Risk and Efficiency among CDFIs: A Statistical Evaluation using Multiple Methods

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Abstract

This introductory essay provides general background information on the institutional differences between regulated CDFIs and mainstream financial institutions. It sets the context for understanding the objections and results of two evaluation studies that can provide insights into the research question of whether CDFIs present greater risk of institutional failure, greater vulnerability to mortgage market downturns, or are less efficient than "mainstream" financial institutions. These include, first, a logistic regression model of the risks of institutional failure within 2 years and the potential for failure of CDFIs compared to mainstream financial entities in the event of a mortgage market collapse; and second, a Data Envelopment Analysis (DEA) that compares the operating efficiency of CDFIs with mainstream financial lenders. Taken together these evaluations indicate that CDFIs show no greater risks of institutional failure than similar "mainstream" peer institutions. Further, given the markets in which CDFIs tend to operate, their overall efficiency and institutional stability is noteworthy.

The primary objective of these research studies is to assist in the evaluation of the CDFI program. The purpose of this evaluation is to determine empirically and through a review of the state-of-art literature whether CDFIs have a higher risk of institutional failure than mainstream financial institutions. This is an especially interesting question given that so many CDFIs target their service efforts to poor and low-income communities, which are perceived *a priori* to be more risky markets for financial institutions to venture.[1]

To meet this objective, we conducted two research studies that can provide insights into the main research questions—first, whether CDFIs present greater risk of institutional failure, including vulnerability to mortgage market downturns, and second whether CDFIs are less efficient than "mainstream" financial institutions. We believe our results are individually rigorous, and cumulatively revealing. These analyses, which readers will find below include: an expansion and improvement on a logistic regression model we have used in our past research on CDFIs (Fairchild & Jia, 2012); an additional improvement to this model that allows for an evaluation of the performance of CDFIs compared to mainstream financial entities in the area of mortgage market systemic risk, and a Data Envelopment Analysis (DEA) comparing the operational efficiency of CDFIs with mainstream financial lenders. We feel that in sum, our results indicate that CDFIs are at no greater risk for institutional failure and are no less efficient than their "mainstream" counterparts, once analytical procedures control for size, scope and institutional differences. In fact, in some of our results, CDFIs appear to be less at risk of institutional failure. Recognizing the old adage that "for every problem, the needed tool may

[1] Although low-income areas are perceived to be riskier, some evidence shows that they are not, controlling for other factors. Mills and Lubuele report that Low-Income communities do not default at greater levels than middle-income neighborhoods (Mills, E.S. and L.S. Lubuele. 1994. "Performance of residential mortgages in low-income and moderate-income neighborhoods". *Journal of Real Estate Finance and Economics* 9(3): 245-260.) Van Order and Zorn[3] report that Low-Income and moderate-income neighborhoods do not default at much higher rates than higher-income areas.

not be a hammer,” We have taken a multi-disciplinary and multi-method approach to investigate whether our logistic regression model, our mortgage market system risk models and our operational efficiency models can empirically show if CDFIs are measure such risks compared to mainstream financial institutions. We feel that our models are robust, and invite comments from academic and practical readers. Our ultimate objective is that these methods are applied to better the service of financial institutions to communities and consumers that would otherwise go overlooked.

The audience of this report is necessarily mixed. We anticipate potential readers including elected officials, members working in roles within executive branches of government agencies and regulatory bodies. In short, we anticipate a readership with primarily practical, rather than scholarly interests. As a result, we have drafted our evaluation in an accessible, and yet professional language. We have labored to give examples of the methods we use that are recognizable to laymen, have provided our statistical results in that fashion, and have provided extensive data and methodological appendices for those interested in greater detail, or explanations of our methods more common to academic audiences.

Background on CDFIs and Risk.

In this section, we will provide some background information on differences between CDFIs that may have bearing on the results found in this evaluation. Since some readers may be relatively less familiar with CDFIs, we provide some background information that we feel will be useful prior to presenting our specific evaluative models and findings. We focus on three areas: differences between CDFIs and mainstream financial institutions (MFIs); service delivery by CDFIs to low-income areas and consumers; the practice of extended forbearance of CDFIs in the field; the delicate balance of social mission and profitability; differences in CDFI capital structure; the role of subsidy and the gap-filling role of CDFIs in austere economic conditions. We recommend that readers consider these as they review the analyses that follow.

Differences between CDFIs and MFIs. At first glance, there is little that is different about regulated CDFIs and MFIs. In our analysis, they are financial intermediary organizations involved in the transformation of capital from one form to another. We have chosen to focus on the 30 percent of regulated CDFIs because unregulated, non-profit CDFIs are not required to report their performance results on regular schedules, and in a systematic fashion—except for those CDFIs which are awardees and those only report for a three-year period. Comparable, regular performance data, ideally on a quarterly basis, is necessary for the statistical analyses we report below. In our past work, we found that many customers of depository CDFIs had no idea that they were not working with a mainstream financial institutions.

