Just How Risky?
Comparative Institutional Risks of Mission-based Depository Institutions (MBDIs)

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Abstract

We examine the relative institutional failure risks for three sets of bank depositories: Community Development Banking Institutions (CDBIs), Minority Depositories (MDIs) and what we term Non-Mission Depository Institutions (hereafter, NMDIs). CDBIs have primary missions of community development and serving underserved populations; MDIs are typically led by minorities and serve minority populations (a single institution can be both a Community Development Banking Institution (CDBI) and an MDI, either or neither). In this analysis, NMDIs represent all other depository banks. Given their operation within lower-income and minority communities, MDIs and CDBIs appear, *prima facie*, to be face greater institutional failure risks. We examine these risks across each set of institutions, *ceteris paribus*. Utilizing data from a number of sources, including the Reports of Condition and Income (Call Reports) for a substantial set of FDIC-insured banks in the United States, we apply a modified Capital Assets Management Earnings and Liquidity (CAMEL) model to measure the predictive likelihood of failure. Recognizing that MDIs are not homogeneous, we also examine relative institutional failure across types of depositories. The results indicate that CDBIs and MDIs are systematically at lower failure risks, and that there are differences across service designations.

Introduction

Community Development Banking Institutions (hereafter, CDBIs) are depository banks that serve low-income, underserved markets. CDBIs are defined as ". . . depository institutions with a stated mission to primarily benefit the underserved communities in which they are chartered to conduct business" (Office of Comptroller of the Currency, 2019). CDBIs provide depository, credit and counseling services to low-and moderate-income (LMI) individuals or communities. They are one category of Community Development Financial Institution (hereafter, CDFI). CDFI is a U.S. Treasury designation of mission-driven financial institutions (and can be credit unions, loan funds, or equity funds).

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Similarly, Minority Depository Institutions (hereafter, MDIs) are a federally-recognized set of banks and credit unions that have missions to provide financial services to minority populations.[2] It is possible for a single depository to be an MDI, a CDBI, neither or both. Hereafter, when referring to both CDBIs and MDIs collectively, we use the term Mission Designated Depository Institution (hereafter, MDDIs). When referring to neither, we will use the term Non-Mission Depository Institutions (NMDIs).[3] As regulated financial institutions, CDBIs and MDIs must meet the same safety and soundness requirements as any other depository.

There are *prima facie* reasons to suspect that MDDIs face greater risks of institutional failure than otherwise similar depositories. Prevailing among these intuitions are concerns that center on these depositories' stated commitment to the provision of financial services to LMI and minority consumers and markets. There is a general recognition that consumers from these households tend to have lower assets, greater risks of occupational disruption (e.g., unemployment), and lower average incomes (De Jong & Madamba, 2001; Pfeffer, Danziger, & Schoeni, 2013). There is a logical progression that the provision of financial services to consumers with these characteristics expose financial institutions to heightened risks of credit default, and thus, institutional failure.

Observables provide some support for an association between MDDIs and heightened failure risks. For example, studies show that CDBIs tend to locate branches to a greater degree in LMI neighborhoods and place more of their loans in these communities as well. A recent report by the National Community Investment Forum (NCIF) found that the median CDBI in 2016 had 55.2% of their branches in LMI communities and made 75.3% of their loans in these as well (Narain & Malehorn, 2018). Comparable NMDIs have considerably lower branching and provision of services in these markets (Porteous & Narain, 2015). Likewise, other researchers report that MDIs are more likely to serve minority consumers than comparable non-MDIs (Kashian & Drago, 2017; Kashian, McGregory, & McCrank, 2014).

Some observable market trends provide a measure of support for the conjecture that service to these consumer segments exposes depositories to undue risks. Contemporary high levels of residential segregation by race, income, and education create clusters of poverty and concomitant social dislocations in geographic space (and thus, in depository operational areas). For example, a recent analysis by Intrator, Tannen, and Massey concluded that "Given their higher overall levels of segregation and income's limited effect on residential attainment, African Americans experience less integration, more neighborhood poverty at all levels of income compared to other minority groups. The degree of Black spatial disadvantage is especially acute in the nation's 21 hypersegregated metropolitan areas" (Fairchild, 2009; Intrator, Tannen, & Massey, 2016). CDBIs and MDIs have made strategic decisions that place branches and staff in areas that are proximal to LMI and ethnic minority consumers.

2 MDIs and CDFIs may be banks or credit unions. In this paper, we restrict our analysis to bank depositories.

3 The acronym is created by the authors as a way of designating for analysis purposes. We recognize that institutions that are neither CDBIs nor MDIs may be mission-driven, and yet are not certified as such.

Because of this conscious choice to locate MDDI branches in LMI and minority neighborhoods, when these banks close it has a disproportionate impact on small businesses located in those neighborhoods. When community banks fail, such as MDDIs, there is a contraction in credit that can last up to 3 years in the LMI and minority neighborhoods around these branches. This impacts both the germination of new businesses and the expansion of existing businesses (Toussiant-Comeau, Wang, & Newberger, 2020). Many of the small businesses that rely on MDDIs for access to credit are constrained in other ways. Minority-owned businesses receive discriminatory treatment from private equity firms (Bates, Bradford, & Jackson, 2018) and are often undercapitalized, when compared to similarly situated white-owned businesses, which limits their ability to expand and survive (Robb & Robinson, 2018; Fairlie & Robb, 2010). While the form of restricted access to credit varies by type, minorities face more discrimination in low-competition markets (Mitchell & Pearce, 2011). Thus, this lack of equality of capital access for minority-owned business, combined with the enabling role MDDIs play in capital provision to minority small businesses, means the fate of minority-owned small businesses is tied to the fate of MDDIs.

