert bank. A bank without expertise detects only a fraction of problem loans, hence its payment from the loans is lower. In the equilibrium, a bank maximizes its expected payoff by choosing the share of loans in each market segment, thereby determining the extent of diversification and its monitoring strategy.

Consider a bank expanding into a new market segment, where its monitoring efficacy is lower than in its domain market segment. In this scenario, a lack of knowledge about the new market segment, an increase in bank size leading to a more complex organizational structure, and an increase in the competition are the possible channels that limit the benefits of diversification. Winton shows that diversification increases the banks' probability of failure if its loan downside risk is high. Intuitively, when a bank's domain market segment is vulnerable to economic downturns, thereby requiring continuous close monitoring, expanding into unfamiliar market segments weakens its monitoring effectiveness and dilutes its surveillance across the segments. As a result, the bank's probability of failure increases. Conversely, Winton shows that diversification of a bank with moderate downside risk in its domain market segment strengthens its monitoring incentives, i.e., it serves as a commitment strategy to monitoring, which also alleviates the agency problem. Therefore, diversification decreases the banks' probability of failure if its loan downside risk is moderate.

To formulate the first hypothesis for MDIs, I exploit the empirical evidence obtained by Breitenstein et al. (2014), Eberley et al. (2019), and Toussaint-Comeau and Newberger (2017) showing that MDIs target and serve individuals in LMI communities.[10] Moreover, Figure 1 depicts the failure rate during 2001–2019 for all banks, MDIs, and non-MDIs included in the sample of this study. It is evident from Figure 1 that the failure rate is more pronounced for MDIs during the economic downturns, suggesting heterogeneous effects of a decline in

that long-term loans with covenants dependent on costly information enhance bank's incentive to monitor.

[10]Breitenstein et al. (2014) and Eberley et al. (2019) note that MDIs are predominantly found in metropolitan areas and serve markets with a greater share of LMI census tracts relative to non-MDIs, including non-MDI community banks. They also show that larger shares of MDI mortgages and small business loans are allocated to individuals and businesses in LMI census tracts. Finally, Breitenstein et al., Eberley et al., and Toussaint-Comeau and Newberger argue that financial crisis disproportionately devastated MDIs' markets.

economic activity on banks' failure rate among MDIs and non-MDIs. The observed trend supports the conjecture that MDIs are more susceptible to economic downturns than non-MDIs and imply that MDIs' loan downside risk is high. At the same time, non-MDIs fail at a moderate rate during economic downturns and are less likely than MDIs to serve individuals in LMI communities, implying that non-MDIs' loans have moderate downside risk. These observations suggest the following hypotheses.

Hypothesis 1: *MDIs more focused on markets with a higher share of distressed communities are less likely to fail relative to less focused MDIs.*

Hypothesis 2: *Non-MDIs more focused on markets with a higher share of distressed communities are more likely to fail relative to less focused non-MDIs.*

The downside risk is also key to a bank's probability of being acquired. Winton notes that competition exacerbates the downside risk of loans in a given market segment and could reduce the benefit of diversification for banks with initially moderate loan downside risk. In general, a bank is less likely to expand into markets with a skilled incumbent bank. As a result, expertise in serving a particular market segment becomes an entry barrier, which can be amplified by an adverse selection problem for an entering inexpert lender. However, diversifying banks may instead acquire an incumbent bank with expertise, especially when obtaining expertise through acquisition is more cost-effective than "learning" and when such diversification strengthens monitoring incentives. Winton explains that expanding banks may find it attractive to acquire banks with moderate downside risk. In contrast, banks with high downside risks are less likely to be attractive despite their expertise. The implication for MDIs is that expertise increases MDIs' comparative advantage in serving LMI neighborhoods and, concurrently, MDIs' attractiveness as acquisition targets. However, MDIs' focus on market segments vulnerable to economic downturns may eclipse their attractiveness as acquisition targets, therefore, banks looking to expand may not find MDIs attractive. The final hypothesis is formulated for MDIs and non-MDIs, given that the downside risk is a critical factor in determining a bank's probability of being acquired.

Hypothesis 3: *A bank relatively more focused on markets with a greater share of distressed communities is less likely to be acquired.*

In general, it is worth noting that MDIs' specialization in serving LMI communities serves as a deterrence strategy against potential entrants and enhances their comparative advantage.[11] The next section shows how hypotheses 1–3 are tested empirically.

3 Empirical Model and Estimation Strategy

To study the effects of market-segment focus on banks' failure or acquisition, I take the competing-risks approach of Wheelock and Wilson (2000) and use a competing-risks duration model. As noted by Wheelock and Wilson, a bank's acquisition by another bank precludes its failure. A competing-risks hazard model is well-suited to identify characteristics leading to each outcome. Another desirable characteristic of the model is that it intrinsically incorporates the time to event occurrence *and* the occurrence of the event itself, therefore making efficient use of the information present in the data relative to other discrete choice models. Following Wheelock and Wilson, I assume that distinct, yet possibly related, processes lead to failure or acquisition of a bank.

I estimate failure and acquisition hazards using a partial-likelihood approach. To describe competing-risks model based on the Cox (1972, 1975) proportional-hazard model, consider the hazard rate of exit at time t for event l

$$\lambda_l(t|\mathbf{x}_{li}(t), \boldsymbol{\beta}_l) = \bar{\lambda}_l(t) \exp [\mathbf{x}'_{li}(t)\boldsymbol{\beta}_l], \tag{1}$$

where $l = 1$ for failed banks and $l = 2$ for acquired banks, $i = 1, \ldots, n$ indexes banks, $\bar{\lambda}_l(t)$ is the baseline hazard, $\mathbf{x}_{li}(t)$ is the vector of time-varying covariates, and $\boldsymbol{\beta}_l$ is the vector

[11] Boot and Thakor (2000) explain that increased interbank competition could motivate a bank to shift its focus toward specialized, relationship lending as a strategy to insulate itself from the competition. Winton (1999) notes that information advantage of the existing bank worsens the quality of loans for an inexpert, expanding bank, thus increasing failure risk and impeding monitoring incentives of the expanding bank.

of parameters to be estimated. In the observed duration data for banks, bank i appears at $(J_i - 1)$ distinct times $t_{i1} < t_{i2} < \ldots < t_{iJ_i-1}$. Moreover, at time $t_{iJ_i} \geq t_{iJ_i-1}$ a bank transitions to its terminal state, i.e., failure or acquisition, or it is censored. I measure time by calendar time such that $t_{i1} = 0 \; \forall \; i$ marks the beginning of the study. Therefore, the sample is constructed as follows. Each time t_{ij} for $j = 1, \ldots, J_i - 1$, has a corresponding vector of time-varying covariates, $\mathbf{x}_{1i}(t)$ or $\mathbf{x}_{2i}(t)$. Then to incorporate the time-varying feature of the covariates into the model, I assume that each vector contains measurable bank characteristics and relevant market-segment focus measures for bank i over the interval $[t_{i,j}, t_{i,j+1})$ such that these measures are constant within each interval but are allowed to vary across the intervals.

