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ESSAYS ON BANK PERFORMANCE, STRATEGIC BEHAVIOR, AND
COMMUNITY DEVELOPMENT WITH A FOCUS ON MINORITY
DEPOSITORY INSTITUTIONS AND THE POLITICAL ECONOMY OF
FORGIVING STUDENT LOANS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Economics

by
Guncha Babajanova
May 2022

Accepted by:
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Abstract

My dissertation explores questions related to financial institutions, the accessibility of financial services, community development, and the political economy of forgiving student loans using the ideas from spatial economics, industrial organization, and public choice. Increased access to financial services improves the economic outcomes of individuals and firms in the community. Understanding sources leading to a lower accessibility of financial services is integral for an effective endeavor to lower barriers to financial services with far-reaching policy and economic implications. The economic literature provides evidence of the beneficial effects of increased access to financial services as well as the adverse effects of diminished access to credit and banking services, for example, due to local bank branch closure. These effects are particularly pronounced for low-income individuals, minorities, and small businesses. The research also shows that, despite the technological advances, credit and depository service markets are local. Hence considering the geographic aspects of these services is essential. My research explores the role of geography in bank exit and entry, which directly affects the spatial accessibility of financial services in a given community.

At the same time, a rapid increase in student-loan debt has drawn much attention and has been a social and political topic of interest. The sharp increase of defaults on student loans accompanied by growing student loan debt during the Great Recession led some political leaders to propose forgiving student loans and making some public higher education tuition-free. The particular importance of the student loan problem is tightly linked to the idea that schooling is beneficial for the schooled since it increases future earnings and lowers search costs in the labor market. Schooling also benefits society since as the proportion of schooled individuals grows, so does the aggregate taxable income in the economy, which results in enhanced unemployment insurance. However, the student-loan debt forgiveness proposals are not supported by all participants in the economy. To understand the political economy of such proposals, I explore the circumstances that motivate the

implementation of the student-loan debt forgiveness policy in a two-period model of schooling and unemployment insurance with search costs.

In the first chapter of my dissertation, I investigate the effects of specializing in serving market segments susceptible to economic downturns on a bank's likelihood of failure and acquisition with an emphasis on Minority Depository Institutions (MDIs). I propose market-segment focus measures that capture the geography and socioeconomic status of MDIs' targeted market segment and construct other measures to capture banks' overall condition. I estimate the effects of market-segment focus measures on a bank's likelihood of exit through failure or acquisition using the Cox proportional-hazard model with competing risks and bank-level data for 2001–2019. The results suggest that MDIs with a greater focus on market segments with a higher share of low-income communities or higher housing vacancy rates are less likely to fail. I also find that management quality is an important factor and show that well-managed MDIs are less likely to fail. The results provide empirical evidence for conjectures 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.

In the second chapter, I investigate bank branching decisions with endogenous location choices and their role in serving low-income communities by focusing on MDIs. I approach the question using a game-theoretic, industrial organization model in which location-choice decisions are formalized through a static two-stage entry-location game. MDI location choices depend endogenously on their rivals' location choices and the location-specific demand. I show that locations with favorable demand characteristics positively affect payoffs while the presence of rivalrous MDIs negatively affects payoffs from that location. The results also indicate that an increase in distance between an MDI and its rivals softens competition. Therefore, since high-demand locations are likely attractive to many banks, some MDIs may choose to locate in low-demand locations to avoid harsher competition. Overall, the findings support the conjecture that the bank-branching decision is a trade-off between favorable location-specific demand characteristics and competition.

The insights from the first two chapters are helpful for devising effective, targeted, and less-invasive strategies to preserve mission-oriented banks and foster community development through increased access to financial services. The information is also instructive to sound, strategic de-

cisions for community development leaders outside the public sector or academia but who have a vested interest in the viability of their institutions. Moreover, the empirical investigation of MDIs' entry-location behavior provides insights into the determinants of mission-oriented banks' spatial positioning as well as the role of competition and local demand characteristics. From the policy perspective, MDIs are strategically important in expanding financial services in low- and moderate-income communities. Hence, knowledge about the factors affecting their branching behavior and the role of competition is constructive for preservation strategies directed at MDIs and for policies concerned with the accessibility of financial services. These insights are important in devising community development policies targeting low-income neighborhoods, businesses, and individuals.

The rapid growth of U.S. student loan debt has drawn attention from scholars and raised public concerns, with 2020 presidential candidates proposing "Student Loan Forgiveness" plans as part of their campaigns. In the third chapter, I explore the political economy of such proposals by developing a two-period model of schooling and unemployment insurance with search costs. Schooling benefits individuals directly through increased future earnings and lower search costs in the labor market and indirectly through increased aggregate taxable income in the economy, which results in enhanced unemployment insurance. The model suggests that the schooled median voter with student-loan debt favors the student-loan debt forgiveness policy. This attitude intensifies as the average probability of employment in the economy falls. However, the median voter's support for the policy and redistribution generally attenuates as his probability of employment increases. By contrast, the unschooled median voter does not favor the student-loan debt forgiveness policy since publicly funding higher education decreases the share of tax revenue redistribution to unemployment insurance. The findings from the model provide insights into the conflict of interest among schooled and unschooled individuals as well as the changes in their attitudes towards the student-loan debt forgiveness policies due to changes in the macroeconomic conditions.

Dedication

To my daughter Güller (Guillie) — your courageous, selfless heart and maturity beyond your age are inspirational. You motivate me when it's hard to keep going. You make me laugh when I am down. You make my every day brighter. I love you with all my heart.

To all the girls in the developing world struggling to fulfill their hunger for knowledge due to cultural biases exacerbated by political barriers or financial circumstances. Do not let cultural norms constrain your choices. Your gender does not determine your academic potential nor the discipline that befits you. The knowledge is universal. Your struggles for knowledge may seem insurmountable, but do not give up. It is your opportunity to be in charge of the choices you can make and the future you can have.

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I am sincerely thankful to my undergraduate professors, Ishuan Li Simonson and Bob Simonson, for taking a chance on a newly transferred foreign girl. Your words of wisdom and outlook have made a profound impact and helped me to take on the rigors of the graduate programs. Dr. Simonson, thank you for patiently listening to me as I explained my goals and for taking me door to door to each professor in search of a mentor. Dr. Li, thank you for mentoring me professionally and personally, pushing me to take on challenges that seemed out of reach, and helping me get on the path to a Ph.D. in Economics. Thank you both for your continuous support throughout the years.

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Chapter 1

Specialization and Bank Exit: The Case of Minority Depository Institutions

1.1 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 impoverished U.S. neighborhoods by locating in them and directing their

¹The 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).

²For example, Tewari (2014) shows that increased access to credit due to the 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 the increased number of bank branches in previously unbanked rural areas of India leads 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).

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

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

³Rosenthal (2018) describes the emergence of the community development finance. Harris (1968) describes the establishment of the 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.

⁴Section 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 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.

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 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 the 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 preva-

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

⁶According 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.

lent in LMI communities. Specialized knowledge and relationship with borrowers 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 (1999) 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 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 1.2 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 1.3. Data and variables used in the analyses are described in Section 1.4. Section 1.5 presents the results, and Section 1.6 concludes.

⁷Winton (1999) 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.

1.2 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 (1984) 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 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 (1999) 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 (1999) 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.

⁸Winton (1999) 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.

⁹Rajan and Winton (1995) explore the link between covenants, collateral, and monitoring. They argue that long-term loans with covenants dependent on costly information enhance bank's incentive to monitor.

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 1.1 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 1.1 that the failure rate is more pronounced for MDIs during the economic downturns, suggesting heterogeneous effects of a decline in 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 (1999) 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 inexperienced bank. 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 (1999) explains that expanding banks may find it attractive to acquire banks with moderate downside risk. In contrast, banks with high downside risk 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,

¹⁰Breitenstein 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. (2014), Eberley et al. (2019), and Toussaint-Comeau and Newberger (2017) argue that financial crisis disproportionately devastated MDIs’ markets.

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.

1.3 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 (2000), 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 (2000), 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

$$\lambda_l(t|\mathbf{x}_{li}(t), \boldsymbol{\beta}_l) = \bar{\lambda}_l(t) \exp[\mathbf{x}'_{li}(t)\boldsymbol{\beta}_l], \quad (1.1)$$

where $l = 1$ for failed banks and $l = 2$ for acquired banks, $i = 1, \dots, n$ 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 of parameters to be estimated. In the observed duration data for banks, bank i appears at $(J_i - 1)$ distinct times

¹¹Boot 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 inexperienced, expanding bank, thus increasing failure risk and impeding monitoring incentives of the expanding bank.

$t_{i1} < t_{i2} < \dots < t_{iJ_i-1}$. 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 $j = 1, \dots, J_i - 1$, 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

$$L_l(\boldsymbol{\beta}_l) = \prod_{i=1}^n \left[\frac{\lambda_{li}(t_{J_i} | \mathbf{x}_{li}(t_{J_i}), \boldsymbol{\beta}_l)}{\sum_{k \in R_i} \lambda_{lk}(t_{J_k} | \mathbf{x}(t_{J_k}), \boldsymbol{\beta}_l)} \right]^{d_{li}} = \prod_{i=1}^n \left[\frac{\exp[\mathbf{x}'_{li}(t_{J_i}) \boldsymbol{\beta}_l]}{\sum_{k \in R_i} \exp[\mathbf{x}'_{lk}(t_{J_k}) \boldsymbol{\beta}_l]} \right]^{d_{li}}, \quad (1.2)$$

where $R_i = \{k | t_{J_k} \geq t_{J_i}, k = 1, \dots, K\}$ 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 (1.2) to obtain the partial log-likelihood function for event l results in

$$\log L_l(\boldsymbol{\beta}_l) = \sum_{i=1}^n d_{li} \left\{ \mathbf{x}'_{li}(t_{J_i}) \boldsymbol{\beta}_l - \log \left[\sum_{k \in R_i} \exp[\mathbf{x}'_{lk}(t_{J_k}) \boldsymbol{\beta}_l] \right] \right\}. \quad (1.3)$$

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 (1.3). 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

¹²Wheelock 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.

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 (2000). 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

$$\frac{\partial \lambda_{li}(t_{J_i} | \mathbf{x}_{li}(t_{J_i}), \boldsymbol{\beta}_l) / \lambda_{li}(t_{J_i} | \mathbf{x}_{li}(t_{J_i}), \boldsymbol{\beta}_l)}{\partial x_{kli} / x_{kli}} = \beta_{kli} x_{kli}, \quad (1.4)$$

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

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,

$$\bar{\Lambda}_l(t) = \int_0^t \bar{\lambda}_l(u) du. \quad (1.5)$$

Tsiatis (1981) and Andersen and Gill (1982) show that the integrated baseline hazard in (1.5) can

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

be consistently estimated by the Breslow (1972) estimator,

$$\widehat{\Lambda}_l(t) = \sum_{t_{J_i} < t_{J_k}}^n \frac{d_{lJ_i}}{\sum_{k \in R_i} \exp[\mathbf{x}'_{lk}(t_{J_k})\widehat{\beta}_l]}, \quad (1.6)$$

where d_{lJ_i} is the count of event l at t_{J_i} , R_i is bank i 's remaining risk, $\exp[\mathbf{x}'_{lk}(t_{J_k})\widehat{\beta}_l]$ 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,

$$S_l(t) = (\exp[-\bar{\Lambda}_l(t)])^{\exp[\mathbf{x}'_{il}(t)\beta_l]} = (\bar{S}_l(t))^{\exp[\mathbf{x}'_{il}(t)\beta_l]}, \quad (1.7)$$

survival and the baseline survival functions are estimated using (1.6) as follows

$$\widehat{S}_l(t) = (\exp[-\widehat{\Lambda}_l(t)])^{\exp[\mathbf{x}'_{il}(t)\widehat{\beta}_l]} = (\widehat{S}_l(t))^{\exp[\mathbf{x}'_{il}(t)\widehat{\beta}_l]}. \quad (1.8)$$

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

$$\widehat{S}_l(t) = (\widehat{S}_l(t))^{\exp[\mathbf{x}'_{il}(t)\widehat{\beta}_l]}. \quad (1.9)$$

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

1.4 Data and Variables

1.4.1 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

¹⁴To 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 package.

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

The 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 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 the 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

¹⁵The 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.

¹⁶Geographic 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.

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 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 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 (2000) note that this approach is conservative in that significance levels for estimated parameters in hazards are reduced.

¹⁷For 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.”

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

1.4.2 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 socio-economic 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

$$LMI_i = \sum_{c=1}^C \sum_{b=1}^{B_i} s_{cb} \times lmi_c, \quad (1.10)$$

where $b = 1, \dots, B_i$ indexes branches of bank i , $c = 1, \dots, C$ 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

$$Vacancy_i = \sum_{c=1}^C \sum_{b=1}^{B_i} s_{cb} \times v_c, \quad (1.11)$$

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

$$Unemployment_i = \sum_{c=1}^C \sum_{b=1}^{B_i} s_{cb} \times u_c, \quad (1.12)$$

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 housing vacancy rate and on markets with higher unemployment rate, respectively, so that higher values indicate a greater focus. Table 1.1 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 the 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 primary causes of housing vacancies and that spatial concentration of vacant housing poses particular concern for community development. He also notes that neighborhoods with a higher rate of poverty and minority population tend to have persistent levels of long-term housing vacancy. Table 1.3 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 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 community bank and MDI indicators.

Table 1.2 presents summary statistics of variables in the analysis for MDIs, non-MDIs,

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

²⁰CAMEL 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.

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-MDI's markets have a higher share of housing 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 1.2 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. The mean nonperforming loans to total assets ratio remained relatively steady for MDIs with $LMI > 0.5$ during the 2008 financial 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.

²¹Hypothesis 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} .

²²Hypothesis 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} .

1.5 Results

1.5.1 Failure Hazard Results

I estimate the model separately for MDIs, non-MDIs, and the pooled sample. Table 1.4 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 1.4 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 1.6 presents the 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 Table 1.7, an increase in *LMI* from the first to the third quartile on average delays failure by about 35 days. Similarly, an increase in *Vacancy* from the first to the 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 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 1.4, operating in markets with greater housing vacancy rates is associated with an acceleration of time to failure suggesting that an increase in *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

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

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. (2006) find that greater diversification benefits banks with moderate loan downside, but not banks with a high downside. Berger and DeYoung (2001) 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 1.4 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 expected 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 1.4 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 1.6. Moreover, according to estimates in Table 1.7, an increase in M from the first to the third quartile on average accelerates the 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 1.4 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 the 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.

1.5.2 Acquisition Hazard Results

Table 1.5 reports acquisition hazard results. The results reveal that banks in markets with higher housing vacancy rates are less likely to be acquired. According to Table 1.7, an increase in *Vacancy* from the first to the 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, target banks with high loan downside risk specializing in serving market segments susceptible to economic downturns are not attractive. Although expanding banks may find acquiring an MDI strategically attractive to subdue competition and 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 1.5 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 to be acquired.

A negative coefficient for an MDI indicator variable in Table 1.7 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 the community bank indicator (CB)

suggests that community banks are less likely to be attractive acquisition targets.

1.6 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 housing 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 serving 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 suggest 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 the 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 cau-

tionary message of these findings is that evaluating portfolio risk based on diversification measures alone could be misleading, and incentives to monitor should be considered.

Table 1.1: Variable Description

Outcome Variables	
<i>Time</i>	<i>Time</i> 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.
<i>Failure</i>	<i>Failure</i> 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.
<i>Acquisition</i>	<i>Acquisition</i> 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	
<i>LMI</i>	$LMI_i = \sum_{c=1}^C \sum_{b=1}^{B_i} s_{cb} \times (li_c + moi_c)$, 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 $lmi_c = li_c + moi_c$.
<i>Vacancy</i>	$Vacancy_i = \sum_{c=1}^C \sum_{b=1}^{B_i} s_{cb} \times v_c$, 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 .
<i>Unemployment</i>	$Unemployment_i = \sum_{c=1}^C \sum_{b=1}^{B_i} s_{cb} \times u_c$, 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 .

Continued on the next page

Table 1.1: Variable Description (*Continued*)

CAMEL Proxy Variables	
<i>CA</i>	Capital adequacy: $CA = \text{Total equity}/\text{Total assets}$.
AQ_{LTA}	Asset Quality: $AQ_{LTA} = \text{Total loans}/\text{Total assets}$.
AQ_{REL}	Asset Quality: $AQ_{REL} = \text{Real estate loans}/\text{Total loans}$.
$AQ_{C\&IL}$	Asset Quality: $AQ_{C\&IL} = \text{Commercial and industrial loans}/\text{Total loans}$.
AQ_{OREO}	Asset Quality: $AQ_{OREO} = \text{Other real estate owned}/\text{Total assets}$.
AQ_{NPL}	Asset Quality: $AQ_{NPL} = \text{Nonperforming loans}/\text{Total assets}$.
<i>M</i>	Managerial quality measure estimated using unconditional (hyperbolic) order- <i>m</i> technical efficiency estimator. Large values of <i>M</i> are associated with less efficient institutions.
<i>EARN</i>	Earnings: $EARN = \text{Net income after taxes}/\text{Total assets}$.
<i>LIQ</i>	Liquidity: $LIQ = (\text{Federal funds purchased and securities sold} - \text{Federal funds sold and securities purchased})/\text{Total assets}$.
Other Variables	
<i>SIZE</i>	Natural logarithm of Total Assets.
<i>AGE</i>	Natural logarithm of bank's age in years.
<i>LLP</i>	$LLP = \text{Loan loss provisions}/\text{Total assets}$. Note: Loan loss provisions measures changes in allowance for loan and lease losses (ALLL). Negative <i>LLP</i> indicates deduction from (a decrease in) ALLL, while positive <i>LLP</i> indicates addition to (an increase in) ALLL. Positive values in <i>LLP</i> signal that banks are expecting quality deterioration of their lending portfolio.
<i>MDI</i>	Binary variable identifying Minority Depository Institutions (MDI). MDI is 1 if bank is an MDI.
<i>CB</i>	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 1.2: Summary Statistics by Bank Type

		Mean	Median	StdDev	Min	Max
Market-Segment Focus Measures						
<i>LMI</i>	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
<i>Vacancy</i>	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
<i>Unemployment</i>	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						
<i>CA</i>	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
<i>AQ_{LTA}</i>	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
<i>AQ_{REL}</i>	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
<i>AQ_{C&IL}</i>	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
<i>AQ_{OREO}</i>	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
<i>AQ_{NPL}</i>	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

Continued on the next page

Table 1.2: Summary Statistics by Bank Type (*Continued*)

CAMEL Proxy Variables (Continued)						
<i>M</i>	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
<i>EARN</i>	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
<i>LIQ</i>	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						
<i>SIZE</i>	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
<i>AGE (Years)</i>	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
<i>LLP</i>	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

End of table

Table 1.3: Market-Segment Focus Measures

Panel A: Correlation Matrix			
	<i>LMI</i>	<i>Vacancy</i>	<i>Unemployment</i>
<i>LMI</i>	1.0000	0.1905***	0.2301***
<i>Vacancy</i>	0.1905***	1.0000	0.0705***
<i>Unemployment</i>	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 1.4: Failure Hazard

	MDI	non-MDI	All
<i>LMI</i>	-3.7878** (1.7623)	0.1070 (0.0918)	0.1049 (0.0897)
<i>Vacancy</i>	-3.1808** (1.3974)	0.1351** (0.0659)	0.1222* (0.0659)
<i>Unemployment</i>	0.3218 (0.6241)	0.0402 (0.0764)	0.0384 (0.0753)
<i>CA</i>	-6.8142*** (2.0382)	-1.8466*** (0.0768)	-1.9122*** (0.0758)
<i>AQ_{LTA}</i>	-0.3372 (0.8601)	0.1660* (0.0959)	0.1209 (0.0917)
<i>AQ_{REL}</i>	-0.9423 (1.4884)	0.0043 (0.1263)	0.0148 (0.1233)
<i>AQ_{C&IL}</i>	1.0948 (0.9892)	0.1585 (0.0972)	0.1641* (0.0944)
<i>AQ_{OREO}</i>	0.3280** (0.1527)	0.1064*** (0.0132)	0.0988*** (0.0130)
<i>AQ_{NPL}</i>	0.5466** (0.2194)	0.2223*** (0.0178)	0.2049*** (0.0160)
<i>M</i>	1.6981* (1.0182)	0.0167 (0.0419)	0.0205 (0.0322)
<i>EARN</i>	0.2672 (0.1740)	0.0289 (0.0212)	0.0279 (0.0206)
<i>LIQ</i>	-1.5539* (0.8062)	-0.2700*** (0.0702)	-0.2890*** (0.0670)
<i>SIZE</i>	1.7458 (1.1368)	0.1389* (0.0775)	0.1109 (0.0771)
<i>AGE</i>	0.9138 (0.9094)	-0.2692*** (0.0619)	-0.3103*** (0.0608)
<i>LLP</i>	0.2580 (0.1736)	-0.0524*** (0.0178)	-0.0512*** (0.0173)
<i>MDI</i>			-0.3664 (0.2958)
<i>CB</i>	10.2431** (5.0881)	-0.2055 (0.2019)	-0.0749 (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 1.5: Acquisition Hazard

	MDI	non-MDI	All
<i>LMI</i>	0.1420 (0.3048)	0.0392** (0.0196)	0.0387** (0.0195)
<i>Vacancy</i>	-0.5966* (0.3531)	-0.0377** (0.0183)	-0.0406** (0.0183)
<i>Unemployment</i>	-0.1282 (0.2730)	-0.1107*** (0.0258)	-0.1102*** (0.0257)
<i>CA</i>	-0.0272 (0.1158)	0.0207 (0.0137)	0.0209 (0.0136)
<i>AQ_{LTA}</i>	-0.1053 (0.1889)	-0.1018*** (0.0201)	-0.1016*** (0.0200)
<i>AQ_{REL}</i>	0.7952** (0.3544)	0.2938*** (0.0248)	0.2970*** (0.0247)
<i>AQ_{C&IL}</i>	0.1882 (0.1760)	0.0800*** (0.0205)	0.0787*** (0.0203)
<i>AQ_{OREO}</i>	0.0659 (0.0812)	-0.0526** (0.0206)	-0.0468** (0.0200)
<i>AQ_{NPL}</i>	-0.1625 (0.1222)	0.0787*** (0.0175)	0.0750*** (0.0171)
<i>M</i>	-0.1095 (0.1842)	-0.1172*** (0.0210)	-0.1196*** (0.0207)
<i>EARN</i>	-0.1878* (0.1123)	-0.0706*** (0.0043)	-0.0703*** (0.0043)
<i>LIQ</i>	-0.0257 (0.1475)	-0.1686*** (0.0129)	-0.1673*** (0.0129)
<i>SIZE</i>	-0.4903** (0.2069)	-0.2397*** (0.0202)	-0.2419*** (0.0201)
<i>AGE</i>	-0.1339 (0.1933)	-0.1665*** (0.0168)	-0.1693*** (0.0168)
<i>LLP</i>	-0.3534*** (0.0968)	-0.0264*** (0.0123)	-0.0314** (0.0128)
<i>MDI</i>			-1.6298*** (0.2150)
<i>CB</i>	-1.4496*** (0.4892)	-1.6130*** (0.0501)	-1.6082*** (0.0497)
LLF	-201.36	-30,005.07	-30,487.93
# banks	171	7,749	7,920
# ac- quired	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 1.6: Mean Elasticity of Marginal Effect on the Hazard Rate (MDIs)

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

Table 1.7: Marginal Changes in Duration for Selected Variables for MDIs (Mean Difference of First and Third Quartiles)

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

Figure 1.1: Failure rate for all banks, non-MDIs, and MDIs during 2001–2019. The count of failed banks also includes assisted mergers.

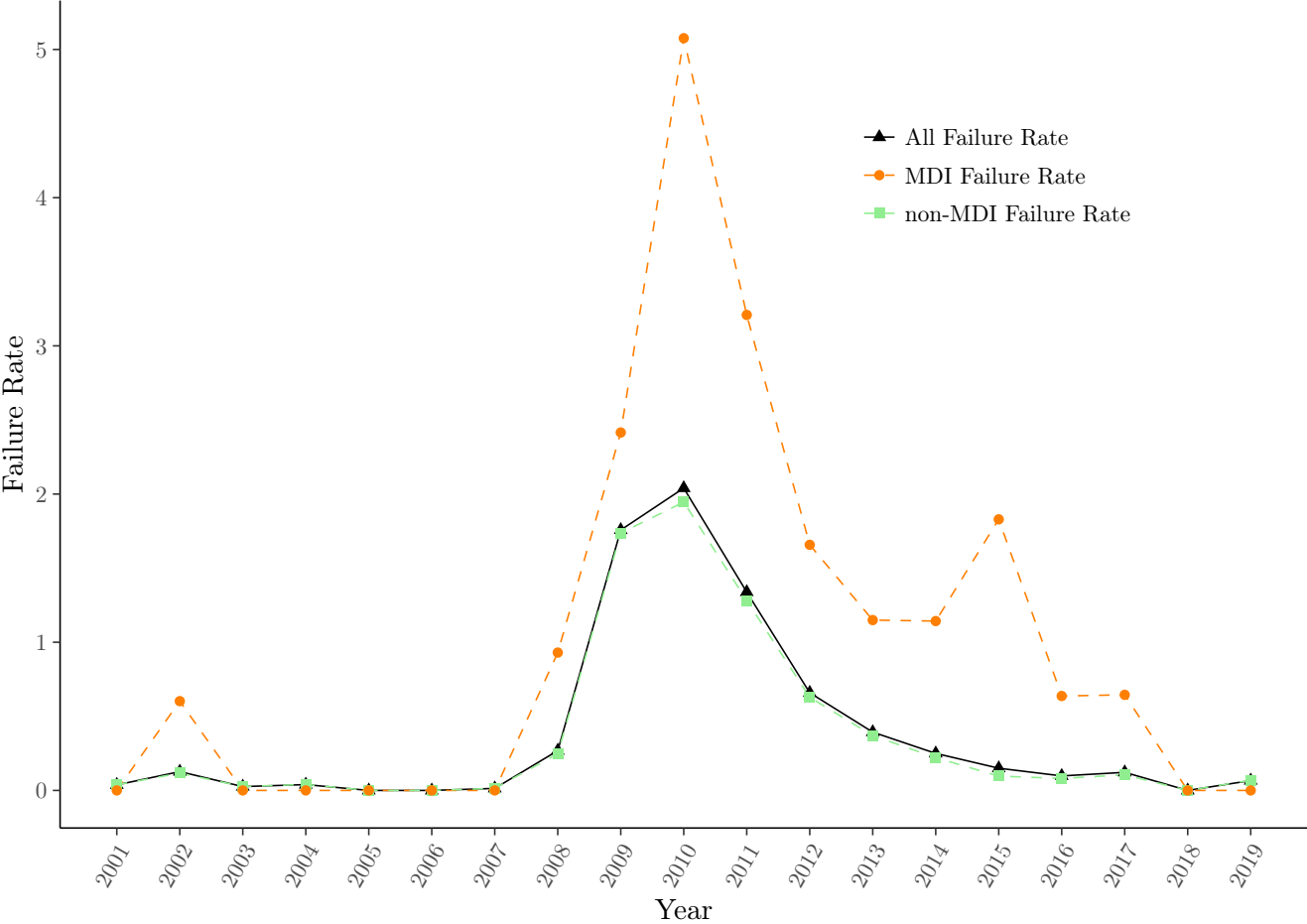
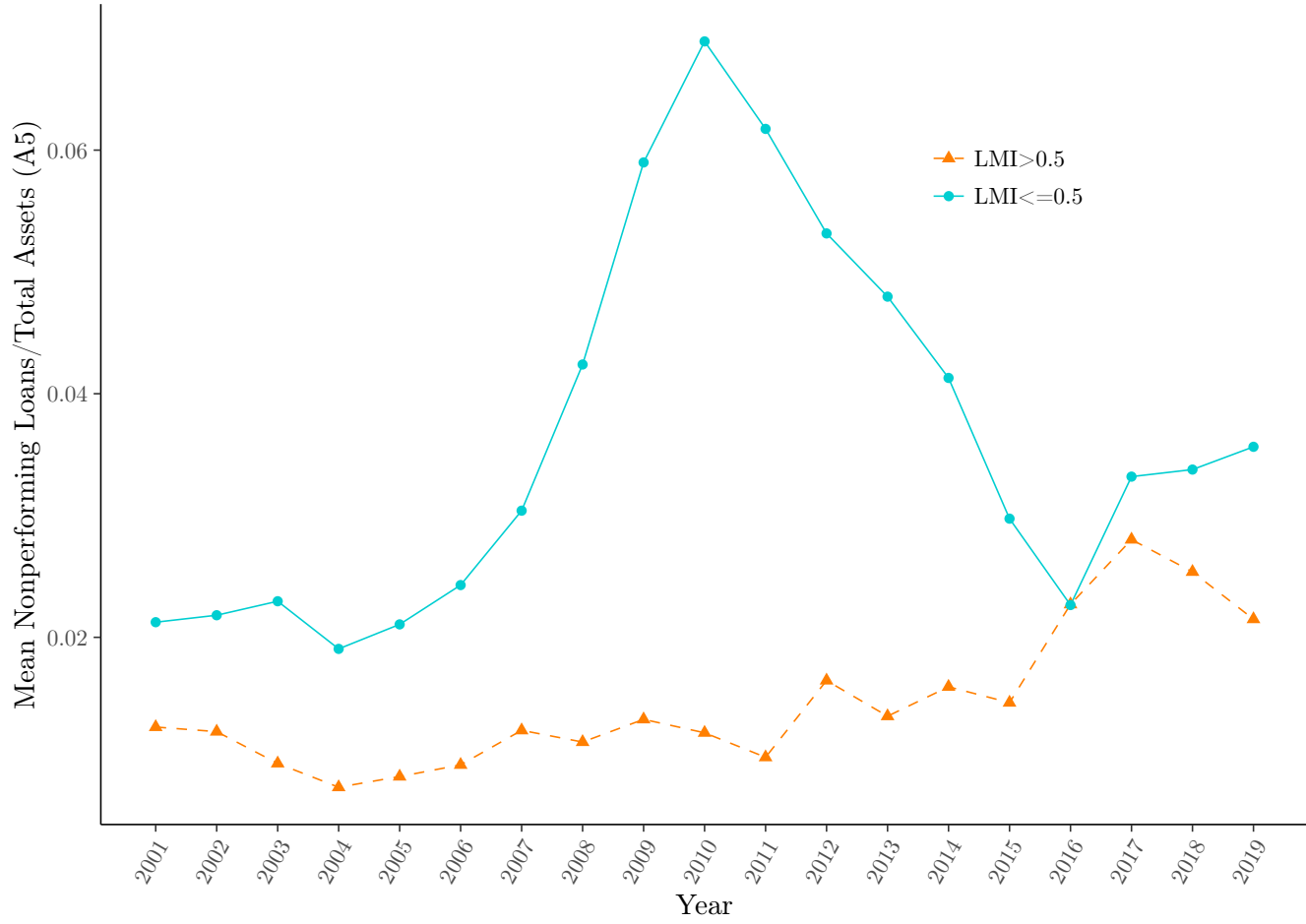


Figure 1.2: Mean nonperforming loans to total assets ratio trends during 2001–2019 for MDIs by *LMI* market-segment focus variable. The graph indicates that on average MDIs with $LMI > 0.5$ have less nonperforming loans as share of their total assets.