However, there are differences on deeper inspection. One of the key differences is related to the level of targeting poor and low-income households. By some estimates, the majority of lending by CDFIs is targeted to low-and-moderate income places and individuals. For example, according to the Carsey Institute CDFI Industry Study CDFIs have been 'stepping into the breach targeting low-income and high poverty area:

> "Analysis of selected CDFI business plans confirms that CDFIs are willing to take risks and serve customers with financial products that traditional capital markets are unlikely to provide. As described in their business plans, business lending CDFIs are making start-up loans, micro-enterprise loans, and providing gap financing, or focusing their lending on minority and/or low-income borrowers in distressed areas. CDFIs that focus on mortgages and other housing-related loans are focusing their products on traditionally underserved populations such as low-income and minority households, and providing low-cost products including home purchase loans, foreclosure prevention loans, emergency loans for seniors, and energy efficiency loans. Real estate development CDFIs are lending to

> developers serving low- and very-low-income populations, not only for development of affordable housing but also for community facilities, retail outlets and charter schools, among other projects." (Swack, Northrup & Hangen, 2012).[2]

Similarly, the National Community Investment Fund (NCIF, www.ncif.org) conducted an analysis of 10-years of data comparing CDFI Banks, Minority Depository Institutions (MDIs),[3] vs. mainstream banks to determine if their mortgages and branches are in low-income areas. In the chart below, the Y axis shows average HMDA mortgage lending in low-income areas over 10-years; the X axis shows bank branches in low income areas by MDIs vs. CDFI Banks. NCIF concluded that CDFI Banks have the greatest social impact by targeting both deposits and mortgage loans to low-income areas, followed by MDIs, with mainstream banks having limited impact. On the next page, chart 1 shows the results of the NCIF analysis of CDFI Social Performance when compared with other financial institutions.[4]

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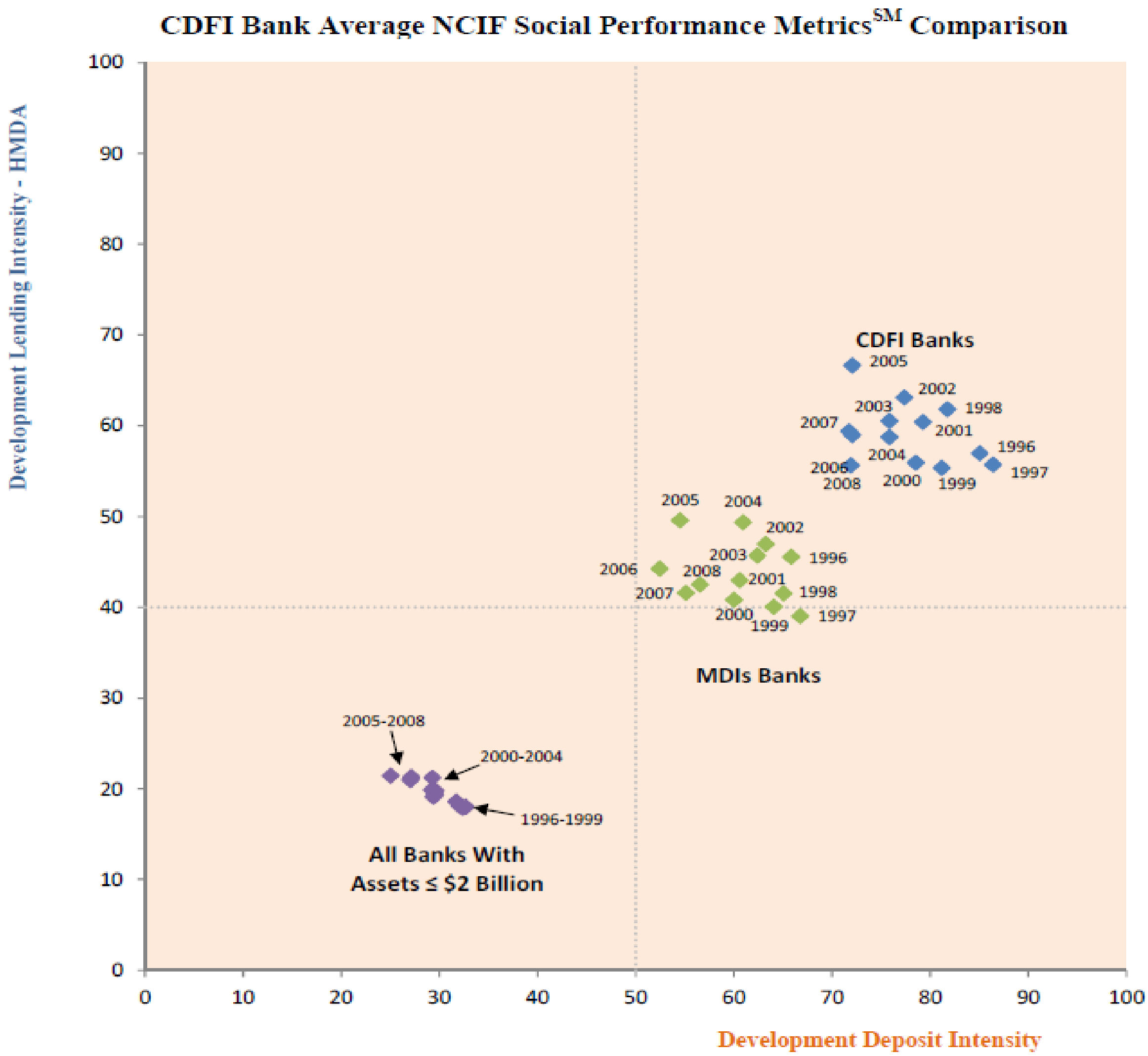
[2] These analyses were not conducted by this research team. Please see the following citation for more details on methodology and results. Swack, M., Northrup, J., & Hangen E. (2012) CDFI Industry Analysis: Summary Report. Carsey Institute: University of New Hampshire.