For the estimation purposes, let d_{li} be an indicator variable such that $d_{li} = 1$ when bank i transitioned to its terminal state l and $d_{li} = 0$ when it is censored. This specification implies that acquired banks are censored in failure hazard estimation. Similarly, failed banks are censored in acquisition hazard estimation. Next, for a given event $l \in \{1, 2\}$ the partial likelihood function is given by

$$L_l(\boldsymbol{\beta}_l) = \prod_{i=1}^{n} \left[\frac{\lambda_{li}(t_{J_i} | \mathbf{x}_{li}(t_{J_i}), \boldsymbol{\beta}_l)}{\sum\limits_{k \in R_i} \lambda_{lk}(t_{J_k} | \mathbf{x}(t_{J_k}), \boldsymbol{\beta}_l)} \right]^{d_{li}} = \prod_{i=1}^{n} \left[\frac{\exp[\mathbf{x}'_{li}(t_{J_i}) \boldsymbol{\beta}_l)]}{\sum\limits_{k \in R_i} \exp[\mathbf{x}'_{lk}(t_{J_k}) \boldsymbol{\beta}_l)]} \right]^{d_{li}}, \tag{2}$$

where $R_i = \{k | t_{J_k} \geq t_{J_i}, k = 1, \ldots, K\}$ is the set of banks with exit or censoring times occurring after t_{J_i} (i.e., bank i's risk set at time t_{J_i}). Then, taking logarithms of equation (2) to obtain the partial log-likelihood function for event l results in

$$\log L_l(\boldsymbol{\beta}_l) = \sum_{i=1}^{n} d_{li} \left\{ \mathbf{x}'_{li}(t_{J_i}) \boldsymbol{\beta}_l - \log \left[\sum_{k \in R_i} \exp[\mathbf{x}'_{lk}(t_{J_k}) \boldsymbol{\beta}_l] \right] \right\}. \tag{3}$$

At this point, it is worth noting a few details with regards to $\bar{\lambda}_l(t)$. The baseline hazard drops out and does not appear in equation (3). Consequently, estimation does not require additional assumptions about the baseline hazard and as such the model is semiparametric.

In addition, though $\bar{\lambda}_l(t)$ is not specified in the estimation process, it absorbs individual bank heterogeneity for banks exiting at different times t.[12]

It is well-known that competing risks model with dependent risks and competing risks model with independent risks are observationally equivalent.[13] Tsiatis (1975) shows that for any joint survival function $S(t)$ with some specified dependence structure there exists a different joint survival function $S^*(t)$ with independent risks that is observationally equivalent to $S(t)$. Hence the observable data do not provide enough information about the dependence structure nor the joint survival function. These results suggest that while it is possible to model dependent hazards after imposing additional assumptions, one cannot test the dependence hypothesis nor test the hypotheses about the assumed structure of the dependence, as recognized by Wheelock and Wilson (2000) and Elandt-Johnson and Johnson (1980), Kalbfleisch and Prentice (2011), and Mouchart and Rolin (2002). Therefore, due to the lack of information on the precise dependence structure and to avoid the risk of assumption-driven results, I estimate failure and acquisition hazards independently and account for the possibility of dependence by including the equity to assets ratio variable in the acquisition hazard as was done by Wheelock and Wilson. They note that the equity to assets ratio is the key indicator of failure, therefore including it in the acquisition hazard amounts to testing the hypothesis of the likelihood of a bank's acquisition being affected by its proximity to failure.

The elasticity of marginal effect of k^{th} covariate on the hazard rate for event l is

$$\frac{\partial\lambda_{li}(t_{J_i}|\mathbf{x}_{li}(t_{J_i}),\boldsymbol{\beta}_l)/\lambda_{li}(t_{J_i}|\mathbf{x}_{li}(t_{J_i}),\boldsymbol{\beta}_l)}{\partial x_{kli}/x_{kli}} = \beta_{kl}x_{kli}, \tag{4}$$

which does not depend on baseline hazard. Since the model is nonlinear, elasticities depend on individual covariates and vary across observations.

[12]Wheelock and Wilson (2000) mention additional advantages of the partial-likelihood estimation strategy this study undertakes. In particular, the authors note that density and survival functions do not need to be specified, therefore avoiding possible endogeneity problems.

[13]See Cox (1962), Tsiatis (1975), and Rose (1978) for details.

Kropko and Harden (2020a) propose a method for obtaining expected durations and marginal changes in duration given a change in a covariate using the nonparametric step-function approach, which requires estimation of the integrated baseline hazard,

$$\bar{\Lambda}_l(t) = \int_0^t \bar{\lambda}_l(u)du. \tag{5}$$

Tsiatis (1981) and Andersen and Gill (1982) show that the integrated baseline hazard in (5) can be consistently estimated by the Breslow (1972) estimator,

$$\widehat{\bar{\Lambda}}_l(t) = \sum_{t_{J_i} < t_{J_k}}^{n} \frac{d_{lJ_i}}{\sum\limits_{k \in R_i} \exp[\mathbf{x}'_{lk}(t_{J_k})\hat{\boldsymbol{\beta}}_l]}, \tag{6}$$

where d_{lJ_i} is the count of event l at t_{J_i}, R_i is bank i's remaining risk, $\exp[\mathbf{x}'_{lk}(t_{J_k})\hat{\boldsymbol{\beta}}_l]$ is the exponentiated linear predictor from the estimated model for the banks remaining in the risk set. Given the relationship between survival and hazards functions,

$$S_l(t) = \left(\exp[-\bar{\Lambda}_l(t)]\right)^{\exp[\mathbf{x}'_{il}(t)\boldsymbol{\beta}_l]} = \left(\bar{S}_l(t)\right)^{\exp[\mathbf{x}'_{il}(t)\boldsymbol{\beta}_l]}, \tag{7}$$

survival and baseline survival functions are estimated using (6) as follows

$$\widehat{S}_l(t) = \left(\exp[-\widehat{\bar{\Lambda}}_l(t)]\right)^{\exp[\mathbf{x}'_{il}(t)\hat{\boldsymbol{\beta}}_l]} = \left(\widehat{\bar{S}}_l(t)\right)^{\exp[\mathbf{x}'_{il}(t)\hat{\boldsymbol{\beta}}_l]}. \tag{8}$$

Therefore, each bank's survival function can be estimated with

$$\widehat{S}_l(t) = \left(\widehat{\bar{S}}_l(t)\right)^{\exp[\mathbf{x}'_{il}(t)\hat{\boldsymbol{\beta}}_l]}. \tag{9}$$

Using the above proposed estimators, Kropko and Harden (2020a) show that expected durations for each bank can be calculated and marginal changes in duration can be obtained.[14]

[14] To obtain marginal changes in duration, additional steps from an algorithm proposed by Kropko and Harden (2020a) are necessary. These calculations are done using Kropko and Harden's (2020b) "coxed" R

4 Data and Variables

4.1 Data Sources

The data used in this study come from various sources. The Federal Financial Institutions Examination Council's (FFIEC) Census Reports and the U.S. Bureau of Labor Statistics (BLS) data are used to capture the geographically heterogeneous socioeconomic status of markets in the constructed market-segment focus measures. The FFIEC data are used by regulators and reporting banks for the Home Mortgage Disclosure Act (HMDA) and the CRA regulation purposes. These data contain demographic measures at the census tract level and could be aggregated to a higher geographic entity, such as Metropolitan Statistical Area (MSA) or county. Most of the FFIEC data are based on the Census files and the 2011–2015 American Community Survey. The measures also incorporate annual county-level unemployment rates from the BLS to capture changing labor-market conditions.