Chapter 2

Bank Branching Decisions with Endogenous Location Choices and Competition

2.1 Introduction

Bank branching and location decisions directly affect the spatial accessibility of banking services in a given community. Increased access to financial services improves the economic outcomes of individuals and firms. Importantly, the evidence in the economic literature indicates that the beneficial effects of increased access to financial services are more pronounced for low-income and minority individuals. For example, Tewari (2014) shows that increased access to credit due to the removal of interstate branching restrictions is pronounced for low- and middle-income groups, young, and black households.¹ Unlike traditional, transaction-oriented banks, Minority Depository Institutions (MDIs) specialize in serving low-income individuals. They have close ties to their local communities, making them strategically important for expanding the provision of banking services in low-income communities and for community development.² Breitenstein et al. (2014) and Eberley

¹Additional studies showing benefits of increased access to financial services include Burgess and Pande (2005), Burgess et al. (2005), Karlan and Zinman (2010), Suri and Jack (2016), and Bachas et al. (2018)

²Section 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

et al. (2019) establish that MDIs are predominantly found in densely populated metropolitan areas and serve markets with a greater share of low- and moderate-income (LMI) census tracts relative to non-MDIs, including non-MDI community banks.³ They also show that a considerable share of MDIs' mortgages and small business loans are allocated to individuals and businesses in LMI census tracts.

In this paper, I explore the role of geography in MDIs' market entry decisions through branching with endogenous location choices. MDIs are good candidates for the analysis of spatial product positioning through branching. Evidence suggests that MDIs have stronger links to their locations relative to non-MDIs due to their specialization in serving poor communities, smaller size, and limited (in geographic scope) operations. Specialization in serving poor communities necessitates MDIs to have closer links to their local geography through providing in-person banking services because, as Bell et al. (2009) show, LMI households are more likely to bank in-person and are less likely to have Internet access relative to other income groups. Moreover, as argued in Chapter 1, MDIs' specialization in serving LMI communities is an integral part of their business strategy, which requires costly and time-consuming investment into a relationship with their local communities.⁴ In Chapter 1, I show that more specialized MDIs are less likely to exit the market than less specialized MDIs, suggesting that expanding operations beyond their specialized market segments is associated with diseconomies of scope. Finally, MDIs finance their operations primarily through deposits and have lower access to the capital markets relative to their larger non-MDI counterparts. Eberley et al. (2019) report that MDIs' extent of operations is local, and their primarily local lending is funded through deposits collected at local markets. Breitenstein et al. (2014) and Eberley et al. (2019) also show that MDIs differ from non-MDI community banks in their location choices and the consumers they serve.⁵ Therefore, location choice is an important element of MDIs' branching decisions, and it is a strategic tool at the MDIs' disposal when it comes to the spatial positioning of their branches.

community that the institution serves are predominantly minority. Given the ambiguity of the phrase "socially and economically disadvantaged individuals", regulators use the term "minority" instead. The FIRREA defines "minority" as any "Black American, Asian American, Hispanic American, or Native American."

³I use the terms "LMI communities" and "low-income communities" 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 communities are consistent with the Community Reinvestment Act (CRA) definition of LMI neighborhoods.

⁴For example, MDIs' specialization in serving LMI communities serves as a deterrence strategy against potential entrants and enhances their comparative advantage.

⁵The study by Eberley et al. (2019) states "The geographic footprint of non-MDI community banks differs substantially from that of most MDIs. Whereas MDIs are overwhelmingly located in the most populous states and metropolitan areas in the country, non-MDI community banks are dispersed throughout the country, including urban and rural counties, and micropolitan areas."

I examine MDIs' branching behavior based on a game-theoretic industrial organization model developed by Seim (2006), where location decisions are formalized through a static two-stage entry-location game. This approach allows one to take advantage of economic theory and use it as the basis for the structural estimation of MDIs' entry and location decisions. Conditional on entry, MDIs' location choices are modeled as a strategic decision that endogenously depends on the location choices of their rivals and the location-specific demand. Favorable local conditions affecting the demand for banking services may prompt MDIs to establish branches in these locations due to the positive effect on their profits. However, favorable local conditions are enticing to many banks, hence such locations are likely to be more competitive than others. Since intense competition negatively affects profits, some MDIs may strategically locate their branches in areas with less favorable demand characteristics as a tactic of evading competition. This behavior is likely further facilitated by adverse selection in credit markets if entrants are faced with the winner's curse.⁶

The results indicate that the presence of rivalrous MDIs has a negative effect while a larger local population has a positive effect on MDIs' profits. Moreover, I show that the competition effect dissipates with distance such that closely located rivals exert more competitive pressure relative to distant rivals. Similarly, an increase in population closest to MDI's own location has a greater positive effect on its profits relative to an increase in population located further away from MDI's own location. Furthermore, the results reveal that locating in LMI locations is associated with a negative effect on MDIs' profits relative to locating in other locations. Finally, the results indicate that sharing a location with a non-MDI branch negatively affects MDIs' profits even though these banks target different market segments. These results suggest that MDIs' branching decisions involve a trade-off between favorable location-specific demand characteristics and competition. Though the promotion and preservation of MDIs are motivated by their assumed mission to serve consumers in LMI locations, my findings offer an alternative explanation for MDIs' observed location choices.⁷

The findings of this paper emphasize the relevance of spatial differentiation in MDIs' location decisions as a strategy to abate the competition and provide a rationale for MDIs' distinctive spatial positioning. These insights are informative for policymakers interested in preserving MDIs

⁶In the presence of information asymmetries, the winner's curse in the lending market for new entrants may arise if well-established incumbents capture the creditworthy share of borrowers resulting in the deterioration of the pool of borrowers for new entrants. An interested reader is referred to Shaffer (1998), Broecker (1990), and Dell'Araccia et al. (1999) for further details.

⁷For example, Federal Deposit Insurance Corporation's (FDIC's) Mission-Driven Bank Fund aims to support mission-driven banks, such as FDIC-insured MDIs, that provide banking services in LMI, minority, and rural communities. Additional information may be found on the FDIC Minority Depository Institutions Program Mission Driven Bank Fund page at <https://www.fdic.gov/regulations/resources/minority/mission-driven/index.html>.

and increasing access to financial services in LMI communities. MDIs' ability to spatially differentiate enhances the spatial accessibility of the financial services to consumers through expanded product variety of available branches at various locations due to the strong incentives to scatter throughout the market space to isolate from rivals. At the same time, MDIs' ability to gain additional profitability by strategically positioning their branches and using distance to subdue intense competition in the market increases their ability to survive. Therefore, my results imply that as long as there is scope for spatial differentiation within a market, MDIs will remain viable by locating and serving their niche market segments.

The rest of the paper is organized as follows. I describe the game-theoretic model and estimation strategy in Section 2.2. Data and variables used in the analyses are described in Section 2.3. Section 2.4 presents the results. Section 2.5 concludes and discusses future work.

2.2 Model and Estimation Strategy

2.2.1 The Model Setup and Assumptions

The model and estimation strategy are similar to Seim (2006). MDIs' location choice behavior is studied formally through a static two-stage entry-location game. Since the model is static, the equilibrium strategies can be computed for many locations. This feature of the model is especially useful given the objective of my study. In the model, each MDI makes an entry decision through branching and chooses a location within a given market based on a comparison of expected post-entry, single-period profits across discrete locations in that market. I assume that profits vary among branch offices in the same location due to differences in costs and other bank-specific factors. However, the bank-specific profit information from any given location is private to the MDI and unobserved by anyone outside the MDI. This assumption allows for idiosyncratic differences in profits due to, for example, familiarity with the location or demand and explicitly accounts for the role of relationship banking that may affect banks' loan monitoring costs and other unobservables. Since costs and other bank-specific factors affecting profits are unobservable at the branch level, the entry and location choices in the model are determined by the demand characteristics in each market location, expected competitor location choices, and idiosyncratic, location-specific bank profit component. Hence, from an MDI's perspective, branch location is an endogenous strategic decision that is jointly determined by the choices of its competitors and other variables in the model.

I begin by establishing notation and defining key elements in the model. The study investigates urban-bank branching decisions with a focus on MDIs. A decision maker is an MDI bank that makes a joint entry and location choice.⁸ Markets are defined as clusters of census tracts in a metropolitan statistical area (MSA). Kwast et al. (1997) report that 90 percent of U.S. households do not travel more than twelve miles for bank checking services. Therefore, markets are selected such that the distance between a tract to its furthest neighboring tract does not exceed twelve miles.⁹ For each market m there are \mathcal{N}_m^p potential bank entrants indexed by $i = 1, \dots, \mathcal{N}_m^p$ simultaneously deciding whether to enter and establish a branch within the market. Only \mathcal{N}_m number of branches are established with $\mathcal{N}_m \leq \mathcal{N}_m^p$. For simplicity, I assume banks make independent branching and location choices. Although the assumption is restrictive, it reduces the computational burden. Alternatives are location choices ℓ available to the bank in market m . I define locations as the population-weighted centroids of census tracts. Let M represent the number of markets and \mathcal{L}_m represent the number of locations in a market m in addition to the option of not entering the market. Then, a set of possible locations in the market is indexed by $\ell = 0, 1, \dots, \mathcal{L}_m$, where $\ell = 0$ is the “outside” option indicating that a bank does not establish any branches in the market m . I consider each market as an independent entry-location game with \mathcal{N}_m^p players.

The contribution to bank i ’s profit from its branch at location ℓ in market m depends on observed and unobserved attributes specified as

$$\Pi_{i\ell m} = \underbrace{\sum_{j=1}^{\mathcal{L}_m} \mathbf{X}_{jm} \beta_{j\ell}}_{\text{demand characteristics}} + \underbrace{\sum_{j=1}^{\mathcal{L}_m} \gamma_{j\ell} n_{jm}}_{\text{competition effects}} + \underbrace{\epsilon_{i\ell m}}_{\text{idiosyncratic profitability}}, \quad (2.1)$$

where \mathbf{X} is a location-specific vector of observed demand characteristics with $\beta_{\ell\ell}$ representing demand effects in branch’s own location ℓ for $j = \ell$, and $\beta_{j\ell}$ is the demand effect in location j for $j \neq \ell$. The unobserved market-specific demand characteristics are represented by ξ_m . Moreover, $\gamma_{\ell\ell}$ is the competition effect on the bank’s profit from its immediate rivals in location ℓ for $j = \ell$, where the bank’s branch is located, and $\gamma_{j\ell}$ is the competition effect from its distant rivals in location j for $j \neq \ell$. I assume that closer rivals have a greater negative effect on the bank profits than rivals located farther away. The number of branches in the branch’s own location ℓ is $n_{\ell m}$ and the number

⁸I use the terms “MDI” and “bank” interchangeably to refer to the decision maker. Henceforth, in Section 2.2, I use the term “bank” exclusively for clarity and brevity.

⁹Specifically, markets are selected such that the distance between population-weighted centroids from a tract to its furthest neighboring tract does not exceed twelve miles due to the definition of a location in this paper.

of branches in each alternative location j is n_{jm} for $j \neq \ell$. The specification of competition effects in (2.1) assumes that competitors' effects are additively separable across locations. Finally, the error term $\epsilon_{i\ell m}$ in (2.1) is the idiosyncratic component of bank i 's profit from operating in location ℓ , which captures all differences in costs and other bank-specific factors at location ℓ . The error is unobserved by the econometrician. Given the profit specification in (2.1), bank entry and location choices are determined by (i) the market and location demand characteristics, (ii) competition faced in each location, and (iii) the bank's location-specific idiosyncratic profitability term whose actual value is assumed to be known by the entering bank only. A bank's joint entry-location decision is based on maximizing the contribution to the bank's profit from its branch. Formally, bank i establishes a branch in location ℓ in market m if

$$\Pi_{i\ell m} > \Pi_{ijm}, \quad \forall j \neq \ell \quad \text{and} \quad j = 0, \dots, \mathcal{L}_m. \quad (2.2)$$

I assume that a bank's expected profit from not entering a market is zero.

As pointed out by Seim (2006), asymmetry of information between banks in the given specification of profits arises due to the bank's location-specific error term. It is assumed that the distribution of this error term is common knowledge, but the realization of the error term is private information and is known by the bank itself only. Bank information sets and types are defined by the following assumption from Seim (2006).

Assumption 1 *Players' profitability types $\epsilon_1, \dots, \epsilon_{N^P}$ are private information to the players and are independently and identically distributed draws from the distribution $G(\cdot)$.*

Therefore, the idiosyncratic error terms of bank profits from operating at location ℓ of market m are assumed to be independent and symmetric. The implication of Assumption 1 is that entrants have symmetric expectations with regards to their rivals' profitability terms. Furthermore, as Seim (2006) notes, profits depend on the number of branches established in each location, but not on their identities.

The differences in area, shape, and population among census tracts mean that distances between any pair of population-weighted census tract centroids are not equal. As Seim (2006) explains, further assumptions are needed to accommodate irregularities in the spatial data that affect the estimation of the model.

Assumption 2 Let D_b and D_{b+1} denote cutoffs that define a distance band around location ℓ such that there are a maximum of B distance bands, indexed by $b = 0, 1, \dots, B$. Let $d_{j\ell}$ and $d_{j'\ell}$ be distances between a branch in location ℓ and its rivals in locations j and j' of market m , respectively. If $D_b \leq d_{j\ell} < D_{b+1}$ and $D_b \leq d_{j'\ell} < D_{b+1}$, then $\gamma_{j\ell} = \gamma_{j'\ell} = \gamma_b$.

Assumption 2 implies that branches in the same distance around location ℓ exert the same competitive pressure regardless of whether they are located in different census tracts j and j' or in the same census tract. Moreover, the incremental effect of an additional branch in a given location j on the profit is assumed to be constant, though rivals located in a distance band closer to the bank's branch location have a greater impact on profits. Assumption 2 eases the computational burden.¹⁰

Using Assumptions 1–2 and omitting index m to simplify the notation, the profit function in (2.1) can now be rewritten as

$$\Pi_{i\ell} = \sum_{b=0}^B \mathbf{X}_{b\ell} \beta_b + \xi + \sum_{b=0}^B \gamma_b N_{b\ell} + \epsilon_{i\ell}, \quad (2.3)$$

where γ_b is the effect of competitors in distance band b , such that γ_b measures the competitive effect of branches at distance between D_b and D_{b+1} with $D_0 = 0$. The total number of branches in a distance band b around location ℓ is $N_{b\ell}$ in equation (2.3). Furthermore, let ℓ be the location of bank i 's branch, j be the location of its rivals, and let $d_{j\ell}$ denote a distance between locations ℓ and j . Then $N_{b\ell} = \sum_{j=1}^{\mathcal{L}} \mathbb{I}_b(d_{j\ell}) \times n_j$, where the indicator function $\mathbb{I}_b(d_{j\ell}) = 1$ when $D_b \leq d_{j\ell} < D_{b+1}$ and zero otherwise, and n_j is a random variable denoting the number of rivalrous branches in location j . Moreover, note that $\sum_{b=0}^B N_{b\ell} = \mathcal{N}$. Finally, $\mathbf{X}_{b\ell}$ is a vector of observed demand characteristics in a distance band b and β_b is the corresponding demand effect. In the next section, I describe banks' equilibrium beliefs and present joint entry-location equilibrium predictions for this imperfect information entry-location game.

2.2.2 The Equilibrium

Bank profit from operating at location ℓ is private knowledge, though the distribution of the profitability terms is common knowledge. Without knowing its rivals' idiosyncratic profitability terms, each bank must form an expectation about its rivals' optimal location choices. As a result, each bank chooses a location that maximizes the branch's contribution to the profit based on the

¹⁰Seim (2006) employs a similar simplification.

expected rival positions across market locations conditional on the bank's own idiosyncratic profitability term. So, bank i 's expected profit contribution from its branch in location ℓ conditional on $\xi, \mathbf{X}, \epsilon, \gamma, \beta$ is

$$\mathbb{E}[\Pi_{i\ell}|\xi, \mathbf{X}, \epsilon, \boldsymbol{\theta}_1] = \sum_{b=0}^B \mathbf{X}_{b\ell} \beta_b + \xi + \sum_{b=0}^B \gamma_b \mathbb{E}[N_{b\ell}] + \epsilon_{i\ell}, \quad (2.4)$$

where $\boldsymbol{\theta}_1 = (\boldsymbol{\beta}, \boldsymbol{\gamma})$ and $\mathbb{E}[N_{b\ell}] = \sum_{j=1}^{\mathcal{L}} \mathbb{I}_b(d_{j\ell}) \mathbb{E}[n_j]$ is the expected number of branches in a distance band b . As a result, a bank's entry and location decision depends on the expected location choices of its rivals. Hence, banks make their location choices by comparing the expected profits in (2.4) for each location and choose location ℓ if $\mathbb{E}[\Pi_{i\ell}|\xi, \mathbf{X}, \epsilon, \boldsymbol{\theta}_1] > \mathbb{E}[\Pi_{ij}|\xi, \mathbf{X}, \epsilon, \boldsymbol{\theta}_1]$ for all $j \neq \ell$.

The symmetry of the players' profitability types in Assumption 1 implies that bank i has the same belief about their rivalrous bank r 's location strategy as the rest of the banks. The conditional probability that rivalrous bank r chooses location ℓ in market m is

$$\begin{aligned} p_{r\ell} &= \Pr(\mathbb{E}[\Pi_{r\ell}|\xi, \mathbf{X}, \epsilon, \boldsymbol{\theta}_1] > \mathbb{E}[\Pi_{rj}|\xi, \mathbf{X}, \epsilon, \boldsymbol{\theta}_1], \forall j \neq \ell) \\ &= \Pr\left(\epsilon_{rj} - \epsilon_{r\ell} \leq \sum_{b=0}^B (\mathbf{X}_{b\ell} - \mathbf{X}_{bj}) \beta_b + \sum_{b=0}^B \gamma_b (\mathbb{E}[N_{b\ell}] - \mathbb{E}[N_{bj}]), \forall j \neq \ell\right). \end{aligned} \quad (2.5)$$

Assuming that error terms $\epsilon_{i\ell}$ are identically, independently distributed (iid) draws from a Type-I Extreme-Value distribution lead to a multinomial logit probability, first introduced by McFadden (1974),

$$p_{r\ell} = \frac{e^{\left(\sum_{b=0}^B \mathbf{X}_{b\ell} \beta_b + \sum_{b=0}^B \gamma_b \mathbb{E}[N_{b\ell}]\right)}}{\sum_{j=1}^{\mathcal{L}} e^{\left(\sum_{b=0}^B \mathbf{X}_{bj} \beta_b + \xi + \sum_{b=0}^B \gamma_b \mathbb{E}[N_{bj}]\right)}}. \quad (2.6)$$

Notice that the market-level demand characteristics, ξ , do not influence location choices within a market. However, as shown below, ξ affects a bank's decision to enter. Using the probability in (2.6), the total number of competitors (excluding itself) that a bank i expects to face in location ℓ can be written as $(\mathcal{N} - 1) \times p_{r\ell}$. Therefore, the number of rivalrous bank branches a bank expects to face in each distance band around location ℓ can be written as

$$\mathbb{E}[N_{b\ell}] = \begin{cases} (\mathcal{N} - 1) \times p_{r\ell} + 1 & \text{if } b = b_0 \\ \sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) \times (\mathcal{N} - 1) \times p_{rj} & \text{if } b \neq b_0, \end{cases} \quad (2.7)$$

where the indicator function $\mathbb{I}_b(d_{j\ell}) = 1$ when $D_b \leq d_{j\ell} < D_{b+1}$ and zero otherwise for distance $d_{j\ell}$ between locations ℓ and j . Note that since each bank knows its own type, location ℓ in the $b = b_0$ distance band includes a bank itself with certainty.

The symmetric Bayesian Nash equilibrium of this imperfect information entry-location game describes the best response that maximizes bank i 's expected profit contribution from its branch, given its belief about the rivalrous banks' strategies. The iid assumption for ϵ implies that every bank has the same equilibrium belief of its rivals' location choices, so that $p_{r\ell} = p_{i\ell} = p_\ell^*$. A bank's equilibrium beliefs over locations ℓ in a each market m is then defined by the following set of \mathcal{L}_m equations $\forall \ell = 1, \dots, \mathcal{L}_m$

$$p_{\ell m}^* = \frac{\exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell m} \beta_b + (\mathcal{N}_m - 1) \left[\gamma_0 p_{\ell m}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell m} \mathbb{I}_b(d_{j\ell}) p_{jm}^* \right) \right] \right\}}{\sum_{k=1}^{\mathcal{L}_m} \exp \left\{ \sum_{b=0}^B \mathbf{X}_{bk m} \beta_b + (\mathcal{N}_m - 1) \left[\gamma_0 p_{km}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq k} \mathbb{I}_b(d_{jk}) p_{jm}^* \right) \right] \right\}}, \quad (2.8)$$

where subscript m is reintroduced for clarity. The system of \mathcal{L}_m equations in (2.8) defines the equilibrium location beliefs as a fixed point of the mapping from the bank's belief of its rivals' strategies into its rivals' beliefs of the bank's own strategy.¹¹ Note, there are a total of M systems of equations associated with each market $m = 1, \dots, M$.

A bank's location choice is conditional on its entry decision. Its entry decision is based on a comparison of the weighted average of profits across all market locations to the profits of not entering. The expected profit conditional on ξ , \mathbf{X} , ϵ , γ , β considered by a bank when making an entry decision is

$$\mathbb{E}[\Pi_{i\ell m}] = \xi_m + \underbrace{\sum_{b=0}^B \mathbf{X}_{b\ell m} \beta_b + \gamma_0 + (\mathcal{N}_m - 1) \left[\gamma_0 p_{\ell m}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) p_{jm}^* \right) \right]}_{\bar{\Pi}_{\ell m}(\mathbf{X}, \mathbf{p}^*, \mathcal{N}, \boldsymbol{\theta}_i)} + \epsilon_{i\ell m},$$

where \mathbf{p}_m^* is a vector of equilibrium beliefs over all locations ℓ in market m . Then, the marginal

¹¹See Seim (2006) for additional details about the existence and uniqueness properties of the equilibrium.

probability of entry can be written as

$$P_m = \frac{e^{\xi_m \left[\sum_{\ell=1}^{\mathcal{L}_m} e^{\bar{\Pi}_{\ell m}(\mathbf{X}, \mathbf{p}^*, \mathcal{N}, \theta_1)} \right]}}{1 + e^{\xi_m \left[\sum_{\ell=1}^{\mathcal{L}_m} e^{\bar{\Pi}_{\ell m}(\mathbf{X}, \mathbf{p}^*, \mathcal{N}, \theta_1)} \right]}}. \quad (2.9)$$

As noted earlier, the market demand characteristics, ξ_m , are relevant to the entry decision, but they do not influence the location decisions within a given market. Combining (2.8) and (2.9) defines the joint equilibrium prediction for the location probabilities and the number of established branches. The next section describes the estimation strategy.

2.2.3 The Estimation Process

Estimation of the described model presents several challenges that need to be addressed. First, the system of equations defining the bank equilibrium beliefs in (2.8) does not have a closed-form solution. Therefore, I solve the system of equations using numerical methods to find the equilibrium location probabilities, $\hat{\mathbf{p}}_m^* = [\hat{p}_{1m}, \hat{p}_{2m}, \dots, \hat{p}_{\mathcal{L}_m m}]$, $m = 1, \dots, M$. Specifically, I use the method of successive approximations to estimate endogenous location choice probabilities for bank branches.

Second, the number of potential entrants, \mathcal{N}_m^p , and the market-level demand characteristics, ξ_m , are unobserved. To overcome this challenge, I set $\mathcal{N}_m^p = 2 \times \mathcal{N}_m$ or such that \mathcal{N}_m^p equals some fixed number in each market, following the approach used by Seim (2006) and Cotterill and Haller (1992). This approach also allows comparing estimated parameters under different values of the expected number of entrants. Moreover, given the iid assumption for ϵ , the expected number of established branch offices in market m is

$$\mathcal{N}_m = \mathcal{N}_m^p \times P_m. \quad (2.10)$$

This method requires an initial guess of \mathcal{N}_m , the number of entrants into the market. To aid the numerical computation, I set \mathcal{N}_m equal to the actual number of branches observed in the data for each market. This step is accomplished by adjusting ξ_m , which is derived from (2.9) and (2.10) by solving for ξ_m which yields an estimate of unobserved market-level demand characteristics, $\hat{\xi}_m$.¹²

¹²Berry (1994), Berry et al. (1995), and Seim (2006) use similar methods in their estimation strategy.

Specifically, equation (2.10) can be rearranged as

$$P_m = \frac{\mathcal{N}_m}{\mathcal{N}_m^p}. \quad (2.11)$$

Then, equating (2.11) to (2.9) and solving for ξ_m results in

$$\widehat{\xi}_m = \ln(\mathcal{N}_m) - \ln(\mathcal{N}_m^p - \mathcal{N}_m) - \ln\left(\sum_{\ell=1}^{\mathcal{L}_m} e^{\bar{\Pi}_{\ell m}(\mathbf{X}, \mathbf{p}^*, \mathcal{N}, \boldsymbol{\theta}_1)}\right). \quad (2.12)$$

Equation (2.12) and the assumptions about \mathcal{N}_m and \mathcal{N}_m^p yield an estimate for market realizations of $\widehat{\xi}_m$. I assume that the market-level random effect ξ_m follows a Normal distribution with mean μ and standard deviation σ , parameters to be estimated. Moreover, I assume that ξ_m and $\epsilon_{i\ell m}$ are independently distributed.

Using the estimates of ξ_m in (2.12), I estimate the parameters of interest, namely $\boldsymbol{\theta}_1 = (\boldsymbol{\beta}, \gamma)$ and $\boldsymbol{\theta}_2 = (\mu, \sigma^2)$, by maximizing the log-likelihood function

$$\ln L(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2 | \mathbf{X}) = \sum_{m=1}^M \mathcal{N}_m \sum_{\ell=1}^{\mathcal{L}_m} \delta_{\ell m} \ln(\widehat{p}_{\ell m}^*) - \frac{M}{2} (\ln(2\pi) + \ln(\sigma^2)) - \frac{1}{2\sigma^2} \sum_{m=1}^M (\widehat{\xi}_m - \mu)^2, \quad (2.13)$$

where $\delta_{\ell m}$ is the share of branches located in each census tract. I estimate the model using a sequential estimation procedure. I first estimate the conditional location probabilities, \mathbf{p}_m^* , for each ℓ in m by numerically solving the system of equations in (2.8) on market-by-market basis for its fixed points using the fixed-point algorithm. The solution for M systems of equations, each with \mathcal{L}_m equations, yields estimates of conditional location probabilities, $\widehat{\mathbf{p}}_m^*$. The obtained estimates of conditional branch location probabilities $\widehat{\mathbf{p}}_m^*$ are matched to the observed branch location pattern summarized by $\delta_{\ell m}$. The share of branches in each location is the ratio of the total number of branches in the census tract to the total number of branches in the market. I also use the estimated branch location probabilities to obtain an estimate of ξ_m as shown in (2.12). The likelihood function in (2.13) is maximized to obtain $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ using the BHHH optimization method of Berndt et al. (1974). Since the sequential estimation of (2.8) and (2.13) is generally associated with biased downward standard errors, I adjust the standard errors using the procedure proposed by White (1982). The future work intends to estimate (2.13) with the fixed-point algorithm nested into it in one step to avoid the loss of information.

For the empirical analysis, I set the number of distance bands $B = 2$ such that $b = 0, 1, 2$. Brevoort and Wolken (2009) find that a majority of banking services remained local during 2003, or within a median distance of five miles. According to the 2004 Survey of Consumer Finances data, the median distance between households and financial institutions is three miles one way for checking accounts. To remain conservative, I set $D_0 = 0.5$ miles and $D_1 = 5$ miles as the distance cutoffs, which results in the three distance bands described earlier. Specifically, the first distance band, b_0 , covers an area with a 0.5-mile radius around the census tract centroid, b_1 covers an area with a 5-mile radius around the census tract centroid excluding b_0 , and b_2 covers area beyond 5 miles around the census tract centroid. Thus, the nearest competitors are located within half a mile, the next closest competitors are located within half-mile and five miles, and most distant competitors are located beyond the five-mile distance band. Moreover, because location characteristics vary within markets, I do not impose any restrictions on competitive effects γ_b as is done by Seim (2006). In the next section, I describe the data and variables used in the analyses.

2.3 Data and Variables

I use the list of commercial bank MDIs from the 2008 Federal Deposit Insurance Corporation (FDIC) MDI historical data to identify MDI branches. The 2008 FDIC annual deposit data from the summary of deposits provide branch addresses for each branch that operated as of June 2008. I use address information to determine branch spatial positions. The summary of deposits data are used by regulators to measure the concentration of local banking markets. At the present time, these data are the best available source providing information about the geography of banks' business activities and are widely used by scholars and regulators. I geocode branch addresses using the ArcGIS Pro geographic information system software and census tract cartographic boundary files from the Census Bureau to obtain Federal Information Processing System codes associated with branch locations. MSA cartographic boundary files from the Census Bureau are used to identify Federal Information Processing System Metropolitan Area (Core-Based Statistical Area) codes for branches and other variables in each market.

Spatial positions of bank branches are meaningful for services that are obtained locally. Kwast et al. (1997) note that households and small businesses obtain their depository services such as checking and savings accounts from a local depository institution. Notably, the authors highlight that

depository services offered by banks are predominantly more local than credit services. Similarly, Bricker et al. (2012) report that 62.6 percent of families in 2010 selected their bank based on the location of the offices of a bank or the ability to obtain many services in one place. Therefore, I consider only full-service brick and mortar as well as full-service retail branch offices. I exclude limited-service administrative branches, limited-service drive-through branches, as well as mobile and seasonal branches that do not have specific, permanent geographic locations associated with them.¹³

The demand for in-person banking services from local branches varies with household income levels. Overall, the FDIC (2009) survey notes that households with higher incomes are more frequent users of banking services, implying higher demand for banking services in high-income versus low-income locations. However, Bell et al. (2009) show that high-income consumers report using online banking as their primary way of banking more frequently than low-income individuals. Their report shows that online banking is the main way of doing business for 42 percent of consumers with household income above the 80th percentile. In contrast, Bell et al. (2009) report that online banking is the main way of doing business for only three and thirteen percent of consumers with household incomes below the 20th percentile and between 21st–40th percentiles, respectively. At the same time, according to the FDIC (2009) survey, in 2009, about 20 percent of low-income households did not have a bank account, and about 24 percent of LMI households were underbanked, i.e., had a checking or savings account but relied on alternative financial services at least once a year. Underbanked and unbanked individuals are more likely to have an inadequate or poor credit history, as noted by Barr (2004), making it challenging to provide financial services to them. MDIs specialize in relationship banking and often have superior expertise in serving LMI communities relative to non-MDIs. Hence, it is plausible that census tracts classified as LMI communities are attractive to MDIs.¹⁴ Nevertheless, the attractiveness of LMI locations relative to other locations as part of joint entry-location decisions for MDIs is an open empirical question given the need of costly and time-consuming investments in relationship with the local communities and the challenges associated with serving LMI communities.

I use tract-level income classifications from the Federal Financial Institutions Examination

¹³Mobile 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.

¹⁴Other possible reasons for MDIs to prefer LMI locations include using specialization in serving LMI communities as a deterrence strategy against potential entrants and enhancing their comparative advantage through specialization, as noted in Chapter 1.

Council's (FFIEC) Census and Demographic Reports to investigate the attractiveness of LMI locations and to control for income levels across locations. The FFIEC data are used by regulators and reporting banks for the Home Mortgage Disclosure Act (HMDA) and the Community Reinvestment Act (CRA) regulation purposes. The HMDA and CRA regulations classify census tracts based on a census tract's median family income relative to their corresponding MSA median family income. Both regulations are concerned with the availability of financial services in LMI census tracts.¹⁵ The use of tract-level income classifications is also advantageous because it avoids the ambiguities associated with the comparison of nominal values of income levels (e.g., median tract income) across locations due to the varying costs of living.