[3] Section 308 of the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 ("FIRREA") requires the Secretary of the Treasury to consult with the Director of the Office of Thrift Supervision and the Chairperson of the FDIC Board of Directors to determine the best methods for preserving and encouraging minority ownership of depository institutions. Section 308 of FIRREA defines the term "minority depository institution" as any depository institution where 51 percent or more of the stock is owned by one or more "socially and economically disadvantaged individuals. The FDIC's Policy Statement defines "minority depository institution" as any Federally insured depository institution where 51 percent or more of the voting stock is owned by minority individuals. "Minority" as defined by Section 308 of FIRREA means any "Black American, Asian American, Hispanic American, or Native American." The voting stock must be held by U.S. citizens or permanent legal U.S. residents to be counted in determining minority ownership. See http://www.fdic.gov/regulations/resources/minority/MDI_Definition.html) Accessed on 19 June 2014).

[4] These analyses were not conducted by this research team. Please see NCIF for more details on methodology and results.



Finally, research conducted by the CDFI Fund of the US Treasury, based on the distribution of lending by census tracts delineated by Median Family Income (MFI) compared to area income, shows that CDFI awardees consistently target their activities in low-income areas and, CDFIs outperform mainstream lenders on this measure as shown in the table below. The share of CDFI-originated loans in low income areas increases from 61% to 75% when low-income targeted populations and other targeted populations are added to the low income census tracts. [5]

How CDFI Fund Programs Target Low-Income Communities and Bridge the Gap[6]

Median Family Income (MFI)	MFI Divided by Area Income	Population Share	Mainstream Lending (including mortgages, banking branches, and business lending)			CDFI Programs		
			HMDA loans	FDIC Branches	FDIC Deposits	CDFI Loans	CDFI BEA	CDFI NMTC
Low-Income	<80%	33%	12%	19%	20%	61%	90%	83%
Moderate-Income	80%<120%	50%	47%	47%	41%	30%	9%	14%
Middle-Income	120%<200%	15%	34%	28%	30%	7%	2%	3%
Higher-Income	>200%	2%	7%	7%	9%	2%	0%	0%

This team of researchers has conducted extensive research on CDFIs using qualitative methods and has developed a number of research monographs and case studies on CDFIs work in low income areas.[7] These reported results, along with our own long qualitative work with CDFIs support a tentative conclusion that CDFIs venture into low-income, underserved markets that their mainstream counterparts generally avoid.

Balancing social mission and profitability. Most CDFIs are non-profits and have a social mission to help impoverished and low-income clients. How do CDFIs balance their social mission with profitability? Our extensive fieldwork with CDFI management teams on their management strategies, lending practices in the field and missions have resulted in a number of case studies now taught in leading undergraduate and graduate business schools. Our findings have consistently shown that there is a productive tension within CDFIs regarding their delivery

[5] These analyses were not conducted by this research team. Please see CDFI Fund for more details on methodology and results.
[6] The analysis presented here was not conducted by this research team. Please see CDFI Fund for more details on methodology and results.
[7] This evaluation project was exclusively focused on quantitative risk assessment. Please contact Gregory Fairchild, FairchildG@darden.virginia.edu for a bibliography of this work, or any copies of these articles or case studies.

of their mission and their fiscal responsibility. Since most CDFIs are not publicly-traded financial institutions required to meet shareholder return expectations, and are more often mission-driven institutions they consider a range of stakeholders in their operations, and are less concerned with shareholder returns. The careful interplay between financial expediency, responsibility and production are unique, relative to these practices within MFIs.[8]

***Extended Forbearance in Lieu of Foreclosure*.** In addition, to fulfill their mission of serving low-income people and places, there is evidence that non-profit CDFIs may have extended forbearance periods that may span more than 180 days before foreclosing on mortgage loans for low-income people (in contrast to the traditional 90 days to consider a mortgage loan in foreclosure). Non-regulated CDFIs may obtain grants to subsidize their activities and to help reduce foreclosures by extending the forbearance period. Although 90-day delinquencies may appear high, CDFIs may not charge-off these losses as a result of philanthropic subsidies.

Capital Ratios for Regulated CDFIs. Unlike regulated banks and Credit Unions, unregulated CDFIs do not have to meet certain capital ratios (such as Tier 1 capital ratios and Risk Weighted Assets for FDIC-insured banks). Thus, non-profit CDFIs may have more flexibility in capital ratio requirements when compared to regulated financial institutions. CDFI banks may receive a “cease and desist” order from regulators such as the FDIC and may be forced to

[8] These questions were outside the scope of the present evaluation. Interested readers should contact the first author for more details

shutter even when unregulated, non-profit CDFI with similar capital ratios may continue to operate.[9]

Role of subsidy – Non-profit CDFIs may receive grants that don't have to be repaid and often these pledges vary in their timing to be considered against debt and loans from private sources in their financial reporting. These grants--from federal, state, and local governments or from private philanthropies—may represent a considerable part of the assets of CDFIs. As a result of the grant cycle (which may not match the timing of the financial reporting cycle), some CDFIs may show low net assets at certain time periods until grant funding is received.