The Federal Deposit Insurance Corporation (FDIC) branch-level, annual deposit data from the Summary of Deposits (SOD) are used to integrate banks' geographic market information with associated socioeconomic conditions in those markets.[15] The branch location information is used to match each bank's branch location to corresponding socioeconomic measures. This step is accomplished with the help of the ArcGIS geographic information system software and census tract cartographic boundary files from the Census Bureau.[16]

Use of the SOD data presents several challenges and is subject to a few limitations. First, information on the geographic composition of bank assets rather than deposits would be a better fit to study the effects of market segment specialization on banks' performance. However, to my knowledge, publicly available data on U.S. commercial banks do not contain such detailed decomposition of their assets by geography. Fortunately, MDIs are smaller

package.

[15]The SOD data are used by regulators to measure the concentration of local banking markets and define a market as an MSA or non-MSA rural county. This study adopts these market definitions.

[16]Geographic delineations for MSAs, counties, and census tracts change over time. To account for possible boundary changes and to match the county and census tract area delineations in the FFIEC files, branch addresses are geocoded, and geographic identifiers associated with each branch are obtained.

in size, and their operations are limited in geographic scope. Therefore, I expect the calculated deposit shares for MDIs to represent the geographic markets they serve reasonably well. Wheelock (2011, p. 422) notes that researchers generally find that households and small businesses rely on banks located in their communities for financial services. Moreover, Nguyen (2019) contends that credit markets are localized, especially for relationship lending, despite the technological advances. Second, the SOD data contain deposit information for cyber as well as mobile and seasonal offices that do not have a specific, permanent geographic location associated with them. Therefore, when incorporating socioeconomic information for cyber offices, I use nationwide measures with an assumption that anyone in the U.S. can be serviced by a cyber branch. For example, the U.S., rather than the location-specific unemployment rate is used with deposit shares for cyber offices. Similarly, for mobile and seasonal branches without a fixed location, the address of the bank headquarters is used since deposits for these offices are reported with the headquarters' address. Mobile and seasonal offices include branches open for a limited period of time during the week, seasonal branches, or mobile branches on wheels that are sometimes used for advertising purposes. The deposits associated with such offices are relatively small. Finally, some institutions are unable to report actual deposit amounts, e.g., due to the centralized nature of keeping records of their financial transactions. In such cases, banks are allowed to report estimated amounts for each branch, with some limitations.[17] Estimated deposits are reported for about three percent to six percent of branches during 2001–2019. Despite these challenges, the SOD data are currently the best available source providing information about the geography of banks' operations and are widely used by scholars and regulators.

The list of failed banks is obtained from the FDIC, which defines failure dates based on two criteria: (1) the date on which a bank was dissolved or (2) the date on which a bank entered government ownership.[18] The list of acquired banks comes from the FFIEC's

[17]For example, it is noted in the FDIC (2020b, p. 33) instructions: "It is not acceptable to perform estimation procedures that result in exactly the same deposit total for each office."

[18]Wheelock and Wilson (2000) also define banks as failed if its equity ratio falls below two percent. This alternative definition did not change their results.

National Information Center (NIC) database. The list of commercial bank MDIs comes from the FDIC MDI historical data. These annual data are available for the years 2001–2020. The bulk of "bank soundness" measures are gathered from the Consolidated Reports of Condition and Income (call reports) obtained from the FFIEC. Call report data are collected for regulatory purposes and contain audited financial information about banks. Commercial banks are required to submit these reports on a quarterly basis, so the current study is based on these end-of-quarter data collected for the 2001–2019 period. Additional information on bank characteristics comes from the FDIC's Institution Directory Reports.

Although there are 8,177 commercial banks in the first quarter of 2001, missing data and other data problems reduce the sample size to 7,920 (171 MDIs and 7,749 non-MDIs). Occasionally, call report information is not filed for a bank in some quarters, therefore as in Wheelock and Wilson (2000), banks missing from call reports for three consecutive quarters are censored on the day of their first missing call report. Failed and acquired banks with call reports missing for more than three consecutive quarters immediately before the date of failure or acquisition are also censored. This precautionary step is necessary to avoid biased hazard-model estimates, which could result from employing obsolete bank characteristics in the estimation rather than characteristics at the time of failure or acquisition. Wheelock and Wilson note that this approach is conservative in that significance levels for estimated parameters in hazards are reduced.

4.2 Variable Description

The vector of time-varying covariates includes market-segment focus measures and bank characteristics intending to capture bank's financial condition over the time interval $(t_{i,j}, t_{i,j+1}]$. Constructed market-segment focus measures intend to capture both the geography and the socioeconomic status of the markets. I use deposit information to calculate a bank's branch-level deposit share in a given MSA or non-MSA rural county. These shares are used as weights to construct aggregate bank-level market-segment focus variables. The first market-segment focus variable is constructed as

$$LMI_i = \sum_{c=1}^{C} \sum_{b=1}^{B_i} s_{cb} \times lmi_c, \tag{10}$$

where $b = 1, \ldots, B_i$ indexes branches of bank i, $c = 1, \ldots, C$ indexes markets (i.e., MSAs and non-MSA rural counties), s_{cb} is branch b's deposit share in the market c for bank i, lmi_c is the low- and moderate-income census tract share in the market c. LMI measures a bank's focus on LMI communities such that a higher LMI value indicates that a bank's operations are focused in markets with a higher share of LMI census tracts. The second market-segment focus measure is

$$Vacancy_i = \sum_{c=1}^{C} \sum_{b=1}^{B_i} s_{cb} \times v_c, \tag{11}$$

where v_c is the percent vacant housing units in an MSA or non-MSA rural county c, and the third variable is

$$Unemployment_i = \sum_{c=1}^{C} \sum_{b=1}^{B_i} s_{cb} \times u_c, \tag{12}$$

where u_c is the unemployment rate in a given MSA or non-MSA rural county c. $Vacancy$ and $Unemployment$ measure a bank's focus on markets with higher vacancy rates and on markets with higher unemployment rate, respectively, so that higher values indicate a greater focus. Table 1 provides detailed descriptions and formulae for variables used in the analysis.