I use population count information from the 2010 Census reports from ArcGIS/ESRI to proxy for demand level. Since locations are defined as the population-weighted centroids of census tracts, I assume that consumers and bank branches are located at the population-weighted centroid of their census tract.¹⁶ I use Euclidean buffers to measure population count within each distance band. Euclidean buffers measure distance on a two-dimensional Cartesian plane, and such buffers would appear as circles if drawn on a flat map. I use the Buffer Analysis tool, which uses data enrichment methodology creating a circle or polygon features with desired demographic information enclosed in each circle or a polygon.¹⁷

Finally, I include the number of non-MDI bank branches in each location to empirically investigate the intricate competitive effects of non-MDI's presence on the MDIs' profit in the same location. MDIs and non-MDIs target and serve different consumers in the same market giving rise to nuanced competitive interactions and behavior, which differ from that of among MDIs themselves. In particular, it is not appropriate to assume that best-response functions and, hence, beliefs among MDIs and non-MDIs are symmetric.¹⁸ The competitive interaction among MDIs and non-MDIs is further complicated by the policies in place and the asymmetric information between banks and consumers in the market.

On the one hand, the business stealing effect of the presence of a non-MDI branch negatively

¹⁵Table 2.1 provides detailed descriptions of variables included in the model.

¹⁶Seim (2006) makes similar assumption to discretize the concept of locations. Population-weighted centroids of census tracts data are available from ArcGIS/ESRI.

¹⁷The Buffer Analysis tool is available in ArcGIS Pro geographic information system software. Further details about the methodology used by the tool are available at ArcGIS/ESRI online references at <https://doc.arcgis.com/en/esri-demographics/reference/data-allocation-method.htm>.

¹⁸The future work intends to refine the present model to accommodate asymmetric beliefs in banks' entry and location decisions. See Corts (1998) and Stole (2007) for discussions about the differences in firm strategic behavior and economic implications in the setting where firms differ in their market segmentation resulting in asymmetric best-response functions. Their discussions are focused on third-degree price discrimination.

affects MDI's profit. This effect is likely exacerbated by the regulatory environment. For example, the CRA requires that MDIs and non-MDIs ascertain and meet the credit needs of the entire community in which these banks have a presence consistent with safe and sound operations.¹⁹ Despite the CRA's community development objective, Toussaint-Comeau and Newberger (2017) suggest that the CRA undermined the viability of smaller banks focused on serving LMI communities such as MDIs due to added competition prompted by the regulation.

On the other hand, the presence of a non-MDI branch may positively affect MDI's profit as a result of regulatory effort to promote collaboration among MDIs and non-MDIs or due to agglomeration effects. Regulators are actively promoting collaboration among MDIs and non-MDIs through the 1995 revisions to the CRA regulations.²⁰ Banks collaborating with specialized, mission-oriented banks such as MDIs may receive "CRA credit" for investments, grants, loans, technical assistance, or joint projects with MDIs. The new rules also encourage and offer CRA credit for the donation, sale on favorable terms, or provision of rent-free branches in a predominantly minority neighborhood to an MDI. Moreover, a nearby bank branch may help mitigate the information asymmetry between banks and consumers in that geographic location through a credit reporting system reducing the cost of information acquisition by banks.²¹ The ultimate effect of the presence of a non-MDI branch on MDI's profit depends on whether the business stealing effect dominates the cost-savings due to agglomeration economies and potential profits generated from the collaboration.

Table 2.2 presents descriptive statistics of the sample used for estimation. Given the objective of the paper, markets are selected conditional on MDI branch presence. The sample consists of 34 markets, with a total of 1,330 locations and 74 MDI branches. Of the 1,330 locations in the sample, 562 (42 percent) are LMI census tracts. The average market consists of 39 census tracts with nearly 17 LMI census tracts. The smallest market in the sample consists of four census tracts and the largest consists of 67 census tracts. The lowest count of LMI census tracts in a market is zero, and the highest is 38. On average, a market contains two MDI branches. The minimum number of MDI branches in a market is one, and the maximum is thirteen. The average population in a census tract is 4,577 residents. I estimate the model using the population count in each distance band ($Population_b \forall b = 0, 1, 2$), tract-level income classification (LMI), as well as MDI and non-MDI

¹⁹As noted by Thomas (1993), Macey and Miller (1993), Santiago et al. (1998), Barr (2005), and Lacker (1995), the CRA is inspired by redlining, decaying urban communities, and community disinvestment.

²⁰All changes are outlined in the CRA Regulations published in the Rules and Regulations (1995).

²¹Avery et al. (2003) provide an elaborate summary of credit reporting. They state that credit reporting companies receive the bulk of the data from "virtually all commercial banks, savings associations, and credit unions; from most finance companies; and from major retailers and many other businesses, such oil and gas companies."

branch location information.

2.4 Results

I estimate the model under two assumptions. Model 1 in Table 2.3 presents parameter estimates under the assumption that the number of potential entrants is twice the observed number of MDI branches in each market. Model 2 in Table 2.3 presents parameter estimates under the assumption that the number of potential entrants is 30 in each market. The results for both model specifications are overall qualitatively similar, though magnitudes for the estimated parameters and standard errors differ. A positive (negative) coefficient suggests that an increase in the corresponding variable positively (negatively) affects MDI's profit.

The estimates for competitive effects γ_b in each distance band $b \in \{0, 1, 2\}$ are negative in both models, as expected.²² The results reveal that an MDI's profit is negatively affected by the presence of rivalrous MDIs around its location. Importantly, the magnitudes of parameter estimates decline with distance, indicating that the competition effect dissipates with distance. The dissipating competition effect implies that more closely located rivals exert greater competitive pressure on MDI's profit relative to its distant rivals. In particular, the results suggest that an increase in the number of rivalrous MDI branches in the first distance band (or within 0.5 miles around an MDI's branch location) is about 64 to 66 percent stronger relative to an increase in the number of rivalrous MDI branches in the second distance band (within half to five miles around an MDI's branch location). Similarly, the negative effect on profit of an additional rival in the second distance band is about 27 to 59 percent stronger relative to an effect of an additional rival in the third distance band covering an area beyond five miles around MDI's branch location. Hence, increasing the number of rivals closest to MDI's own location has a greater negative effect on its profit than increasing the number of distant rivals, highlighting the importance of strategically selecting locations and accounting for rivals' behavior. The results also emphasize the relevance of spatial differentiation as a tool to avoid harsher competition.

The signs of the coefficient estimates for population count ($Population_b$) in each distance band $b \in \{0, 1, 2\}$ are positive in both models. Positive coefficients indicate that a larger local

²²The first distance band, b_0 , covers an area with a 0.5-mile radius around the census tract centroid, b_1 covers an area with a 5-mile radius around the census tract centroid excluding b_0 , and b_2 covers area beyond 5 miles around the census tract centroid, as noted earlier.

population positively affects MDIs' profits. The magnitudes of parameter estimates decline sharply with distance suggesting a greater positive effect on profits from populations closest to the branch. The results suggest that the positive effect on profit of an increase in population within 0.5 miles around an MDI's branch location is about 97 percent stronger relative to an effect of an increase in population within half to five miles around an MDI's branch location. Likewise, the positive effect on profit of an increase in population within half to five miles around an MDI's branch location is about 92 percent stronger relative to an increase in population in locations beyond five miles around MDI's branch location. Therefore, population size is another key determinant of spatial differentiation among MDIs. Moreover, the effect of population count $Population_b$ on the profit is counteracted by the competitive effects of γ_b in each distance band, confirming the trade-off faced by MDIs in choosing their locations.

The coefficient sign for LMI locations (LMI) is negative in both model specifications, suggesting that entering LMI locations is associated with a negative effect on an MDI's profit relative to locating in other locations. The result implies that regardless of MDI's specialization and comparative advantage in serving LMI communities, the challenges associated with serving LMI communities put downward pressure on the MDI's profit. As reported in the FDIC (2009) survey, LMI households are more likely to be unbanked or underbanked.²³ Barr (2004) argues that unbanked and underbanked are more likely to have problems with managing a bank account, lack, or have an insufficient credit history. Hence, providing banking services in LMI communities is often riskier and requires specialized financial products, such as bank accounts without overdraft capability. Moreover, as noted in Chapter 1, LMI communities are more vulnerable to economic downturns, imposing additional costs on banks operating in these communities. Hence, all else equal, the costs and challenges associated with operating in LMI communities reduce the attractiveness of LMI locations relative to other locations.

The coefficient estimates for *non-MDIs* are negative in both models implying that an additional non-MDI branch in MDI's location negatively affects MDI's profit. As noted earlier, the competitive effect of non-MDIs' presence depends on the interplay between the business stealing effect, agglomeration effect, and collaboration among MDIs and non-MDIs. The result suggests that the business stealing effect from the non-MDI's presence overcompensates any benefits that may be

²³Unbanked are individuals without a bank account. Underbanked are individuals with a checking or savings account that use alternative financial services at least once a year.

accruing from collaborative partnerships or potential cost savings due to agglomeration economies. Therefore, all else equal, the empirical evidence implies that sharing a location with a non-MDI is not desirable for an MDI, hence spatial differentiation is an important tool at MDI's disposal to shield itself from competition coming from non-MDIs. This finding also implies that regulatory effort to encourage collaboration among MDIs and non-MDIs to produce profitable lending and investment has limited effect.

The differing assumptions about the number of potential entrants in the two models are apparent for the parameter estimate of μ determining the mean of the distribution of the unobserved market-level demand characteristics, ξ_m . The parameter estimate for μ in Model 1 is positive and larger than the estimate in Model 2. The market-level demand characteristics ξ_m influence banks' entry decisions and reflect the attractiveness of entry relative to the outside option of no entry. Model 1 assumes that the number of potential entrants is twice the observed number of MDI branches in each market, implying that half of the potential entrants enter the market. In contrast, Model 2 assumes that the number of potential entrants is 30 in each market, implying that the share of actual entrants even in the market with the largest number of entrants is around 43 percent. Therefore, the lower estimate of μ reflects that entry is less attractive in the second model, given the smaller share of potential entrants entering the market. The parameter estimates of σ^2 determining the variance of the distribution of the unobserved market-level demand characteristics, ξ_m , are qualitatively similar in both models.

Altogether, these results reveal that MDIs' branching decisions involve a trade-off between favorable location-specific demand characteristics and competition. MDIs face a strong incentive to spatially differentiate from their MDI and non-MDI rivals. Although MDIs serve markets with a greater share of LMI census tracts relative to non-MDIs, I show that locating in LMI census tracts has a negative impact on MDI's profit. This empirical result provides evidence of MDIs' strategic behavior in choosing LMI locations to avoid the intense competition they would face in other locations. Though the promotion and preservation of MDIs are motivated by their assumed mission to serve consumers in LMI locations, my findings suggest that MDIs also consider competitive pressures when choosing their locations.

2.5 Conclusion

I study bank branching decisions with endogenous location choices and competition among commercial bank MDIs. MDIs specialize in serving poor communities and are strategically important for increasing access to financial services in LMI communities. I investigate MDIs' entry-location decisions using an incomplete-information game-theoretic model of entry and competition. In the model, MDIs' location decisions are formalized through a static two-stage entry-location game, such that locations within a market provide scope for differentiation as a tool to soften competition. MDIs' location choices endogenously depend on their rivals' location choices and the location-specific demand. This approach permits the explicit study of the trade-off between available demand and intensity of competition faced by MDIs, thus shedding light on the incentives underlying their branching and location decisions.

Using economic theory as the basis for structural estimation of MDIs' entry and location decisions, I show that that MDIs have incentives to spatially differentiate and distance plays an important role in softening competition from rivals but possibly at the cost of forgoing access to favorable demand characteristics. The results indicate that local demand characteristics such as population size and higher income positively affect MDIs' profits hence increasing the attractiveness of high demand locations. Conversely, all else equal, high-demand locations are attractive to many MDIs, suggesting that competition in such locations is likely to be more intense. I show that the presence of rivalrous MDIs, as well as non-MDIs, negatively affects MDIs' profits. Moreover, closer rivalrous MDIs have greater negative effects on MDIs' profits than distant rivals.

These results are consistent with theoretical predictions and provide evidence that MDIs are subject to the trade-off between available demand and the intensity of competition. The findings in this paper also highlight that the observed MDIs' preference to locate in LMI locations is likely driven by the strategic considerations to avoid the intense competition in other locations. Though policies directed to promoting and preserving MDIs' are inspired by MDIs' mission to serve LMI communities, the strategic considerations uncovered in this paper provide an additional explanation for their observed spatial positions.

The analysis of bank branching and location decisions contributes to the literature on entry, competition, and product differentiation among financial institutions. The empirical investigation of MDIs' entry-location behavior provides insights into the determinants of mission-oriented banks'

spatial positioning as well as the role of competition and local demand characteristics. Given MDIs' role in expanding financial services in LMI communities and policymakers' interest in promoting MDIs, knowledge about their branching behavior and the role of competition is informative for preservation strategies directed at MDIs and for policies concerned with spatial accessibility of banking services. From the policy perspective, the incentives motivating MDIs' desire to spatially differentiate discourage clustered allocation of branches within a market, thereby improving spatial accessibility through increased spatial variation of available branches for consumers. Concurrently, additional profitability afforded by spatial differentiation is beneficial for MDIs' viability.

The future investigation of MDIs' entry-location decisions aims to estimate the model using recent data. Employing recent data would serve as a robustness check for the present results and provide an opportunity to incorporate additional variables not available in the current sample. For example, utilization of daytime population information from ArcGIS/ESRI, consumer spending, and business density (including location information) data from the Clemson Center for Geospatial Technologies would become feasible for the analysis focusing on branches that operated in 2020. In the absence of zoning information, determining locations designated for residential use is challenging, and the use of residential population count may not appropriately reflect the available demand and attractiveness of some locations. Therefore, the use of daytime rather than residential population count would be a better proxy for available demand around bank branch locations. The future work also intends to expand the current analysis by allowing differential competitive effects among MDIs and non-MDIs by distance bands. Exploring the intensity of competitive effects among MDIs and non-MDIs by distance would yield additional insights about the incentives faced by MDIs to spatially differentiate. These insights would be informative for policies and strategies seeking to preserve and promote these mission-oriented banks.

Table 2.1: Variable Description

Variables Included in the Model	
<i>MDIs</i> (count)	The number of MDI bank branches in each census tract in a given market.
<i>Non-MDIs</i> (count)	The number of non-MDI bank branches in each census tract in a given market.
<i>Population₀</i>	Population count (thousands) of the total resident population within the first distance band. The first distance band is 0.5 miles around the census tract centroid.
<i>Population₁</i>	Population count (thousands) of the total resident population within the second distance band. The second distance band is between 0.5 and 5 miles around the census tract centroid.
<i>Population₂</i>	Population count (thousands) of the total resident population within the third distance band. The third distance band is between 5 miles around the census tract centroid to the market boundary.
LMI	Low- and moderate-income (LMI) census tracts. Census tracts are identified as low- or moderate-income at the tract level. If the tract median family income is >0 percent and <50 percent of the MSA median family income, then it is a low-income tract. If the 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.

Table 2.2: Descriptive Statistics

	Mean	Min	Max
Market Level			
Tracts (count)	39.12	4.000	67.000
LMI Tracts (count)	16.53	0.000	38.000
MDI Branches (count)	2.176	1.000	13.000
Non-MDI Branches (count)	1.103	0.000	18.000
By Distance Band			
$Population_0$ (000s)	4.577	0.010	15.629
$Population_1$ (000s)	117.310	0.000	308.170
$Population_2$ (000s)	91.030	0.000	290.950

Population in each distance band is defined as the population count of the total residents in thousands. Subscripts 0, 1, and 2 denote locations in the first, second, and third distance band, respectively. $Population_0$ is the population within 0.5 miles around the tract centroid. $Population_1$ is the population within 0.5 – 5 miles around tract centroid. $Population_2$ is the population within 5 miles around tract centroid to the market boundary).

Table 2.3: Parameter Estimates

	Model 1	Model 2
Competition Effects		
γ_0	-2.53537*** (0.12249)	-3.13416*** (0.08622)
γ_1	-0.90575*** (0.04650)	-1.06235*** (0.02329)
γ_2	-0.65943*** (0.08904)	-0.43458*** (0.08359)
Observed Demand Characteristics		
<i>Population</i> ₀ (000s)	0.14265*** (0.03490)	0.21955*** (0.02974)
<i>Population</i> ₁ (000s)	0.00398** (0.00126)	0.00487*** (0.00100)
<i>Population</i> ₂ (000s)	0.00027 (0.00122)	0.00040 (0.00114)
<i>LMI</i>	-1.71630*** (0.15582)	-1.83901*** (0.14894)
Other Controls		
<i>non-MDIs</i>	-1.85938*** (0.04265)	-2.33022*** (0.03637)
Unobserved Demand Characteristics		
μ	1.62092*** (0.01981)	-1.56713*** (0.11642)
σ^2	5.46274*** (0.02099)	6.96551*** (0.05461)
LLF	-2,994.8490	-2,999.2010
Total Markets (M)	34	34
Total Locations ($\sum_{m=1}^M \mathcal{L}_m$)	1,330	1,330
Total MDIs ($\sum_{m=1}^M \mathcal{N}_m$)	61	61

Standard errors (in parentheses) are calculated using White's (1982) robust "sandwich" estimator. Subscripts 0, 1, and 2 denote locations in the first, second, and third distance band, respectively. Population in each distance band is defined as the population count of the total residents in thousands. One, two, or three asterisks indicate significance at 0.1, 0.05, or 0.01, respectively.

Chapter 3

The Political Economy of Forgiving Student Loans

3.1 Introduction

For years student-loan debt has been a social and political topic of interest, with the rapid growth of student loans and defaults during the Great Recession leading some political leaders to propose forgiving student loans and making some higher education tuition-free (Minsky, 2019; Friedman, 2020; Mitchell, 2020).¹ For example, proposals by 2020 presidential candidates Senator Elizabeth Warren, Senator Bernie Sanders, and President Joe Biden suggest that student-loan debt repayment hinders the U.S. economy by placing a hurdle before individuals whose *ex post* earnings are below their *ex ante* expectations, particularly due to macroeconomic shocks. As stated on President Biden’s website:

“Almost one in ten Americans in their 40s and 50s still hold student loan debt. But, college debt has especially impacted Millennials who pursued educational opportunities during the height of the Great Recession and now struggle to pay down their student loans instead of buying a house, opening their own business, or setting money aside for retirement.”²

¹For example, under Joe Biden’s plan, families with an income below \$125,000 would not have to pay tuition at a public college or university. Senator Warren and Senator Sanders also proposed tuition-free public colleges and universities but under different conditions.

²Source: “The Biden Plan for Education Beyond High School”, <https://joebiden.com/beyondhs/#>

These proposals raise a question: what circumstances motivate the implementation of a student-loan debt forgiveness policy? In particular, the goal of this study is to understand when voters find student-loan debt forgiveness plan appealing and the circumstances that make its implementation more likely. This paper focuses on the federal student loans only. This differentiation is important for the purpose of loan cancellation for two main reasons: (i) the interest rate in the student-loan market is predetermined by the federal government and does not vary with the individual, and (ii) how the burden of debt cancellation is distributed importantly depends on who the lender is. In the student-loan market, the interest rate does not vary with the borrower and, therefore, does not reflect the idiosyncratic riskiness of the borrowers. Moreover, the fact that the lender is the federal government implies that debt cancellation has to be financed through some form of tax revenues.³

I propose a two-period insurance and schooling model with search costs to investigate this question. The proposed insurance and schooling model with search costs incorporates some features from the Persson and Tabellini (1996) risk-sharing model and some from the Ben-Porath (1967) schooling model. The model focuses on the individual's work and schooling behavior that takes place in the first period. Uncertainty and information problems are introduced to the labor market in the second period to study the behavior changes. Given that schooling increases the future wage rate, individuals face a trade-off between expected increased earnings and foregone earnings. It is assumed that individuals borrow to pay for schooling in the first period, therefore, accumulated debt decreases the expected future earnings.

To analyze the circumstances motivating the implementation of student-loan debt forgiveness, the model adds another layer to the decision-making process, where agents vote for their favorite policy. The voters face trade-offs in the two-dimensional policy space, where they decide on their favorite tax and debt-forgiveness policies.⁴ In the presence of search costs, student-loan debt forgiveness policy leads to more individuals investing in schooling, thus increasing aggregate income in the economy, which results in better financial protection against the risk of unemployment for schooled and unschooled (i.e., a higher consumption level in case of unemployment). However, debt forgiveness also leads to a higher tax burden on the employed, thus making it less attractive. In the equilibrium, under the assumption of a majority rule voting system, the policy set that is favored

³In the model I assume that cancellation of debt results in higher proportional taxes on income.

⁴Although debt cancellation comes in several forms, the model assumes that the entire debt accumulated by the borrower is forgiven.

by the median voter gets implemented.

The model predicts that as the median voter's prospect of employment improves, he prefers lower taxes and is not in favor of the debt-forgiveness policy. This result is hardly surprising since the increased probability of employment implies decreasing need for unemployment insurance (i.e., the unemployment transfer). The model also suggests that, *ceteris paribus*, the debt-forgiveness policy becomes more appealing as the average probability of employment in the economy decreases. This trend exists irrespective of which policy set is initially preferred by the median voter. Perhaps this finding is particularly interesting since it resembles the student-loan environment in the U.S., and it corresponds with the rationale of the proposed student loan forgiveness plans. It is documented in the literature that defaults on student loans rose sharply during the Great Recession, while student-loan debt continued increasing, unlike other forms of debt (Dynarski, 2015; Lochner and Monge-Naranjo, 2015). This prompted policy responses such as interest rate reduction, some forms of student loan forgiveness, and flexible repayment plans (Dynarski, 2015).

These findings also explain the most recent policies that were implemented in response to increased uncertainty in the labor market due to the COVID-19 pandemic. The Coronavirus Aid, Relief, and Economic Security Act (CARES Act) that was passed in March 2020 includes the student-loan debt relief plan. Under this temporary student-loan relief plan, loan payments were suspended, collections on defaulted loans stopped, and interest rates were set to 0 percent.⁵

3.2 Background

Student loan debt differs from other forms of debt in two major aspects. First, a student loan is unsecured, meaning the borrower provides no collateral. Consequently, student loans are riskier than secured debt, resulting in fewer privately issued student loans. This is one of the justifications for governments to lend money to students seeking higher education degrees (Dynarski, 2015).

Second, in 2005 all student-loan debt was made nondischargeable with some exceptions (Pottow, 2006), meaning they cannot be eliminated through bankruptcy.⁶ The inability to discharge student debt deteriorates borrowers' insurance against negative economic shocks, and it may deter individuals from borrowing for schooling. Conversely, dischargeable student-loan debt could lead to alternative problems such as a higher risk of default, higher interest rates, and even possible exclusion

⁵The U.S. Department of Education, www.studentaid.gov.

⁶One exception includes undue hardship, the burden of demonstrating which the student bears (Pottow, 2006).

of future borrowers from the loan market. My model assumes student loans are nondischargeable, so all students must repay their debt. The reason for this assumption is twofold. First, it reflects the current environment of student loans. Second, the assumption of nondischargeable student loans implies there is no arbitrage opportunity for students with high levels of student loan debt, low assets and savings, and high expected earnings.⁷

Besides these peculiarities, individuals take out student loans to invest in their human capital to increase expected future earnings. In addition to private benefits, investments in human capital enhance society's welfare by increasing aggregate taxable income. Higher aggregate income permits enhanced public unemployment insurance. However, uncertainties and information problems in the labor market may restrict these benefits by influencing individuals' schooling-labor decisions in distinctive ways. Therefore, to study the effect of each, the model incorporates labor-market uncertainties and information problems.

I conjecture that as the prevalence of macroeconomic shocks increases, individuals with a high probability of unemployment favor student-loan debt forgiveness policy irrespective of their schooling status. Uncertainties in the labor market, such as macroeconomic downturns, affect schooling decisions through decreasing future expected earnings. Because schooling decisions are made taking these exogenous employment shocks as given, some individuals may forgo schooling as their employment prospects worsen. A student-loan debt forgiveness policy could improve unemployment insurance for unemployed individuals by encouraging more individuals to invest in schooling, thus increasing aggregate taxable income in the economy. However, labor-market uncertainties alone cannot explain if more individuals would invest in schooling when student loans are forgiven. In particular, an economy with a higher unemployment rate requires a higher tax rate to pay for unemployment insurance. These higher tax rates may encourage some individuals to forgo schooling.

The model also includes search costs to enrich the set of incentives faced by individuals. The effect of information problems in the labor market on schooling decisions differs from uncertainties in two ways. First, all individuals must engage in search of employment before their employment status is known. Therefore, search costs are sunk costs that decrease the future earnings of all individuals regardless of their employment and schooling status. Second, individuals can decrease

⁷Discharging the student loan debt becomes very tempting once the degree is attained since, upon graduating, a typical student has little to no assets and savings, meaning that there is not much to lose. The option to file for bankruptcy is perhaps even more compelling for a graduate with large debt and large potential earnings. In such situations, bankruptcy nondischargeability presents an opportunity for the student to "get rid" of the loan and enjoy the higher earnings without the need to make payments.

their search costs through schooling. For example, Stigler (1962, p.94) explains, “If he is an unskilled or a semi-skilled worker, the number of potential employers is strictly in the millions. Even if he has the specialized training, the number of potential employers will be in the thousands...” Therefore, uncertainties and information problems affect schooling-labor decisions through different channels.

Finally, the debt-forgiveness policy in the model refers to the cancellation of the entire student-loan debt held by individuals and entails the provision of publicly funded higher education. Generally, debt cancellation comes in several forms. Canceling the entire or part of the debt and stopping or slowing the accumulation of debt are considered debt cancellations. Moreover, forgiving student loans necessitates addressing the question of who pays for higher education? This question intimately relates to the way the debt cancellation policy is funded. The model assumes that the debt-forgiveness policy is financed through income tax revenues, therefore, it follows that higher education is publicly funded. This setting of the model conforms with the student-loan forgiveness proposals by 2020 presidential candidates.

3.3 Economic Model

In this section, I present the economic model. I begin by setting the stage and introducing notation for the economic model to study labor-schooling decisions. Section 3.4 describes the political model, which adds another layer to the decision-making process, taking the economic model as given. This approach enables the analysis of voter behavior and its determinants. In Section 3.5, I describe the policy equilibrium and discuss findings under alternative debt cancellation policies.

3.3.1 Economic Model Set-up

Consider a continuum of \mathcal{N} agents living in an economy that lasts for two periods, $t \in \{1, 2\}$. In each period t , each agent allocates 1 unit of time between labor (L_t) and schooling ($1 - L_t$). An agent with H_t units of human capital earns $H_t L_t$ that finances current consumption. Schooling increases future human capital, and hence future wages. All agents begin with H_1 units. To simplify the algebra, I assume that $L_1 \in \{\frac{1}{2}, 1\}$. Individuals pay for schooling by accumulating debt d per unit of schooling ($1 - L_1$). Student loans are offered through government at fixed and predetermined interest rate that does not vary with the borrower. For added simplicity and without

loss of generality, I assume that all students face the same interest rate of zero percent.⁸ The wage rate earned by individuals at $t = 2$ is $w_2 = H_1 + \alpha H_1^\gamma (1 - L_1) \forall L_1 \in \{\frac{1}{2}, 1\}$, where $\alpha, \gamma \in (0, 1)$ and $H_1 > 0$. The parameter α captures the ability effect of the individual and parameter γ captures the effect due to forgone earnings. Individuals face uncertainty in the second period. Specifically, an agent i is employed at $t = 2$ with probability $p^i \in (0, 1)$ and unemployed with probability $1 - p^i$, where $p^i \sim F(\cdot)$ such that $F(\cdot)$ is a left-skewed distribution with mean \bar{p} and median p^m (i.e., $\bar{p} < p^m$). Moreover, the second-period income is taxed at rate $\tau \in [0, 1]$ and each unemployed individual receives a lump-sum transfer T .

Moreover, in the second period, all agents must engage in search activity for employment before the employment status of an agent is realized (i.e., before the agent knows if he is employed or unemployed). However, agents are still aware of their probability of employment, p^i , as noted earlier. The schooling dependent search cost function is described by

$$\lambda = a - b(1 - L_1), \quad (3.1)$$

where a and b are constants such that $a, b \in (0, 1)$. Notice that $\frac{\partial \lambda}{\partial L_1} > 0$ and $\frac{\partial \lambda}{\partial (1-L_1)} < 0$, i.e., cost of search decreases with the amount of schooling. This assumption can be interpreted as search costs being lower due to schooling, specialized skill, or ability. Note, because all individuals engage in search before they know if they will be unemployed, λ is a fixed (or sunk) cost. Because the focus of this paper is the student-loan debt forgiveness policy, the decision about the amount of search for agents is not considered, and it is taken as given instead.⁹

Individuals share the same utility function, though the individual's expected utility is unique to him. Let c_1, c_2 be consumption in $t = 1$ and $t = 2$, respectively. The preferences are given by $U(c_1, c_2)$ such that $U'(\cdot) > 0$ and $U''(\cdot) < 0$ (i.e., individuals are risk-averse). Specifically, I assume that $U(c_1, c_2) = \ln c_1 + \ln c_2$. This functional form of utility assumes that each period utility is additively separable and there is no discounting.

Next, I define an individual's budget constraints. Let d be debt borrowed per unit of

⁸As noted earlier, the interest rate in the federal student loan market is predetermined by the federal government and does *not* vary with the individual. Therefore, assumption of zero percent is chosen to simplify the analysis, but does not affect its validity.

⁹Stigler (1962, 1961) provides examples and a clear explanation of the search decision process.

schooling and f be the price per unit of schooling. Define an indicator function

$$\mathbb{I}(D) = \begin{cases} 1 & \text{if } D = \text{forgive all debt} \\ 0 & \text{if } D = \text{do not forgive.} \end{cases}$$

Then individual's budget constraints are given by,

$$\begin{aligned} c_1 &= w_1 L_1 - (f - d)(1 - L_1), \\ c_2^e &= (1 - \tau)w_2 L_2 - d(1 - L_1)(1 - \mathbb{I}(D)) - \lambda, \text{ with probability } p^i \\ c_2^u &= T - d(1 - L_1)(1 - \mathbb{I}(D)) - \lambda, \text{ with probability } (1 - p^i), \end{aligned}$$

where c_2^e and c_2^u are the consumption levels at $t = 2$ when agent is employed and unemployed, respectively.

3.3.2 Individual's Problem

Combining the information for the economic model, the individual's problem can be described by

$$\max_{c_1, c_2^e, c_2^u} U^i(c_1, c_2^e, c_2^u) = \ln c_1 + p^i \ln c_2^e + (1 - p^i) \ln c_2^u \quad (3.2)$$

subject to the constraints

$$\begin{aligned} c_1 &= w_1 L_1 - (f - d)(1 - L_1), \\ c_2^e &= (1 - \tau)w_2 L_2 - d(1 - L_1)(1 - \mathbb{I}(D)) - \lambda \\ c_2^u &= T - d(1 - L_1)(1 - \mathbb{I}(D)) - \lambda. \end{aligned} \quad (3.3)$$

I assume $f = d$ for simplicity. Then, an individual invests in schooling if his expected utility with schooling exceeds his utility without schooling, $U^{\text{schooling}} \geq U^{\text{no schooling}}$, under both debt-forgiveness policies. Also, notice that in the second period, the agents dedicate the entire unit of time to labor ($L_2 = 1$) because there is no incentive to invest in schooling.