CDFIs May be Countercyclical During Recessionary Times. Some CDFIs may be involved with federal government programs associated with the American Recovery and Reinvestment Act (ARRA, Public Law 111-5, February 2009), a countercyclical government stimulus program aimed at mitigating cyclical recessionary business cycles. Thus, during recessions, when federal programs expand social safety nets temporarily, CDFIs may actually receive additional funding. Second, the nonprofit funders of CDFIs may actually request that CDFIs extend an even greater portion of their lending capital in low income areas during these periods. The hypothesis is these organizations is that the non-profit missions of CDFIs require them to enter low-income, underserved markets during counter-cyclical periods when MFIs may be restricting or contracting credit.

The foregoing considerations help frame the institutional and operational differences between CDFIs and MFIs.

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[9] This research team conducted an earlier study examining this question using CDFI and non-CDFI credit unions. Interested readers should contact this study's first author.

Institutional and Mortgage Interconnectedness Risk among depository CDFIs, 2002-2011

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Abstract

In this evaluation, we employ a logistic regression model (Logit) to assess the institutional failure risk of a large sample group of CDFI depositories. This evaluation builds on our past work examining institutional failure risk among CDFIs (Fairchild & Jia, 2012). To analyze systemic mortgage risk, we extended our prior work to include statistical measures of the degree of a depository institution's market interconnectedness. We have three primary findings: first, CDFIs credit unions and banks were found to be no more risky than other financial institutions; second, there is a greater risk of failure for banks that are more centrally connected in a mortgage market network, and less risk for CDFIs banks that tend to dominate their markets; and third, neither the degree of network connectedness or dominance in their market were found to influence the likelihood of risk within credit unions.

Introduction

Because Community Development Financial Institutions (CDFIs) operate in lower-income, higher unemployment or underserved areas, are they more likely to be at risk for failure than similar financial institutions? In the event of a mortgage market failure, are CDFIs more vulnerable to failure than other types of financial institutions? This evaluation examines these questions and finds that credit union and bank CDFIs are at no greater risk for failure than what might be called "Mainstream Financial Institutions" (MFIs). We perform this evaluation using a statistical modeling process called logistic regression, and we limit our analysis to regulated CDFIs because of their requirement to regularly provide performance data in a systematic fashion. We have used this method before to measure risk in CDFIs with considerable promise. This work builds on this past work by updating the years of analysis, expanding the base of analysis to banks, including Home Mortgage Disclosure Act (HMDA) data, and statistically controlling for the risk of a systemic mortgage market collapse. In brief, the findings of this research shows that in the event of a substantial decline in mortgage market values CDFIs face no greater risk of institutional failure than similar financial institutions.

Institutional Risks of Failure. Questions of the failure risks of individual CDFIs have been examined by this research team in the past, and have also been covered by other researchers. Michael Swack and his colleagues in the Carsey Institue reported in an analysis of CDFI and similar financial institutions that CDFI credit union portfolios grew faster than their traditional counterparts from 2005 through 2010, with increasing concentration of first mortgages (from 18 percent of loans in 2005 to 26 percent of loans in 2010) (Swack, Northrup & Hangen, 2012). They also found that CDFI credit unions experienced declining earnings and rising delinquency rates during the financial crisis, showing higher delinquency rates than the credit union industry as a whole (Carsey, 2012). Likewise, Carsey Institute researchers found that CDFIs tended to hold a greater percentage of real estate loans in their portfolios (mortgages) (Swack et. al. 2012). For these reasons, and the anecdotal information that can be gleaned from CDFI mission statements and business plans, CDFIs might appear to be at greater risk than comparable institutions for failure due to mortgage market declines.

This research team performed a prior analysis of banks, credit unions and loan funds using logistic regression and found an ability to accurately predict a CDFIs likelihood of failure within two years of operation. For example, our model could examine the health of a CDFI using financial ratios and could predict the likelihood of either regulatory merger or outright closure within two years of operation analysis (Fairchild & Jia, 2012). To be more specific, if a given bank was to fail in the Fall of 2009, all points for that bank between the Fall of 2007 and Fall of 2009 are classified as a failure. This model and approach has been applied elsewhere in CDFI risk assessment, including in the CDFI Fund Bond Guarantee Program model. The sample used in our original paper spanned ten years (2000-2010) of quarterly financial and descriptive data from banks, credit unions, and loan funds. The sample included over 3,000 banks, 6,000 credit unions, and 600 loan funds. The dependent variable used in the sample was the failure or non-failure of the institution, coded such that 8 quarters (inclusive) before failure is categorized as a failure as well. This captures the underperformance of the financial institution in periods leading up to a failure. This indicator for failure within two years was used in order to account for the relatively small number of failures within the time period. Robust statistical techniques were applied to adjust for the relatively small number of failure events.