The construction of LMI and $Unemployment$ variables is motivated by the empirical evidence in Eberley et al. (2019) and Toussaint-Comeau and Newberger (2017), who show that MDIs provide a larger share of their services to individuals and businesses in LMI census tracts relative to non-MDIs, and that census tracts with only MDI bank branches tend to have unemployment rates above national level. I include the $Vacancy$ variable to proxy for declining neighborhoods. The evidence in the literature indicates that the presence of vacant properties lowers the value of neighboring properties and is associated with higher crime rates.[19] Immergluck (2016) suggests that urban decline, depopulation, and foreclosure are

[19]For example, Griswold and Norris (2007), Han (2014), Molloy (2016), Mikelbank (2008), and Whitaker

primary causes of housing vacancies and that spatial concentration of vacant housing poses a particular concern for community development. He also notes that neighborhoods with higher rate of poverty and minority population tend to have persistent levels of long-term housing vacancy. Table 3 presents the correlation matrix among the three focus measures in Panel A and the eigensystem decomposition in Panel B. I follow the method described in Wilson (2018) for eigensystem decomposition. The low correlation suggests that the effects of these measures on the probability of failure or acquisition may be different. Moreover, according to the eigensystem decomposition, the first principal component contains only 45 percent of the independent linear information. The first two principal components contain about 76 percent of the independent linear information. These results suggest that leaving out any of the market-segment focus variables may result in omitted variable bias.

I construct measures characterizing CAMEL rating components in the analysis to control for other contributing factors affecting the probability of failure and acquisition.[20] In their analysis of the characteristics affecting banks' probability of failure or acquisition, Wheelock and Wilson (2000) use variables reflecting the components of CAMEL rating assigned by regulators in the evaluations of individual banks. In addition, to estimate the management quality measure, I use the unconditional order-m efficiency estimator. The estimator provides a measure of technical inefficiency of individual banks, which allows for formal and meaningful comparison of the production processes to relevant peers, as noted by Wheelock and Wilson (2008). Technical details on constructing the management quality variable are provided in Appendix C. The order-m efficiency estimator proposed by Cazals et al. (2002) and further developed by Wilson (2011) is advantageous because it is robust with respect to outliers. Moreover, the values of the unconditional order-m estimates can be computed

and Fitzpatrick IV (2013) are among studies that looked into vacancies and the values of neighboring properties. Branas et al. (2012) and Cui and Walsh (2015) are among studies that looked into vacancies and crime rates.

[20]CAMEL is a supervisory rating system used to evaluate a bank's overall condition. CAMEL is an acronym referring to its components: capital adequacy, asset quality, management, earnings, and liquidity. I construct variables reflecting CAMEL components using bank balance sheet data; all dollar balance sheet measures are converted to 2000 dollars using the Annual Average Consumer Price Index for All Urban Consumers Research Series (CPI-U-RS) available from the BLS or the U.S. Census Bureau.

fast and efficiently due to Daraio et al. (2020). Finally, the analysis includes additional bank characteristic measures describing the bank's size, age, loan loss provisions, as well as a community bank and MDI indicators.

Table 2 presents summary statistics of variables in the analysis for MDIs, non-MDIs, and all banks. The samples include banks that existed in the first quarter of 2001 with complete information. The summary statistics reveal that MDIs are generally younger and serve markets with a higher share of LMI census tracts relative to non-MDI banks. Moreover, on average, MDIs' markets tend to have a higher unemployment rate. These are generally in accordance with trends described by Toussaint-Comeau and Newberger (2017), Breitenstein et al. (2014) and Eberley et al. (2019). However, on average, non-MDIs' markets have a higher share of vacancy rates.

About 4 percent (337 of 7,920) of banks in the sample failed during 2001–2019, but the numbers by MDI status are much different. Specifically, 14.6 percent (25 of 171) of MDIs versus 4 percent (312 of 7,749) of non-MDIs failed during 2001–2019.[21] The higher failure rate for MDIs suggests that they are more vulnerable to economic downturns. At the same time, around 46 percent (3,627 of 7,920) of banks were acquired during 2001–2019. However, the acquisition rates for MDIs and non-MDIs look different. Only 30 percent (50 of 171) of MDIs were acquired during 2001–2019 versus 46 percent (3,577 of 7,749) of non-MDIs.[22] The lower acquisition rate for MDIs suggests they are not attractive acquisition targets.

Figure 2 explores the differences within MDIs by the LMI market-segment focus measure through differences in the mean nonperforming loans to total assets ratio trends during 2001–2019. The figure reveals interesting trends showing that MDIs with greater focus ($LMI > 0.5$) have lower nonperforming loans to total assets ratios. Higher values of nonperforming loans as a share of total assets signal problem loans. Mean nonperforming loans to total assets ratio remained relatively steady for MDIs with $LMI > 0.5$ during the 2008 financial

[21]Hypothesis test comparing MDI and non-MDI failure rates (i.e., comparison of the two binomial proportions) suggests that these rates are significantly different with a p-value of 4.189×10^{-11}.

[22]Hypothesis test comparing MDI and non-MDI acquisition rates suggests that acquisition rates for the two groups are significantly different with a p-value of 1.593×10^{-5}.

crisis. These trends suggest that less focused MDIs experienced more extensive deterioration of their loan portfolios during the economic downturn. Nonetheless, these trends represent simple correlations, therefore further analysis is necessary.

5 Results

5.1 Failure Hazard Results

I estimate the model separately for MDIs, non-MDIs, and the pooled sample. Table 4 presents the failure hazard results. A positive (negative) coefficient suggests that an increase in the corresponding variable increases (decreases) the failure or acquisition hazard. All continuous variables are rescaled before estimation to have a standard deviation of one.

The estimation results in Table 4 indicate that MDIs whose operations are focused in markets with a higher share of LMI census tracts (LMI) and in markets with higher housing vacancy rates ($Vacancy$) are less likely to fail. This suggests that as an MDI becomes increasingly focused on markets with a higher share of LMI census tracts and on markets with higher housing vacancy rates, the hazard of its failure declines, and the time until failure increases. Table 6 presents mean elasticities of marginal effects on the failure and acquisition hazard rates for MDIs.[23] I estimate that a one percent increase in LMI and $Vacancy$ decreases failure hazard by eight and by four percent, respectively. Moreover, according to estimated marginal changes in duration until failure for MDIs in of Table 7, an increase in LMI from first to third quartile on average delays failure by about 35 days. Similarly, an increase in $Vacancy$ from first to third quartile on average delays failure by about 107 days. A possible implication of these findings is that serving geographic regions susceptible to shocks requires greater monitoring effort to avoid exacerbating an already high probability of failure. Hence, the results suggest that banks specializing in serving

[23]The mean elasticity of a given variable is obtained by first computing an elasticity for each observation and then averaging them.

economically distressed communities are better off focusing on those market segments rather than diversifying, since focusing reduces the risk of detracting from their monitoring efficacy.