A recent analysis suggests that the aggregate number of MDIs has dropped faster than non-MDIs, and that their smaller relative asset sizes are associated with institutional failure risks: "Accordingly, and for Black MDIs in particular, the smaller scale may translate to difficulty navigating and operating in a highly regulated, quickly transforming industry, which limits their ability to serve the communities that need their help" (Barth, Betru, Brigida & Lee, 2019, 3-4).

Noting recent marked increases in the number and regional presence of CDBIs, other observers have examined institutional indicators among CDBIs and come to alternate conclusions (Narain & Malehorn, 2018). An analysis from the National Community Investment Forum (NCIF) reports that between 2001 and 2017, the number of certified CDBIs grew from 39 to 136, with total assets increasing from $5.2B to $48.1B. They also find evidence that CDBIs grew regionally. Notably, the number of CDBIs in a select set of Southern states grew from 9 in 2001 to 79 in 2017 (i.e., Alabama, Arkansas, Georgia, Mississippi, and Tennessee) (Narain & Malehorn, 2018, 3).

While these may seem suggestive of healthy growth, increases in the number of CDBIs and assets under management may not fully satisfy. Aggregate market trends may be due to factors other than robustness: first, existing depositories may have recently certified and registered to become CDBIs; second, increased institutional counts may be due to *de novo* depositories, while obscuring failure risks at the institutional level or within certain subsegments. The NCIF report did not examine whether there are differential failure risks at the institutional level, only overall size and scope trends, so this work is silent regarding these queries.

If the profile of MDDI's customers and market areas was not sufficient reason for these questions, the recent recession of the late 2000s further contributed to this skepticism. The period brought on a record number of banking failures, including MDDIs. The prevailing perception that the crisis was due to questionable lending practices, especially among what became known as "subprime markets" led to questions in some quarters about the viability of MDDIs due to their proximity to neighborhoods impacted by subprime lending rather than the their actual practices (Spader & Quercia, 2012).

Even without the economic uncertainty brought on by the recession and related banking failures, the question of whether CDBIs or MDIs were likely to face higher institutional failure risks has been a topic of public policy interest for some time. One reason is that once certified, MDDIs are able to receive various forms of governmental and philanthropic support–technical assistance, training and education. In addition, certified CDFIs generally and CDBIs specifically also receive financial subsidy from foundations, governments, and individuals in the form of grants or low-interest investments.

It follows that external observers–academic, policy, or philanthropic–might wonder whether these economic and non-economic supports find placement in institutions with high likelihood of failure. If MDDIs are indeed more likely to fail, some observers might question whether these institutions should receive these supports at all. Should these funds instead be distributed to institutions with better survival prospects? Another concern might be that if these institutions do indeed face lower likelihood of survival, are these supports prescriptive? That is, do depositories facing significant market challenges benefit from these supports, and would they have an even greater rate of failure without them?

Given a linkage between the mission-based strategic orientations of MDDIs to normatively-desirable societal goals, understanding their relative failure risks has many potential economic and societal benefits. Economically, these goals include aiding in creating financial security for LMI populations, increasing affordable home ownership, and providing capital to minority entrepreneurs (Barth, Betru, Brigida, & Lee, 2019; Canner & Passmore, 1994; Matasar & Pavelka, 2004; Narain & Malehorn, 2018; Toussiant-Comeau, Wang, & Newberger, 2020). In social terms, these efforts can help to diminish wealth and socioeconomic gaps between racial groups and status groups.

For some proponents of MDDIs, there is the presumption that without these mission-driven depositories, these customer segments may not be served at all, or would be underserved. If there is truth to these notions, it represents a form of market failure or a reflection of measured market response, respectively. In the case of market failure, then there is an opportunity cost being paid: the diminishment of potential economic output at the national and community level. At this point, these are largely rhetorical debates. There is very little careful, rigorous analysis to determine the relative risks of MDDIs.

Although there are propositions suggestive of facilitative functions of MDDIs in the development of LMI and minority communities, there is limited evidence and lingering questions about the relative failure risks facing these institutions. Achieving a better understanding of the comparative performance of mission-driven institutions like MDDIs may have considerable policy and societal impact. This research takes these questions seriously. In this paper, we respond to practical and scholarly interests in the failure risks of these financial institutions, employing a modification of an approach commonly used in prediction of depository failure risks: Capital Adequacy, Asset Quality, Management, Earnings, and Liquidity (known by the acronym CAMEL).

What are CDBIs and MDIs?

MDIs were created by the Financial Institutions Reform, Recovery, and Enforcement Act in 1989 (FIRREA). Of course, ethnic and racial minority-serving institutions existed prior. Informal financial collectives existed among freed slaves prior to the Civil War and, during the war, military savings banks were created by the Union army for Black troops (Fleming, 2018). After the war, the U.S. government created the Freedman's Savings Bank in 1865 as a component of a suite of policies that became known as Reconstruction.

The MDI designation was created as a component of FIRREA, with the objective of sustaining and increasing the number and capacity of depositories operating in minority markets. From a definitional standpoint, "a minority institution" is determined by either (1) a concentration of ownership among members of a certain minority group, or (2) a concentration of board membership among that minority group by an institution that primarily serves that minority group.[4] Relevant minority groups include: Blacks or African Americans, Hispanic or Latinx, Asian or Pacific Islanders, Native Americans or Alaska Native Americans, and Multi-racial Americans.[5] Specifically, section 308 of the FIRREA of 1989 defines MDIs as "any depository institution where 51 percent or more of the stock is owned by one or more 'socially and economically disadvantaged individuals'" (Federal Deposit Insurance Corporation, 2019). This is commonly called "the ownership test." The FDIC regularly updates the list of MDIs and certifies their consistency with the program's objectives using historical data (Federal Deposit Insurance Corporation, 2019).