Then, an agent invests in schooling in the first period if

$$\begin{aligned} \ln(c_1|L_1 = \frac{1}{2}) + p^i \ln(c_2^e|L_1 = \frac{1}{2}) + (1 - p^i) \ln(c_2^u|L_1 = \frac{1}{2}) &\geq \\ \ln(c_1|L_1 = 1) + p^i \ln(c_2^e|L_1 = 1) + (1 - p^i) \ln(c_2^u|L_1 = 1). \end{aligned} \quad (3.4)$$

Solving (3.4) for p_i yields

$$p^i \geq \ln \left(\frac{(T-a)[2((1-\tau)H_1-a) - (1-\tau)\alpha H_1^\gamma + d(1-\mathbb{I}(D)) - b]}{[(1-\tau)H_1-a][2(T-a) + b - d(1-\mathbb{I}(D))]} \right). \quad (3.5)$$

When the debt is forgiven, solving for the optimal labor choice in the first period yields

$$L_1^1 = \begin{cases} \frac{1}{2} & \text{for } \mathbb{I}(D) = 1 \text{ and } p^i \geq \phi_1(\tau, T) \\ 1 & \text{for } \mathbb{I}(D) = 1 \text{ and } p^i < \phi_1(\tau, T), \end{cases} \quad (3.6)$$

where $\phi_1(\tau, T) = \ln \left(\frac{(T-a)[2((1-\tau)H_1-a) - (1-\tau)\alpha H_1^\gamma - b]}{[(1-\tau)H_1-a][2(T-a) + b]} \right)$. Numerical investigations of ϕ_1 indicate that it tends to be very small and can take negative values. In rare cases, it can be positive and large, especially for high tax rates. This implies that when debt is forgiven, it is optimal for individuals to invest in schooling. This result is not surprising given the sunk search costs. Since schooling lowers search costs, the debt-forgiveness policy encourages more individuals to invest in schooling.

Similarly, when debt is not forgiven, the optimal labor choice in the first period is

$$L_1^2 = \begin{cases} \frac{1}{2} & \text{for } \mathbb{I}(D) = 0 \text{ and } p^i \geq \phi_2(\tau, T) \\ 1 & \text{for } \mathbb{I}(D) = 0 \text{ and } p^i < \phi_2(\tau, T) \end{cases} \quad (3.7)$$

where $\phi_2(\tau, T) = \ln \left(\frac{(T-a)[2((1-\tau)H_1-a) - (1-\tau)\alpha H_1^\gamma + d - b]}{[(1-\tau)H_1-a][2(T-a) + b - d]} \right)$. Numerical investigations of ϕ_2 indicate that ϕ_2 varies considerably more than ϕ_1 and is between zero and one. In general, larger taxes were associated with large values of ϕ_2 . Thus, when debt is not forgiven and when tax rates are large, the individuals choose not to invest in schooling.

3.4 Political Model

3.4.1 Political Model Set-up

To study the political decisions of the hypothetical economy described above, I define the political model, taking the economic model as given. In particular, the voters in this model are the same individuals as in the economic model. The voters vote for their favorite policy set that consists of (i) a proportional tax $\tau \in [0, 1]$ on second-period income, (ii) a targeted transfer T to unemployed in the

second period, and (iii) a student-loan debt forgiveness policy $D \in \{\text{forgive all debt, do not forgive}\}$. The voting takes place in the first period, at which time there is uncertainty about second-period employment. The voter knows his individual probability of employment in the second period, p^i , and $F(\cdot)$. The policy set is chosen according to pure democracy rule in a direct democracy setting. I assume that voting is sincere, i.e., an agent i votes for policy a over a' whenever $a \succ a'$. All three policies are chosen at $t = 1$.

In addition, taking individual preferences as given, the voter's preferences are described by an expected utility function

$$V^i(\tau, D) = U(\tau; L_1) + p_i U(\tau; L_1) + (1 - p_i) \tilde{U}(\tau).$$

Let $\delta_n^{\mathbb{I}(D)}$ be a fraction of unschooled population, $\delta_s^{\mathbb{I}(D)}$ be a fraction of schooled population, $\bar{p}_n^{\mathbb{I}(D)}$ and $\bar{p}_s^{\mathbb{I}(D)}$ be average probability of being employed for unschooled and schooled populations, respectively.

Then government budget constraint is given by

$$(1 - \bar{p})T + \delta_s^{\mathbb{I}(D)} \frac{d}{2} \mathbb{I}(D) = \tau \left[\bar{p}_n^{\mathbb{I}(D)} \delta_n^{\mathbb{I}(D)} H_1 + \bar{p}_s^{\mathbb{I}(D)} \delta_s^{\mathbb{I}(D)} \left(H_1 + \frac{\alpha H_1^\gamma}{2} \right) \right] L_2$$

where $\delta_n^{\mathbb{I}(D)} + \delta_s^{\mathbb{I}(D)} = 1$ and $\bar{p} = \bar{p}_n^{\mathbb{I}(D)} \delta_n^{\mathbb{I}(D)} + \bar{p}_s^{\mathbb{I}(D)} \delta_s^{\mathbb{I}(D)}$. There is an important point that is due at this point. Notice that the average probability of employment differ not only within population based on the agent's schooling status, but also across student-loan debt forgiveness policies.

Given the optimal labor choice L_1^* in (3.6) and (3.7), voter's problem is to choose optimal policies that maximize voter's utility

$$\begin{aligned} \max_{\tau, D, T} V^i(\tau) &= \ln [H_1 L_1^*] + p^i \ln [(1 - \tau)[H_1 + \alpha H_1^\gamma (1 - L_1^*)] L_2 - d(1 - L_1^*)(1 - \mathbb{I}(D)) - (a - b(1 - L_1^*))] \\ &\quad + (1 - p^i) \ln [T - d(1 - L_1^*)(1 - \mathbb{I}(D)) - (a - b(1 - L_1^*))] \end{aligned} \quad (3.8)$$

subject to the government budget constraint

$$(1 - \bar{p})T + \delta_s^{\mathbb{I}(D)} \frac{d}{2} \mathbb{I}(D) = \tau \left[\bar{p}_n^{\mathbb{I}(D)} \delta_n^{\mathbb{I}(D)} H_1 + \bar{p}_s^{\mathbb{I}(D)} \delta_s^{\mathbb{I}(D)} \left(H_1 + \frac{\alpha H_1^\gamma}{2} \right) \right] L_2. \quad (3.9)$$

The voter's problem is solved for the two cases noted earlier: (i) when all debt is forgiven (i.e., $\mathbb{I}(D) = 1$) and (ii) when debt is not forgiven (i.e., $\mathbb{I}(D) = 0$).

3.4.2 Voter's Favorite Tax when Student Loans are Forgiven

Under the student loan forgiveness policy ($\mathbb{I}(D) = 1$) the optimal labor choice is given by (3.6) and the government budget constraint can be written as

$$T = \frac{1}{(1-\bar{p})} \tau \left[\bar{p}_n^1 \delta_n^1 H_1 + \bar{p}_s^1 \delta_s^1 \left(H_1 + \frac{\alpha H_1^\gamma}{2} \right) \right] - \frac{1}{(1-\bar{p})} \frac{\delta_s^1}{2} d. \quad (3.10)$$

Using the budget constraint in (3.10), the voter's problem can be written as an unconstrained optimization problem given by

$$\begin{aligned} \max_{\tau} V^i(\tau) = & \ln[H_1 L_1] + p^i \ln[(1-\tau)[H_1 + \alpha H_1^\gamma(1-L_1^*)] - (a - b(1-L_1^*))] \\ & + (1-p^i) \ln \left[\frac{1}{(1-\bar{p})} \tau \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right] - \frac{1}{(1-\bar{p})} \frac{\delta_s^1}{2} d - (a - b(1-L_1^*)) \right]. \end{aligned} \quad (3.11)$$

Solving (3.11) for voter's optimal tax rate yields

$$\tau_1^* = (1-p^i) + \frac{p^i \delta_s^1 d}{2 \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} + \left[\frac{p^i(1-\bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1-p^i)}{w_2(L_1^*)} \right] \lambda(L_1^*), \quad (3.12)$$

where $w_2(L_1^*) = H_1 + \alpha H_1^\gamma(1-L_1^*)$ and $\lambda(L_1^*) = a - b(1-L_1^*)$. Notice, the components of τ_1^* can be thought of as follows

$$\tau_1^* = \underbrace{(1-p^i)}_{\text{insurance}} + \underbrace{\frac{p^i \delta_s^1 d}{2 \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]}}_{\text{tax burden due to debt forgiveness}} + \underbrace{\left[\frac{p^i(1-\bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1-p^i)}{w_2(L_1^*)} \right]}_{\text{tax burden due to search costs}} \lambda(L_1^*),$$

where the insurance component is decreasing in p^i , the tax burden due to the debt-forgiveness policy is increasing in p^i , and the tax burden due to search costs is increasing as search costs increase. The intuition of each component is presented below.

Insurance. The unemployment insurance policy component is negatively correlated with the agent's probability of employment. This result is expected since an agent prefers less insurance as his probability of employment increases. On the other hand, an individual who is more likely to be unemployed prefers more unemployment insurance.

Debt Forgiveness. The debt-forgiveness policy is positively correlated with the agent's probability of employment. This component elucidates a trade-off between the debt-forgiveness

policy and the unemployment insurance faced by the agents. Specifically, as an agent's probability of employment decreases, he prefers to have larger unemployment transfers and less debt-forgiveness. In other words, an agent with a greater probability of being unemployed would prefer to have a larger share of the tax to be allocated to unemployment insurance rather than the debt-forgiveness policy.

Search Costs. Higher search costs increase the burden of tax because as search costs increase, more agents become unemployed. Consequently, all else equal, as the number of employed individuals in the economy falls, the total taxable income falls as well. As a result, the tax rate must increase to finance unemployment insurance and the debt-forgiveness policy.

In addition, notice that the optimal tax rate for agent i varies with the idiosyncratic probability of employment p_i as well as with schooling. Therefore, schooled agent with the same probability of employment as the unschooled agent has different "favorite" tax rates τ_1^* .

3.4.3 Voter's Favorite Tax when Student Loans are Not Forgiven

The optimal labor choice when the student loan forgiveness policy is not implemented ($\mathbb{I}(D) = 0$) is given by (3.7) and the government budget constraint can be written as

$$T = \frac{1}{(1-\bar{p})} \tau \left[\bar{p}_n^0 \delta_n^0 H_1 + \bar{p}_s^0 \delta_s^0 \left(H_1 + \frac{\alpha H_1^\gamma}{2} \right) \right]. \quad (3.13)$$

Using the budget constraint in (3.13), the voter's problem can be written as an unconstrained optimization problem given by

$$\begin{aligned} \max_{\tau} V^i(\tau) &= \ln [H_1 L_1] + p^i \ln [(1-\tau)[H_1 + \alpha H_1^\gamma (1-L_1^*)] - d(1-L_1^*) - (a-b(1-L_1^*))] \\ &+ (1-p^i) \ln \left[\frac{1}{(1-\bar{p})} \tau \left[\bar{p} H_1 + \bar{p}_s^0 \delta_s^0 \frac{\alpha H_1^\gamma}{2} \right] - d(1-L_1^*) - (a-b(1-L_1^*)) \right]. \end{aligned} \quad (3.14)$$

Solving (3.14) for the optimal tax rate τ under no student-loan debt forgiveness policy yields

$$\tau_2^* = (1-p^i) + \left[\frac{p^i(1-\bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1-p^i)}{w_2(L_1^*)} \right] (1-L_1^*)d + \left[\frac{p^i(1-\bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1-p^i)}{w_2(L_1^*)} \right] \lambda(L_1^*),$$

where $w_2(L_1^*) = H_1 + \alpha H_1^\gamma (1-L_1^*)$ and $\lambda(L_1^*) = a - b(1-L_1^*)$. Notice, the components of τ_2^* can

be thought of as follows

$$\tau_2^* = \underbrace{(1 - p^i)}_{\text{insurance}} + \underbrace{\left[\frac{p^i(1 - \bar{p})}{\left[\bar{p}H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1 - p^i)}{w_2(L_1^*)} \right]}_{\text{tax burden due to debt forgiveness}} (1 - L_1^*)d + \underbrace{\left[\frac{p^i(1 - \bar{p})}{\left[\bar{p}H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1 - p^i)}{w_2(L_1^*)} \right]}_{\text{tax burden due to search costs}} \lambda(L_1^*),$$

where the insurance component is decreasing in p^i because an agent “likes” less insurance as the probability of employment increases, the tax burden due to student loan debt is increasing in the amount of schooling, and the tax burden due to search costs is increasing as search costs increase (or as schooling decreases). The first and last components of τ_2^* remain unchanged. Since the interpretation of the first and last components is unchanged, I omit them here.

Debt Forgiveness. The tax burden due to debt component varies with schooling. Schooled voter prefers higher tax rate than unschooled voter. The schooled voter, if unemployed, will have a lower consumption level in the second period due to his student-loan debt that must be repaid. Therefore, schooled voter’s preference for higher tax rate suggests that schooled individuals factor their debt burden into their favorite tax rate.

Finally, it is worth noting that optimal tax rate (τ_2^*) for agent i varies more relative to τ_1^* . In other words, the optimal taxes for agents in the population is more dispersed when debt is not forgiven. The dispersion of the optimal tax rates stems from (i) idiosyncratic probability of unemployment, (ii) debt burden due to schooling, and (iii) search costs.

3.5 Policy Equilibrium

The assumed functional form for the preferences of individuals in the economy satisfies the single-peakedness assumption. Therefore, individuals can be ordered according to the order of their favorite policy, and the unique Condorcet winning policy set among voters exists based on the median voter theorem. However, the outcome of the policy depends on the distribution of the probability p^i .

The following definition of the policy equilibrium is largely borrowed from Persson and Tabellini (1996).

Definition 1 *Let a feasible policy be a nonnegative vector $a \equiv [\tau, T, D]$ that satisfies the government budget constraint in (3.9). Then, a political equilibrium under direct democracy is a feasible policy*

that cannot be beaten by any other policy proposal a' under majority rule.

Moreover, Persson and Tabellini (1996) show that the equilibrium policy a maximizes the expected utility of the voter with the p^m , the median probability of being employed.

Given that the median voter is an agent with a probability of employment p^m , to determine the conditions under which certain policy set gets implemented, I compare utility of the median voter when debt is forgiven to when it is not forgiven (i.e., determine whether $U(c_1, c_2^e, c_2^y | \tau_1, T_1, \mathbb{I}(D) = 1) - U(c_1, c_2^e, c_2^y | \tau_2, T_2, \mathbb{I}(D) = 0) \gtrless 0$). Note, the investigations of ϕ_1 implied mostly negative values for ϕ_1 under the debt-forgiveness policy. This simplifies the analysis of the policy equilibrium to two cases described below, such that the tax policy is determined by the median voter.

I investigate the changes in $U(\cdot | \tau_1^m, T_1^m, \mathbb{I}(D) = 1) - U(\cdot | \tau_2^m, T_2^m, \mathbb{I}(D) = 0)$ numerically by assuming some values for the parameters and variables in the model. According to Berman and Zehngbot (2017), a student working part-time at a minimum-wage salary would be able to cover 68.2 percent of the cost for University of Central Florida in 2016. Using this information, it means that if $d = 1$ then $w_1 = H_1 = 0.68$. Therefore, I let $\alpha = 0.65$, $\gamma = 1$, $H_1 = 0.68$, and $d = 1$. Moreover, Torpey (2018) reported an unemployment rate among bachelors degree graduates at about 2.5 percent in 2017 in the U.S. Moreover, according to April 2020 BLS Economic News Release, about 66.2 percent of high-school graduates enrolled in College in 2019. Hence, I set $\bar{p}_s^1 = 0.97$, $\delta_s^1 = 0.67$, $\bar{p}_s^0 = 0.975$, and $\delta_s^0 = 0.5$. Moreover, the changes in $U(\cdot | \tau_1^m, T_1^m, \mathbb{I}(D) = 1) - U(\cdot | \tau_2^m, T_2^m, \mathbb{I}(D) = 0)$ due changes in p^m and \bar{p} , were examined for $\bar{p} = 0.98, 0.96, 0.94$, and 0.90 .

3.5.1 Schooled Median Voter Under Both Debt-Forgiveness Policies

Given some probability p^m such that $p^m \in [\phi_2, 1)$, the median voter is schooled under both debt-forgiveness policies. Thus the median voter's favorite tax policies are given by

$$\tau_1^m = (1 - p^m) + \frac{p^m \delta_s^1 d}{2 \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} + \left[\frac{p^m (1 - \bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1 - p^m)}{w_2(L_1^*)} \right] \lambda(L_1^*),$$

when debt is forgiven and by

$$\tau_2^m = (1 - p^m) + \left[\frac{p^m (1 - \bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1 - p^m)}{w_2(L_1^*)} \right] (1 - L_1^*) d + \left[\frac{p^m (1 - \bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1 - p^m)}{w_2(L_1^*)} \right] \lambda(L_1^*),$$

when debt is not forgiven. To determine whether τ_1^m or τ_2^m gets implemented, I compare utilities obtained under each policy, i.e., compare $U(\cdot|\tau_1^m, T_1^m, \mathbb{I}(D) = 1)$ to $U(\cdot|\tau_2^m, T_2^m, \mathbb{I}(D) = 0)$. The tax rate τ_1^m is implemented if

$$U(\cdot|\tau_1^m, T_1^m, \mathbb{I}(D) = 1) \geq U(\cdot|\tau_2^m, T_2^m, \mathbb{I}(D) = 0), \quad (3.15)$$

and tax rate τ_2^m is implemented if condition in (3.15) is not satisfied.

Using the assumed values described above, I investigate the condition in (3.15) graphically. The results are presented in Figure 3.1. According to the Figure 3.1, the median voter's unambiguously prefers τ_1^m, T_1^m , and to forgive student loans. All else equal, the policy set becomes less attractive as the median voter's probability of employment increases, although the effect is weak.

In addition, all else equal, as the average probability of employment in the economy decreases, the model suggests that the student-loan debt forgiveness policy becomes more attractive than the alternative policy. In other words, implementation of the student-loan debt forgiveness policy is more likely when there are greater uncertainties in the labor market. Interestingly, this prediction of the model offers an explanation for the oscillating notice paid to the student-loan debt in the U.S. For example, the interest and concerns about student loan debt was particularly heightened around the Great recession and 2020, at the beginning of the pandemic. Both of these time periods had a common feature — greater uncertainty in the labor market.

Research indicates that during the Great Recession, defaults on student loans rose sharply while student loan debt continued increasing (Dynarski, 2015; Lochner and Monge-Naranjo, 2015). These trends combined with the high unemployment rate and the uncertainty in the labor market prompted policy responses, such as interest rate reductions, some form of student-loan debt forgiveness, and flexible repayment plans (Dynarski, 2015). Indeed, Lechner and Monge-Naranjo (2015) suggest that the Great Recession was the onset of increased concern about the levels of student-loan debt, which was exacerbated by increased uncertainty in the labor market.

Similarly, in 2020, the increased uncertainty in the labor market due to the COVID-19 pandemic led to CARES Act which includes the student-loan debt relief plan (Friedman, 2020). In addition, the New York Representative Carolyn Maloney introduced Student Loan Forgiveness for Frontline Health Workers Act. Under the act, the federal and private student-loan debt is forgiven

for certain COVID-19 frontline health care workers.¹⁰ Therefore, the proposed model can predict these observations and, more importantly, provides an explanation to the questions (i) when do voters find student-loan debt forgiveness policy appealing, and (ii) under which circumstances are the implementation of the student loan debt-forgiveness policy more likely?

3.5.2 Schooled vs. Unschooled Median Voter

Given some probability p^m such that $p^m \in (0, \phi_2,)$, the median voter is schooled when debt is forgiven and unschooled when debt is not forgiven. Thus the median voter's favorite tax policy when debt is forgiven is given by

$$\tau_1^m = (1 - p^m) + \frac{p^m \delta_s^1 d}{2 [\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2}]} + \left[\frac{p^m (1 - \bar{p})}{[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2}]} - \frac{(1 - p^m)}{w_2(L_1^*)} \right] \lambda(L_1^*),$$

when debt is forgiven and by

$$\tau_2^m = (1 - p^m) + \left[\frac{p^m (1 - \bar{p})}{[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2}]} - \frac{(1 - p^m)}{w_2(L_1^*)} \right] (1 - L_1^*) d + \left[\frac{p^m (1 - \bar{p})}{[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2}]} - \frac{(1 - p^m)}{w_2(L_1^*)} \right] \lambda(L_1^*),$$

when debt is not forgiven. To determine whether τ_1^m or τ_2^m is implemented, I compare utilities obtained under each policy, i.e., compare $U(\cdot | \tau_1^m, T_1^m, \mathbb{I}(D) = 1)$ versus $U(\cdot | \tau_2^m, T_2^m, \mathbb{I}(D) = 0)$. The tax rate τ_1^m is implemented if

$$U(\cdot | \tau_1^m, T_1^m, \mathbb{I}(D) = 1) \geq U(\cdot | \tau_2^m, T_2^m, \mathbb{I}(D) = 0), \quad (3.16)$$

and the tax rate τ_2^m is implemented if condition in (3.16) is not satisfied.

As before, I investigate the difference in the utilities numerically. The results are presented in Figure 3.2. The figure suggests that the median voter prefers τ_2^m , T_2^m , and no debt forgiveness policy set for the given parameter values. All else equal, the policy set becomes less attractive as the median voter's probability of employment decreases.

¹⁰See H.R.2418 — Student Loan Forgiveness for Frontline Health Workers Act at www.congress.gov.

3.6 Conclusion

This paper introduces a two-period insurance and schooling model to explain what circumstances motivate the implementation of student-loan debt forgiveness policies. One of the primary implications of the model is that the average probability of employment in the economy is an important determinant of voters' attitude toward debt-forgiveness policy. Particularly, all else equal, the debt-forgiveness policy becomes more attractive as the average probability of employment in the economy falls. This effect due to uncertainty conforms to the conjectures that the Great Recession is the origin of concerns about the levels of student-loan debt. Indeed, these concerns resulted in programs such as the Income-Based Repayment plan, under which a portion of the debt is forgiven.¹¹ This implication also proposes an explanation to a heightened interest in the student-loan debt and higher education topics on the social media, in particular during the Great Recession and the pandemic.

The analysis of individuals' labor-schooling decisions in Section ?? implies that sunk search costs induce more individuals to pursue higher-education degrees under the debt-forgiveness policy. All else equal, when search costs are unavoidable and could be reduced through schooling, more individuals find it optimal to invest in schooling if student loans are forgiven. This suggests student loan forgiveness accompanied by publicly funded higher education results in more individuals pursuing higher education.

The model also suggests that debt-forgiveness policy is less attractive in economies whose decisive voters are unschooled individuals without student-loan debt. Moreover, as described in Section 3.5.2, voters' probability of employment is negatively correlated with the attractiveness of the debt-forgiveness policy. The model elucidates the reasons for this relationship. Although unschooled individuals do not benefit directly through the debt-forgiveness policy, they may support it as their employment prospect deteriorates due to indirect benefits. Specifically, forgiving student loans leads to more individuals pursuing higher education, consequently leading to higher aggregate taxable income in the economy. Increased taxable income in the economy implies enhanced unemployment insurance. Therefore, as the probability of employment decreases, an enhanced debt-forgiveness policy could become more attractive to unschooled voters inclusively.

¹¹Specifically, under this plan, after 25 years of "qualifying payments," the remainder of the debt is forgiven. The Department of Education provides a detailed definition of a "qualifying payment" on their website: www.studentaid.gov.

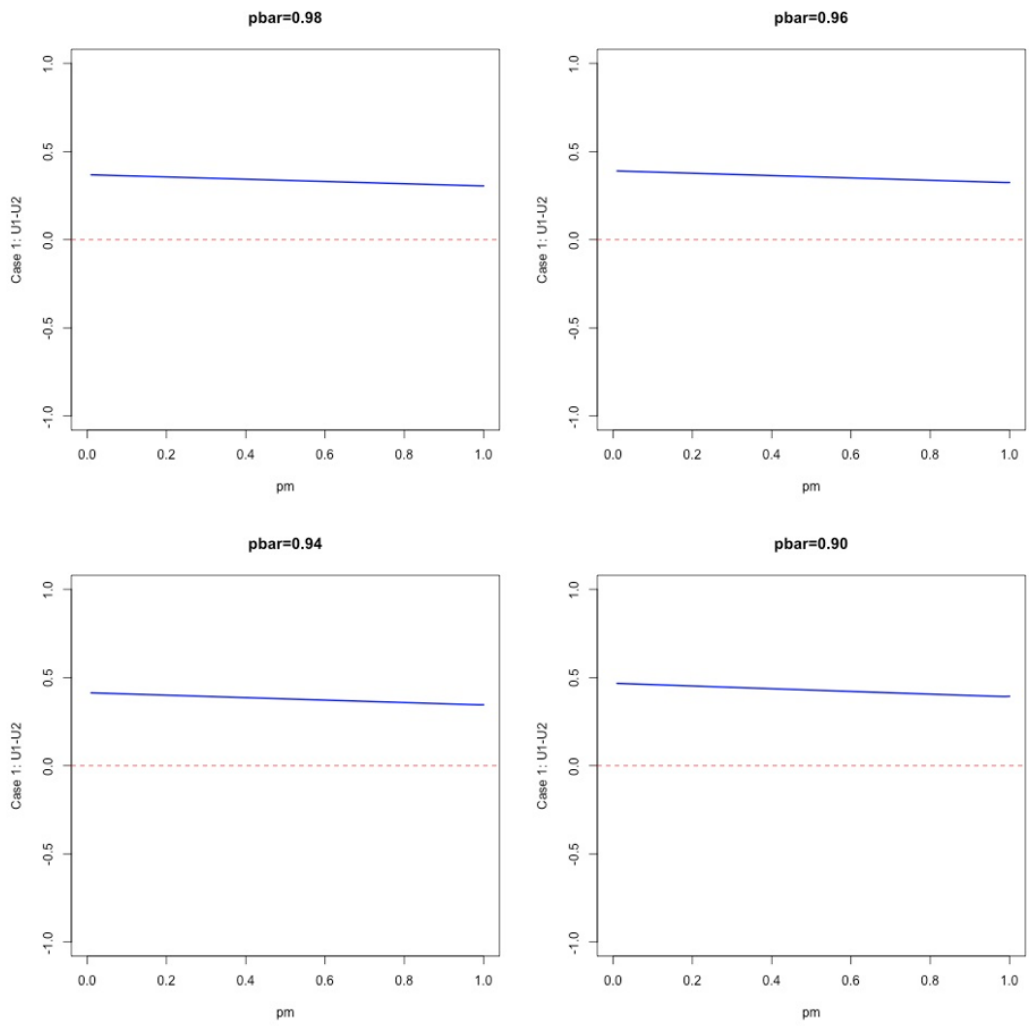


Figure 3.1: Case I: The median voter is schooled under both debt-forgiveness policies

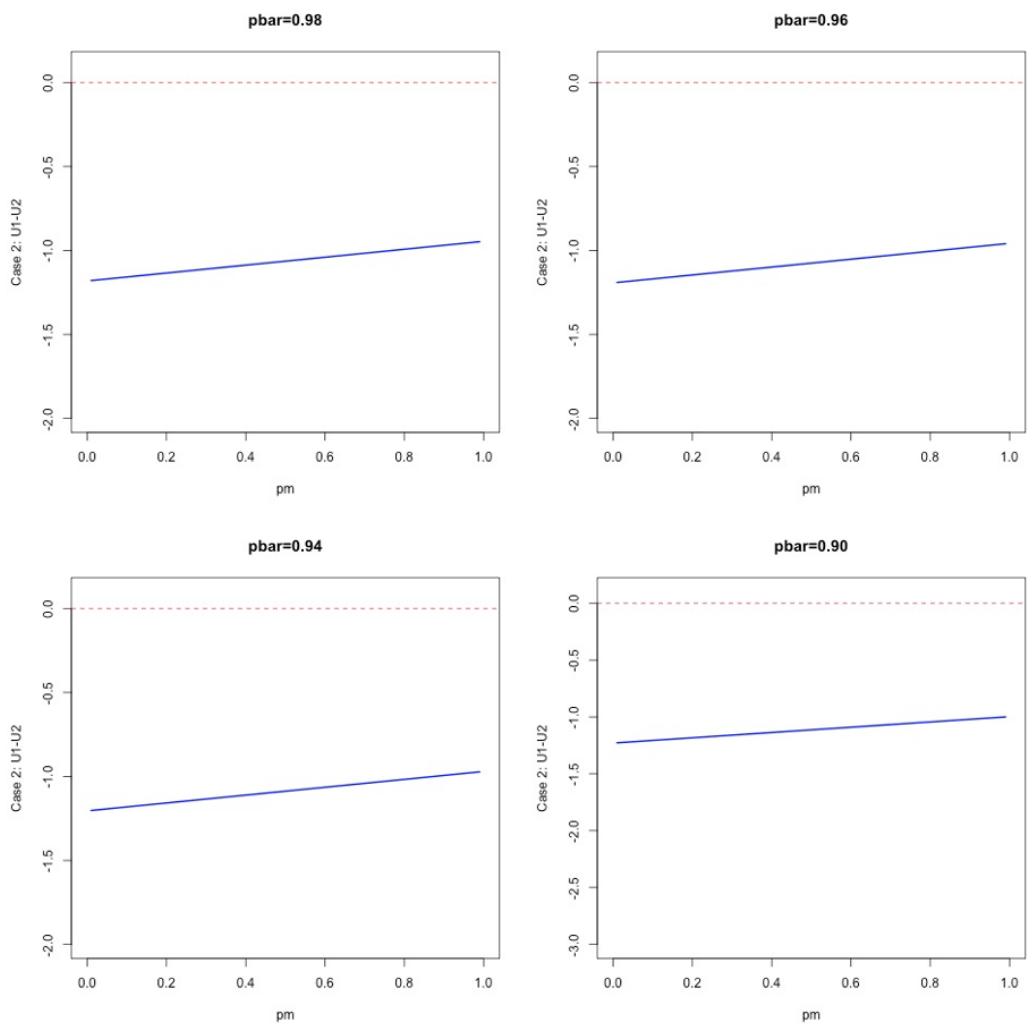


Figure 3.2: Case II: Schooled median voter when $\mathbb{I}(D) = 1$ versus unschooled median when $\mathbb{I}(D) = 0$

Appendices

Appendix A MDI Policy Overview for Chapter 1

The U.S. government has devised programs, initiatives, and policies to support and preserve Minority Depository Institutions (MDIs), given the challenges associated with operating in economically distressed communities. Price (1990) notes that the goal of the Minority Bank Deposit Program (MBDP), established in 1969, is to strengthen MDIs by encouraging public and private organizations to bank with MDIs. However, Lawrence (1997) suggests that the volatile nature of government deposits may have undermined the viability of MDIs. Kashian et al. (2014) provide more optimistic evidence on the effects of MBDP, showing that government deposits are associated with higher interest paid on certificates of deposit held by MDIs' depositors. Therefore, Kashian et al. suggest that the benefits of the MBDP are passed on to the communities served by MDIs.

Section 308 of the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989 sets forth more ambitious objectives to support MDIs. The policy requires regulators to (i) preserve the number of MDIs, (ii) preserve the minority character during merger and acquisition of MDIs, (iii) provide technical assistance to prevent insolvency of MDIs that are not yet insolvent, (iv) encourage the establishment of new MDIs, and (v) provide for training, technical assistance, and educational programs.¹ The policy is inspired by the MDIs' provision of bank services to low-income populations and their role in fostering development in impoverished U.S. communities. Findings by Eberley et al. (2019), Breitenstein et al. (2014), Toussaint-Comeau and Newberger (2017) provide some support for the policy's premise. Eberley et al. and Breitenstein et al. note that the share of mortgages to individuals residing in LMI census tracts and to minority borrowers is larger for MDIs versus non-MDIs. Eberley et al. also report that a portion of small business loans to businesses in LMI census tracts or in tracts with a higher share of minority residents is greater for MDIs in contrast to non-MDIs. Furthermore, Nguyen's (2019) findings that branch closings have long-lasting, persistent negative effects on credit supply, which concentrate in LMI communities and particularly affect small businesses, also provide support for the policy's objective. Nguyen shows that the entry of new banks does not alleviate the credit needs of small businesses in any material way since information-intensive, relationship lending requires time and cannot be readily replaced. These studies suggest that the failure of an MDI or its acquisition by a non-MDI, e.g., by

¹These requirements are listed in FIRREA Section 308 enacted by 101st Congress (1989). FIRREA Section 308 was amended by section 367 of the Dodd-Frank Act enacted by 111th Congress (2010) to require an annual report to the Congress of actions taken by the regulators to support MDIs.

a transaction-oriented bank, can be devastating to the local community. My research complements these studies by investigating the role of market segment focus in MDIs' failure and acquisition and provides insights essential for an effective preservation strategy.