Interestingly, comparing the above results to non-MDIs' reveals that there is no advantage of market segment focus for non-MDIs. Based on the failure hazard results in the non-MDI column of Table 4, operating in markets with greater vacancy rates is associated with an acceleration of time to failure suggesting that $Vacancy$ measure of market segment focus increases the likelihood of failure for non-MDIs. Moreover, a positive sign on $Vacancy$ for the pooled sample suggests that banks whose operations are focused on markets with higher housing vacancy rates are more likely to fail. The result is likely driven by a large number of non-MDI banks in the sample, emphasizing the importance of differentiating banks according to their regional expertise and vulnerability to economic downturns. Overall, these findings are consistent with theoretical predictions discussed earlier and with findings by Acharya et al. (2006) and Berger and DeYoung (2001). Acharya et al. find that greater diversification benefits banks with moderate loan downside, but not banks with a high downside. Berger and DeYoung find a positive and negative relationship between geographic diversification and bank efficiency, although the authors do not differentiate banks by their loan downside risk.

The signs of parameter estimates in Table 4 for variables reflecting the components of CAMEL are similar for MDIs, non-MDIs, and all banks. Negative coefficients for capital adequacy (CA) indicate that banks with higher equity as a percentage of total assets are less likely to fail. The result is consistent with expectations since well-capitalized banks can better withstand adverse shocks and are more likely to survive. Results reveal that higher values of total loans to total assets ratio (AQ_{LTA}) for non-MDIs as well as higher values of commercial and industrial loans ($AQ_{C\&IL}$), other real estate owned (AQ_{OREO}), and nonperforming loans (AQ_{NPL}) as shares of total assets are more likely to fail. However, the result for $AQ_{C\&IL}$ dissipates when the pooled sample is split into MDIs and non-MDIs. Wheelock and Wilson (2000) explain that other real estate owned indicates foreclosed property, hence signal problem loans. Since nonperforming loans (AQ_{NPL}) also indicate poor loan quality, the result is not surprising.

A positive coefficient estimate for managerial quality measure (M) for MDIs in Table 4 indicates that less technically efficient MDIs are more likely to fail. However, no statistically significant effects of this measure in the non-MDI and the pooled samples are detected. A possible implication is that lending to individuals and businesses in LMI communities requires qualified staff and expertise to effectively monitor and screen creditworthy borrowers. This interpretation is consistent with conjectures that lending in markets with larger shares of LMI communities is more information-intensive. Therefore, managerial quality is important for managing portfolio risk for MDIs. I estimate that a one percent increase in M, indicating deterioration of managerial quality, increases failure hazard by five percent as reported in Table 6. Moreover, according to estimates in Table 7, an increase in M from first to third quartile on average accelerates time to failure by 73 days.

Consistent with previous literature, liquid banks (LIQ), older banks (AGE), and banks with higher values of loan loss provisions as a share of total assets (LLP) are less likely to fail. The MDI sample coefficient estimates for AGE and LLP are insignificant. Banks use loan loss provisions to reserve funds for problem loans. Therefore, the results imply that banks with more provisions to cover loan losses perform better during turbulent times. A positive coefficient for $SIZE$ in Table 4 for non-MDIs suggests that bigger non-MDIs are more likely to fail. The non-MDI sample includes three large banks that maintained their operations with government assistance and are treated as failed on the date when they received government assistance. I investigate the role of the government bailouts in the Appendix B. The findings reveal that censoring or excluding bailed out banks results in insignificant effects of the bank size. Finally, a positive coefficient for community bank indicator (CB) for the MDI sample indicates that community bank MDIs are at greater risk of failure. This result could be driven by unobserved differences between these two groups of MDIs, e.g., community bank MDIs could be targeting and serving the population with distinct characteristics relative to MDIs that are not community banks.

5.2 Acquisition Hazard Results

Table 5 reports acquisition hazard results. The results reveal that banks in markets with higher vacancy rates are less likely to be acquired. According to Table 7, an increase in $Vacancy$ from first to third quartile on average delays an MDI's acquisition by 304 days. Consistent with theoretical predictions, the result suggests that expanding banks may strategically consider their post-merger monitoring incentives and failure probability. Hence market segment focused target banks with high loan downside risks are not attractive. Although expanding banks may find acquiring an MDI strategically attractive to subdue competition and to obtain local expertise through acquisition, such temptation appears to be offset by the MDIs' susceptibility to economic downturns. This interpretation is consistent with Winton's (1999) conjectures that specialized banks with higher loan downside are less attractive acquisition targets.

Similarly, consistent with theoretical predictions in Winton (1999), acquisition hazard parameter estimates for $Unemployment$ for non-MDI and the pooled samples suggest that banks operating in markets with higher unemployment rates are less likely to be acquired. Interestingly, parameter estimates for LMI reveal that non-MDIs whose primary service areas are in markets with higher shares of LMI communities are more likely to be acquired. A similar result is found for the pooled sample, but no significant effects are detected for MDIs. This effect may be driven by regulatory action. Regulators use their authority over merger application approvals as a mechanism to enforce CRA regulations. Mergers that could potentially result in diminished bank services in LMI communities or merger requests by banks with poor CRA ratings are subject to closer scrutiny, and, in extreme cases, such requests could be denied.

Although the parameter estimates for capital adequacy (CA) for MDIs, non-MDIs, and the pooled sample in Table 5 are not significant, the inclusion of a bank's equity to asset ratio serves as a dependence test between the failure and acquisition hazards. As mentioned earlier, Wheelock and Wilson (2000) note that CA is a principal signal of a looming failure, hence including this variable in the acquisition hazard amounts to testing the hypothesis of the proximity to a failure affecting the likelihood of a bank's acquisition. Therefore, the parameter estimates for CA do not reveal any apparent dependence between failure and acquisition hazards in these samples. The results further indicate that lower values of total loans to total assets ratio (AQ_{LTA}), other real estate owned as a share of total assets (AQ_{OREO}) or higher values of real estate loans as a share of total loans (AQ_{REL}), commercial and industrial loans as a share of total loans ($AQ_{C\&IL}$), nonperforming loans as a share of total loans (AQ_{NPL}) are attractive acquisition targets. However, parameter estimate for AQ_{REL} is the only statistically significant effect in the MDI sample.

Managerial quality measure (M) parameter estimates in the acquisition hazard suggest that poorly managed banks are less likely to be acquired, though the result is statistically insignificant for the MDI sample. As noted by Wheelock and Wilson (2000), poor management may be a signal of more complicated underlying issues with the bank, thus making it risky to acquire. Consistent with previous literature, banks with higher earnings ($EARN$), liquid banks (LIQ), bigger ($SIZE$) and older (AGE) banks are less likely to be acquired. Furthermore, the results indicate that banks with higher values of loan loss provisions as a share of total assets (LLP) are less likely be acquired.

A negative coefficient for an MDI indicator variable in Table 7 indicates that banks with an MDI designation are less likely to be acquired. There are several possible explanations for this result. One implication is that banks may implicitly use an MDI status of a bank as an indicator of their portfolio downside risk. Therefore, an acquiring bank may strategically avoid merging with an MDI if it believes that an MDI's loans have a high downside. Alternatively, the result could be driven by regulatory action. Policies aiming to preserve MDIs' minority nature regulate the types of institutions that could acquire an MDI, with preference given to minority-owned institutions. Finally, a negative parameter estimate for community bank indicator (CB) suggests that community banks are less likely to be attractive acquisition targets.