Comparatively, The Riegle Community Development and Regulatory Improvement Act of 1994 (P.L. 103-325) established the Community Development Financial Institutions Fund as a "wholly owned government corporation to promote economic revitalization and community development." The Fund was initially proposed by President Bill Clinton and was at least partially based on his own experience with community banking prior to his election (Martin, 1994). In his public pronouncements, the mission-driven aspects of the program are clearly mentioned: "by ensuring greater access to capital and credit, we will tap the entrepreneurial energy of America's poorest communities and enable individuals and communities to become self-sufficient."[6]

The Fund was created within the U.S. Treasury and is a component of the programs of the Under Secretary's Office of Domestic Finance. Because of its focus on financial institutions, it is organized under the Assistant Secretary for Financial Institutions. In terms of type of institution, CDFIs can take a number of forms, including banks and credit unions, nonprofit loan funds, and equity funds. Estimates of the total number of CDFIs nationally vary, though most sources indicate that there are approximately 1,100. At least one reason for the variance in estimated presence in the field is the procedural requirement to self-certify, and to recertify over time. Because of that process necessity, an institution may be certified at one point in their operational history, and not at another even as operations continue unabated.

If a bank or credit union is not currently a CDBI or MDI, it can self-certify, pending CDFI Fund or FDIC confirmation. For this reason, the aggregate number of CDBIs or MDIs may change over time without there being actual creation or failure of institutions–

this presents unique problems for researchers, as we discuss above. In the next section, we provide a preliminary set of arguments for potential heightened institutional failure risks of MDDIs.

MDDIs and Institutional Failure Risks—A Few Considerations

A review of the prevailing arguments in the scholarly and practical discourse on MDDIs return a common set of hypotheses about the sources of differential operation risks for MDDIs relative to NMDIs: these include the clients served, capability endowments, informational asymmetry, and contagion. We discuss each of these briefly below.

Clients

Due to persistent racial segregation by income, socioeconomic status, and race in the U.S., the workplace, K-12 schools, and residential neighborhoods are clustered across socioeconomic factors. For example, Bischoff, and Reardon (2014) find that income segregation has grown substantially in recent decades, with the bulk of this increased spatial dissimilarity happening between 1980-2000. Likewise, researchers have found considerable levels of residential segregation by social economic status (SES), with Iceland and Wilkes (2006) finding class sorting effects in neighborhoods even after controlling for racial demography. Similarly, in an analysis of racial residential segregation in major cities and suburbs since 1970, Massey and Tannen (2018) find that even by 2010, Blacks faced falling but high levels of residential segregation, while Asians and Hispanics experienced moderate levels. It is noteworthy that the increases in segregation by race and its durability occur years after the passage of the federal housing legislation.[7]

Residential clustering and segregation segments consumers into submarkets across geographic space. One benefit of these patterns is that they facilitate effective customer targeting and service matching. Segregation is a likely influential factor on the tendency of MDDIs to locate branches and operate in LMI or predominantly minority neighborhoods. Given high levels of social-, neighborhood- and workplace-segregation, consumers tend to interact within their respective racial and status groups (Kornienko, Santos, & Updegraff, 2015; Toussaint-Comeau & Newberger, 2017). Recognizing these behavioral engagement patterns, many MDDIs also hire demographically-matched service staffs.

Although segregation may facilitate market segmentation, these residential patterns also cluster poverty and associated social ills (Cutler, Glaeser, & Vigdor, 1999; Fairchild, 2009; Massey & Denton, 1993). If the neighborhoods in which MDDIs operate have higher levels of poverty and unemployment, some financial services providers may avoid operating there (Greer & Gonzalez, 2017; Runck, 1996). There is a logic to this approach. For example, communities with substantially higher levels of unemployment and underemployment may be especially vulnerable to economic shocks and downturns. This vulnerability might sub-

7 Title VIII of the US Civil Rights of 1968 is called the Fair Housing Act, which intended to limit and decrease housing discrimination.

ject consumers and their providers to a greater likelihood of credit default. Relatedly, Wang (2018) finds that minority-owned businesses are clustered into a relatively small set of industries, and that these are often those with marginal profits.

A relative absence of financial providers in a market can be viewed as evidence of market failure, in most circumstances a negative outcome. However, market incumbents may have another way of looking at these conditions: diminished competition among providers may create "captive" market conditions for depositories operating in these neighborhoods. Institutions servicing these neighborhoods may face fewer pressures to invest in capabilities that would provide service or product advantages. These monopolistic conditions would allow these institutions to charge higher rates and rely to a greater degree on captive consumer loyalty. Taken together, consumers in segregated LMI and minority markets may pay higher rates for their products, receive fewer service innovations, and may patronize providers that lower, rather than raise, their wealth. For example, Hyra, Squires, Renner, and Kirk (2013) find that even after controlling for neighborhood demographic characteristics and real estate trends, segregation was a significant predictor of the proportion of subprime loans originated in the largest 200 U.S. metropolitan areas between 2000 and 2006. While there is no evidence that MDDIs engaged in what could be described as predatory practices, they nonetheless operate in LMI and minority markets where their clients contend with poverty and wealth-reducing practices from other financial institutions. Taken together, client characteristics could impact the financial viability of MDDIs, which is the primary interest of this analysis.

Capability Endowments

CDBIs and MDIs tend to be smaller in relative asset sizes. Some researchers have argued that relatively undercapitalized depositories may have challenges in attracting and securing state-of-the-art capabilities and resources (Barth, Betru, Brigida, & Lee, 2019). Additionally, locations in LMI and minority neighborhoods may be less attractive to some employees, and physical and technological infrastructure may be of lower quality. The people, processes, and systems in MDDIs may not be as adept at providing competitive advantage or may be more costly to provide.