What are systemic risks? The phrase "systemic risks" generally refers to either to the likelihood of a significant portion of the financial system being affected by either a cascade of failures across banks, or a series of failures created by the interconnections between banks that share experience in their mortgage markets. A similar situation is found with contagious diseases. An individual's likelihood of catching the flu is directly related to the number of contagious people that you may connect with during flu season. We are evaluating a similar relationship in this study through the connectedness of local mortgage markets, since this is a market area that individual financial institutions share. The value of an individual loan in a bank's portfolio, and the likelihood of a loan default are directly related to the health of other homeowners within the same service area. For the purposes of this evaluation, our interest is in the influence of the degree of mortgage market interconnectedness on the financial fortunes of an individual bank or credit union (*i.e.,* depository CDFIs).

Why should we care about systemic risks? During the recent global financial crisis, there were a record number of banking failures, and by some accounts the potential for catastrophic banking collapse without government intervention. One of the primary factors influencing the large scale of institutional failures was the significant decline in the value of mortgage portfolios of individual financial institutions, and a record number of delinquencies. In some cases, the value of an individual bank's portfolio was negatively impacted by the actions of other financial institutions. In these cases, poorly qualified loans made by other banks caused negative implications on their peers. This systemic risk analysis is intended to model the impact of such a market collapse in the mortgage industry, and to better understand whether CDFIs are more vulnerable to such a mortgage market decline. This evaluation builds on our past work (Fairchild & Jia, 2012) in a number of ways: by updating the years of analysis, expanding the base of analysis to banks, including Home Mortgage Disclosure Act (HMDA) data, and statistically controlling for the risk of a systemic mortgage market collapse.

Literature Review

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 1960's (Altman E. I., 1968). Altman 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 5 weighted areas of financial performance, which we will specifically provide. The model used in this analysis predicts whether a firm will fail within a given period (*e.g.,* 8 quarters) if its particular sum falls below a certain threshold.

As a tool for analysis, Logistic regression Z-score model's most useful feature is that predicted values are discrete, rather than continuous. That is, these models predict the likelihood or probability of an event happening (*e.g.,* failure within two years). In fact, the use of these models to monitor banks was first proposed in 1977 by Daniel Martin and it has remained a staple of the credit risk and banking ever since the publication of this paper (See earlier citations, also Thomas, 2002). Many regulatory and rating agencies have their own proprietary methods for evaluating the risk of institutional failure, as do many private consulting firms working in related areas. It should be noted that all of these models are derivatives of the logistic regression Z-score approaches, with differences in either the use of various datasets, or choice of individual variables that suit the purposes of specific research teams. Thus it is reasonable to assume that with the exception of points at the observational extreme, most of the classification methods presently used are essentially identical.

Systemic Risks. To examine systemic risks for this evaluation, we focused on the way various firms hold similar assets that are correlated with one another. Because specific holdings of financial institutions are rarely public and available for analysis, research in this area generally looks at the way in which the performance of different financial institutions with similar distributions of assets (in this case, mortgage loans) trend with one another with respect to return and volatility (Das et al., 2007, Duffie, 2011). Given past research that indicates that CDFIs have not only different missions, but may be lending in different areas, researchers should be careful to adjust for these factors when comparing CDFIs to Mainstream Financial Institutions (MFIs). This systemic risks evaluation takes a networked view of interbank relations based on shared experiences in mortgage markets. We define shared markets based on the overlap two firms have with respect to a region in which they do mortgage origination. We do so because bank failures affect other financial institutions by undermining the stability of asset holdings they all share, and their valuations (*e.g.*, the transmission mechanisms through valuation changes, debt obligations). Therefore firms that overlap in their mortgage lending can affect one another in this way (Duffie, 2011).

Network connectedness. Network analysis began in the social sciences as symbolic representations of the relationships between different entities. The most common visualization of these relationships was through sociograms where individuals were connected to others they had a relationship with inside a graphic set of relationships. One set of network properties of interest that may arise from a set of interconnections such as these is in how connected various individuals or organizations are to one another. The simplest measure of this quality is simply counting the number of connections any particular individual, family or organization has with others. By this standard, A single focal unit may be more connected than another because it holds a larger aggregate number of connections.

However, this measure is somwhat limiting because a focal unit could actually be more well connected than a similar unit, even though both have the same number of connections. The difference would lie in what is termed network distance, or the number of steps needed to reach any other family. In this fashion, two firms could have the same number of connections, but the network length to reach other untis in the network is on average shorter for one than another. This is a statement of how well connected one's connections are, or put differently, how differences exist in the *centrality* of connections. In this sense, while two firms could both be directly connected to the same number of connections, one could be connected to other firms in ways that increase its overall, system-level connectedness.

A set of measures have been developed that attempt to capture the degree of centrality for an individual or institution's connections within a network. The two measures of interest to us in this work are eigenvector centrality and Bonacich centrality.[10] These are commonly used in network analysis, and we apply them here as measures of connectedness across a set of mortgage markets. In our analysis we use both measures to understand how central,

[10] Both eigenvector centrality and Bonacich centrality measures are similar calculations but there are differences between the two that make us consider the utility of both in this analysis. Eigenvector centrality captures how "in the middle" of things any particular point is in a network. As a measure, eigenvector centrality is scaled between 0 to 1, as such it is context specific to the network being studied. Bonacich centrality is similar because it incorporates how connected various individuals are, where it differs from eigenvector centrality is that it attempts to measure how dominated or dominating a firm is based on where it is connected.

dominated or dominating a financial institution may be at a given point in time. Our approach provides a measure of how in the “thick of things” firms may be, but also how dominated they are by those around them.