Acquisition of a non-failing bank is also subject to laws and regulations. Merger applications are inspected by supervisory agencies (i.e., the Federal Deposit Insurance Corporation (FDIC) or the Board of Governors of the Federal Reserve System) for (i) market concentration concerns and (ii) additional considerations under the Community Reinvestment Act (CRA).² Applications to acquire an MDI are additionally reviewed for FIRREA requirements to preserve the minority character of the bank. According to Wheelock (2011), mergers resulting in the attainment of over 10 percent of total U.S. deposits or over 30 percent of a single state's total deposits are not allowed under federal law.³ The assessments and enforcement of antitrust policies require a definition of a relevant market, which is also assumed to be local in nature. As a rule, regulators define markets as Metropolitan Statistical Areas (MSAs) or non-MSA rural counties.⁴ Regulators also consider the effect of a proposed merger on the convenience and needs of the communities affected. The primary objective for evaluating these factors is to prevent the diminution of bank services, particularly in LMI communities.

Although the policies discussed earlier aim to preserve MDIs, some scholars note conflicting effects of the CRA regulation. The CRA requires commercial banks to ascertain and meet the credit needs of the entire community in which the bank has a presence through its branches, including LMI neighborhoods, consistent with safe and sound operations. The law is inspired by *redlining*, decaying urban communities, and *community disinvestment* (e.g., Thomas, 1993; Macey and Miller, 1993; Santiago et al., 1998; Barr, 2005; and Lacker, 1995).⁵ Although the CRA and FIRREA Section 308 share similar community development objectives, Macey and Miller (1993) and Thomas (1993) note that the CRA imposes high compliance costs on banks, particularly encumbering smaller banks. Toussaint-Comeau and Newberger (2017) suggest that the CRA undermined the viability of smaller banks focused on serving a particular market segment such as MDIs due to added competition. Thomas (1993) notes that factors such as special services for minorities, char-

²I use the terms "acquisitions" and "mergers" interchangeably throughout the article.

³Regulators use post-merger Herfindahl-Hirschman Index (HHI) value and the Department of Justice guidelines for market concentration to assess proposed mergers. According to Wheelock (2011), HHI values below 1800 or an increase in the HHI of less than 200 points in the relevant market are not challenged.

⁴Wheelock (2011) notes that the market definitions used by regulators have been criticized, but according to Gilbert and Zaretsky's (2003) survey of the literature, small businesses and households still rely on local banks. Nguyen (2019) also argues that credit markets are local despite the progress in information technology.

⁵Thomas (1993) states: "*Redlining* refers to the practice of geographic (not racial) discrimination in the granting of credit to qualified applicants in certain "redlined" or targeted neighborhoods." *Community disinvestment* is a practice of collecting deposits from a community but lending it elsewhere, as explained by Santiago et al. (1998).

itable contributions to community development organizations, or community development projects have “little or no bearing” on a bank’s CRA performance, leading to poor CRA ratings for some community-oriented banks. Finally, Lacker (1995) notes that community-development lending involves specialized services and expertise and argues that the CRA goals are better met through specialized, mission-oriented organizations.

Some of these concerns are addressed by the 1995 revisions to the CRA regulations affecting examination and enforcement of the regulation. The changes retain the policy’s community-development objectives without significantly undermining the preservation of MDIs.⁶ The updated regulations offer “CRA credit” to banks collaborating with specialized, mission-oriented banks such as MDIs.⁷ Hence, banks may receive CRA credit for investments, grants, loans, technical assistance, and joint projects with MDIs. The new rules also encourage and offer CRA credit for the donation, sale on favorable terms, or provision of rent-free branches in a predominantly minority neighborhood to an MDI. These changes are in greater harmony with the policies looking to preserve MDIs and more accommodating to the MDIs’ mission. However, encouraging collaborations with MDIs, rather than serving LMI communities directly, inevitably serves as an incentive for MDIs to specialize through further concentrating their operations in LMI areas while allowing traditional banks to limit theirs. My findings provide further insights into the possible implications of these changes. The empirical evidence contributes to the CRA literature and agrees with the views that community-development lending requires vigilant, expert banks.

Other interim programs supporting MDIs have also been implemented. During the 2008 crisis, Toussaint-Comeau and Newberger (2017) note that MDIs benefited from the Community Development Capital Initiative for mission-oriented banks, an element of the Troubled Asset Relief Program introduced by the Treasury. According to Toussaint-Comeau and Newberger, the initiative offered better terms than the Capital Purchase Program and aimed to recapitalize mission-oriented banks. Finally, the Emergency Capital Investment Program was established in 2021 to support MDIs during the economic downturn brought about by the 2019 Coronavirus pandemic. As noted in the FDIC’s Financial Institution Letter from March 9, 2021, the program allows MDIs to apply for direct capital investments from the Treasury to help MDIs meet the financial needs of the small

⁶All changes are outlined in the CRA Regulations published in the Rules and Regulations (1995).

⁷The updated regulations also allow collaborations with Community Development Financial Institutions (CDFIs). Some MDIs are also CDFIs and enjoy additional benefits offered by the CDFI Fund as described on their website, www.cdffund.gov.

or minority-owned businesses and individuals in LMI communities. The policies aimed at MDIs are motivated by their community-development aspirations and concurrently are based on the premise that MDIs are vulnerable to slowdowns in economic activity. This work takes a closer look at the delicate balance maintained by MDIs, the balance between providing banking services to the poor while maintaining their viability. At the heart of the issue are MDIs' market segment focus on distressed communities and their probability of exiting the market, which I investigate.

Appendix B Chapter 1 Robustness Checks, Additional Results, and Tests

In this section, I present additional results not included in the main paper. Several studies, e.g., Toussaint-Comeau and Newberger (2017), Elyasiani and Mehdian (1992), Henderson (1999), Breitenstein et al. (2014), and Eberley et al. (2019), postulate that minority-owned banks are likely different from their non-MDI peers due to the characteristics of locations they operate in. Therefore, Likelihood Ratio tests are performed to test the possibility of differential effects of covariates on the failure and acquisition probabilities between MDIs and non-MDIs. I estimate three separate models for MDIs, non-MDIs, and the pooled sample, including all banks, to test the hypothesis that MDIs are different from the rest of the banks. Table B1 presents the failure hazard results and Table B2 presents the acquisition hazard results for the three models. The Likelihood Ratio test results for failure and acquisition hazards are presented in Table B3. The null hypothesis in both tests is that all effects are homogeneous between MDIs and non-MDIs. The model estimated using the pooled sample with all banks corresponds to the null hypothesis. The null hypothesis is rejected. The results suggest that MDIs and non-MDIs are significantly dissimilar in failure and acquisition hazards. Therefore, estimating separate models for each group is beneficial since at least one effect differs by MDI status.

As an additional check of the possibility of differential effects of market segment focus covariates on the failure and acquisition probabilities between MDIs and non-MDIs, I test the goodness-of-fit of the model using the Likelihood Ratio. The goodness-of-fit test is performed for a model with interactions between the market segment focus measures and an MDI indicator versus a model without interactions for failure and acquisition hazards. Table B4 presents the failure hazard results and Table B5 presents the acquisition hazard results for the goodness-of-fit tests. The goodness-of-fit test (Likelihood Ratio test) results for failure and acquisition hazards are presented in Table B6. The null hypothesis assumes that the model without interaction terms is true, therefore the model associated with the null hypothesis is the one without the interactions. Based on the results, I fail to reject the null hypothesis. Therefore, the three additional interaction terms do not improve the fit of the model in the given sample, given the power to detect such differences. However, it is worth noting that the *MDI* and *LMI* interaction term in the failure hazard is negative and significant, consistent with findings in the main analysis for MDIs. Nevertheless, given the Likelihood Ratio

test results, the main analysis does not include interaction terms.

The positive coefficient for *SIZE* in the failure hazard 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. To investigate the role of the government bailouts, I estimate failure and acquisition hazards for non-MDIs with two additional samples. In one of these samples, three banks that received government assistance are censored. All three banks are excluded from the other sample. The results for the sample with bailed out banks censored are presented in Table B7 and with bailed out banks excluded in Table B8. The findings reveal that censoring or excluding bailed out banks results in insignificant effects of the bank size. These additional results suggest that the coefficient for *SIZE* is influenced by the bailed out banks that are treated as failed in the main analysis. Hence, treating bailed out banks as operational disguises the effect of bank size on the likelihood of failure.

Table B1: Failure Hazard used in the “Pooling” Likelihood Ratio Test

	MDI	non-MDI	All
<i>LMI</i>	-4.9077*** (1.8084)	0.1070 (0.0918)	0.1049 (0.0897)
<i>Vacancy</i>	-3.3419** (1.4026)	0.1351** (0.0659)	0.1222* (0.0659)
<i>Unemployment</i>	0.2318 (0.6051)	0.0402 (0.0764)	0.0384 (0.0753)
<i>CA</i>	-7.0038*** (1.9258)	-1.8466*** (0.0768)	-1.9122*** (0.0758)
<i>AQ_{LTA}</i>	-0.1820 (0.7409)	0.1660* (0.0959)	0.1209 (0.0917)
<i>AQ_{REL}</i>	-0.5275 (1.3444)	0.0043 (0.1263)	0.0148 (0.1233)
<i>AQ_{C&IL}</i>	1.1812 (1.0096)	0.1585 (0.0972)	0.1641* (0.0944)
<i>AQ_{OREO}</i>	0.2850** (0.1297)	0.1064*** (0.0132)	0.0988*** (0.0130)
<i>AQ_{NPL}</i>	0.4214*** (0.1632)	0.2223*** (0.0178)	0.2049*** (0.0160)
<i>M</i>	1.5332* (0.8867)	0.0167 (0.0419)	0.0205 (0.0322)
<i>EARN</i>	0.3115* (0.1580)	0.0289 (0.0212)	0.0279 (0.0206)
<i>LIQ</i>	-1.1122* (0.6228)	-0.2700*** (0.0702)	-0.2890*** (0.0670)
<i>SIZE</i>	0.9474 (0.7741)	0.1389* (0.0775)	0.1109 (0.0771)
<i>AGE</i>	0.4592 (0.7198)	-0.2692*** (0.0619)	-0.3103*** (0.0608)
<i>LLP</i>	0.3261* (0.1687)	-0.0524*** (0.0178)	-0.0512*** (0.0173)
<i>MDI</i>	-	-	-0.3664 (0.2958)
<i>CB</i>	6.9438** (3.4799)	-0.2055 (0.2019)	-0.0749 (0.2024)
LLF	-17.26	-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.

Hazard estimation for MDI sample does not control for timing of MDI status designations.

Table B2: Acquisition Hazard used in the “Pooling” Likelihood Ratio Test

	MDI	non-MDI	All
<i>LMI</i>	-0.1181 (0.3293)	0.0392** (0.0196)	0.0387** (0.0195)
<i>Vacancy</i>	-0.4965 (0.3565)	-0.0377** (0.0183)	-0.0406** (0.0183)
<i>Unemployment</i>	-0.1306 (0.2549)	-0.1107*** (0.0258)	-0.1102*** (0.0257)
<i>CA</i>	-0.0272 (0.1291)	0.0207 (0.0137)	0.0209 (0.0136)
<i>AQ_{LTA}</i>	0.0308 (0.1901)	-0.1018*** (0.0201)	-0.1016*** (0.0200)
<i>AQ_{REL}</i>	0.5028 (0.3145)	0.2938*** (0.0248)	0.2970*** (0.0247)
<i>AQ_{C&IL}</i>	0.1332 (0.1576)	0.0800*** (0.0205)	0.0787*** (0.0203)
<i>AQ_{OREO}</i>	0.0435 (0.0813)	-0.0526** (0.0206)	-0.0468** (0.0200)
<i>AQ_{NPL}</i>	-0.1883 (0.1224)	0.0787*** (0.0175)	0.0750*** (0.0171)
<i>M</i>	-0.0098 (0.1834)	-0.1172*** (0.0210)	-0.1196*** (0.0207)
<i>EARN</i>	-0.2507*** (0.0955)	-0.0706*** (0.0043)	-0.0703*** (0.0043)
<i>LIQ</i>	-0.1217 (0.1444)	-0.1686*** (0.0129)	-0.1673*** (0.0129)
<i>SIZE</i>	-0.4365** (0.2134)	-0.2397*** (0.0202)	-0.2419*** (0.0201)
<i>AGE</i>	-0.1226 (0.1883)	-0.1665*** (0.0168)	-0.1693*** (0.0168)
<i>LLP</i>	-0.4448*** (0.0910)	-0.0264*** (0.0123)	-0.0314** (0.0128)
<i>MDI</i>	-	-	-1.6298*** (0.2150)
<i>CB</i>	-1.4229*** (0.4985)	-1.6130*** (0.0501)	-1.6082*** (0.0497)
LLF	-223.17	-30,005.07	-30,487.93
# banks	171	7,749	7,920
# merged	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.

Hazard estimation for MDI sample does not control for timing of MDI status designations.

Table B3: The “Pooling” Likelihood Ratio Test Results

	Failure Hazard	Acquisition Hazard
Likelihood Ratio	206.16	519.38
Degrees of Freedom	1	1
P-value	9.4554×10^{-47}	5.7734×10^{-115}

The Likelihood Ratio test is used to test differences in the effects of covariates between MDIs and non-MDIs. The test is conducted for failure and acquisition hazards. The null hypothesis in both tests assumes that all effects are homogeneous between the two groups. The model that corresponds to the null hypothesis is the one estimated with pooled data. The test results suggest that at least one coefficient differs by MDI status for both failure and acquisition hazards. Therefore, failure and acquisition hazards are estimated for MDIs, non-MDIs, and the pooled sample.

Table B4: Failure Hazard used in Testing “Goodness of Fit”

	All Banks	All banks with Interactions
<i>LMI</i>	0.1049 (0.0897)	0.1143 (0.0897)
<i>Vacancy</i>	0.1222* (0.0659)	0.1283* (0.0658)
<i>Unemployment</i>	0.0384 (0.0753)	0.0440 (0.0756)
<i>MDI</i>	-0.3664 (0.2958)	4.4167** (0.2025)
<i>MDI × LMI</i>		-1.3726** (0.6961)
<i>MDI × Vacancy</i>		-0.8031 (0.6410)
<i>MDI × Unemployment</i>		-0.2213 (0.2952)
<i>CA</i>	-1.9122*** (0.0758)	-1.9080*** (0.0760)
<i>AQ_{LTA}</i>	0.1209 (0.0917)	0.1278 (0.0920)
<i>AQ_{REL}</i>	0.0148 (0.1233)	0.0068 (0.1232)
<i>AQ_{C&IL}</i>	0.1641* (0.0944)	0.1592* (0.0944)
<i>AQ_{OREO}</i>	0.0988*** (0.0130)	0.1000*** (0.0129)
<i>AQ_{NPL}</i>	0.2049*** (0.0160)	0.2064*** (0.0161)
<i>M</i>	0.0205 (0.0322)	0.0212 (0.0323)
<i>EARN</i>	0.0279 (0.0206)	0.0273 (0.0207)
<i>LIQ</i>	-0.2890*** (0.0670)	-0.2864*** (0.0675)
<i>SIZE</i>	0.1109 (0.0771)	0.1114 (0.0772)
<i>AGE</i>	-0.3103*** (0.0608)	-0.3094*** (0.0608)
<i>LLP</i>	-0.0512*** (0.0173)	-0.0516*** (0.0173)
<i>CB</i>	-0.0749 (0.2024)	-0.0730 (2.0002)
LLF	-1,715.02	-1,712.814
# banks	7,920	7,920
# failed	337	337

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

Table B5: Acquisition Hazard used in Testing “Goodness of Fit”

	All Banks	All banks with Interactions
<i>LMI</i>	0.0387** (0.0195)	0.0398** (0.0195)
<i>Vacancy</i>	-0.0406** (0.0183)	-0.0404** (0.0183)
<i>Unemployment</i>	-0.1102*** (0.0257)	-0.1100** (0.0257)
<i>MDI</i>	-1.6298*** (0.2150)	-0.5688 (0.0497)
<i>MDI × LMI</i>		-0.5015 (0.3977)
<i>MDI × Vacancy</i>		-0.0484 (0.3421)
<i>MDI × Unemployment</i>		0.0225 (0.2233)
<i>CA</i>	0.0209 (0.0136)	0.0209 (0.0136)
<i>AQ_{LTA}</i>	-0.1016*** (0.0200)	-0.1016*** (0.0200)
<i>AQ_{REL}</i>	0.2970*** (0.0247)	0.2966*** (0.0247)
<i>AQ_{C&IL}</i>	0.0787*** (0.0203)	0.0783*** (0.0203)
<i>AQ_{OREO}</i>	-0.0468** (0.0200)	-0.0469** (0.0200)
<i>AQ_{NPL}</i>	0.0750*** (0.0171)	0.0751*** (0.0171)
<i>M</i>	-0.1196*** (0.0207)	-0.1193*** (0.0207)
<i>EARN</i>	-0.0703*** (0.0043)	-0.0703*** (0.0043)
<i>LIQ</i>	-0.1673*** (0.0129)	-0.1672*** (0.0129)
<i>SIZE</i>	-0.2419*** (0.0201)	-0.2419*** (0.0201)
<i>AGE</i>	-0.1693*** (0.0168)	-0.1693*** (0.0168)
<i>LLP</i>	-0.0314** (0.0128)	-0.0314** (0.0128)
<i>CB</i>	-1.6082*** (0.0497)	-1.6089*** (1.1347)
LLF	-3,0487.93	-3,0487.10
# banks	7,920	7,920
# merged	3,627	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.

Table B6: Goodness-of-fit Test Results (The Likelihood Ratio Test)

	Failure Hazard	Acquisition Hazard
Likelihood Ratio	4.4169	1.6544
Degrees of Freedom	3	3
P-value	0.2198	0.6471

The Likelihood Ratio test is used to test the goodness-of-fit of the model with interactions versus without interactions. The test is conducted for failure and acquisition hazards. The null hypothesis in both tests assumes that the model without interaction terms is true. The base model for both tests is the hazard without the interaction terms. The results imply that the three additional interaction terms do not improve the fit of the model in the given sample, given the power to detect such differences.

Table B7: Failure and Acquisition Hazards for Non-MDI Banks: Bailed out banks are censored

	Failure Hazard	Acquisition Hazard
<i>LMI</i>	0.0867 (0.0932)	0.0345* (0.0197)
<i>Vacancy</i>	0.1257* (0.0655)	-0.0407** (0.0183)
<i>Unemployment</i>	0.0249 (0.0771)	-0.1141*** (0.0259)
<i>CA</i>	-1.8726*** (0.0766)	0.0298* (0.0134)
<i>AQ_{LTA}</i>	0.1744* (0.0977)	-0.0979*** (0.0200)
<i>AQ_{REL}</i>	0.0319 (0.1306)	0.2935*** (0.0244)
<i>AQ_{C&IL}</i>	0.1551 (0.1001)	0.0778*** (0.0203)
<i>AQ_{OREO}</i>	0.1015*** (0.0133)	-0.0530** (0.0207)
<i>AQ_{NPL}</i>	0.2234*** (0.0179)	0.0764*** (0.0176)
<i>M</i>	0.0218 (0.0394)	-0.1197*** (0.0210)
<i>EARN</i>	0.0300 (0.0215)	-0.0580*** (0.0038)
<i>LIQ</i>	-0.2562*** (0.0719)	-0.1708*** (0.0130)
<i>SIZE</i>	0.0487 (0.0807)	-0.2440*** (0.0204)
<i>AGE</i>	-0.3550*** (0.0700)	-0.1990*** (0.0181)
<i>LLP</i>	-0.0524*** (0.0177)	-0.0163 (0.0117)
<i>CB</i>	-0.1699 (0.2078)	-1.6038*** (0.0502)
LLF	-1,559.433	-30,004.11
# banks	7,749	7,749
# failed	309	-
# merged	-	3,577

One, two, or three asterisks indicate significance at 0.1, at 0.05, or at 0.01, respectively. Standard errors are in parentheses. *M* is the management quality measure estimated using order-*m* estimator. Large values of *M* are associated with *less* efficient institutions.

Table B8: Failure and Acquisition Hazards for Non-MDI Banks: Bailed out banks are excluded

	Failure Hazard	Acquisition Hazard
<i>LMI</i>	0.0867 (0.0932)	0.0335* (0.0197)
<i>Vacancy</i>	0.1257* (0.0655)	-0.0409** (0.0183)
<i>Unemployment</i>	0.0250 (0.0771)	-0.1126*** (0.0259)
<i>CA</i>	-1.8722*** (0.0766)	0.0236* (0.0137)
<i>AQ_{LTA}</i>	0.1742* (0.0977)	-0.0998*** (0.0200)
<i>AQ_{REL}</i>	0.0315 (0.1306)	0.2991*** (0.0245)
<i>AQ_{C&IL}</i>	0.1548 (0.0999)	0.0853*** (0.0202)
<i>AQ_{OREO}</i>	0.1015*** (0.0133)	-0.0571*** (0.0208)
<i>AQ_{NPL}</i>	0.2234*** (0.0179)	0.0760*** (0.0176)
<i>M</i>	0.0217 (0.0394)	-0.1222*** (0.0211)
<i>EARN</i>	0.0297 (0.0213)	-0.0707*** (0.0043)
<i>LIQ</i>	-0.2562*** (0.0719)	-0.1705*** (0.0130)
<i>SIZE</i>	0.0490 (0.0802)	-0.2435*** (0.0203)
<i>AGE</i>	-0.3546*** (0.0699)	-0.1977*** (0.0181)
<i>LLP</i>	-0.0524*** (0.0177)	-0.0253** (0.0121)
<i>CB</i>	-0.1703 (0.2078)	-1.6084*** (0.0501)
LLF	-1,559.41	-29,991.11
# banks	7,746	7,746
# failed	309	-
# merged	-	3,577

One, two, or three asterisks indicate significance at 0.1, at 0.05, or at 0.01, respectively. Standard errors are in parentheses. *M* is the management quality measure estimated using order-*m* estimator. Large values of *M* are associated with *less* efficient institutions.

Appendix C Chapter 1 Efficiency Estimation and Results

To measure unconditional, hyperbolic technical efficiency, I use the order- m method proposed by Cazals et al. (2002) and further developed by Wilson (2011). As noted by Wilson (2011), rather than estimating distance to the full frontier, the order- m approach obtains technical efficiency estimates relative to a partial frontier that lie close to it. In other words, only the partial frontier close to the boundary of the production set is estimated. According to Wilson, the approach is advantageous since the order- m estimator achieves the root- n rate of convergence and is asymptotically normal.¹ Moreover, the obtained estimates are robust with respect to outliers, unlike the estimates obtained using traditional efficiency estimators such as the free-disposal hull (FDH) or data envelopment analysis (DEA).

Wilson extends the conditional input- or output-oriented order- m efficiency estimator to an *unconditional, hyperbolic* order- m efficiency estimator, which is measured along a hyperbolic path such that inputs and outputs are adjusted simultaneously. Wheelock and Wilson (2008) and Wilson (2011) discuss the advantages of the unconditional versus directional order- m efficiency estimators.² Finally, the computational burden of nonparametrically estimating order- m technical efficiencies is much less relative to the FDH and DEA estimators. The estimation approach proposed by Daraio et al. (2020) allows for fast and more accurate computation of the order- m estimates.

C.1 The Statistical Model

Consistent with theory of firms, it is assumed that production process requires use of inputs to produce output(s) (e.g., Koopmans, 1951; Debreu, 1951; and Shephard, 1970). Let $\mathbf{x} \in \mathbb{R}_+^p$ be a column vector of non-stochastic input quantities and $\mathbf{y} \in \mathbb{R}_+^q$ be a column vector of non-stochastic output quantities. Then, as noted by Cazals et al. (2002), Wheelock and Wilson (2008), and Wilson (2011), the production set or the set of feasible combinations of inputs and outputs can be written as

$$\Psi := \{(\mathbf{x}, \mathbf{y}) \mid \mathbf{x} \text{ can produce } \mathbf{y}\} \subset \mathbb{R}_+^{p+q}. \quad (\text{C.1})$$

¹The root- n rate is not achieved even with order- m estimator if it is estimated relative to *full* rather than partial frontier, which is controlled by choice of m or the “trimming parameter” of the frontier. Cazals et al. (2002) note that as $m \rightarrow \infty$ the order- m estimator approaches the FDH estimator.

²For example, the obtained unconditional estimates avoid interpretation ambiguities and the need of making a choice between the input- or output-oriented estimators. Moreover, Wheelock and Wilson, p. 212 state that the use of unconditional efficiency estimators “results in near-automatic identification of relevant peers for meaningful comparisons among firms.”

The input requirement set of the production set is $\mathcal{X}(\mathbf{y}) = \{\mathbf{x} \in \mathbb{R}_+^p \mid (\mathbf{x}, \mathbf{y}) \in \Psi\}$ and the output correspondence set is $\mathcal{Y}(\mathbf{x}) = \{\mathbf{y} \in \mathbb{R}_+^q \mid (\mathbf{x}, \mathbf{y}) \in \Psi\}$.

The upper edge of Ψ^t represents the technology (i.e., the efficient frontier) of Ψ^t and is defined as

$$\Psi^\partial := \{(\mathbf{x}, \mathbf{y}) \mid (\delta^{-1}\mathbf{x}, \delta\mathbf{y}) \notin \Psi \forall \delta > 1\}. \quad (\text{C.2})$$

The conventional to this literature assumptions defining an economic model with regards to Ψ are presented below (e.g., Cazals et al., 2002; Wilson, 2011; Wheelock and Wilson, 2008; and etc.).

Assumption 1 Ψ is compact.

Assumption 2 $(\mathbf{x}, \mathbf{y}) \notin \Psi$ if $\mathbf{x} = 0, \mathbf{y} \geq 0, \mathbf{y} \neq 0$.

Assumption 3 For $\bar{\mathbf{x}} \geq \mathbf{x}, \bar{\mathbf{y}} \leq \mathbf{y}$ if $(\mathbf{x}, \mathbf{y}) \in \Psi$ then $(\bar{\mathbf{x}}, \mathbf{y}) \in \Psi$ and $(\mathbf{x}, \bar{\mathbf{y}}) \in \Psi$.³

Assumption 1 is needed to ensure that the limit of the set Ψ is contained in Ψ and for statistical consistency, as noted by Wilson (2011). Assumption 2 eliminates the possibility of output production without the use of input. Assumption 3 requires that the frontier is weakly monotone (i.e., strong disposability of inputs and outputs).

Next, I introduce the hyperbolic measure of efficiency, and because it has to be estimated, additional assumptions follow to complete the statistical model. The hyperbolic graph measure of efficiency due to Färe et al. (1985) is given by

$$\gamma(\mathbf{x}, \mathbf{y} \mid \Psi) := \inf \{ \gamma > 0 \mid (\gamma\mathbf{x}, \gamma^{-1}\mathbf{y}) \in \Psi \}, \quad (\text{C.3})$$

and measures the feasible, proportionate, simultaneous reduction in input levels and expansion in output levels by the same proportion. As noted by Wilson (2011), the measure in (C.3) is a measure of the technical efficiency as a distance of a firm at a fixed point $(\mathbf{x}, \mathbf{y}) \in \Psi$ along a hyperbolic path to Ψ^∂ .

The assumptions required to complete the statistical model are described in Wilson and are as follows.

³The vector inequalities are defined on an element-by-element basis.

Assumption 4 *The sample observations $\mathcal{S} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^n$ are realizations of identically, independently distributed random variables with probability density function $f(\mathbf{x}, \mathbf{y})$ with support over Ψ .*

Assumption 5 *At the frontier, $f_0 = f(\mathbf{x}_0^{\partial}, \mathbf{y}_0^{\partial}) > 0$ (i.e., the density f is strictly positive) and sequentially Lipschitz continuous.*

Assumption 6 *For all (\mathbf{x}, \mathbf{y}) in the interior of Ψ , $\gamma(\mathbf{x}, \mathbf{y})$ is twice continuously differentiable in both arguments.*

Under the Assumption 4, Cazals et al. (2002) note that the density function $f(\mathbf{x}, \mathbf{y})$ entails a well-defined probability function $H(\mathbf{x}, \mathbf{y}) = \Pr(\mathbf{X} \leq \mathbf{x}, \mathbf{Y} \geq \mathbf{y})$.⁴ As illustrated by Wilson, the hyperbolic graph measure of efficiency in equation C.3 could be written using this probability function as

$$\gamma(\mathbf{x}, \mathbf{y}) := \inf \{ \gamma > 0 \mid H(\gamma \mathbf{x}, \gamma^{-1} \mathbf{y}) > 0 \}. \quad (\text{C.4})$$

Then, extending the ideas of Cazals et al., Wilson derives an unconditional, hyperbolic measure of order- m efficiency as follows. For a set of m identically, independently distributed random variables $\{(\mathbf{X}_j, \mathbf{Y}_j)\}_{j=1}^m$ drawn from the density function $f(\mathbf{x}, \mathbf{y})$, Wilson defines the random set as

$$\Psi_m := \bigcup_{j=1}^m \left\{ (\mathbf{x}, \mathbf{y}) \in \mathbb{R}_+^{p+1} \mid \mathbf{x} \geq \mathbf{X}_j, \mathbf{y} \leq \mathbf{Y}_j \right\}, \quad (\text{C.5})$$

and the random distance measure for any $(\mathbf{x}, \mathbf{y}) \in \mathbb{R}_+^{p+1}$ as

$$\gamma_m(\mathbf{x}, \mathbf{y}) := \inf \{ \gamma \mid (\gamma \mathbf{x}, \gamma^{-1} \mathbf{y}) \in \Psi_m \}. \quad (\text{C.6})$$

Finally, Wilson shows that the expected hyperbolic order- m efficiency is

$$\bar{\gamma}_m(\mathbf{x}, \mathbf{y}) := \mathbb{E}(\gamma_m(\mathbf{x}, \mathbf{y})) = \int_0^{\infty} [1 - H(u\mathbf{x}, u^{-1}\mathbf{y})]^m du. \quad (\text{C.7})$$

Then, using the empirical distribution based on the sample \mathcal{S}_n for $H(\mathbf{x}, \mathbf{y})$ given by

$$\hat{H}_n(\mathbf{x}, \mathbf{y}) = n^{-1} \sum_{i=1}^n \mathbb{I}(\mathbf{x}_i \leq \mathbf{x}_0, \mathbf{y}_i \geq \mathbf{y}_0), \quad (\text{C.8})$$

⁴Wilson discusses additional properties of the probability function. An interested reader is referred to Wilson and Cazals et al..

the estimator of the hyperbolic order- m efficiency in C.7 is derived by replacing $H(ux, u^{-1}y)$ with the empirical distribution,

$$\hat{\gamma}_m(\mathbf{x}, \mathbf{y}) = \hat{\mathbb{E}}(\gamma_m(\mathbf{x}, \mathbf{y})) = \int_0^\infty \left[1 - \hat{H}(ux, u^{-1}y)\right]^m du. \quad (\text{C.9})$$

Wilson establishes the asymptotic properties of the estimator in C.9. For example, if used to estimate technical efficiency relative to a *partial* frontier, the hyperbolic order- m estimator enjoys a root- n convergence rate. This property is not common to nonparametric estimators such as, the FDH and the DEA estimators. Therefore, estimations of technical efficiency for small samples benefit from using order- m estimators.⁵

Until recently, the order- m estimator was computed using Monte Carlo methods. However, Daraio et al. (2020) present a new approach to computing estimates of the hyperbolic order- m efficiency estimator that is less computationally-burdensome. Daraio et al. (2020) provide Matlab code for their computation approach in the Appendix section of their paper. The order- m efficiency estimates in this paper are obtained using Wilson’s (2008) FEAR package in R programming language. Finally, Cazals et al. and Simar (2003) explain how m can reasonably be chosen. Simar also discusses economic interpretation of m . For example, Simar notes that since order- m estimator is estimated relative to partial frontier, which is controlled by the choice of m , it provides “a reasonable benchmark value” for an operating unit among m firms drawn from some population of firms. Moreover, Cazals et al. note that m is a “trimming parameter” of the order- m estimator, and, as noted by Simar, even with large values of m the order- m estimator does not envelop all of the observations in the data making it more robust to outliers.