6 Conclusion

This paper analyzes the relationship between market segment focus and bank exit through failure or acquisition, particularly for MDIs. The investigations discover that market segment focus on markets with higher shares of LMI communities and with higher vacancy rates could delay failure and acquisition of MDIs. The evidence suggests that market segment specialization improves the survival prospects of specialized banks with high downside risk, such as MDIs. These findings are consistent with theoretical predictions derived by Winton (1999) and emphasize the importance of differentiating banks according to their loan downside risk. The results provide useful insights about mission-oriented, specialized banks' decision to focus or to diversify and contribute to the large body of literature in bank performance, corporate finance, and community development. The empirical investigations reveal that banks' decision to diversify is a complex affair and the relationship between market segment focus and bank performance is not as simple as implied by some theoretical models.

MDIs locate and provide banking services in communities with high vulnerability to economic downturns. Unlike their peers, MDIs tend to direct more of their lending activities toward information-intensive loans that require costly and time-consuming investments in relationship with their local communities. Monitoring efforts required to effectively and safely serve LMI communities are sizeable. The findings of this study imply that operating in such geographies requires dedicated, vigilant monitoring. Moreover, expanding operations for banks committed to serve LMI communities is associated with diseconomies of scope.

The results provide important implications for the optimal geographic scope of specialized banks and strategies that could be implemented to improve their performance. Although the traditional views of banks as monitors suggests that banks are made better off by diversifying as in Diamond (1984), the results in this paper suggest that diversification into new market segments could lead to deterioration of assets and increase chances of failure for mission-oriented, specialized banks, such as MDIs when their downside risk is high. This result does not hold for traditional, non-specialized banks. Concurrently, locating in distressed communities negatively affects a bank's merger prospects due to the challenges associated with operating in such communities. The cautionary message of these findings is that evaluating portfolio risk based on diversification measures alone could be misleading, and incentives to monitor should be considered.

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Tables and Figures

Table 1: Variable Description

Outcome Variables	
$Time$	$Time$ is the time to failure or acquisition. The time to event is measured in calendar-day intervals. Time-dependent variables are relevant from the start of the interval, while failure or acquisition occur at the end of the interval.
$Failure$	$Failure$ is 1 if bank failed over the time interval and 0 otherwise. It describes if an interval in the failure hazard ends in an event.
$Acquisition$	$Acquisition$ is 1 if bank is acquired over the time interval and 0 otherwise. It describes if an interval in the acquisition hazard ends in an event.
Market-Segment Focus Measures	
LMI	$LMI_i = \sum_{c=1}^{C}\sum_{b=1}^{B_i} s_{cb} \times (li_c + moi_c)$, where s_{cb} is branch b's deposit share in the MSA or non-MSA rural county c for bank i, li_c is the low-income area share and moi_c is the moderate-income area share in the MSA or non-MSA rural county c. Areas are identified as low- or moderate-income at the tract level. If tract median family income is >0 percent and <50 percent of the MSA median family income, then it is a low-income tract. If tract median family income is ≥50 percent and <80 percent of the MSA median family income then it is identified as a moderate-income tract. Note that $lmi_c = li_c + moi_c$.
$Vacancy$	$Vacancy_i = \sum_{c=1}^{C}\sum_{b=1}^{B_i} s_{cb} \times v_c$, where s_{cb} is branch b's deposit share in the MSA or non-MSA rural county c for bank i and v_c is the percent vacant housing units in an MSA or non-MSA rural county c.
$Unemployment$	$Unemployment_i = \sum_{c=1}^{C}\sum_{b=1}^{B_i} s_{cb} \times u_c$, where s_{cb} is branch b's deposit share in the MSA or non-MSA rural county c for bank i and u_c is the unemployment rate in a given MSA or non-MSA rural county c.
CAMEL Proxy Variables	
CA	Capital adequacy: CA = Total equity/Total assets.
AQ_{LTA}	Asset Quality: AQ_{LTA} = Total loans/Total assets.
AQ_{REL}	Asset Quality: AQ_{REL} = Real estate loans/Total loans.
$AQ_{C\&IL}$	Asset Quality: $AQ_{C\&IL}$ = Commercial and industrial loans/Total loans.
AQ_{OREO}	Asset Quality: AQ_{OREO} = Other real estate owned/Total assets.
AQ_{NPL}	Asset Quality: AQ_{NPL} = Nonperforming loans/Total assets.
M	Managerial quality measure estimated using unconditional (hyperbolic) order-m technical efficiency estimator. Large values of M are associated with less efficient institutions.
$EARN$	Earnings: $EARN$ = Net income after taxes/Total assets.
LIQ	Liquidity: LIQ = (Federal funds purchased and securities sold − Federal funds sold and securities purchased)/Total assets.

Continued on next page

Table 1: Variable Description (*Continued*)

	Other Variables
$SIZE$	Natural logarithm of Total Assets.
AGE	Natural logarithm of bank's age in years.
LLP	LLP = Loan loss provisions/Total assets. Note: Loan loss provisions measures changes in allowance for loan and lease losses (ALLL). Negative LLP indicates deduction from (a decrease in) ALLL, while positive LLP indicates addition to (an increase in) ALLL. Positive values in LLP signal that banks are expecting quality deterioration of their lending portfolio.
MDI	Binary variable identifying Minority Depository Institutions (MDI). MDI is 1 if bank is an MDI.
CB	An indicator identifying community banks. Community banks are identified by the FDIC based on the criteria defined in the community banking study. The focus of the study and the definition is based on banks' "traditional relationship banking" and their limited geographic scope of operations.
	End of table