Informational Asymmetry

Another barrier to effective operation within LMI and minority communities may be differential access to data or relationship networks that make the determination of creditworthiness and risk scoring daunting, even to the degree of deterring action. For example, consumer financial services credit-granting decisions rely on both quantifiable data, like credit scores, and less on qualitative, unmeasurable data, like on-the-ground, local tacit knowledge. Lee (2019) finds that character-based lending, which relies on personal characteristics, is a key factor in lending to women-owned and minority-owned businesses. The amount, scope and quality of typical credit scoring indicators tend to be negatively correlated with income, wealth, and educational attainment. Further, in communities where there has traditionally been less lending, there is less specific tacit knowledge to aid lenders in making credit decisions. Taken together, quantitative and qualitative indicators of creditworthiness may simply be less available, whether they support the notion of a lack of creditworthiness or not. A lack of information is associated with uncertainty, which is a challenge, if not a deterrent, to lending.

Contagion

MDDIs might face another vulnerability that accrues from interlinked market contagion. Put differently, an individual MDDI may have constructed loans with strong underwriting, and still be vulnerable to the collapse of loans made by other providers. As noted above, there is a correlation between subprime mortgage loans and higher levels of residential segregation (Hyra et al., 2013). It logically follows that a shared market presence with a preponderance of poorly-performing loans may lead to a contagion cascade, even when not made by the focal lender. There is some evidence for this effect. First, Fairchild and Jia (2015) find that CDFIs are not more prone to institutional failure once they control for interlocking neighborhood mortgage network effects. Similarly, other researchers find an 18% increased risk of neighborhood contagion for foreclosures among minority mortgage loans (Towe & Lawley, 2013).

The effort in this section was to catalogue a set of common themes in scholarly and policy discourse about these institutions and associated programs, and not to provide a comprehensive set of potential arguments for heightened risks. In the next section, we review the related literature scholarly work on predicting depository failure, along with CDFIs, CDBIs, MDIs and their institutional failure risks.

Literature Review

Our review of the literature reveals that precious little has been written in the scholarly literature about MDIs or CDBIs. More specifically, even less on their relative institutional risks. There is a small and growing literature that has focused on MDDI's operational efficiencies, which we also review below.

Modeling Institutional Risks

The use of statistical methods in assessing the risk of either institutional failure or payment default has roots in the work of Edward Altman in the late 1960s. Altman (1968) introduced a method of predicting corporate failure using a combination of financial ratios of the firm. The resulting model, generally referred to as Altman's Z-score, is the sum of related financial and operational ratios. Altman's model was able to predict whether a firm was at risk for failure within a given period if its particular sum falls below a certain threshold (e.g., over 8 quarters). Altman's Z-score is based on a linear discriminant analysis approach, which has several strong assumptions (e.g. covariance matrices between distressed and safe firms are equal).

Since its publication, Altman's model and its approach have been updated and expanded to cover a broader number of industries and settings, including financial intermediaries such as banks (Altman, 1977; Altman, Brady, Resti, & Sironi, 2005). The use of logistic regression approaches to monitor banks was first proposed in 1977 by Daniel Martin (1977).

The use of CAMEL models to predict institutional failure risks for US banking institutions dates back to the 1970s. They rely on a combination of financial ratios and direct observation, and are generally structured as logistic regression models. Presently, CAMEL models are the prevailing method used by regulators to determine safety and soundness of banks (used by the Federal Reserve System, Office of the Comptroller of the Currency [OCC], and the Federal Deposit Insurance Corporation [FDIC]). CAMEL models are logistic regressions that predict the probability of institutional failure as a dependent variable and apply the balance sheet and income statement ratios as predictor variables. Specific CAMEL measures are generally kept proprietary and individual institutional CAMEL ratings of banks are confidential. Thus, researchers must develop their own measures through a combination of comparisons in the literature and data mining techniques (Cole & White, 2012; Fairchild & Jia, 2015).

Although broadly used, CAMEL models have known limitations, including their reliance on past data being predictive of present and future operational conditions, reliance on internal analysis of the bank's operations rather than external, local economic conditions, and that they are only a 'snapshot' measure at a given period of time and do not systematically track risk factors over time. Nevertheless, CAMEL remains the dominant approach to estimating likelihood of institutional failure by researchers (Cole & White, 2012; Curry, O'Keefe, Coburn, & Montgomery, 1999; Hays, De Lurgio, & Gilbert, 2009; Whalen, 2005).

A few scholars have explicitly focused on the operational efficiency of MDDIs. Researchers generally report an efficiency gap between MDIs and non-MDIs, although it should be acknowledged that levels of operational efficiency are a related, though separate matter from the risks of institutional failure (Chang, 1994; Elyasiani & Mehdian, 1992; Fairchild, Kim, Juelfs, & Betru, 2020; Hasan & Hunter, 1996; Iqbal, Ramaswamy, & Akhigbe, 1999; Kashian & Casillas, 2011; Kashian, McGregory, & McCrank, 2014; Kashian & Drago 2017; Lawrence, 1997; Spellman, Osborne, & Bradford, 1977).

CAMEL Models and MDDIs

In terms of scholarly research examining the institutional failure risks of CDBIs or MDIs, there is even less in the extant literature. First, Fairchild & Jia (2015) used a modified CAMEL model to predict the comparative likelihood of failure among CDFI banks and credit unions, finding that CDFIs were not statistically different in their failure risks. Second, Kashian and Drago (2017) used CAMEL models to examine the risks of MDI failures from 2009-2014, finding that failure rates were high among Black- and Asian-MDIs. Past these, there appears to be very little research carefully examining CDFI or MDI institutional failure risks. This project adds to this limited field by considering both CDFIs and MDIs together, and expanding the span of the research beyond the years immediately following the Great Recession.