One way of explaining centrality is that a credit union or bank can choose its lending territory within certain bounds it has very limited ability to choose the lending territory of its opponents in general. Similarly, a typical firm has some discretion in choosing its competitors but it probably cannot choose its competitors' opponents. If this focal firm has opponents who operate in many different territories and the focal firm is competitive in its market, then it exerts influence over a wider region beyond where it is simply operating, while also is susceptible to the activities of these other arenas because of its competitive ties. Thus a financial institution that is overlapping with other financial institutions with disparate regions of activity is more likely to influence and be influenced by a larger number of regions than one whose economic activity is more limited in scope. These network theory concepts and their applications are common in economics and sociology. Readers interested in learning more about the concept of network dominance can review the work of Mark Granovetter on *The Strength of Weak Ties* (Granovetter, 1973*)*. The remainder of this paper is organized as follows. The next section describes the data and methods employed, the fourth section reviews our findings, and the last section provides tentative conclusions.

Methods & Data

Institutional Risks. For this study, each observation is a firm-quarter which represents the conditions of a particular institution at a particular quarter between 2001 and 2012. Logistic regression models were completed on all CDFI depositories, with the dependent variable being whether or not the firm would fail within two years or less. For example, if a bank was to fail in

Fall of 2009, all points of that bank between Fall 2007 and Fall 2009 are classified as being 1. All other points for this bank are classified as 0. Obviously firms that did not fail have 0 for all periods.

For this study, covariates were developed in accords with approaches taken in past research, and trimmed using what is known as a backwards selection process. These covariates were also chosen because each reflects one of the standards of the Capital, Assets Management, Earnings and Liquidity (CAMEL) rating system (Capital, Assets Management, Earnings and Liquidity), which is used by federal banking regulators to rate banks. Specifically, one or more of the variables in this model reflects all CAMEL measures, although there is no generally accepted measure for Management. There are a number of ways that regulators and researchers apply the Management measure, but we have chosen to exclude this measure in this analysis because of the lack of access to such data. Assets were included for credit unions, because unlike other depositories, it has a protective effect for larger firms. The variables for the logistic regression model were selected to mitigate any issues with multicollinearity and double-counting, particularly since some variables appear to be the inverse of others (*e.g.,* Gearing inverse). In the instance of Gearing Inverse, the statistical model includes both capital/assets and assets/equity in order to capture a non-linear effect of leverage on the probability of failure.[11] Though the two financial ratios are operationally the inverse of one

[11] Leverage is a measure of the extent to which a firm has been financed by debt. These are generally used in the form of financial ratios. For more information on Leverage ratios, including Gearing Inverse, please see Hulster, Katia. (2009) The Leverage Ratio, World Bank, Private Sector Development Vice Presidency. The World Bank. http://www.worldbank.org/financialcrisis/pdf/levrage-ratio-web.pdf (Accessed on 20 June 2014).

another, this does not cause multicollinearity in the model because the two ratios are not linear transformations of one another.[12]

Adjacency and Centrality Measures*.* In this model, our primary interest is the influence of overlapping mortgage markets on the risks faced by individual financial institutions. To determine the degree of market overlap, we applied what are called Bonacich and Eigenvector centrality measures. Technical details on how these measures were developed can be found in Appendix A.

Systemic Risk Measurement. We applied a logistic regression on a number of explanatory variables derived from a prior CAMEL model we developed and applied to CDFIs.[13] We also included rural-urban commuting area (RUCA) codes for firm headquarters in this model to capture the effect of being in a rural, rather than an urban location. To examine the influence of being an identified low-income serving depository institution, we added dummy variables for CDFIs, and in the case of credit unions, Low-Income Credit Unions (LICUs). Lastly, we separated banks and credit unions because of their differences in business goals as well as regulatory settings. More information about how all of these measures were developed can be found in Appendix A.

The definitions for each of the model covariates are detailed in Table 1 below.

[12] The Logit Model was tested for multicollinearity; Chi squared tests show that the model is significant at the 1 percent level. For readers desiring greater specificity in the data and models used in the institutional risks portion of this analysis, please consult Appendix A.

[13] See: CDFI Institutional Risk Modeling: a Logistics Regression (Logit) Approach by Gregory B. Fairchild and Ruo Jia, 2011.

Table 1
Definitions of Regression Model Variables

Variable	Definition
NPA Over Assets	This is the percentage of assets held by a firm that are considered non-performing.
ROAA	This is the average return on equity, based on financial performance over a year.
CF	Cost of Funds, the interest rate paid by financial institutions to their depositors.
Reserves over Loans	This is the ratio of reserves held over loans assets as a percentage
Yield Cost Spread/ Yieldcostratio	The spread between average interest for borrowers and average interest paid to depositors.
OpRe/rOpExp	The Ratio of operational revenue over operational costs expressed as a percentage.
Equity Assets Ratio	The ratio of Equity over Assets.
RUCA_V2	The Rural Urban Commuting Area Codes for a firm
Liquidity_Ratio	The Ratio of liquid assets over short term obligations for a firm.
LN_TA	The natural log of firm assets.
CDFI Desig	A dummy variable for CDFI designation.
LICU Desig	A dummy variable for LICU designation.
LC: CDFI * LICU	*Interaction based on the designations*
EC1	The eigenvector centrality of a firm based on applications received.
BC	The Bonacich centrality of a firm based on applications received.
T_Apps	1 – E_{ii} for a firm where E_{ii} is defined from applications received.
Branch Poverty %	percentage of branches in high poverty areas.
Loan Poverty %	percentage of loans in high poverty areas.
dependent variable (banks)	Failure within 24 months
dependent variable (CUs)	Failure within 12 months