C.2 Data and Estimation Results

The data for the efficiency estimation come from the Consolidated Reports of Condition and Income (call reports) for the 2001–2019 period obtained from the FFIEC. Call report data are collected quarterly for regulatory purposes and contain audited financial information about banks. The vector of inputs includes three variables, total deposits (X_1), the number of full-time equivalent employees (X_2), and the book value of premises and fixed assets (X_3). The output vector contains

⁵Input- and output-oriented order- m estimators introduced by Cazals et al. (2002), input- and output-oriented order- α efficiency estimator introduced by Daouia and Simar (2007), and hyperbolic order- α efficiency estimator of Wheelock and Wilson (2008) also enjoy a root- n convergence rate.

a single variable, total loans and leases (Y).

I estimate technical efficiency using a hyperbolic order- m estimator for all banks in each quarter during the 2001–2019 period with reduced dimensions. I use the dimension-reduction technique proposed by Wilson (2018) to improve the convergence of the estimator and for improved accuracy. The method uses the moment matrices of input ($\mathbf{X}'\mathbf{X}$) and output ($\mathbf{Y}'\mathbf{Y}$) variables. Specifically, Wilson (2018) defines a measure

$$R_x := \frac{\lambda_{xj}}{\sum_{j=1}^p \lambda_{xj}}, \quad (\text{C.10})$$

where $\lambda_{x1}, \dots, \lambda_{xj}$ are the eigenvalues of $\mathbf{X}'\mathbf{X}$ in descending order. R_y can be defined in a similar manner.

The technical efficiency estimates are calculated for $m = 100, 250, 500,$ and 750 and the summary statistics for obtained estimates are reported in Table C2. As is expected, a different value for m results in different estimates, and larger values of m are associated with larger estimates. The estimates obtained for $m = 750$ only slightly increased relative to estimates obtained for other values of m . Figure C1 presents a plot matrix of order- m efficiency estimates plotted relative to each other for the four values of m mentioned earlier. Specifically, each panel in the matrix presents a relationship between a pair of order- m variables for different m , e.g., a plot in the lowest panel of the first row compares estimates obtained for $m = 100$ against $m = 750$. Wheelock and Wilson (2008) use a similar panel plot approach to select the α for the α -quantile estimator, which also uses the partial frontier estimation approach. Therefore, following Wheelock and Wilson’s intuition and observing that many points are on or near the straight line, the rankings of operating units (i.e., banks) with respect to their estimated efficiency are similar for the four chosen values of m . Therefore, given that efficiency estimates for $m = 500$ and $m = 750$ are reasonably close, the choice of $m = 500$ seems reasonable. The hazard coefficient estimates (not reported) are robust with respect to the choice of m . Therefore, the order- m technical efficiency estimates obtained with $m = 500$ are selected to include in the main analysis of this study.

Figure C2 presents the trends in the mean order- m efficiency estimates for MDIs, non-MDIs, and the pooled sample. Higher values of the technical efficiency estimates indicate greater inefficiency. The figure reveals that MDIs do not follow the general trend. On average, MDIs were

less efficient than their non-MDI peers before the financial crisis, but MDIs were more efficient than non-MDIs during the 2008–2018 period.

Table C1: Inputs and Output Variables Used for Efficiency Estimations

Variable	Description
Inputs	
X_1	Total deposits.
X_2	Number of full-time equivalent employees.
X_3	Book value of premises and fixed assets.
Output	
Y	Total loans and leases.

Table C2: Summary Statistics of Efficiency Estimates by MDI status

		Mean	Median	StdDev	Min	Max
$M_{m=100}$	non-MDI	1.2899	1.2603	0.4075	0.0647	50.5034
	MDI	1.2982	1.2645	0.4063	0.4024	4.2523
	all	1.2901	1.2603	0.4075	0.0647	50.5034
$M_{m=250}$	non-MDI	1.4836	1.4459	0.4738	0.1477	58.4445
	MDI	1.5016	1.4621	0.4587	0.5443	5.0100
	all	1.4839	1.4461	0.4735	0.1477	58.4445
$M_{m=500}$	non-MDI	1.5951	1.5522	0.5141	0.2358	66.5730
	MDI	1.6164	1.5743	0.4872	0.6542	5.3533
	all	1.5955	1.5525	0.5136	0.2358	66.5730
$M_{m=750}$	non-MDI	1.5720	1.5308	0.5057	0.3025	66.8435
	MDI	1.5861	1.5479	0.4714	0.7172	5.1833
	all	1.5723	1.5310	0.5051	0.3025	66.8435

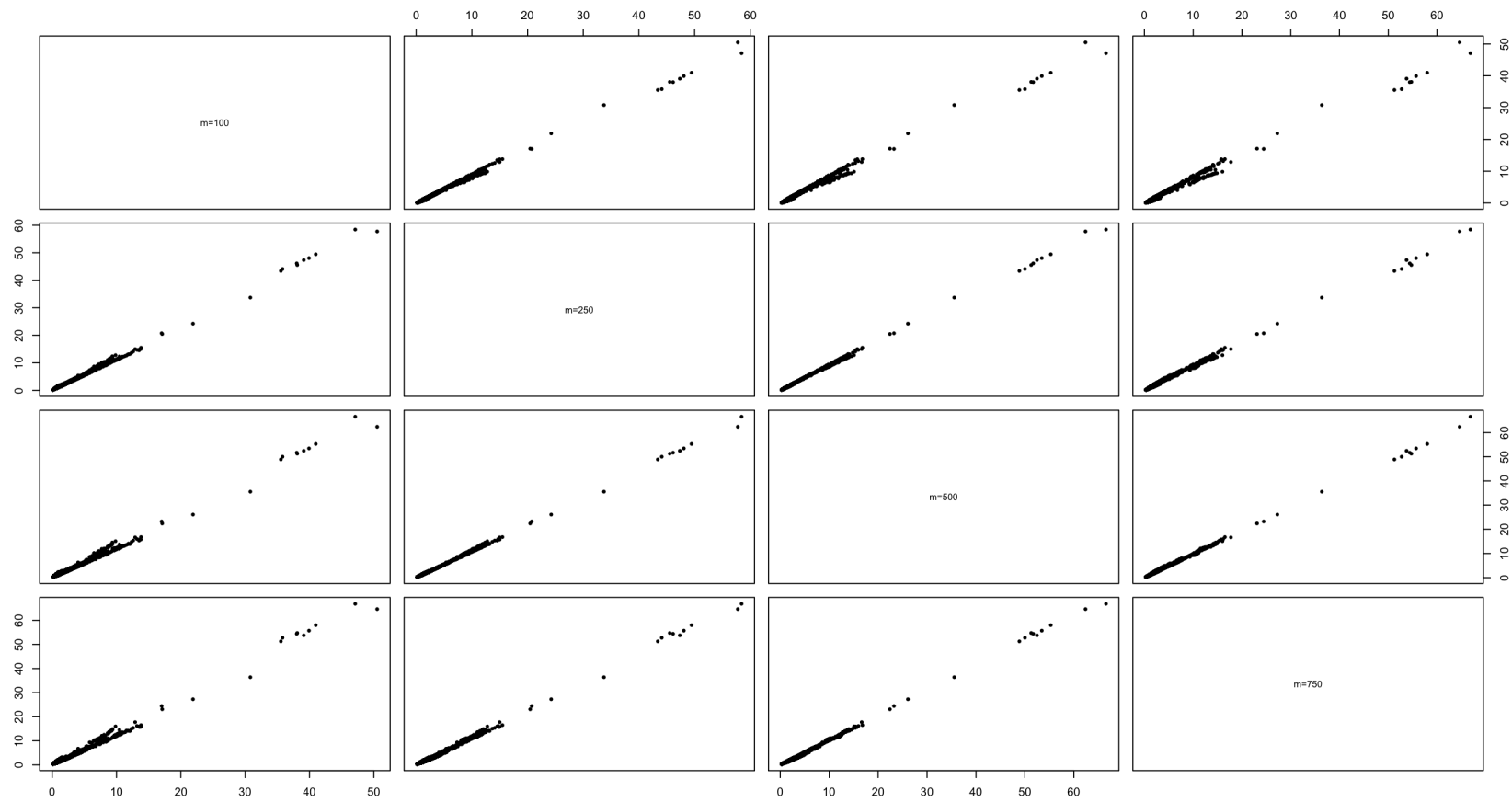


Figure C1: Unconditional, hyperbolic order- m efficiency estimates.

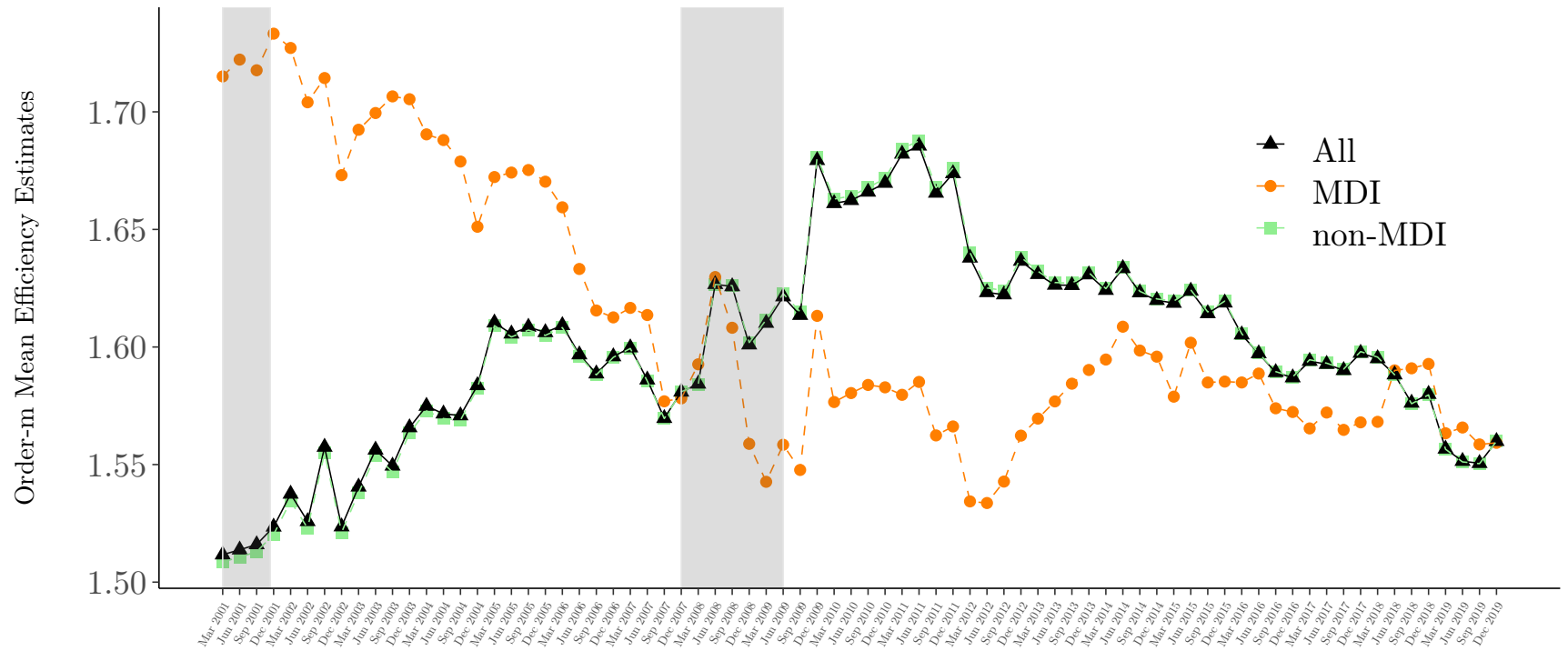


Figure C2: Mean order- m efficiency estimates for $m = 500$. Higher values indicate greater inefficiency.

Appendix D Additional Exploratory Data Visualizations for Chapter 1

This section presents additional exploratory data visualizations for MDIs. MDIs differ from traditional, non-MDI banks in many aspects. MDIs target and serve individuals in low-income communities. For example, Breitenstein et al. (2014) and Eberley et al. (2019) show that MDIs are predominantly found in populous metropolitan areas and serve markets with a greater share of low- and moderate-income (LMI) census tracts relative to non-MDIs, including non-MDI community banks. Toussaint-Comeau and Newberger (2017) show that Census tracts with only MDI bank branches tend to have poverty and unemployment rates above the national level. Breitenstein et al. (2014) and Eberley et al. (2019) show that a considerable share of MDIs' mortgages and small business loans are allocated to individuals and businesses in LMI census tracts. I find that MDI characteristics in my sample are consistent with these findings.

Figure D1 presents a map showing the percent of the population with income below the poverty level in 2010 at the county level. On the map, geocoded MDI branches in the sample are represented with white bubbles. The counties are colored based on the percent of the population below poverty in the county. Darker green counties indicate a relatively low percentage of the population below the poverty level, with darkest green counties indicating the percent of the population below the poverty level is less than five percent. Darker red counties indicate a relatively high percentage of the population below the poverty level, with darkest red counties indicating percent of the population below the poverty level is more than 25 percent above. The map indicates that most, though not all, MDI branches are located in counties with a higher percentage of the population with income below the poverty level.

Figure D2 presents a map showing the unemployment rate in 2010 at the county level. On the map, geocoded MDI branches in the sample are represented with white bubbles. The counties are colored based on the unemployment rate in the county. Darker green counties indicate a relatively low unemployment rate, with darkest green counties indicating a county with an unemployment rate of less than five percent. Darker red counties indicate a relatively high unemployment rate, with darkest red counties indicating a county with an unemployment rate of more than ten percent. According to the map, most MDI branches are located in counties with a higher unemployment rate.

Figure D3a explores the differences within MDIs by the *LMI* market segment focus measure

through differences in the mean other real estate owned to total assets ratio (AQ_{OREO}) trends during 2001–2019. The figure shows that MDIs with greater focus ($LMI > 0.5$) have lower other real estate owned to total assets ratios. As Wheelock and Wilson (2000) explain, other real estate owned indicates foreclosed property, hence signal problem loans. Mean other real estate owned to total assets ratio remained relatively steady for MDIs with $LMI > 0.5$ during the 2008 financial crisis. Figure D3b investigates the differences within MDIs by the LMI market segment focus measure through differences in the earnings ($EARN$) trends during 2001–2019. Consistent with Figure D3a, less focused MDIs (i.e., MDIs with $LMI < 0.5$) experienced a greater decrease in earnings during the 2008 financial crisis relative to MDIs with $LMI > 0.5$.

Figures D4a – D6b explore the differences in market segment focus measures, LMI , $Vacancy$, and $Unemployment$ within MDIs by the failure and acquisition status during 2001–2019. The blue circles in the figures represent the mean market segment focus measures for failed or acquired banks in the sample in a given year. The orange triangles are mean market segment focus measures for banks that never failed or were never acquired. For example, a blue circle for 2008 in Figure D4a represents an average of LMI measure for banks that failed in 2008, while an orange triangle for 2008 represents an average of LMI measure for banks that *never* failed during the study period of 2001–2019. For estimation purposes, failed and acquired banks with call reports missing for more than three consecutive quarters immediately before the date of failure or acquisition are censored.¹ Therefore, the censored banks are included in the orange triangle. The patterns observed in Figures D4a – D6b suggest that more focused MDIs are less likely to exit the market through failure or acquisition. The pattern is most pronounced for the $Unemployment$ market segment measure. Nonetheless, these trends represent simple correlations and summary statistics, therefore further analysis is necessary.

¹See the main article for the reasoning and other details.

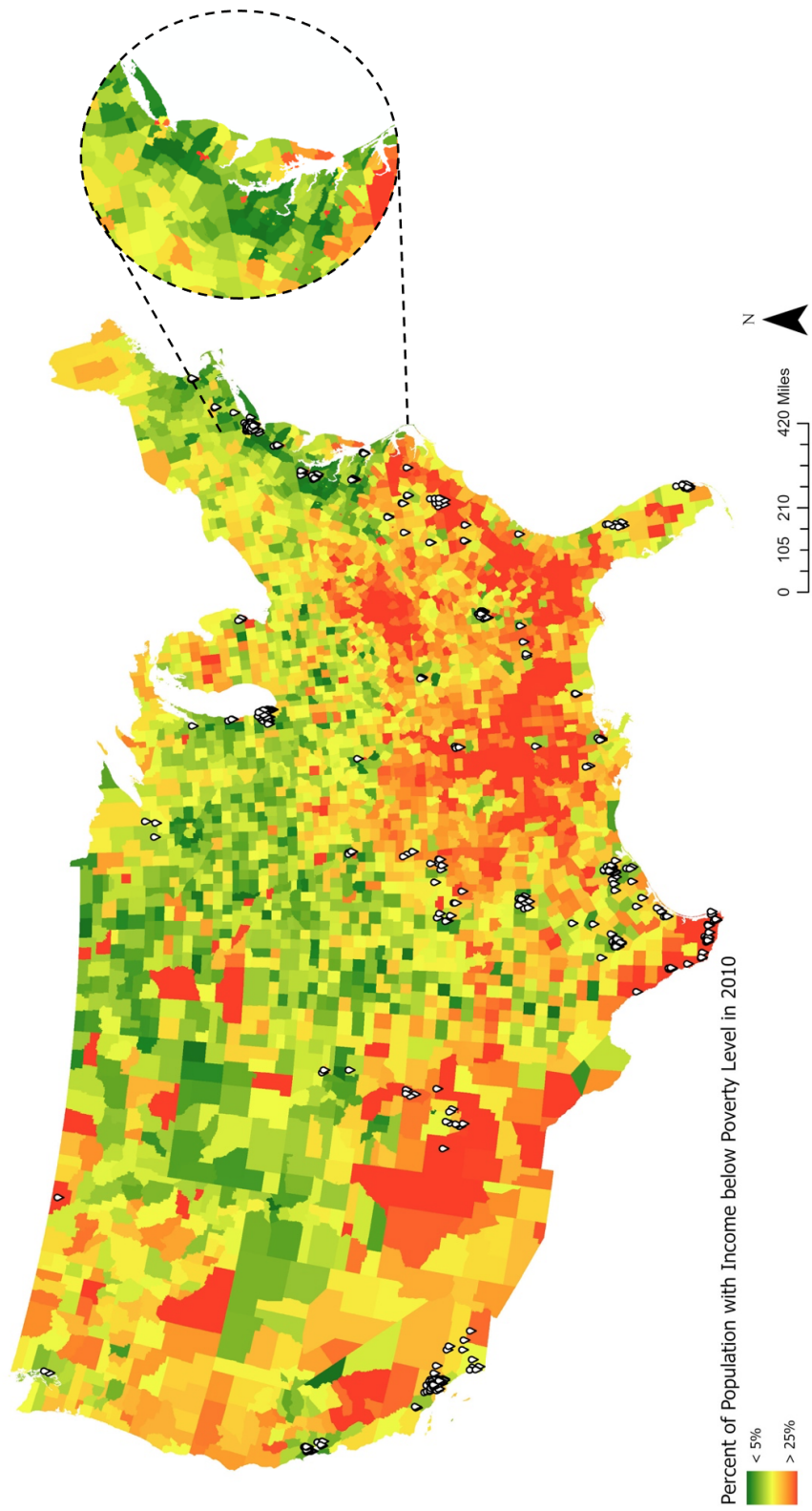


Figure D1: Percent of population with income below poverty level in 2010 at the county level.

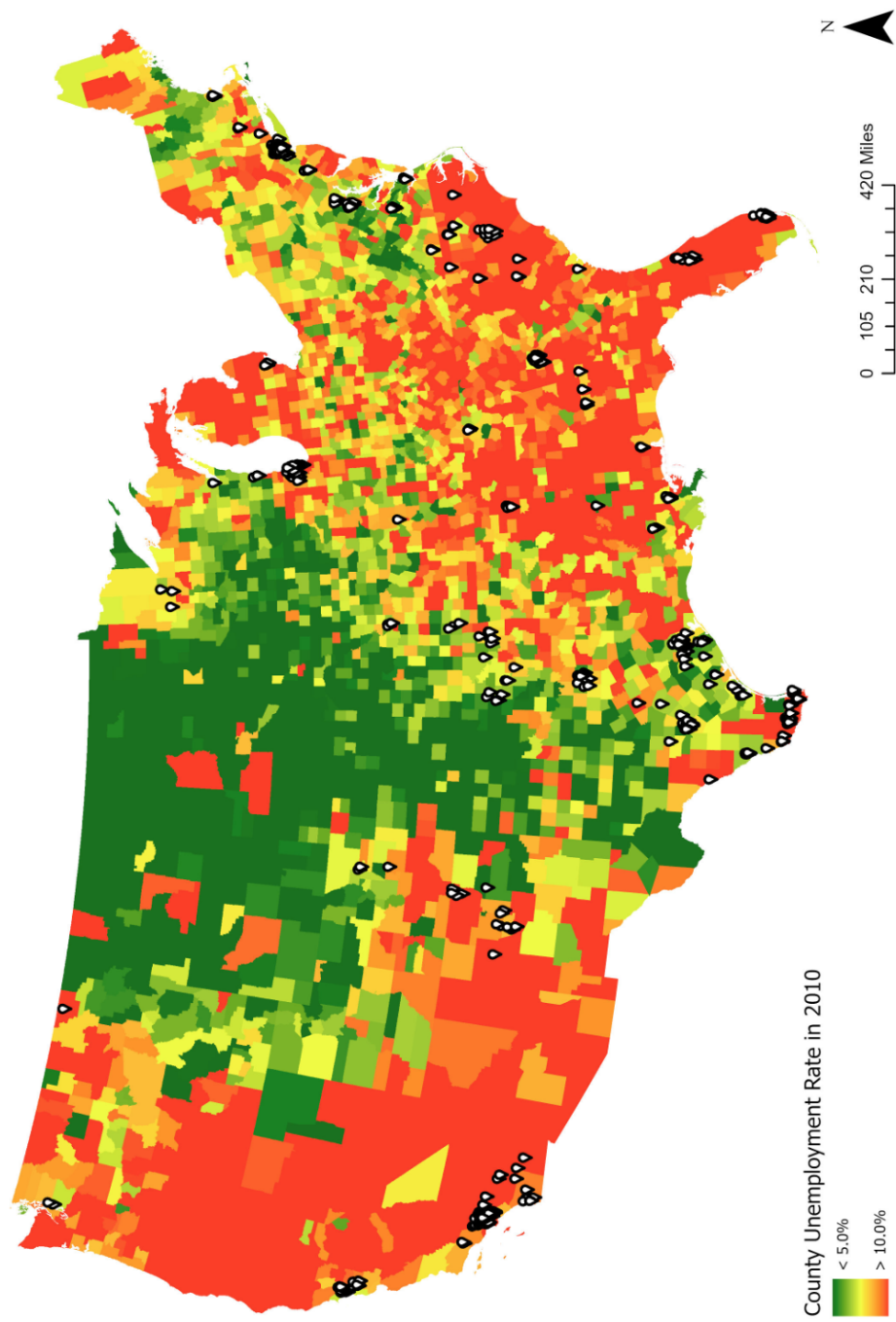
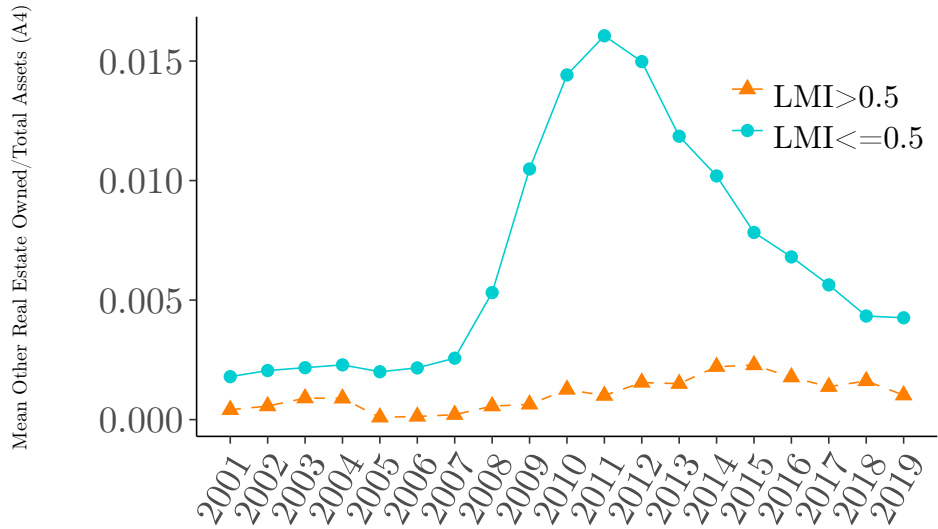
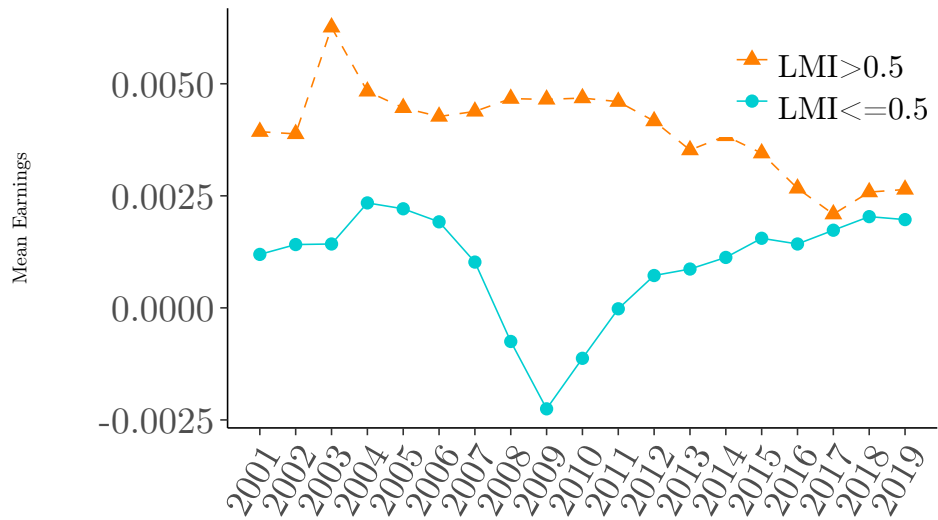


Figure D2: The unemployment rate in 2010 at the county level.

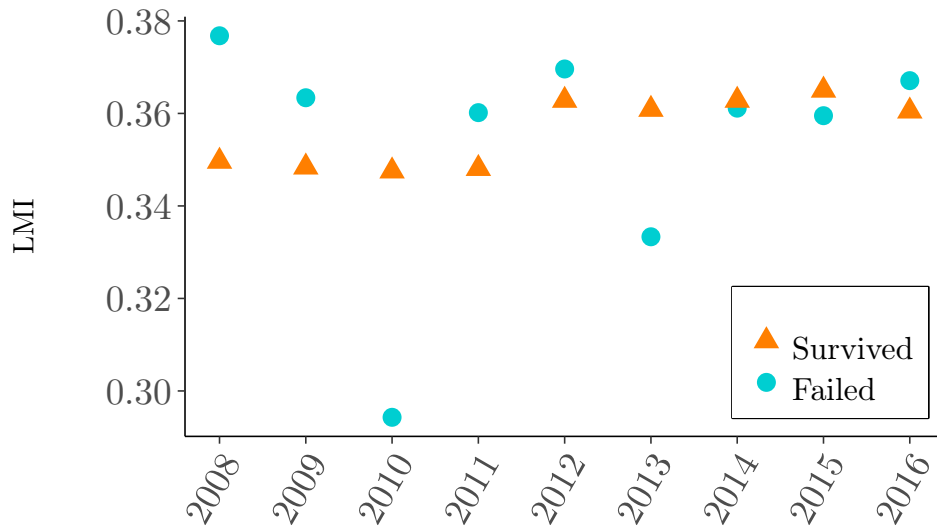


(a) Mean other real estate owned to total assets ratio trends for MDIs by *LMI* measure of market segment focus.

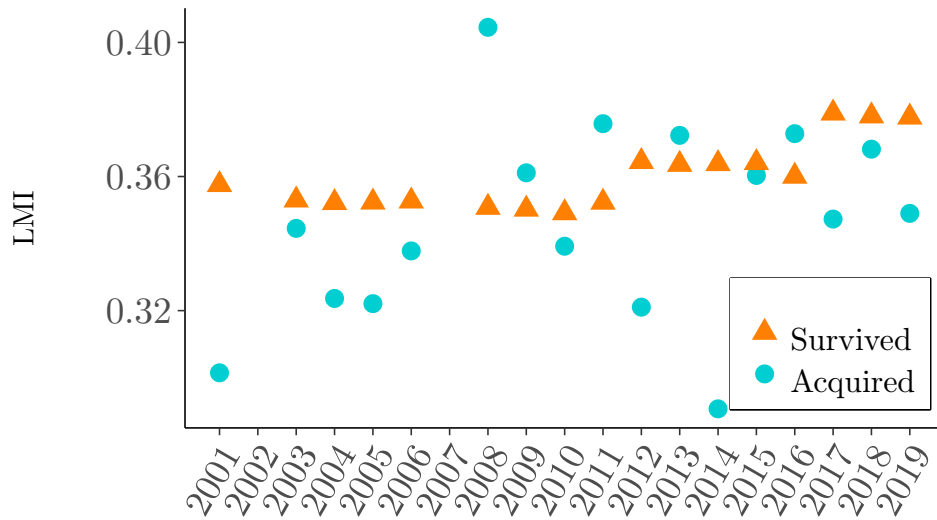


(b) Mean earnings for MDIs by *LMI* measure of market segment focus.

Figure D3: The differences within MDIs: mean *OREO* and mean *EARN* by *LMI*.

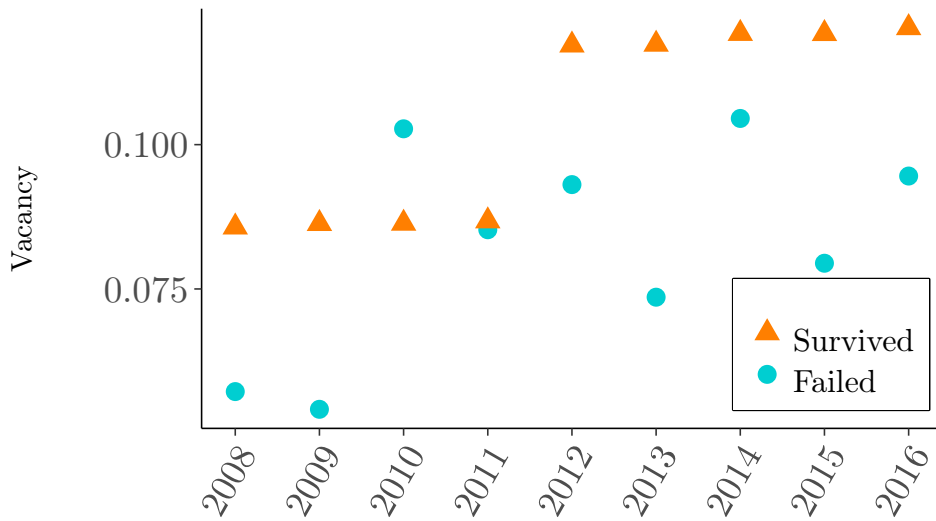


(a) Mean *LMI* measure of market segment focus for failed MDIs versus *never* failed MDIs.