Table 2: Summary Statistics by Bank Type

		Mean	**Median**	**StdDev**	**Min**	**Max**
		Market-Segment Focus Measures				
LMI	non-MDI	0.2026	0.2141	0.1636	0.0000	1.0000
	MDI	0.3551	0.3632	0.1292	0.0000	1.0000
	all	0.2062	0.2185	0.1645	0.0000	1.0000
$Vacancy$	non-MDI	0.1202	0.1014	0.0705	0.0232	0.8163
	MDI	0.0956	0.0866	0.0530	0.0252	0.3642
	all	0.1196	0.1008	0.0702	0.0232	0.8163
$Unemployment$	non-MDI	0.0574	0.0527	0.0223	0.0038	0.2630
	MDI	0.0640	0.0581	0.0238	0.0210	0.2450
	all	0.0575	0.0529	0.0224	0.0038	0.2630
		CAMEL Proxy Variables				
CA	non-MDI	0.1079	0.1005	0.0366	−0.1351	0.9746
	MDI	0.1076	0.0991	0.0403	−0.0325	0.5447
	all	0.1079	0.1005	0.0367	−0.1351	0.9746
AQ_{LTA}	non-MDI	0.6260	0.6471	0.1568	0.0001	0.9897
	MDI	0.6534	0.6768	0.1482	0.0617	0.9838
	all	0.6266	0.6478	0.1567	0.0001	0.9897
AQ_{REL}	non-MDI	0.6611	0.6927	0.1841	0.0000	1.0000
	MDI	0.7693	0.7960	0.1653	0.0108	1.0000
	all	0.6636	0.6953	0.1845	0.0000	1.0000
$AQ_{C\&IL}$	non-MDI	0.1493	0.1283	0.1002	0.0000	1.0000
	MDI	0.1576	0.1296	0.1306	0.0000	0.9968
	all	0.1495	0.1283	0.1011	0.0000	1.0000
AQ_{OREO}	non-MDI	0.0036	0.0005	0.0094	0.0000	0.2872
	MDI	0.0061	0.0009	0.0149	0.0000	0.1958
	all	0.0036	0.0005	0.0095	0.0000	0.2872
AQ_{NPL}	non-MDI	0.0207	0.0141	0.0240	0.0000	0.5630
	MDI	0.0346	0.0200	0.0444	0.0000	0.6772
	all	0.0211	0.0142	0.0248	0.0000	0.6772
M	non-MDI	1.5954	1.5526	0.5141	0.2358	66.5730
	MDI	1.6004	1.5502	0.4915	0.6542	5.3533
	all	1.5955	1.5525	0.5136	0.2358	66.5730
$EARN$	non-MDI	0.0023	0.0025	0.0038	−0.3385	0.3331
	MDI	0.0011	0.0018	0.0059	−0.1270	0.0750
	all	0.0022	0.0025	0.0039	−0.3385	0.3331
LIQ	non-MDI	−0.0167	−0.0024	0.0605	−0.9748	0.7816
	MDI	−0.0334	−0.0121	0.0648	−0.8937	0.2743
	all	−0.0171	−0.0026	0.0606	−0.9748	0.7816
		Other Variables				
$SIZE$	non-MDI	11.7311	11.5849	1.3187	7.2740	21.1862
	MDI	11.9696	11.7619	1.3674	8.5310	17.2050
	all	11.7367	11.5883	1.3204	7.2740	21.1862
AGE ($Years$)	non-MDI	77.5951	88.4932	39.7476	0.0247	227.9973
	MDI	37.3119	27.9041	29.9955	0.0986	127.9973
	all	76.6487	87.3863	40.0140	0.0247	227.9973
LLP	non-MDI	0.0007	0.0002	0.0022	−0.2120	0.2004
	MDI	0.0010	0.0003	0.0031	−0.0352	0.0609
	all	0.0007	0.0002	0.0022	−0.2120	0.2004

Table 3: Market-Segment Focus Measures

Panel A: Correlation Matrix

	LMI	$Vacancy$	$Unemployment$
LMI	1.0000	0.1905***	0.2301***
$Vacancy$	0.1905***	1.0000	0.0705***
$Unemployment$	0.2301***	0.0705***	1.000

Panel B: Eigensystem Decomposition

Number of the First Largest Eigenvalues in the Numerator	**Value of the Ratio**
1	$R_1 = 0.4452$
2	$R_2 = 0.7555$
3	$R_3 = 1$

One, two, or three asterisks indicate significance at 0.1, at 0.05, or at 0.01, respectively.

The eigensystem decomposition method uses the moment matrices of market-segment focus measures as explained in Wilson (2018). R_1 represents the ratio of the first largest eigenvalue to the sum of all eigenvalues, R_2 represents the ratio of the sum of the first two largest eigenvalues to the sum of all eigenvalues, and R_3 represents the ratio of the sum of the first three largest eigenvalues to the sum of all eigenvalues. Note, $R_3 = 1$ because there are only three variables and, as a result, three eigenvalues in the numerator and the denominator.

Table 4: Failure Hazard

	MDI	**non-MDI**	**All**
LMI	$\mathbf{-3.7878}^{**}$	0.1070	0.1049
	(1.7623)	(0.0918)	(0.0897)
$Vacancy$	$\mathbf{-3.1808}^{**}$	$\mathbf{0.1351}^{**}$	$\mathbf{0.1222}^{*}$
	(1.3974)	(0.0659)	(0.0659)
$Unemployment$	0.3218	0.0402	0.0384
	(0.6241)	(0.0764)	(0.0753)
CA	$\mathbf{-6.8142}^{***}$	$\mathbf{-1.8466}^{***}$	$\mathbf{-1.9122}^{***}$
	(2.0382)	(0.0768)	(0.0758)
AQ_{LTA}	-0.3372	$\mathbf{0.1660}^{*}$	0.1209
	(0.8601)	(0.0959)	(0.0917)
AQ_{REL}	-0.9423	0.0043	0.0148
	(1.4884)	(0.1263)	(0.1233)
$AQ_{C\&IL}$	1.0948	0.1585	$\mathbf{0.1641}^{*}$
	(0.9892)	(0.0972)	(0.0944)
AQ_{OREO}	$\mathbf{0.3280}^{**}$	$\mathbf{0.1064}^{***}$	$\mathbf{0.0988}^{***}$
	(0.1527)	(0.0132)	(0.0130)
AQ_{NPL}	$\mathbf{0.5466}^{**}$	$\mathbf{0.2223}^{***}$	$\mathbf{0.2049}^{***}$
	(0.2194)	(0.0178)	(0.0160)
M	$\mathbf{1.6981}^{*}$	0.0167	0.0205
	(1.0182)	(0.0419)	(0.0322)
$EARN$	0.2672	0.0289	0.0279
	(0.1740)	(0.0212)	(0.0206)
LIQ	$\mathbf{-1.5539}^{*}$	$\mathbf{-0.2700}^{***}$	$\mathbf{-0.2890}^{***}$
	(0.8062)	(0.0702)	(0.0670)
$SIZE$	1.7458	$\mathbf{0.1389}^{*}$	0.1109
	(1.1368)	(0.0775)	(0.0771)
AGE	0.9138	$\mathbf{-0.2692}^{***}$	$\mathbf{-0.3103}^{***}$
	(0.9094)	(0.0619)	(0.0608)
LLP	0.2580	$\mathbf{-0.0524}^{***}$	$\mathbf{-0.0512}^{***}$
	(0.1736)	(0.0178)	(0.0173)
MDI			-0.3664
			(0.2958)
CB	$\mathbf{10.2431}^{**}$	-0.2055	-0.0749
	(5.0881)	(0.2019)	(0.2024)
LLF	-15.36	$-1,594.68$	$-1,715.02$
# banks	171	7,749	7,920
# failed	25	312	337

One, two, or three asterisks indicate significance at 0.1, at 0.05, or at 0.01, respectively. Standard errors are in parentheses.

The MDI sample includes banks identified as an MDI at any point during 2001–2019, hence hazard estimation for MDI sample also controls for timing of MDI status designations.