Models. For each group, banks and credit unions, we ran three models to examine institutional and systemic risks. The base "*institutional risk*" model includes basic financial measures from the quarterly balance sheets of reporting banks and credit unions, whether they are CDFI-designated, and some measures of local market conditions like RUCA codes. The second "*general systemic risks*" model includes the variables of the first model but also includes two of the centrality measures we used. The third "*CDFI systemic risks*" model includes the variables of the second model but also includes a measure to determine whether being a CDFI and having higher levels of centrality was associated with higher risks of institutional failure.

The specific variables used for the bank regression can be found in Table 2, and the variables used for the credit unions regressions are provided in Table 3.

Table 2
Bank Centrality Regression Model Variables

Model 1	Model 2	Model 3
NPAoverAssets	NPAoverAssets	NPAoverAssets
ReservesOverNPA	ReservesoverNPA	ReservesoverNPA
ROAA	ROAA	ROAA
LiquidityRatio	LiquidityRatio	LiquidityRatio
Yield_Cost_Ratio	YieldCostRatio	YieldCostRatio
Equity Assets Ratio	EA_Ratio	EA_Ratio
RUCA_V2	RUCA_V2	RUCA_V2
CDFI_Designation	CDFI_Designation	CDFI_Designation
	EC1	EC1
	BC	BC
	T_Apps	T_Apps
		CDFI_Designation*EC1
		CDFI_Designation*BC
		CDFI_Designa*T_Value

Table 3
Model Variables
Credit Union Centrality Regression

Model 1 (Base Case)	Model 2 (No Interactions)	Model 3 (Full Model)
NPAoverAssets	NPAoverAssets	NPAoverAssets
ROAA	ROAA	ROAA
ReservesOverLoans	ReservesOverLoans	ReservesOverLoans
Yield_Cost_Spread	Yield_Cost_Spread	Yield_Cost_Spread
OpRevOverOpExp	OpRevOverOpExp	OpRevOverOpExp
Gearing	Gearing	Gearing
CF	CF	CF
RUCA_V2	RUCA_V2	RUCA_V2
CDFI	CDFI	CDFI
LICU	LICU	LICU
LC	LC	LC
LN_TA	LN_TA	LN_TA
	EC1	EC1
	BC	BC
	T_Apps	CDFI*EC1
		CDFI*BC
		T_Apps
		CDFI*T_Apps

The important thing for readers to understand is that these models predict the risks of failure within two years. Based on their reported financial results, these models can indicate the characteristics of banks that tend to fail within 2 years of operation. Thus, these models could indicate the risks of a certain bank failing in the fall of 2006, even though the bank's actual closure may not occur until 2008. The first time that a bank falls into a "risky" profile, these models would capture that period of heightened failure risk. The relative likelihood of an event occurring is expressed as an odds ratio of more than 1.00 or less than 1.00. Odds ratios above 1.00 indicate that an increase in the covariate results in a greater likelihood of the outcome of the dependent variable (in these models, failure within two years). Odds ratios below 1.00, including negative ratios, indicate that more of the covariate makes the outcome less likely.

Findings

Bank findings. Table 4 provides the test of the risks of institutional risks for banks using what is know as a Maximum Likelihood Estimation (MLE) logistic regression. There are three models reported here. A first "original" model, excluding centrality measures; a second model that includes centrality measures but without interaction terms; and a third "full" model that provides results of everything in the prior models and the interaction terms for whether the financial institution was a certified CDFI (a full list of the CDFIs that were used in the analysis can be found in Appendix A). The prime difference between the second and third models in Table 4 and the first one is that these models capture (a) the additional risk of a bank or credit union being connected to other banks; (b) a bank or credit union dominating it's local market area; (c) the risk of being a CDFI that either dominates it's local market or is highly connected to other banks.

In the initial bank model, we have the expected finding that the balance sheet ratios contribute to the log odds of failure as we might anticipate. Interestingly, the CDFI designation has a log odds of -0.90, indicating that CDFIs were less likely to fail, at least in this dataset. The second model adds in the predictors for centrality. Only the eigenvector centrality measure was statistically significant and indicated heightened risks of failure with greater centrality in the network of banking institutions (log odds 1.5437). The coefficient for Bonacich centrality was insignificant in this model. In the third model, we find that the eigenvector centrality remains significant and expresses the strongest likelihood of any covariate. We also find an interaction term between Bonacich centrality and CDFIs is significant (log odds of 0.52), even as the single Bonacich predictor remains insignificant. This suggests that for CDFIs, greater levels of dominance over the markets in which they operate was not associated with a higher likelihood of failure within 2 years. However, greater degrees of mortgage market overlap with other banks was associated with failure.