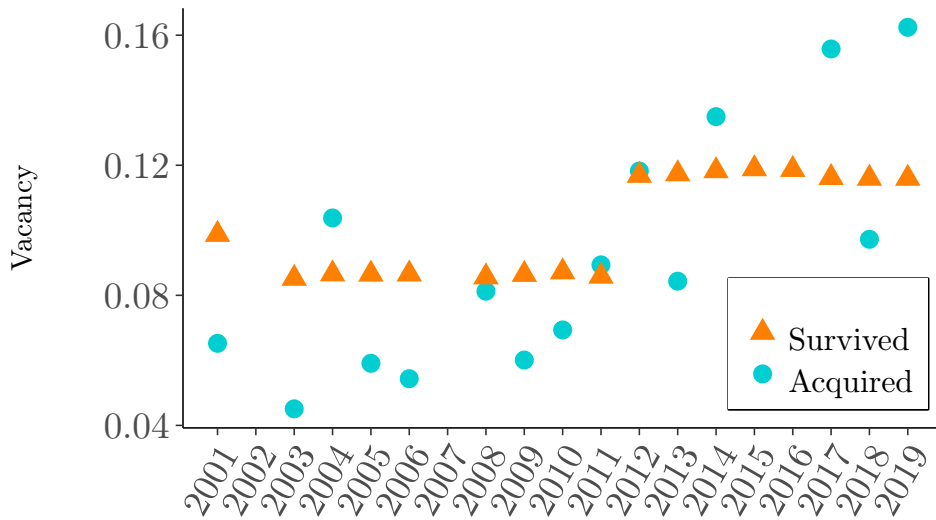


(b) Mean *LMI* measure of market segment focus for acquired MDIs versus MDIs that were *never* acquired.

Figure D4: Mean *LMI* for *Failure* and *Acquisition*.

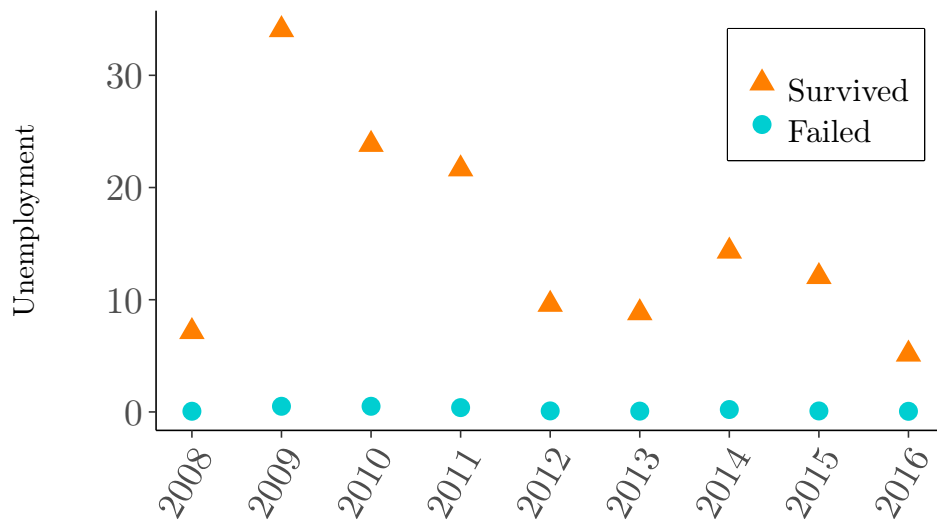


(a) Mean *Vacancy* measure of market segment focus for failed MDIs versus *never* failed MDIs.

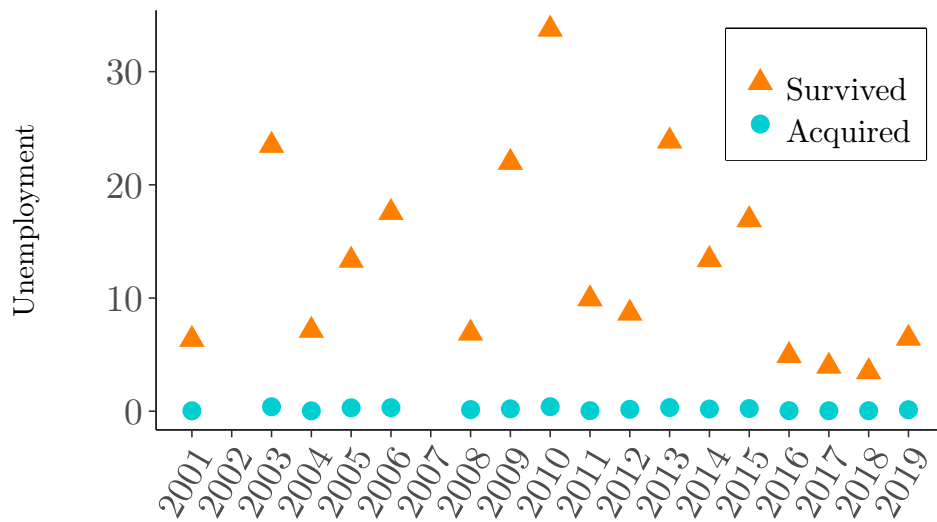


(b) Mean *Vacancy* measure of market segment focus for acquired MDIs versus MDIs that were *never* acquired.

Figure D5: Mean *Vacancy* for *Failure* and *Acquisition*.



(a) Mean *Unemployment* measure of market segment focus for failed MDIs versus *never* failed MDIs.



(b) Mean *Unemployment* measure of market segment focus for acquired MDIs versus MDIs that were *never* acquired.

Figure D6: Mean *Unemployment* for *Failure* and *Acquisition*.

Appendix E Chapter 2 Nested Logit Model of Entry and Endogenous Location Choice

The purpose of this document is to provide a brief description of the details and intuition of the empirical model developed by Seim (2006), which I implement in the paper. It is useful to think of the entry and location decision in the framework of the two-level Nested Logit model. It is then intuitive to think of the decision process as a joint (i.e., one-shot) entry-location decision. Hence, MDIs' choice process involves two parts: (i) deciding whether to enter and (ii) conditional on the entry decision, choosing the location. The joint entry-location choice tree diagram associated with this two-part decision process is presented in Figure H1. The tree is helpful in visualizing the decision and visually breaking it down into an upper model with two branches (nests) and two lower models such that one is degenerate with one twig (the deterministic choice of $\ell = 0$) and the other is non-degenerate with a total of \mathcal{L} choices (twigs).

To set up the model, I first introduce the notation to be used in any given market $m \in \{1, \dots, M\}$. Note that the tree in Figure H1 represents the decision process in one market. So, for ease of notation and without loss of generality, I omit index m from the exposition below. The notation to be used is described next. Bank branches are indexed by $i = 1, \dots, \mathcal{N}^p$ indexes bank branches, where \mathcal{N}^p is the number of *potential* entrants. The number of potential entrants \mathcal{N}^p is unobserved and requires additional assumptions in the estimation process. As in Seim (2006) and Cotterill and Haller (1992), \mathcal{N}^p can be set to a fixed number, which may vary by market. The number of *actual* entrants predicted by the model is \mathcal{N} such that $\mathcal{N}^p \geq \mathcal{N}$. As explained in the paper, I assume that \mathcal{N} is the number of entrants observed in the market to aid the estimation of the model. Similar approach is taken by Berry (1994), Berry et al. (1995), and Seim (2006). The nests in Figure H1 are indexed by $e = 0, 1$ such that $e = 0$ when entry does not occur and $e = 1$ when entry occurs. Location choices are indexed by $\ell = 0, 1, \dots, \mathcal{L}$ such that $\ell = 0$ if $e = 0$ and $\ell = 1, \dots, \mathcal{L}$ if $e = 1$. In other words, $\ell = 0$ is the “outside” option. Therefore, the entry branch for $e = 0$ is degenerate as depicted in the tree. Distance bands are indexed by $b = 0, 1, \dots, B$. I use $b = 0, 1, 2$ in this paper, so $B = 2$ and there are a total of $B + 1 = 3$ distance bands.

The profit (or utility) contribution of bank branch i from location ℓ in nest e is

$$\Pi_{i\ell e} = \xi_e + V_{\ell e} + \epsilon_{i\ell e}, \tag{E.1}$$

where ξ_e is market specific attribute unobserved by econometrician (i.e., not present in data). The second component in the profit, $V_{\ell e}$, is the deterministic component of profit given by $V_{\ell e} = \sum_{b=0}^B X_{b\ell e} \beta_b + h(\gamma_b, \mathcal{N}_\ell)$ where $X_{b\ell e}$ are demand characteristics in each distance band from location ℓ , $h(\gamma_b, \mathcal{N}_\ell)$ is a function of competitive effects from rivals in each distance band b from location ℓ , β_b and γ_b are parameters to be estimated. Finally, the last component of the profit function in (E.1), $\epsilon_{i\ell e}$, is the error term unobserved by econometrician and the realization of $\epsilon_{i\ell e}$ is unobserved by the bank's rivals. Therefore, the error term is the source of idiosyncratic variation in profit and gives rise to the asymmetry of information between banks. I assume that banks know the distribution of $\epsilon_{i\ell e}$, but only observe the realized value of $\epsilon_{i\ell e}$ for its own branch.¹

Next, assume $\epsilon_{i\ell e} \stackrel{iid}{\sim}$ Type-II GEV, such that

$$\begin{aligned} F(\epsilon_{i\ell e}) &= \exp \left[- \sum_{e=0}^1 \gamma_e \left(\sum_{\ell=0}^{\mathcal{L}} \exp[-\rho \epsilon_{i\ell e}] \right)^{\frac{1}{\rho}} \right] \\ &= \exp \left[-\gamma_0 \exp[-\epsilon_{i00}] - \gamma_1 \left(\sum_{\ell=1}^{\mathcal{L}} \exp[-\rho \epsilon_{i\ell 1}] \right)^{\frac{1}{\rho}} \right], \end{aligned} \quad (\text{E.2})$$

where γ_e is the Euler constant (note, the conventional notation for the Euler constant is γ . However, I am also using γ_b to denote a parameter to be estimated in the paper). In the given specification of $\Pi_{i\ell e}$ in (E.1), the Euler constant γ_1 is absorbed in ξ for $e = 1$ and the Euler constant γ_0 is normalized to zero (i.e., $\gamma_0 = 0$) for $e = 0$.² Moreover, ρ is the similarity coefficient (see, e.g., McFadden (1978) and Seim (2001) for details), which could be estimated in principle but I set $\rho = 1$ for simplicity. In Seim (2006), $\rho = 1$ as well, as a result the model simplifies to Multinomial Logit.

Given the assumption about $\epsilon_{i\ell e}$, the joint entry-location probability can be decomposed as

$$\underbrace{P_{i\ell e}}_{\text{joint probability}} = \underbrace{P_{ie}}_{\text{marginal entry probability}} \times \underbrace{P_{i\ell|e}}_{\text{conditional location probability}}, \quad (\text{E.3})$$

where $P_{i\ell e}$ is the joint probability of entry-location decision, P_{ie} is the marginal probability of entry, $e \in \{0, 1\}$, for the upper model, and $P_{i\ell|e}$ is the conditional probability of choosing location

¹The imperfect-information nature of the model is one of its primary advantages since it simplifies the estimation process and can be computed for many locations relative to other static, complete-information models, e.g., in Bresnahan and Reiss (1990), Bresnahan and Reiss (1991a), Berry (1992), and Mazzeo (2002). At the same time, imperfect information assumption allows for differences in costs among branches in the same location, which more closely conforms to reality.

²Under these assumptions, the mean of ϵ_{i00} for $e = 0$ is zero, implying that the mean profits from not entering is also zero. I provide additional details about $\epsilon_{i\ell e}$ in the upcoming text.

ℓ conditional on entry decision e . For the problem at hand, $P_{i\ell|e}$ is *endogenously determined*. Therefore, the estimation $P_{i\ell|e}$ in the given setting requires solving a system of equations, as described later in text.

Using the idea of composite utility from Ben-Akiva and Bierlaire (1999), the corresponding, decomposed profit function can be written as

$$\begin{aligned}\Pi_{i\ell e} &= \underbrace{\Pi_{ie}}_{(*)} + \underbrace{\Pi_{i\ell|e}}_{(**)} \\ &= \underbrace{[\xi_e + V_{ie} + \epsilon_{ie}]}_{(*)} + \underbrace{[V_{i\ell|e} + \epsilon_{i\ell|e}]}_{(**)},\end{aligned}\tag{E.4}$$

where $(*)$ is profit from entry and $(**)$ is profit from location ℓ conditional on e . Given the assumed specification of $\Pi_{i\ell e}$ in (E.1), we can decompose it according to (E.4) as

$$\begin{aligned}\Pi_{i\ell e} &= \xi_e + \sum_{b=0}^B X_{b\ell e} \beta_b + h_e(\gamma_b, \mathcal{N}_{\ell|e}) + \epsilon_{i\ell e} \\ &= [\xi_e + \epsilon_{ie}] + \left[\sum_{b=0}^B X_{b\ell|e} \beta_b + h_e(\gamma_b, \mathcal{N}_{\ell|e}) + \epsilon_{i\ell|e} \right].\end{aligned}\tag{E.5}$$

To be explicit, profit when entry does not occur ($e = 0$) is

$$\Pi_{i00} = \underbrace{[\epsilon_{i0}]}_{\text{Upper Model}} + \underbrace{[0]}_{\text{Lower Model}}, \quad \text{for } \ell = 0,\tag{E.6}$$

and profit when entry occurs ($e = 1$) is

$$\Pi_{i\ell 1} = \underbrace{[\xi_1 + \epsilon_{i1}]}_{\text{Upper Model}} + \underbrace{\left[\sum_{b=0}^B X_{b\ell|1} \beta_b + h_1(\gamma_b, \mathcal{N}_{\ell|e}) + \epsilon_{i\ell|1} \right]}_{\text{Lower Model}}, \quad \forall \ell = 1, \dots, \mathcal{L},\tag{E.7}$$

such that the deterministic profit components V_{ie} and $V_{i\ell|e}$ become

$$V_{i0} = 0 \quad \text{for } e = 0,\tag{E.8}$$

$$V_{i1} = \xi_1 \quad \text{for } e = 1,\tag{E.9}$$

$$V_{i0|0} = 0 \quad \text{for } e = 0, \quad (\text{E.10})$$

and

$$V_{i\ell|1} = \sum_{b=0}^B X_{b\ell|1} \beta_b + h_1(\gamma_b, \mathcal{N}_{\ell|1}), \quad \text{for } e = 1. \quad (\text{E.11})$$

Given the assumptions and derivations in the paper, we can rewrite (E.11) as

$$V_{i\ell|1} = \sum_{b=0}^B X_{b\ell|1} \beta_b + \gamma_0 + (\mathcal{N} - 1) \left[\gamma_0 P_{\ell|1}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{j|1}^* \right) \right], \quad (\text{E.12})$$

where, for cutoffs D_b defining a distance band around location ℓ , distance bands $b = 1$ and $b = 2$, we have

$$\mathbb{I}_1(d_{j\ell}) = \begin{cases} 1 & \text{if } D_1 \leq d_{j\ell} < D_2 \\ 0 & \text{otherwise,} \end{cases}$$

and

$$\mathbb{I}_2(d_{j\ell}) = \begin{cases} 1 & \text{if } d_{j\ell} \geq D_2 \\ 0 & \text{otherwise.} \end{cases}$$

Note that in the paper, I use p_ℓ^* (rather than $P_{\ell|1}^*$) following the notation introduced by Seim (2006) to help readers compare the model in the two papers. I use $P_{\ell|1}^*$ here to explicitly highlight the fact that this is *conditional* (on entry) probability. Then, using this explicit notation, the conditional location probability for $e = 1$ is given by

$$P_{\ell|1}^* = \frac{\exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell|1} \beta_b + \gamma_0 + (\mathcal{N} - 1) \left[\gamma_0 P_{\ell|1}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{j|1}^* \right) \right] \right\}}{\sum_{k=1}^{\mathcal{L}} \exp \left\{ \sum_{b=0}^B \mathbf{X}_{bk|1} \beta_b + \gamma_0 + (\mathcal{N} - 1) \left[\gamma_0 P_{k|1}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq k} \mathbb{I}_b(d_{jk}) P_{j|1}^* \right) \right] \right\}}. \quad (\text{E.13})$$

Since the conditional location probability is endogenous, it cannot be estimated using the traditional maximum likelihood approach. Instead, $P_{\ell|e}^*$ is estimated by numerically solving a system of nonlinear equations, in which the conditional probability of choosing location ℓ depends on the

conditional probability of choosing location ℓ and all other locations j with $j \neq \ell$. Intuitively, it can be interpreted as follows: conditional on entry, an MDI's probability of choosing a location ℓ endogenously depends on its rivals' location-choice probabilities. The unique solution for the system of equations in (E.13) yields the equilibrium beliefs of an entering bank over locations ℓ in a given market (hence the star over the conditional location probabilities).

The conditional probability for $e = 0$ is given by $P_{0|0} = 1$ (degenerate branch). The marginal probability of entry is

$$P_1 = \frac{\exp\{\xi_1\} I_1}{1 + \exp\{\xi_1\} I_1}, \quad (\text{E.14})$$

where I_1 is

$$I_1 = \sum_{\ell=1}^{\mathcal{L}} \exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell|1} \beta_b + \gamma_0 + (\mathcal{N} - 1) \left[\gamma_0 P_{\ell|1}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{j|1}^* \right) \right] \right\}. \quad (\text{E.15})$$

Note that $\exp\{\xi_0\} = 1$ since $\xi_0 = 0$ and $I_0 = 1$ for $e = 0$ if the bank does not enter the market, hence $\exp\{\xi_0\} I_0 = 1$.³ Finally, putting it all together yields the joint probability of entry (i.e., for $e = 1$) is

$$P_{\ell 1} = \frac{\exp\{\xi_1\} I_1}{1 + \exp\{\xi_1\} I_1} \frac{\exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell|1} \beta_b + \gamma_0 + (\mathcal{N} - 1) \left[\gamma_0 P_{\ell|1}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{j|1}^* \right) \right] \right\}}{I_1}.$$

Next, rewrite $\mathbf{P}^* = [P_{1|1}^*, \dots, P_{\mathcal{L}|1}^*]'$, where \mathbf{P}^* is a vector of endogenously determined conditional location probabilities in the lower model.

Additional nuances to note are as follows. The conditional location probabilities, $P_{j|1}^*$ and $P_{\ell|1}^*$, are determined symmetrically due to assumptions about $\epsilon_{i\ell e}$. Moreover, notice that ϵ_{ie} is the error term for the upper model and $\epsilon_{i\ell|e}$ is the error term for the lower model. I assume that $\epsilon_{ie} \stackrel{iid}{\sim}$ Extreme Value with location parameter = 0, scale parameter = 1, and shape parameter = 0.⁴ For $\epsilon_{i\ell|1}$, I assume that $\epsilon_{i\ell|1} \stackrel{iid}{\sim}$ Extreme Value with location parameter = 0, scale parameter = ρ ,

³Notice that $\log(I_e)$ is the inclusive value for branch e . As Train (2009) states, I_e "links the upper and lower models by bringing information from the lower model into the upper model." One can think of I_e as of the expected profit that the MDI obtains from its decision. See Williams (1977), Small and Rosen (1981), and Train (2009) for additional insights.

⁴Together with the assumptions described for (E.2), this implies that for $e = 0$, mean of $\epsilon_{i0} = 0$. However, for each individual bank i , ϵ_{i0} does not have to be zero (i.e., $\epsilon_{i0} \neq 0$). One interpretation of this assumption is that an MDI that decides against entry "earns" the value of retaining an option to use its managerial talent on other projects.

and shape parameter = 0. As mentioned earlier, I constrain $\rho = 1$ for simplicity, hence the model simplifies to Multinomial Logit. Moreover, by assumption $\epsilon_{i0|0} = 0$ when an MDI decides not to enter a market.

So far, the model has been described for one market, though the goal is to estimate the entry-location choices for many markets and locations. Therefore, I now introduce the subscript m in the notation to explicitly emphasize that the model is estimated for many markets and locations. Then, noting that the observed variables do *not* vary with i (only the unobserved errors are), the full information maximum likelihood (FIML) maximizes (*across markets* $m = 1, \dots, M$)

$$\mathcal{L} = \prod_{m=1}^M \left[(P_{me})^{y_{me}} \prod_{\ell=0}^{\mathcal{L}_m} (P_{\ell m|e}^*)^{y_{\ell m|e}} \right], \quad (\text{E.16})$$

where

$$y_{me} = \begin{cases} 1 & \text{if } e = 1 \text{ in } m \\ 0 & \text{otherwise.} \end{cases}$$

and, conditional on entry,

$$y_{\ell m|e} = \begin{cases} 1 & \text{if } \ell \text{ in } m \text{ chosen} \\ 0 & \text{otherwise.} \end{cases}$$

To estimate the model, we cannot maximize (E.16) without further assumptions. Specifically, ξ_{me} are unobserved and require further assumptions. I assume that $\xi_{me} \stackrel{iid}{\sim} N(\mu, \sigma^2)$ for $e = 1$ such that μ and σ^2 are additional parameters to be estimated. Hence, given the distributional assumptions about ξ_{me} , (E.16) becomes

$$\mathcal{L} = \prod_{m=1}^M N(\mu, \sigma^2) \prod_{\ell=0}^{\mathcal{L}_m} (P_{\ell m|e}^*)^{y_{\ell m|e}}. \quad (\text{E.17})$$

Next, define $\delta_{\ell m|e}$ as the share of branches located in ℓ , such that $\delta_{\ell m|e} = \frac{\sum_{i=1}^{\mathcal{N}_{m|e}} \mathbb{I}(\ell)}{\mathcal{N}_{m|e}} = \frac{n_{m\ell|e}}{\mathcal{N}_{m|e}}$, with

$n_{m\ell|e}$ equal the total number of branches in ℓ and

$$\mathbb{I}(\ell) = \begin{cases} 1 & \text{if } i \text{ is in } \ell \\ 0 & \text{otherwise} \end{cases}$$

Think of $\delta_{\ell m|e}$ as a summary of branch location pattern. Then, given the assumptions about error terms implying that mean profits equal zero for $e = 0$, the likelihood function is

$$\mathcal{L} = \left(\prod_{m=1}^M N(\mu, \sigma^2) \right) \left(\prod_{m=1}^M \prod_{\ell=1}^{\mathcal{L}_m} (P_{\ell m|e}^*)^{\mathcal{N}_{m|e} \delta_{\ell m|e}} \right), \quad (\text{E.18})$$

and the log-likelihood function is

$$\log(\mathcal{L}) = \left(-\frac{M}{2} (\log(2\pi) + \log(\sigma^2)) - \frac{1}{2\sigma^2} \sum_{m=1}^M (\xi_{me} - \mu)^2 \right) + \left(\sum_{m=1}^M \sum_{\ell=1}^{\mathcal{L}_m} \mathcal{N}_{m|e} \delta_{\ell m|e} \log(P_{\ell m|e}^*) \right). \quad (\text{E.19})$$

Further assumptions are required to estimate the model. I assume that the actual number of entrants predicted by the model, $\mathcal{N}_{m|e}$, equals the actual number of branches observed in the market. I also assume that $\mathcal{N}_m^p = 2 \times \mathcal{N}_{m|e}$ or that \mathcal{N}_m^p equals some fixed number in each market as is done in Seim (2006). Following Seim (2006) and as discussed in the paper, adjustment of the actual entrants predicted by the model simplifies the estimation of the model and results in an estimate of ξ_m

$$\widehat{\xi}_{me} = \log(\mathcal{N}_{m|e}) - \log(\mathcal{N}_m^p - \mathcal{N}_{m|e}) - \log(I_{me}). \quad (\text{E.20})$$

Given these assumptions, the explicit log-likelihood function is given by

$$\begin{aligned} \log(\mathcal{L}) = & \left[-\frac{M}{2} (\log(2\pi) + \log(\sigma^2)) - \frac{1}{2\sigma^2} \sum_{m=1}^M (\log(\mathcal{N}_{m|e}) - \log(\mathcal{N}_m^p - \mathcal{N}_{m|e})) \right. \\ & \left. - \log \left(\sum_{\ell=1}^{\mathcal{L}} \exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell|e} \beta_b + \gamma_0 + (\mathcal{N}_{m|e} - 1) \left[\gamma_0 P_{\ell|e}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{j|e}^* \right) \right] \right\} \right) - \mu)^2 \right] \\ & + \left[\sum_{m=1}^M \sum_{\ell=1}^{\mathcal{L}_m} \mathcal{N}_{m|e} \delta_{\ell m|e} \log(P_{\ell m|e}^*) \right]. \end{aligned} \quad (\text{E.21})$$

Appendix F Chapter 2 Data Construction

In this section, I describe the data and information used to estimate the model. I omit the subscript e for ease of exposition in this and subsequent sections. I begin with smaller components and then describe the data matrix, matrix of competitive effects, and the vector of estimated conditional location probabilities. To estimate the model, we must define a market. As explained in Seim (2006), markets should be large enough to allow for MDIs' ability to differentiate over geographic space adequately. At the same time, markets should not be excessively large to avoid the inclusion of distant competitors that would not compete for local customers. Once markets are defined, we need to determine the number of markets M , the number of actual entrants \mathcal{N}_m in each market (i.e., the number of observed branches in each market as noted earlier), the number of potential entrants \mathcal{N}_m^p in each market (see earlier discussion), and the number of established branches in each location ℓ and market m to calculate $\delta_{\ell m}$.

The data matrix of demand characteristics in the current version of the paper is given by

$$\mathbf{X}_m = \begin{bmatrix} X_{10} & X_{11} & X_{12} & X_{13} & X_{14} \\ X_{20} & X_{21} & X_{12} & X_{23} & X_{24} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{\mathcal{L}_m 0} & X_{\mathcal{L}_m 1} & X_{\mathcal{L}_m 2} & X_{\mathcal{L}_m 3} & X_{\mathcal{L}_m 4} \end{bmatrix},$$

such that the first three columns are the column vectors containing location-specific population count, $\mathbf{X}_{0\ell m}$, $\mathbf{X}_{1\ell m}$, $\mathbf{X}_{2\ell m}$, in the first, second, and third distance bands (i.e., population count for $b = 0, 1, 2$), respectively. I obtain these data for population count information from the 2010 Census reports from ArcGIS/Esri using the Buffer Analysis geoprocessing tool in the ArcGIS Pro geographic information system software. The fourth column of \mathbf{X}_m is the tract-level income classification $LMI_{\ell m}$ and the last column of \mathbf{X}_m is the count of non-MDI branches in a given location ℓ . The tract-level income classification information is obtained from the Federal Financial Institutions Examination Council's Census and Demographic Reports. Hence, the data matrix can be visualized as

$$\begin{bmatrix} \overbrace{X_{10}}^{\mathbf{X}_{0\ell m}} & \overbrace{X_{21}}^{\mathbf{X}_{1\ell m}} & \overbrace{X_{22}}^{\mathbf{X}_{2\ell m}} & \overbrace{X_{23}}^{LMI_{\ell m}} & \overbrace{X_{24}}^{non-MDI_{\ell m}} \\ X_{20} & X_{21} & X_{22} & X_{23} & X_{24} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{\mathcal{L}_m 0} & X_{\mathcal{L}_m 1} & X_{\mathcal{L}_m 2} & X_{\mathcal{L}_m 3} & X_{\mathcal{L}_m 4} \end{bmatrix}.$$

Next, I define a matrix of competitive effects, $\mathbf{\Gamma}_m$, which is an $\mathcal{L}_m \times \mathcal{L}_m$ matrix containing competitive effects $\gamma_{j\ell}$ for each location pair in a market,

$$\mathbf{\Gamma}_m = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1\mathcal{L}_m} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2\mathcal{L}_m} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{\mathcal{L}_m 1} & \gamma_{\mathcal{L}_m 2} & \cdots & \gamma_{\mathcal{L}_m \mathcal{L}_m} \end{bmatrix}, \quad (\text{F.1})$$

where $\gamma_{j\ell} \in \{\gamma_0, \gamma_1, \gamma_2\} \forall j, \ell$ such that $\ell = 1, \dots, \mathcal{L}_m$ and $j = 1, \dots, \mathcal{L}_m$. In other words, $\gamma_{j\ell}$ represents a competitive effect on a branch in location ℓ from a rival in location j . Due to the Assumption 2, rivalrous branches in the same distance around location ℓ (i.e., within the same distance band) exert the same competitive pressure. Each column and each row of $\mathbf{\Gamma}_m$ corresponds to a location in market m . The order of columns and rows matter — the order of columns and the rows of $\mathbf{\Gamma}_m$ must be the same. Therefore, the diagonal of $\mathbf{\Gamma}_m$ will represent the competitive effect of the location ℓ with itself.

To be clear, consider a hypothetical 5×5 market shown in Figure H2. Assume that each cell in this market represents a location, hence this market consists of 25 locations. Next, define three distance bands $b = 0, 1, 2$ such that the first band $b = 0$ includes the location (cell) itself, $b = 1$ includes the immediately adjacent locations (cells) only, and $b = 2$ includes all the remaining locations (cells). For example, for location $\ell = 1$ the first distance band $b = 0$ will only include location $\ell = 1$. The second distance band $b = 1$ will include locations immediately adjacent to location $\ell = 1$, i.e., locations $j = 2, 7, 6$. The third distance band $b = 2$ will include all the remaining locations.

The corresponding matrix $\mathbf{\Gamma}_m$ for the hypothetical 5×5 market is shown in Figure H3. The diagonal of the matrix (the darkest colored cells) in Figure H3 contains competitive intensity between branch in location ℓ and its rivals in its own location ℓ (i.e., in the first distance band,

$b = 0$). Slightly lighter colored cells in Figure H3 contain competitive intensity between branch in location ℓ and its rivals in immediately adjacent locations to ℓ (i.e., in the second distance band, $b = 1$). The lightest colored cells in Figure H3 contain competitive intensity between branch in location ℓ and its rivals in the remaining locations (i.e., in the third distance band, $b = 2$). A unique matrix $\mathbf{\Gamma}_m$ must be constructed for each market.

I use $\mathbf{\Gamma}_m$ to estimate endogenously determined conditional location probabilities in (E.13). To construct the matrix $\mathbf{\Gamma}_m$ for each market m , I obtain distances *for each location pair* in the market m using the Generate Near Table ArcGIS Pro geoprocessing tool. I define locations as population-weighted tract centroids following Seim (2006). Therefore, I calculate the distances for each pair of population-weighted tract centroids in a given market. For each location ℓ in the market, I use calculated distances and defined cutoffs defining distance bands around location ℓ to identify whether a given location j ($j \neq \ell$) is in $b = 0$, $b = 1$, or $b = 2$ from ℓ . Once the necessary information is collected, each column of $\mathbf{\Gamma}_m$ is constructed to represent the competitive intensity between rivals in location 1 through \mathcal{L}_m for the branch in location ℓ .