Table 5: Acquisition Hazard

	MDI	non-MDI	All
LMI	0.1420	**0.0392****	**0.0387****
	(0.3048)	(0.0196)	(0.0195)
$Vacancy$	**−0.5966***	**−0.0377****	**−0.0406****
	(0.3531)	(0.0183)	(0.0183)
$Unemployment$	−0.1282	**−0.1107*****	**−0.1102*****
	(0.2730)	(0.0258)	(0.0257)
CA	−0.0272	0.0207	0.0209
	(0.1158)	(0.0137)	(0.0136)
AQ_{LTA}	−0.1053	**−0.1018*****	**−0.1016*****
	(0.1889)	(0.0201)	(0.0200)
AQ_{REL}	**0.7952****	**0.2938*****	**0.2970*****
	(0.3544)	(0.0248)	(0.0247)
$AQ_{C\&IL}$	0.1882	**0.0800*****	**0.0787*****
	(0.1760)	(0.0205)	(0.0203)
AQ_{OREO}	0.0659	**−0.0526****	**−0.0468****
	(0.0812)	(0.0206)	(0.0200)
AQ_{NPL}	−0.1625	**0.0787*****	**0.0750*****
	(0.1222)	(0.0175)	(0.0171)
M	−0.1095	**−0.1172*****	**−0.1196*****
	(0.1842)	(0.0210)	(0.0207)
$EARN$	**−0.1878***	**−0.0706*****	**−0.0703*****
	(0.1123)	(0.0043)	(0.0043)
LIQ	−0.0257	**−0.1686*****	**−0.1673*****
	(0.1475)	(0.0129)	(0.0129)
$SIZE$	**−0.4903****	**−0.2397*****	**−0.2419*****
	(0.2069)	(0.0202)	(0.0201)
AGE	−0.1339	**−0.1665*****	**−0.1693*****
	(0.1933)	(0.0168)	(0.0168)
LLP	**−0.3534*****	**−0.0264*****	**−0.0314****
	(0.0968)	(0.0123)	(0.0128)
MDI			**−1.6298*****
			(0.2150)
CB	**−1.4496*****	**−1.6130*****	**−1.6082*****
	(0.4892)	(0.0501)	(0.0497)
LLF	−201.36	−30,005.07	−30,487.93
# banks	171	7,749	7,920
# acquired	50	3,577	3,627

One, two, or three asterisks indicate significance at 0.1, at 0.05, or at 0.01, respectively. Standard errors are in parentheses.

The MDI sample includes banks identified as an MDI at any point during 2001–2019, hence hazard estimation for MDI sample also controls for timing of MDI status designations.

Table 6: Mean Elasticity of Marginal Effect on the Hazard Rate (MDIs)

	Failure	**Acquisition**
LMI	-8.1730	0.3063
$Vacancy$	-4.3280	-0.8117
$Unemployment$	0.9194	-0.3664
CA	-20.0040	-0.0799
AQ_{LTA}	-1.4062	-0.4392
AQ_{REL}	-3.9302	3.3166
$AQ_{C\&IL}$	1.7072	0.2935
AQ_{OREO}	0.2088	0.0420
AQ_{NPL}	0.7628	-0.2268
M	5.2920	-0.3413
$EARN$	0.0755	-0.0530
LIQ	0.8557	0.0141
$SIZE$	15.8300	-4.4440
AGE	3.5850	-0.5252
LLP	0.1156	-0.1584
CB	9.1190	-1.2910

Table 7: Marginal Changes in Duration for Selected Variables for MDIs (Mean Difference of First and Third Quartiles)

	Mean Difference	**Interpretation**
		Failure
LMI	34.902	An increase in LMI from first to third quartile on average *delays failure* by 35 days.
$Vacancy$	107.068	An increase in $Vacancy$ from first to third quartile on average *delays failure* by 107 days.
CA	89.461	An increase in CA from first to third quartile on average *delays failure* by 90 days.
AQ_{OREO}	-6.53	An increase in AQ_{OREO} from first to third quartile on average *accelerates time to failure* by 6.5 days.
AQ_{NPL}	-23.07	An increase in AQ_{NPL} from first to third quartile on average *accelerates time to failure* by 23 days.
M	-73.397	An increase in M from first to third quartile on average *accelerates time to failure* by 73 days.
LIQ	42.78	An increase in LIQ from first to third quartile on average *delays failure* by 43 days.
CB	-114.708	A discrete change in CB status from 0 to 1 (i.e., becoming a community bank) on average *accelerates time to failure* by 115 days.
		Acquisition
$Vacancy$	304.131	An increase in $Vacancy$ from first to third quartile on average *delays acquisition* by 304 days.
AQ_{REL}	-559.713	An increase in AQ_{REL} from first to third quartile on average *accelerates time acquisition* by 560 days.
$EARN$	79.703	An increase in $EARN$ from first to third quartile on average *delays acquisition* by 80 days.
$SIZE$	388.889	An increase in $Vacancy$ from first to third quartile on average *delays acquisition* by 389 days.
LLP	83.541	An increase in LLP from first to third quartile on average *delays acquisition* by 84 days.
CB	$1,164.973$	A discrete change in CB status from 0 to 1 (i.e., becoming an commercial bank) on average *delays acquisition* by 1,165 days.

Figure 1: Failure rate for all banks, non-MDIs, and MDIs during 2001–2019. The count of failed banks also includes assisted mergers.

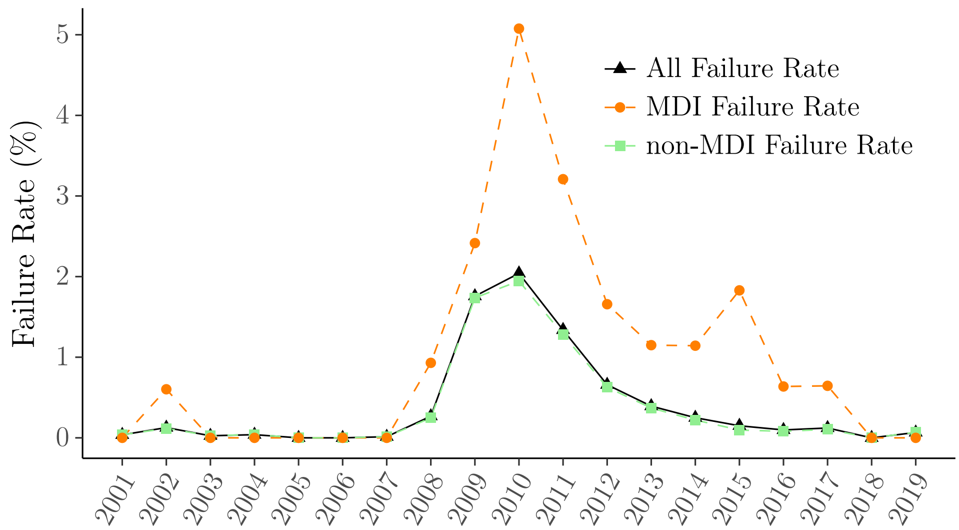

Figure 2: Mean nonperforming loans to total assets ratio trends during 2001–2019 for MDIs by LMI market-segment focus variable. The graph indicates that on average MDIs with $LMI > 0.5$ have less nonperforming loans as share of their total assets.