In a summation of the prevailing, there is a sizable base of research on the use of CAMEL models to predict the likelihood of depository institutional failure. There is a smaller literature on the relative operational efficiency of MMDIs and scant literature on their institutional failure risks.

Data Overview

For this analysis, we compiled Reports of Condition and Income (Call Reports) for most FDIC-insured banks in the United States between Q1 2001 and Q4 2018. Call Reports are generated quarterly by the Federal Financial Institutions Examination Council (2019). The status of ownership for each institution was obtained from the CDFI Fund's list of depository CDBIs, and from the FDIC's list of MDIs (U.S. Department of the Treasury Community Development, 2019; Federal Deposit Insurance Corporation, 2019). When an institution is a certified MDI, the reference racial group is also provided (e.g., Asian-owned MDI). As noted above, both CDBI and MDI certification is based on verifiable data and can change over time. Our final dataset captures quarterly results of 10,778 institutions across 72 quarters over a time period from Q1 2001 to Q4 2018. Of these institutions, there are approximately 125 unique CDBIs, 279 unique MDIs, and 30 institutions with both designations.

The environmental control variables come from the U.S. Census (2000, 2010) and American Community Survey (ACS) 5-year aggregate files for 2011–2017. The ACS data is used to represent the environmental variables of the last year in the 5-year aggregate files. Finally, the Rural Urban Commuting Area (RUCA) data is used to estimate the urban, suburban, and rural nature of bank locations (based on zip code). One virtue of this study period is that it encompasses the recent 2008 financial crisis in which a number of financial institutions defaulted, with appreciably high rates of failure among MDIs.[8]

8 MDIs are tracked across time using yearly data from the FDIC. CDFIs are a snapshot of the data in 2019 from the U.S. Department of the Treasury.

Table 1. Descriptive Statistics: CDFI

Statistics	N	Mean	St. Dev.	Min	Median	Max
Bank failed	7,299	0.000	0.012	0	0	1
Minority depository inst.	7,299	0.199	0.399	0	0	1
Non-performing assets over total assets	7,299	0.011	0.012	0.000	0.007	0.073
Return on assets	7,299	0.005	0.006	-0.036	0.005	0.046
Yield-cost ratio	7,299	6.146	4.610	1.579	4.386	32.243
Operating revenue/operating expense	7,299	1.039	0.264	0.032	1.029	3.475
Equity-to-asset ratio	7,299	0.107	0.026	0.035	0.103	0.341
Log of total assets	7,299	11.986	0.880	8.749	11.989	14.838
Liquidity ratio	7,299	0.170	0.113	0.006	0.145	0.924
Gearing ratio	7,299	8.827	2.179	1.932	8.725	27.370
Cost of funds	7,299	0.010	0.009	0.000	0.007	0.073
CDFI	7,299	1.000	0.000	1	1	1
RUCA	7,299	4.651	3.350	1	4	11
Poverty rate	7,299	25.125	9.039	3.600	24.600	59.100
Percent co-ethnic	7,299	0.530	0.251	0.000	0.557	0.984

Table 2. Descriptive Statistics: MDI

Statistics	N	Mean	St. Dev.	Min	Median	Max
Bank failed	8,565	0.002	0.042	0	0	1
Minority depository inst.	8,565	1.000	0.000	1	1	1
Non-performing assets over total assets	8,565	0.013	0.015	0.000	0.007	0.073
Return on assets	8,565	0.003	0.009	-0.036	0.003	0.046
Yield-cost ratio	8,565	5.536	3.921	1.289	4.256	30.900
Operating revenue/operating expense	8,565	0.995	0.340	0.100	0.967	3.082
Equity-to-asset ratio	8,565	0.114	0.040	0.032	0.106	0.346
Log of total assets	8,565	12.063	1.156	8.778	11.902	16.490
Liquidity ratio	8,565	0.175	0.129	0.005	0.143	0.964
Gearing ratio	8,565	8.717	3.121	1.893	8.394	30.723
Cost of funds	8,565	0.011	0.010	0.000	0.007	0.073
CDFI	8,565	0.169	0.375	0	0	1
RUCA	8,565	1.783	2.032	1	1	10
Poverty rate	8,565	21.620	12.329	1	18.6	72
Percent co-ethnic	8,565	0.417	0.315	0.000	0.388	0.998

In Tables 1 and 2 we share descriptive statistics tables by institution type. Table 3 provides the descriptive statistics for the depositories that are NMDIs. There are minimal differences by institutional type for a few variables and for the most part, these fit the expectations regarding the market service areas of MDDIs. In terms of financial measures, the only marked difference is in the Return on Assets (ROA) across institution types. The ROA for CDBIs is 0.005, for MDIs is 0.003 and for NMDIs is 0.009. All other financial indicators are essentially the same.

Notable differences between institutional types are found in their market characteristics. For example, MDIs are less likely to operate in rural areas than the other two types (RUCA code of 1.78 versus 4.65 and 4.54–higher codes indicate less urbanity). CDBIs and MDIs are more likely to be located in zip codes with higher poverty levels (25.13% for CDBIs, 21.63% for MDIs and 13.37% for NMDIs). Finally, the percentage of co-ethnic[9] clients is substantially higher for NMDIs at 82.3%, when compared to 53% (CDBIs), and 42% (MDIs).