Although $\mathbf{\Gamma}_m$ is useful for computation of conditional location probabilities in the fixed-point algorithm, it is easier to work with a decomposed version of $\mathbf{\Gamma}_m$ for maximum likelihood optimization. Decomposing $\mathbf{\Gamma}_m$ for each distance band allows isolating each of the competitive effects γ_b thus easing the optimization of the log-likelihood function with respect to γ_b and other parameters. To decompose $\mathbf{\Gamma}_m$ in (F.1), define an indicator function $\mathbb{I}_b(d_{j\ell})$ for each distance band, $b = 0, 1, 2$ such that

$$\mathbb{I}_b(d_{j\ell}) = \begin{cases} 1 & \text{for } D_b \leq d_{j\ell} < D_{b+1} \\ 0 & \text{otherwise} \end{cases},$$

where D_b and D_{b+1} are cutoffs that define a distance band around location ℓ , and $d_{j\ell}$ is a distance between a branch in location $\ell \in \{1, \dots, \mathcal{L}_m\}$ and its rivals in location $j \in \{1, \dots, \mathcal{L}_m\}$. Then we

can rewrite $\mathbf{\Gamma}_m$ in (F.1) as

$$\mathbf{\Gamma}_m = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1\mathcal{L}_m} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2\mathcal{L}_m} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{\mathcal{L}_m 1} & \gamma_{\mathcal{L}_m 2} & \cdots & \gamma_{\mathcal{L}_m \mathcal{L}_m} \end{bmatrix} = \gamma_0 \begin{bmatrix} \mathbb{I}_0(d_{11}) & \mathbb{I}_0(d_{12}) & \cdots & \mathbb{I}_0(d_{1\mathcal{L}_m}) \\ \mathbb{I}_0(d_{21}) & \mathbb{I}_0(d_{22}) & \cdots & \mathbb{I}_0(d_{2\mathcal{L}_m}) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{I}_0(d_{\mathcal{L}_m 1}) & \mathbb{I}_0(d_{\mathcal{L}_m 2}) & \cdots & \mathbb{I}_0(d_{\mathcal{L}_m \mathcal{L}_m}) \end{bmatrix}$$

$$+ \gamma_1 \begin{bmatrix} \mathbb{I}_1(d_{11}) & \mathbb{I}_1(d_{12}) & \cdots & \mathbb{I}_1(d_{1\mathcal{L}_m}) \\ \mathbb{I}_1(d_{21}) & \mathbb{I}_1(d_{22}) & \cdots & \mathbb{I}_1(d_{2\mathcal{L}_m}) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{I}_1(d_{\mathcal{L}_m 1}) & \mathbb{I}_1(d_{\mathcal{L}_m 2}) & \cdots & \mathbb{I}_1(d_{\mathcal{L}_m \mathcal{L}_m}) \end{bmatrix} + \gamma_2 \begin{bmatrix} \mathbb{I}_2(d_{11}) & \mathbb{I}_2(d_{12}) & \cdots & \mathbb{I}_2(d_{1\mathcal{L}_m}) \\ \mathbb{I}_2(d_{21}) & \mathbb{I}_2(d_{22}) & \cdots & \mathbb{I}_2(d_{2\mathcal{L}_m}) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{I}_2(d_{\mathcal{L}_m 1}) & \mathbb{I}_2(d_{\mathcal{L}_m 2}) & \cdots & \mathbb{I}_2(d_{\mathcal{L}_m \mathcal{L}_m}) \end{bmatrix}.$$

Denote each matrix of zeros and ones as follows,

$$\mathbf{\Gamma}_{0m} = \begin{bmatrix} \mathbb{I}_0(d_{11}) & \mathbb{I}_0(d_{12}) & \cdots & \mathbb{I}_0(d_{1\mathcal{L}_m}) \\ \mathbb{I}_0(d_{21}) & \mathbb{I}_0(d_{22}) & \cdots & \mathbb{I}_0(d_{2\mathcal{L}_m}) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{I}_0(d_{\mathcal{L}_m 1}) & \mathbb{I}_0(d_{\mathcal{L}_m 2}) & \cdots & \mathbb{I}_0(d_{\mathcal{L}_m \mathcal{L}_m}) \end{bmatrix},$$

$$\mathbf{\Gamma}_{1m} = \begin{bmatrix} \mathbb{I}_1(d_{11}) & \mathbb{I}_1(d_{12}) & \cdots & \mathbb{I}_1(d_{1\mathcal{L}_m}) \\ \mathbb{I}_1(d_{21}) & \mathbb{I}_1(d_{22}) & \cdots & \mathbb{I}_1(d_{2\mathcal{L}_m}) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{I}_1(d_{\mathcal{L}_m 1}) & \mathbb{I}_1(d_{\mathcal{L}_m 2}) & \cdots & \mathbb{I}_1(d_{\mathcal{L}_m \mathcal{L}_m}) \end{bmatrix},$$

and

$$\mathbf{\Gamma}_{2m} = \begin{bmatrix} \mathbb{I}_2(d_{11}) & \mathbb{I}_2(d_{12}) & \cdots & \mathbb{I}_2(d_{1\mathcal{L}_m}) \\ \mathbb{I}_2(d_{21}) & \mathbb{I}_2(d_{22}) & \cdots & \mathbb{I}_2(d_{2\mathcal{L}_m}) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{I}_2(d_{\mathcal{L}_m 1}) & \mathbb{I}_2(d_{\mathcal{L}_m 2}) & \cdots & \mathbb{I}_2(d_{\mathcal{L}_m \mathcal{L}_m}) \end{bmatrix}.$$

Intuitively, $\mathbf{\Gamma}_m$ captures the pattern of intensity of competition in a given market m , while each of

the matrices $\mathbf{\Gamma}_{0m}$, $\mathbf{\Gamma}_{1m}$, and $\mathbf{\Gamma}_{2m}$, captures the pattern of intensity of competition for each distance band $b = 0, 1, 2$ in a given market m .

Estimation of the model also requires a column vector of conditional location-choice probabilities (with some initial starting values) for each market,

$$\mathbf{P}_m^* = \begin{bmatrix} P_{1m}^* \\ P_{2m}^* \\ \vdots \\ P_{\mathcal{L}_m m}^* \end{bmatrix},$$

to solve the system of equations in (E.13). We will also need a column vector (with starting values) of demand effects ,

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix},$$

and, for maximum likelihood routine in the second step, starting values for μ and σ^2 . Note that the log-likelihood function in (E.21) has terms (denoted by a_1 , a_2 , a_3 and a_4 below) that are fixed in the maximum likelihood estimation

$$\begin{aligned} \log(\mathcal{L}(\boldsymbol{\theta}|\mathbf{X})) &= \underbrace{\left[\sum_{m=1}^M \sum_{\ell=1}^{\mathcal{L}_m} \mathcal{N}_m \delta_{\ell m} \log(P_{\ell m}^*) \right]}_{a_1} - \frac{M}{2} (\log(2\pi)) \\ &\quad - \underbrace{\frac{M}{2} (\log(\sigma^2))}_{a_2} - \frac{1}{2\sigma^2} \sum_{m=1}^M \left(\underbrace{\log(\mathcal{N}_m) - \log(\mathcal{N}_m^p - \mathcal{N}_m)}_{a_3} \right) \\ &\quad - \log \left(\sum_{\ell=1}^{\mathcal{L}} \exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell} \beta_b + \gamma_0 + \underbrace{(\mathcal{N}_m - 1)}_{a_4} \left[\gamma_0 P_{\ell}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_j^* \right) \right] \right\} \right) - \mu \Big)^2, \end{aligned}$$

where $\boldsymbol{\theta} = [\boldsymbol{\beta}, \boldsymbol{\gamma}, \mu, \sigma^2]$ is vector of parameters to be estimated. The terms a_1 , a_2 , a_3 and a_4 could be pre-calculated before optimizing the log-likelihood to avoid recalculation at each iteration. If estimation is *not* done sequentially, and maximum likelihood estimation is performed with the fixed-point algorithm nested into it, then components of a_1 must be computed at each iteration.

Appendix G Chapter 2 Estimation Strategy Details

G.1 Estimation Part I: Fixed-Point Algorithm for the Lower Model

In this section, I briefly describe the estimation of the lower model via the fixed-point algorithm. I begin by briefly summarizing the key estimation components. The conditional location-choice probability is

$$P_{\ell m}^* = \frac{\exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell m} \beta_b + \gamma_0 + (\mathcal{N}_m - 1) \left[\gamma_0 P_{\ell m}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{jm}^* \right) \right] \right\}}{\sum_{k=1}^{\mathcal{L}_m} \exp \left\{ \sum_{b=0}^B \mathbf{X}_{bk m} \beta_b + \gamma_0 + (\mathcal{N}_m - 1) \left[\gamma_0 P_{km}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq k} \mathbb{I}_b(d_{jk}) P_{jm}^* \right) \right] \right\}}, \quad (\text{G.1})$$

which represents the system of \mathcal{L}_m equations and also defines the equilibrium location beliefs as a fixed point of the mapping from the MDI's belief of its rivals' strategies into its rivals' beliefs of the MDI's own strategy. Seim (2006) provides details about the existence and uniqueness properties of the equilibrium. The marginal probability of entry is

$$P_m = \frac{\exp \{ \xi_m \} I_m}{1 + \exp \{ \xi_m \} I_m}, \quad (\text{G.2})$$

where

$$I_m = \sum_{\ell=1}^{\mathcal{L}_m} \exp \left\{ \sum_{b=0}^B \mathbf{X}_{b\ell m} \beta_b + \gamma_0 + (\mathcal{N} - 1) \left[\gamma_0 P_{\ell m}^* + \sum_{b=1}^B \gamma_b \left(\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{jm}^* \right) \right] \right\}. \quad (\text{G.3})$$

The share of branches in ℓ

$$\delta_{\ell m} = \frac{n_{m\ell}}{\mathcal{N}_m}, \quad (\text{G.4})$$

and the log-likelihood function is

$$\log(\mathcal{L}) = \sum_{m=1}^M \sum_{\ell=1}^{\mathcal{L}_m} \mathcal{N}_m \delta_{\ell m} \log(P_{\ell m}^*) - \frac{M}{2} (\log(2\pi) + \log(\sigma^2)) - \frac{1}{2\sigma^2} \sum_{m=1}^M (\xi_m - \mu)^2. \quad (\text{G.5})$$

Moreover, the actual number of entrants, \mathcal{N}_m , equals the actual number of branches observed in the market and $\mathcal{N}_m^p = 2 \times \mathcal{N}_m$ or $\mathcal{N}_m^p = 30 \forall m = 1, \dots, M$ by assumption. Note, it is advised

to estimate the model with other values of \mathcal{N}_m^p for robustness (and perhaps to learn the model behavior). Finally, given the assumptions, an estimate of ξ_m is given by

$$\widehat{\xi}_m = \log(\mathcal{N}_m) - \log(\mathcal{N}_m^p - \mathcal{N}_m) - \log(I_m). \quad (\text{G.6})$$

We now have all the components needed for the empirical implementation of the model. In the current version of the paper, I estimate the model using a sequential estimation procedure. I begin by estimating the lower model. Conditional on entry, the lower model describes the bank's location choice behavior. Bank's location decision is endogenously determined due to its strategic nature. Therefore, I estimate the conditional, endogenous location-choice probabilities, \mathbf{P}_m^* , for each ℓ and m by solving the system of equations in (G.1) on a market-by-market basis. Note that there are a total of M systems of equations, each containing \mathcal{L}_m equations. Therefore, as the number of markets and locations grows, the estimation becomes computationally more burdensome. The system of equation in (G.1) in matrix notation can be written as

$$\mathbf{P}_m^* = \frac{\exp\{\mathbf{X}_m\boldsymbol{\beta} + (\mathcal{N}_m - 1)\boldsymbol{\Gamma}_m\mathbf{P}_m^*\}}{\sum_{\ell=1}^{\mathcal{L}_m} [\exp\{\mathbf{X}_m\boldsymbol{\beta} + (\mathcal{N}_m - 1)\boldsymbol{\Gamma}_m\mathbf{P}_m^*\}]_{\ell}} \quad (\text{G.7})$$

The use of $\boldsymbol{\Gamma}_m$ becomes more explicit from the exposition of the system of equations in (G.7). The system of equations in (G.7) yields $\widehat{\mathbf{P}}_1^*, \dots, \widehat{\mathbf{P}}_M^*$, where each $\widehat{\mathbf{P}}_m^*$ to be used in the next step of the estimation process is given by

$$\widehat{\mathbf{P}}_m^* = \begin{bmatrix} \widehat{P}_{1m}^* \\ \widehat{P}_{2m}^* \\ \vdots \\ \widehat{P}_{\mathcal{L}_m m}^* \end{bmatrix}.$$

The steps of the fixed-point algorithm can be summarized as follows:

1. Define a vector \widehat{P}_m^0 containing starting points for each market $m = 1, \dots, M$.
2. Using \widehat{P}_m^0 , calculate \widehat{P}_m^1 according to the system of equations described in (G.7).
3. Calculate error, $\|\widehat{P}_m^1 - \widehat{P}_m^0\|$. If error is greater than the pre-defined tolerance threshold, set $\widehat{P}_m^0 = \widehat{P}_m^1$ and repeat steps 2 and 3 until error is less than or equals to the pre-defined tolerance

threshold.

G.2 Estimation Part II: Maximum Likelihood Estimation of the Upper Model

The goal of the upper-model estimation is to obtain parameter estimates for $\theta = [\beta, \gamma, \mu, \sigma^2]$. First, I use the estimates of \mathbf{P}_m^* from the lower model and match them to the observed share of branches in ℓ , $\delta_{\ell m}$, resulting in $\delta_{\ell m} \log(P_{\ell m}^*)$. Concurrently, I match $\widehat{\mathbf{P}}_m^*$ to the matrices of competitive effects (described in Section F). This step yields $\sum_{j \neq \ell} \mathbb{I}_b(d_{j\ell}) P_{jm}^*$. Finally, using the obtained information I optimize the log-likelihood function

$$\begin{aligned} \log(\mathcal{L}(\theta|\mathbf{X})) = a_1 - a_2 (\log(\sigma^2)) - \frac{1}{2\sigma^2} \sum_{m=1}^M \left(\mathbf{a}_3 - \log \left(\exp \left\{ \mathbf{X}_m \boldsymbol{\beta} + \gamma_0 \right. \right. \right. \\ \left. \left. \left. + \mathbf{a}_4 [\gamma_0 \boldsymbol{\Gamma}_{0m} \mathbf{P}_m^* + \gamma_1 \boldsymbol{\Gamma}_{1m} \mathbf{P}_m^* + \gamma_2 \boldsymbol{\Gamma}_{2m} \mathbf{P}_m^*] \right\} \right) - \mu \right)^2, \end{aligned} \quad (\text{G.8})$$

where

$$a_1 = \left[\sum_{m=1}^M \sum_{\ell=1}^{\mathcal{L}_m} \mathcal{N}_m \delta_{\ell m} \log(P_{\ell m}^*) \right] - \frac{M}{2} (\log(2\pi)),$$

$$a_2 = \frac{M}{2},$$

$$\mathbf{a}_3 = \log(\mathcal{N}) - \log(\mathcal{N}^p - \mathcal{N}),$$

$$\mathbf{a}_4 = \mathcal{N} - 1,$$

with $\mathcal{N}^p = [\mathcal{N}_1^p, \dots, \mathcal{N}_M^p]'$ and $\mathcal{N} = [\mathcal{N}_m, \dots, \mathcal{N}_M]'$. The likelihood function in (G.8) is maximized to obtain $\widehat{\theta} = [\widehat{\beta}, \widehat{\gamma}, \widehat{\mu}, \widehat{\sigma}^2]$ using BHHH procedure proposed by Berndt et al. (1974). The advantage of sequential estimation is that it is easier to implement relative to the full information maximum likelihood (FIML) estimation procedure. The sequential estimation is also computationally less burdensome, while the obtained estimates are asymptotically consistent (see, e.g., Greene's (2003)

Econometric Analysis textbook). The ease of implementation and less computational burden come at the cost of efficiency loss, therefore it is necessary to adjust standard errors. Without adjustments, standard errors are biased downwards. The standard errors can be calculated or adjusted in several ways: bootstrapping standard errors, use adjustment procedure proposed by White (1982), or other methods. In this paper I adjust the standard errors using White’s (1982) robust “sandwich” estimator (also described Greene’s (2003) econometrics textbook).

Alternatively, the log-likelihood function in (G.8) could be optimized using the Nelder-Mead (or other) optimization method with the fixed-point algorithm (in (G.7)) nested into it. There are several ways of implementing a FIML estimation procedure. First, one may write two loops, (i) one with the fixed-point algorithm and (ii) another with the maximum likelihood (ML) routine optimizing the $\log(\mathcal{L}(\boldsymbol{\theta}|\mathbf{X}))$. The fixed-point algorithm can be nested into the ML routine, such that the $\widehat{\mathbf{P}}_m^*$ from the fixed-point algorithm is fed into the ML algorithm, and the resulting $\widehat{\boldsymbol{\theta}} = [\widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\gamma}}, \widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\sigma}}^2]$ is fed back into the fixed-point algorithm to restart the process. The “nested” fixed-point algorithm would converge when both loops converge, given some tolerance threshold.

Alternatively, if using the Nelder-Mead algorithm (or maybe another gradient-free optimization method) to carry out FIML estimation, one may write a function for $\log(\mathcal{L}(\boldsymbol{\theta}|\mathbf{X}))$ taking a vector $\boldsymbol{\theta}_0 = [\boldsymbol{\beta}_0, \boldsymbol{\gamma}_0, \boldsymbol{\mu}_0, \boldsymbol{\sigma}_0^2]$ with starting values as an argument and with the fixed-point algorithm “built into” it. That way, when starting values are supplied to this function, it performs the fixed-point algorithm and evaluates the LLF using the probabilities resulting from the fixed-point algorithm. This function could then be supplied to pre-built optimization routines. This estimation approach avoids efficiency loss. However, since there are a total of M systems of equations, each containing \mathcal{L}_m equations, the nested-likelihood function optimization procedure is computationally burdensome. This is particularly true for the Nelder-Meade method, which is robust but is slow to converge. Moreover, “bad” initial guesses can interrupt the estimation process. I plan to implement the FIML estimation procedure in the future versions of the paper.

Appendix H Figures for Chapter 2 Appendices

Figure H1: Joint Entry and Location Choice Tree Diagram for One Market

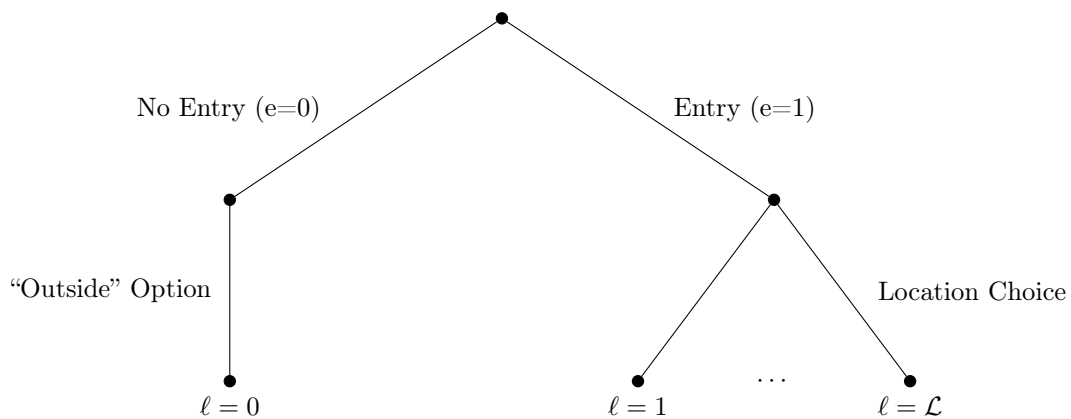


Figure H2: Hypothetical 5×5 Market with 25 Locations

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

Figure H3: Matrix of Competitive Effects for the Hypothetical 5×5 Market

ℓ	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	ℓ
1	█	█				█	█																			1
2	█	█	█			█	█	█																		2
3		█	█	█			█	█	█																	3
4			█	█	█			█	█	█																4
5				█	█				█	█																5
6	█	█				█	█				█	█														6
7	█	█					█	█				█	█													7
8		█	█					█	█				█	█												8
9			█	█					█	█				█	█											9
10				█	█					█	█				█	█										10
11						█	█				█	█				█	█									11
12							█	█				█	█				█	█								12
13								█	█				█	█				█	█							13
14									█	█				█	█				█	█						14
15										█	█					█	█				█	█				15
16											█	█					█	█				█	█			16
17												█	█					█	█				█	█		17
18													█	█					█	█				█	█	18
19														█	█					█	█				█	19
20															█	█					█	█			█	20
21																█	█					█	█		█	21
22																	█	█					█	█	█	22
23																		█	█					█	█	23
24																			█	█					█	24
25																				█	█				█	25
ℓ	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	ℓ

Appendix I Chapter 3 Solutions for the Debt-Forgiveness Model with Search Costs

I.1 Individual's Problem with Search Costs

Given the additional information about search costs, the individual's problem can be described by

$$\max_{c_1, c_2^e, c_2^u} U^i(c_1, c_2^e, c_2^u) = \ln c_1 + p^i \ln c_2^e + (1 - p^i) \ln c_2^u \quad (\text{I.1})$$

subject to constraints

$$c_1 = w_1 L_1 - (f - d)(1 - L_1), \quad (\text{I.2})$$

$$c_2^e = (1 - \tau)w_2 L_2 - d(1 - L_1)(1 - \mathbb{I}(D)) - \lambda, \quad (\text{I.3})$$

$$c_2^u = T - d(1 - L_1)(1 - \mathbb{I}(D)) - \lambda. \quad (\text{I.4})$$

As before, I assume $f = d$ for simplicity. Then, an individual will invest in schooling if $U^{\text{schooling}} \geq U^{\text{no schooling}}$ under both debt-forgiveness policies.

Then, an agent will invest in schooling in the first period if

$$\begin{aligned} \ln(c_1|L_1 = \frac{1}{2}) + p^i \ln(c_2^e|L_1 = \frac{1}{2}) + (1 - p^i) \ln(c_2^u|L_1 = \frac{1}{2}) &\geq \\ \ln(c_1|L_1 = 1) + p^i \ln(c_2^e|L_1 = 1) + (1 - p^i) \ln(c_2^u|L_1 = 1), & \end{aligned} \quad (\text{I.5})$$

or equivalently if

$$\begin{aligned} \ln\left(\frac{H_1}{2}\right) + p^i \ln\left((1 - \tau)\left[H_1 + \frac{\alpha H_1^\gamma}{2}\right] - \frac{d}{2}(1 - \mathbb{I}(D)) - \left[a - \frac{b}{2}\right]\right) \\ + (1 - p^i) \ln\left(T - \frac{d}{2}(1 - \mathbb{I}(D)) - \left[a - \frac{b}{2}\right]\right) \\ \geq \ln(H_1) + p^i \ln((1 - \tau)H_1 - a) + (1 - p^i) \ln(T - a). \end{aligned} \quad (\text{I.6})$$

The inequality in I.6 simplifies to

$$\begin{aligned} p^i \ln\left[\frac{(T - a)[2((1 - \tau)H_1 - a) + (1 - \tau)\alpha H_1^\gamma - d(1 - \mathbb{I}(D)) + b]}{[(1 - \tau)H_1 - a][2(T - a) + b - d(1 - \mathbb{I}(D))]} + \ln\left[\frac{2(T - a) + b - d(1 - \mathbb{I}(D))}{4(T - a)}\right]\right] &\geq 0, \end{aligned} \quad (\text{I.7})$$

which leads to

$$p^i \geq \frac{\left[\ln \left(\frac{4(T-a)}{2(T-a)+b-d(1-\mathbb{I}(D))} \right) \right]}{\left[\ln \left(\frac{(T-a)[2((1-\tau)H_1-a)+(1-\tau)\alpha H_1^\gamma-d(1-\mathbb{I}(D))+b]}{[(1-\tau)H_1-a][2(T-a)+b-d(1-\mathbb{I}(D))]} \right) \right]}. \quad (\text{I.8})$$

Then, solving for the optimal labor choice in the first period when the debt yields

$$L_1^1 = \begin{cases} \frac{1}{2} & \text{for } \mathbb{I}(D) = 1 \text{ and } p^i \geq \phi_1(\tau, T) \\ 1 & \text{for } \mathbb{I}(D) = 1 \text{ and } p^i < \phi_1(\tau, T), \end{cases} \quad (\text{I.9})$$

where $\phi_1(\tau, T) = \frac{\left[\ln \left(\frac{4(T-a)}{2(T-a)+b} \right) \right]}{\left[\ln \left(\frac{(T-a)[2((1-\tau)H_1-a)+(1-\tau)\alpha H_1^\gamma+b]}{[(1-\tau)H_1-a][2(T-a)+b]} \right) \right]}.$

Similarly, the optimal labor choice in the first period when debt is not forgiven is

$$L_1^2 = \begin{cases} \frac{1}{2} & \text{for } \mathbb{I}(D) = 0 \text{ and } p^i \geq \phi_2(\tau, T) \\ 1 & \text{for } \mathbb{I}(D) = 0 \text{ and } p^i < \phi_2(\tau, T) \end{cases} \quad (\text{I.10})$$

where $\phi_2(\tau, T) = \frac{\left[\ln \left(\frac{4(T-a)}{2(T-a)+b-d} \right) \right]}{\left[\ln \left(\frac{(T-a)[2((1-\tau)H_1-a)+(1-\tau)\alpha H_1^\gamma-d+b]}{[(1-\tau)H_1-a][2(T-a)+b-d]} \right) \right]}.$

I.2 Voter's Problem with Search Costs

Given the optimal labor choice L_1^* in I.9 and I.10, voter's problem is to choose optimal policies that maximize voter's utility

$$\begin{aligned} \max_{\tau, D, T} V^i(\tau) &= \ln [H_1 L_1^*] + p^i \ln [(1-\tau)[H_1 + \alpha H_1^\gamma(1-L_1^*)]L_1 - d(1-L_1^*)(1-\mathbb{I}(D)) - (a-b(1-L_1^*)) \\ &\quad + (1-p^i) \ln [T - d(1-L_1^*)(1-\mathbb{I}(D)) - (a-b(1-L_1^*))] \end{aligned} \quad (\text{I.11})$$

subject to government budget constraint

$$(1-\bar{p})T + \delta_s^{\mathbb{I}(D)} \frac{d}{2} \mathbb{I}(D) = \tau \left[\bar{p}_n^{\mathbb{I}(D)} \delta_n^{\mathbb{I}(D)} H_1 + \bar{p}_s^{\mathbb{I}(D)} \delta_s^{\mathbb{I}(D)} \left(H_1 + \frac{\alpha H_1^\gamma}{2} \right) \right] L_2, \quad (\text{I.12})$$

where $\bar{p}_n^{\mathbb{I}(D)}$ is an average probability of being employed among non-schooled population, $\bar{p}_s^{\mathbb{I}(D)}$ is an average probability of being employed among schooled population, $\delta_n^{\mathbb{I}(D)}$ and $\delta_s^{\mathbb{I}(D)}$ are a fraction of unschooled and schooled population respectively. Moreover, $\delta_n^{\mathbb{I}(D)} + \delta_s^{\mathbb{I}(D)} = 1$ and $\bar{p} = \bar{p}_n^{\mathbb{I}(D)} \delta_n^{\mathbb{I}(D)} + \bar{p}_s^{\mathbb{I}(D)} \delta_s^{\mathbb{I}(D)}.$

I.2.1 Voter's Favorite Tax when Student Loans are Forgiven

Under the student loan forgiveness policy (i.e., when $\mathbb{I}(D) = 1$) the optimal labor choice is given by I.9 and the government budget constraint can be written as

$$T = \frac{1}{(1-\bar{p})} \tau \left[\bar{p}_n^1 \delta_n^1 H_1 + \bar{p}_s^1 \delta_s^1 \left(H_1 + \frac{\alpha H_1^\gamma}{2} \right) \right] - \frac{1}{(1-\bar{p})} \frac{\delta_s^1}{2} d. \quad (\text{I.13})$$

Using the budget constraint in I.13, the voter's problem can be written as an unconstrained optimization problem given by

$$\begin{aligned} \max_{\tau} V^i(\tau) = & \ln[H_1 L_1] + p^i \ln[(1-\tau)[H_1 + \alpha H_1^\gamma(1-L_1^*)] - (a - b(1-L_1^*))] \\ & + (1-p^i) \ln \left[\frac{1}{(1-\bar{p})} \tau \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right] - \frac{1}{(1-\bar{p})} \frac{\delta_s^1}{2} d - (a - b(1-L_1^*)) \right]. \end{aligned} \quad (\text{I.14})$$

The first order conditions are given by

$$\begin{aligned} \frac{dV^i(\tau)}{d\tau} = & p^i \frac{\partial \ln[(1-\tau)(H_1 + \alpha H_1^\gamma(1-L_1^*)) - (a - b(1-L_1^*))]}{\partial \tau} \\ & + (1-p^i) \frac{\partial \ln \left[\frac{1}{(1-\bar{p})} \tau \left(\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right) - \frac{1}{(1-\bar{p})} \frac{\delta_s^1 d}{2} - (a - b(1-L_1^*)) \right]}{\partial \tau} = 0, \end{aligned} \quad (\text{I.15})$$

which simplifies to

$$\begin{aligned} & \frac{-p^i [H_1 + \alpha H_1^\gamma(1-L_1^*)]}{(1-\tau)[H_1 + \alpha H_1^\gamma(1-L_1^*)] - [a - b(1-L_1^*)]} \\ & + \frac{(1-p^i) \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]}{\tau \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right] - \frac{\delta_s^1 d}{2} - (1-\bar{p})[a - b(1-L_1^*)]} = 0 \end{aligned} \quad (\text{I.16})$$

Then, solving I.16 for optimal tax rate yields

$$\tau_1^* = (1-p^i) + \frac{p^i \delta_s^1 d}{2 \left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} + \left[\frac{p^i(1-\bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1-p^i)}{w_2(L_1^*)} \right] \lambda(L_1^*), \quad (\text{I.17})$$

where $w_2(L_1^*) = H_1 + \alpha H_1^\gamma(1-L_1^*)$ and $\lambda(L_1^*) = a - b(1-L_1^*)$.

I.2.2 Voter's Favorite Tax when Student Loans are Not Forgiven

The optimal labor choice when the student loan forgiveness policy is not implemented (i.e., when $\mathbb{I}(D) = 0$) is given by I.10 and the government budget constraint can be written as

$$T = \frac{1}{(1-\bar{p})} \tau \left[\bar{p}_n^0 \delta_n^0 H_1 + \bar{p}_s^0 \delta_s^0 \left(H_1 + \frac{\alpha H_1^\gamma}{2} \right) \right]. \quad (\text{I.18})$$

Using the budget constraint in I.18, the voter's problem can be written as an unconstrained optimization problem given by

$$\begin{aligned} \max_{\tau} V^i(\tau) = & \ln [H_1 L_1] + p^i \ln [(1-\tau)[H_1 + \alpha H_1^\gamma (1-L_1^*)] - d(1-L_1^*) - (a-b(1-L_1^*))] \\ & + (1-p^i) \ln \left[\frac{1}{(1-\bar{p})} \tau \left[\bar{p} H_1 + \bar{p}_s^0 \delta_s^0 \frac{\alpha H_1^\gamma}{2} \right] - d(1-L_1^*) - (a-b(1-L_1^*)) \right]. \end{aligned} \quad (\text{I.19})$$

The first order conditions are given by

$$\begin{aligned} \frac{dV^i(\tau)}{d\tau} = & p^i \frac{\partial \ln [(1-\tau)[H_1 + \alpha H_1^\gamma (1-L_1^*)] - d(1-L_1^*) - (a-b(1-L_1^*))]}{\partial \tau} \\ & + (1-p^i) \frac{\partial \ln \left[\frac{1}{(1-\bar{p})} \tau \left[\bar{p} H_1 + \bar{p}_s^0 \delta_s^0 \frac{\alpha H_1^\gamma}{2} \right] - d(1-L_1^*) - (a-b(1-L_1^*)) \right]}{\partial \tau} = 0. \end{aligned} \quad (\text{I.20})$$

Solving I.20 for optimal tax rate τ under no student loan forgiveness policy yields

$$\tau_2^* = (1-p^i) + \left[\frac{p^i(1-\bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1-p^i)}{w_2(L_1^*)} \right] (1-L_1^*)d + \left[\frac{p^i(1-\bar{p})}{\left[\bar{p} H_1 + \bar{p}_s^1 \delta_s^1 \frac{\alpha H_1^\gamma}{2} \right]} - \frac{(1-p^i)}{w_2(L_1^*)} \right] \lambda(L_1^*),$$

where $w_2(L_1^*) = H_1 + \alpha H_1^\gamma (1-L_1^*)$ and $\lambda(L_1^*) = a - b(1-L_1^*)$.

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