Table 3. Descriptive Statistics: Neither CDFI nor MDI

Statistics	N	Mean	St. Dev.	Min	Median	Max
Bank failed	424,360	0.009	0.094	0	0	1
Minority depository inst.	424,360	0.000	0.000	0	0	0
Non-performing assets over total assets	424,360	0.009	0.011	0.000	0.005	0.073
Return on assets	424,360	0.005	0.006	-0.036	0.005	0.047
Yield-cost ratio	424,360	5.506	4.581	0.000	3.719	32.947
Operating revenue/operating expense	424,360	1.014	0.300	-1.538	0.992	3.578
Equity-to-asset ratio	424,360	0.110	0.035	0.031	0.101	0.348
Log of total assets	424,360	11.892	1.240	7.740	11.784	19.479
Liquidity ratio	424,360	0.170	0.130	0.000	0.136	1.150
Gearing ratio	424,360	8.873	2.626	1.874	8.855	30.999
Cost of funds	424,360	0.15	0.653	0.000	0.008	265.132
CDFI	424,360	0.000	0.000	0	0	0
RUCA	424,360	4.541	3.562	1.000	4.000	10.600
Poverty rate	424,360	13.369	8.376	0.000	11.704	80.300
Percent co-ethnic	424,360	0.820	0.190	0.002	0.894	1.000

9 The co-ethnic variable looks at the racial referent associated with each bank–MDIs are identified by their racial and ethnic classification of their owners–and matches that to the population proportion in the zip code of their address. Thus for a Black-owned bank, the percent co-ethnic would reflect the percent of Black individuals in their area. For banks that are not certified as an MDI, we assume that their racial reference group is white. Thus for non-MDIs, percent co-ethnic is the percent of white individuals in their area.

Table 4. Variables Used in CAMEL Logistic Regression

Name of Variable	Definition
Bank Failed	Bank ceases operation (voluntary or involuntary) – 1:00 = failure
Minority Depository Inst.	Depository is a certified MDI
Non-Performing Assets over Total Assets	Percentage of delinquent loans relative to total asset size
ROA	Return on Assets
Yield Cost Ratio	Financial sufficiency ratio – rate of return from loans relative to costs
Operating Revenue/Operating Expense	Operating Efficiency - Total Income adjusted for total expense
Equity to Assets Ratio	Percentage of assets owned
Log of Total Assets	Aggregate loans on balance sheet (logged)
Liquidity ratio	Ability to service current debts without need for external capital
Gearing ratio	Equity to debt ratio (degree of leverage)
Cost of Funds	Interest rates on debt holdings
CDFI	Depository is a Community Development Financial Institution
RUCA	Population density, urbanization, daily commuting within a service area
Poverty rate	Percentage of households below the poverty level
Percent Co-Ethnic	Percentage of households from the same ethnic group

Method and Results

Our primary research question was whether MDDIs tend to have different levels of institutional failure risks than NMDIs, *ceteris paribus*. To examine this question, we utilized a logistic regression modeling method and applied a customized CAMEL model on a robust set of bank depository predictors. As stated above, CAMEL is the generally accepted approach used by bank examiners, though the specific measures are generally kept proprietary and individual institutional CAMEL ratings are confidential.

As an analytical tool, CAMEL provides a set of logistic regression coefficients that allow researchers to determine the variables most likely to predict institutional failure, and whether certain types of institutions are at greater or lesser failure risk. In the results below, the unit of analysis is one institution per quarter. The resulting unit-quarters were then grouped by CDBI or MDI certification overall and by MDI racial referent grouping (i.e., Black, Asian, Hispanic, other minorities).

Variable Selection

For this study, covariates were developed in accords with approaches taken in past research, and trimmed through backwards selection. The final covariates are found in table 4. These covariates were also chosen because each reflects one of the standards of the CAMEL rating system. Capital adequacy, Asset quality, Earnings, and Liquidity are all reflected by one or more of the variables; there is no accepted measure for Management (so, the model is actually a CAEL specification). Our models have also added covariates for RUCA codes, Poverty rate and Percentage Co-Ethnic, which are meant as environmental control variables. After dropping observations that exhibited missing values for any of the covariates, or were extreme outlines,[10] the parameters for each were estimated. Table 5 includes the correlation matrix for the model predictors. There are no predictors that are highly correlated, and thus, multicollinearity concerns are reduced.

Table 5. Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Bank Failed	1														
2. MDI	-0.01	1													
3. Non-performing assets over total assets	0.00	0.05	1												
4. Return on Assets	-0.03	-0.05	-0.24	1											
5. Yield-cost ratio	0.01	0.00	-0.03	0.06	1										
6. Operating revenue / operating expense	-0.01	-0.01	-0.09	0.46	0.58	1									
7. Equity-to-asset ratio	0.01	0.02	-0.05	0.02	0.10	0.14	1								
8. Log of assets	0.01	0.02	0.06	0.06	0.11	0.23	-0.15	1							
9. Liquidity ratio	-0.00	0.01	-0.07	-0.04	0.10	-0.00	0.15	-0.26	1						
10. Gearing ratio	0.00	-0.01	0.07	-0.09	-0.13	-0.20	-0.89	0.13	-0.13	1					
11. Cost of funds	-0.00	-0.00	-0.00	0.01	-0.01	-0.00	0.01	0.01	0.01	-0.00	1				
12. CDFI	-0.01	0.17	0.03	0.00	0.02	0.01	-0.01	0.01	0.00	-0.00	-0.00	1			
13. RUCA	-0.02	-0.11	-0.05	0.15	-0.04	0.03	0.04	-0.40	0.14	-0.07	-0.00	0.01	1		
14. Poverty Rate	-0.00	0.13	0.05	0.02	0.13	0.12	0.03	0.10	0.04	-0.04	0.00	0.17	0.06	1	
15. Co-ethnic	-0.01	-0.27	-0.05	0.06	-0.12	-0.07	-0.01	-0.24	0.01	0.00	-0.01	-0.18	0.30	-0.51	1

Model Construction and Sensitivity Testing

The resulting model was applied to our database of existing depositories with the goal of determining a robust set of measures that could predict the likelihood of failure. The predictive ability for the model was assessed based on the rate of false positives, rate of false negatives, specificity, and sensitivity.

10 Outliers are values more than 6 times above/below the value of the interquartile range on any of the variables.

Table 6. Predictive Accuracy of Logistic Regression Model

Banks	*Predicted Safe*	*Predicted Failed*
Safe	2993 (98.3%)	29 (1.0%)
Failed	8 (0.3%)	16 (0.5%)

The rate of false positives is calculated by (False Positives / (True Positives + False Positives)) and the rate of false negatives by (False Negatives / (False Negatives + True Negatives). Specificity is defined as (True Negatives) / (False Negatives + True Negatives) and sensitivity is defined as (True Positives) / (False Positives + True Positives). The matrix of model predictive ability is found in Table 6. Overall, the model correctly predicted failure and continuance 98.8% of the time, including false positives and false negatives.

Logistic Regression Model Results

Tables 7 and 8 contain the results of the logistic regression models. The regression models are essentially identical, with the difference that the second regression includes dummy variables for each of the MDIs by ethnic ownership type (i.e., Asian-owned, Black-owned, Hispanic-owned, Native American-owned). Each model estimation has five stages: first, the predictions regarding MDI status; second, a model including the income and balance sheet measures; third, whether the institution is a CDBI; fourth, the model includes control variables representing the markets of operation (i.e., degree of urbanity and poverty rate); and fifth, the percentage of co-ethnic consumers.

The output confirms many of the intuitions for what would predict failure in distressed depository institutions. For example, ROA has a strong negative influence on the potential of failure in both models, and this is also true for Equity to Assets ratio. Both of these suggest that failure is associated with relatively lower financial returns, *ceteris paribus*. In terms of the influence of market area covariates, higher degrees of urbanity were associated with higher likelihood of failure (i.e., the negative coefficient for RUCA codes–higher numbers represent less urban areas); and higher percentages of co-ethnic consumers were associated with survival.

There were a number of coefficients that were the primary focus of this analysis: the dummy variables for CDBI status, MDI status and, in the second regression, the MDI status by racial referent ownership grouping. These provided a set of results that are counter to what, for some, may be commonly accepted beliefs that MDIs and CDBIs are at greater risk for institutional failure.

Specifically, the coefficient for MDIs is statistically significant at the 0.001 level and is negative, suggesting that when controlling for financial indicators and operating market characteristics, MDIs are less likely to fail. In the model in which MDI types are disaggregated by racial ownership group, Asian-owned and Hispanic-owned MDIs are found to be less likely to fail at the 0.001 level of statistical significance. Native American-owned MDIs are also found to be less likely to fail, though at a lower level of statistical significance. Black-owned MDIs are also less likely to fail, although the coefficient is both less strong and is only at the 0.10 level of significance. In terms of CDBI status, both models show a strong and statistically significant lower likelihood of failure. As noted above, one limitation of both models is that neither includes a covariate for managerial quality (the "M" in CAMEL).

Table 7. Logistic Regression Predicting Institutional Risks

	Bank failed				
	(1)	(2)	(3)	(4)	(4)
MDI	-1.845***	-1.905***	-1.739***	-1.748***	-1.919***
	(0.258)	(0.259)	(0.258)	(0.260)	(0.262)
Non-performing assets over total assets		-2.675*	-2.527*	-2.596*	-2.591*
		(1.447)	(1.444)	(1.495)	(1.484)
Return on assets		-28.459***	-28.326***	-24.354***	-23.576***
		(2.740)	(2.743)	(2.919)	(2.917)
Yield-cost ratio		0.049***	0.050***	0.047***	0.046***
		(0.004)	(0.004)	(0.004)	(0.004)
Operating Revenue/operating expense		-0.795***	-0.792***	-0.657***	-0.651***
		(0.087)	(0.087)	(0.093)	(0.093)
Equity-to-asset ratio		6.921***	6.768***	6.020***	5.863***
		(0.740)	(0.742)	(0.785)	(0.785)
Log of total assets		0.106***	0.105***	0.022	0.012
		(0.014)	(0.014)	(0.016)	(0.016)
Liquidity ratio		-0.254*	-0.256*	-0.124	-0.149
		(0.131)	(0.131)	(0.138)	(0.138)
Gearing ratio		0.078***	0.076***	0.072***	0.071***
		(0.011)	(0.011)	(0.011)	(0.011)
Cost of funds		-0.002	-0.002	-0.002	-0.002
		(0.009)	(0.009)	(0.009)	(0.009)
CDFI			-4.004***	-3.973***	-4.067***
			(1.002)	(1.003)	(1.003)
RUCA				-0.057***	-0.046***
				(0.006)	(0.006)
Poverty rate				0.005***	-0.003
				(0.002)	(0.002)
Percent co-ethnic					-0.652***
					(0.103)
Constant	-4.706***	-6.741***	-6.686***	-5.576***	-4.842***
	(0.015)	(0.253)	(0.253)	(0.281)	(0.307)
Observations	499,090	477,831	477,831	438,844	438,773
Lob likelihood	-25,108.750	-23,643.760	-23,594.800	-21,402.360	-21,381.690
Akaike Inf. Crit.	50,221.500	47,309.530	47,213.600	42,832.720	42,793.380
Notes:	*** Significant at the 1 percent level ** Significant at the 5 percent level * Significant at the 10 percent level Models are run with clustered standard errors				

Table 8. Logistic Regression Predicting Institutional Risks by Racial MDI

	Bank failed				
	(1)	(2)	(3)	(4)	(4)
Asian-owned	-1.606***	-1.657***	-1.587***	-1.672***	-1.930***
	(0.333)	(0.332)	(0.332)	(0.334)	(0.334)
Black-owned	-1.380***	-1.593***	-0.918*	-0.971**	-0.848*
	(0.489)	(0.494)	(0.476)	(0.484)	(0.488)
Hispanic-owned	-3.080***	-3.105***	-3.070***	-2.853***	-2.852***
	(1.003)	(1.004)	(1.004)	(1.007)	(1.006)
Native American-owned	-2.461**	-2.375**	-2.183**	-2.208**	-2.628**
	(1.021)	(1.024)	(1.027)	(1.028)	(1.029)
Non-performing assets over total assets		-2.689*	-2.577*	-2.657*	-2.654*
		(1.446)	(1.445)	(1.495)	(1.484)
Return on assets		-28.400***	-28.253***	-24.317***	-23.545***
		(2.741)	(2.742)	(2.918)	(2.916)
Yield-cost ratio		0.049***	0.050***	0.047***	0.046***
		(0.004)	(0.004)	(0.004)	(0.004)
Operating Revenue/ operating expense		-0.795***	-0.792***	-0.657***	-0.650***
		(0.087)	(0.087)	(0.093)	(0.093)
Equity-to-asset ratio		6.925***	6.769***	6.020***	5.851***
		(0.740)	(0.742)	(0.785)	(0.785)
Log of total assets		0.106***	0.106***	0.023	0.012
		(0.014)	(0.014)	(0.016)	(0.016)
Liquidity ratio		-0.256*	-0.257**	-0.127	-0.150
		(0.131)	(0.131)	(0.138)	(0.138)
Gearing ratio		0.078***	0.076***	0.072***	0.071***
		(0.011)	(0.011)	(0.011)	(0.011)
Cost of funds		-0.002	-0.002	-0.002	-0.002
		(0.009)	(0.009)	(0.009)	(0.009)
CDFI			-4.041***	-4.011***	-.4.116***
			(1.003)	(1.003)	(1.005)
RUCA				-0.057***	-0.046***
				(0.006)	(0.006)
Poverty rate				0.005**	-0.004
				(0.002)	(0.002)
Percent co-ethnic					-0.664***
					(0.103)
Constant	-4.706***	-6.746***	-6.693***	-5.583***	-4.830***
	(0.015)	(0.253)	(0.253)	(0.281)	(0.307)
Observations	499,090	477,831	477,831	438,844	438,773
Lob likelihood	-25,107.240	-23,642.780	-23,592.780	-21,401.190	-21,379.120
Akaike Inf. Crit.	50,224.480	47,313.560	47,215.560	42,836.380	42,794.250
Notes:	*** Significant at the 1 percent level ** Significant at the 5 percent level * Significant at the 10 percent level Models are run with clustered standard erros				

Another limitation is in the use of this form of modeling to predict failure. No matter how robust the model in sensitivity, these failure predictions are applying economic data (financial information or market values) to predict a legal or regulatory action (a depository choosing to enter bankruptcy or being forced to close). This distinction is important to note, because however sensitive and robust the model at predicting failure, there is a regulatory black box in terms of the full set of factors in a decision.

Summary and Conclusions

The question of whether MDIs or CDFIs have systematically greater risks of failure has been a topic of some practical and limited scholarly interest. Generally speaking, there have been a set of prevailing notions based on observed characteristics at the consumer, household and neighborhood level that are suggestive of credit default (e.g., relatively lower incomes and higher poverty rates of the populations they serve, quality and availability of technological infrastructure, differences in capability endowments, market contagion). These observables have fostered a set of logics that have considerable face validity, though have seldom been tested. This research is an effort to close the gap between commonly-held wisdom and careful analysis.

To engage with these questions, we share results of an analysis of the relative institutional default risks of both CDBIs and Minority Depositories Institutions (MDIs) between the years 2001 and 2018. We examine these risks using a modified version of a logistic regression modeling technique with broad applicability, CAMEL. One virtue of this study period is that it encompasses the recent 2008 financial crisis in which a number of financial institutions defaulted, with appreciably high rates of failure among MDIs. Utilizing a set of robust data, including Call Reports and controls for areas of market operation, we tested the question of differential institutional default risk. Recognizing high rates of segregation by race and the likelihood of organizations to serve co-ethnic populations, one of our interests was in the relative institutional risks across types of MDIs by racial/ethnic grouping (i.e., Black, Asian, Hispanic, and other types of MDIs). Recognizing high rates of segregation by class, we were interested in CDBIs' relative institutional risk.

Our model's results provide insight on this study's primary research question. Specifically, we find that not only are CDBIs and MDIs not systematically more likely to fail, but that a surprising counter notion is true: these institutions are less likely to fail, *ceteris paribus*. Additionally, we find differences across MDI types, with a rank ordering of relative risks across racial referent groups. Asian- and Hispanic-owned MDIs have the least likelihood of failure, followed by Native American-owned institutions. We even found a small protective effect for Black-owned MDIs, although the significance was relatively weak (0.10 level of significance). Our results suggest that given the goals of the Treasury's CDFI Fund and the FDIC's MDI program–to support the viability and expansion of these institutions–their ability to provide financial services products to the communities they serve has merit. Put differently, CDBIs and MDIs may actually prove less likely to fail than their NMDI counterparts.

These questions have policy import. First, because of the decades-long support government agencies have given to these organizations in the forms of subsidy and technical assistance, and second, because some have argued that the viability and expansion of these types of institutions can have normatively desirable impacts (Barth, Betru, Brigida, & Lee, 2019). Expansions of these institutional types is not only consistent with desires for safety and soundness, but increased investments in these institutions could result in enhanced LMI and minority participation in financial services. These could lead to decreases in the considerable wealth gaps across racial and income groups.

There is no doubt that MDDIs and the communities they serve face considerable challenges. Also, it is clear that these institutions are less capitalized, *ceteris paribus*. Those facts being recognized, they are not necessarily at greater risk for failure.

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