Credit union findings. The modeling approach for credit unions was virtually identical to that for banking institutions: A first "original" model, excluding centrality measures; a second model that includes centrality measures but without interaction terms; and a third "full" model that provides results of everything in the prior models and the interaction terms for CDFIs, LICUs, or both (institutions can have neither, either, or both designations).

The original, base case credit union model shows the expected influence of the credit union balance sheet measures, and with a clear, strong influence of poor performing loans. In this model, being a rural credit union and being a designated low-income serving credit union (LICU) were associated with less risks of failure. This model also showed a protective effect for size (log of net assets). In the second and third models, only the following three covariates remained significant (NPA over assets, Return on Average Assets (ROAA), Size (log of net assets). These results suggests that neither eigenvector centrality (mortgage market connectedness) or Bonacich centrality (mortgage market dominance) were predictors of risks for credit unions.

Table 4
Model Results
Bank Centrality Regressions

	Model 1 (Base Case)		Model 2 (No Interactions)		Model 3 (Full Model)	
Intercept	-2.3723	***	0.0682		0.0599	
NPAoverAssets	0.2651	***	0.2213	***	0.2252	***
ReservesoverNPA	-0.00004	*	-0.00478	***	-0.00467	***
ROAA	-0.1588	***	-0.1451	***	-0.1439	***
LiquidityRatio	-0.0484	***	-0.0518	***	-0.0522	***
YieldCostRatio	-0.3507	***	-0.9848	***	-0.9955	***
EA_Ratio	0.000027		-0.00014		-0.00016	
RUCA_V2	-0.1012	***	-0.0459		-0.0467	
CDFI_Designation	-0.8968	***	-1.1458	***	-0.8475	
EC1			1.5437	***	1.5231	***
BC			0.00913		-0.0449	
T_Apps			-0.00033		-0.00033	
CDFI_Designation*EC1					0.7799	
CDFI_Designation*BC					0.9201	***
CDFI_Designa*T_Apps					-0.00001	
Hosmer-Lemeshow Goodness of Fit Test						
Chi-Square	288.4042		15.6497		18.5204	
DF	8		8		8	
Pr > ChiSq	<.0001		0.0477		0.0176	

*** = <.0001, ** = < 0010, * = < .01

Table 5
Model Results
Credit Union Centrality Regressions

	Model 1 (Base Case)		Model 2 (No Interactions)		Model 3 (Full Model)	
Intercept	1.0625	***	3.981		4.1052	
NPAoverAssets	6.9159	***	26.4975	***	26.662	***
ROAA	-0.062	***	-0.2246	***	-0.2226	***
ReservesOverLoans	-0.0192	*	-8.4744		-8.6374	
Yield_Cost_Spread	0.00505	***	0.1685		0.1802	
	0.00022	*				
OpRevOverOpExp	8		-0.00003		-0.00003	
Gearing	-4.0994	***	-5.4573		-5.7626	
CF	1.9668		-30.1713		-22.4953	
RUCA_V2	-0.0269	***	-0.7602		-0.7896	
CDFI	-0.333	*	0.5943		-0.0308	
LICU	-1.9463	***	-1.3392		-1.348	
LC	1.0183	***	-4.3376		-4.6996	
LN_TA	-0.4034	***	-0.6797	***	-0.695	***
EC1			-0.0001		-0.0624	
BC			-0.1782		-0.247	
CDFI*EC1			0.000455		8.6237	
CDFI*BC					0.8437	
T_Apps					0.00043	
CDFI*T_Apps					0.00119	
Hosmer-Lemeshow Goodness of Fit Test						
Chi-Square	114.345		12.4293		10.6455	
DF	8		8		8	
Pr > ChiSq	<.0001		0.1331		0.2226	

*** = <.0001, ** = < 0010, * = < .01

Limitations of this logistic regression evaluation method. Although we feel that the present analysis is robust, there are a few limitations and considerations that should be noted by readers of this evaluation. First, the model used here is based on financial performance measures and therefore does not directly integrate the subjective impact of management performance measures. Traditionally, when CAMEL models are applied in the field, evaluators score each organization for their degree of management quality. Given the large number of CDFIs (over 400), and even larger number of non-CDFI banks and credit unions this was not feasible in this evaluation. A second limitation is that the model results are estimated using bank and CU information only. Thus, these results may reflect firm behavior that is true of regulated financial institutions. This model may capture idiosyncrasies of the CDFI industry, but we recommend that future researchers include extra attributes for non-bank and non-credit union CDFIs to mitigate biases that the Logit Model might contain towards regulated entities. Third, these results may be true of net asset sizes reflected in the sample datasets. Since loan funds may be much smaller than the average CDFI bank or credit union, extra adjustments may need to be made when applying the model to loan funds.

Avenues for future research. The research in this evaluation is well formulated, and we feel confident in our approach. However, we recognize that this original research is exploratory and a few of our findings gave us pause and call for future research examination. Two examples are the lower risk for Low Income Credit Unions (LICUs); and the lower default risks for CDFI banks that dominate their markets. First, the finding of a lower risk for designated Low-Income Credit Unions (LICUs) is surprising, especially given the perception of many that serving low-income markets is associated with higher degrees of risk. We have a number of hypotheses about this finding. However, each is purely speculative at this point, and we recommend further investigation in future research, applying methods not used here. First, one hypothesis is that the difference is managerial. One of the predictive factors not examined in this research is the quality of the management (The ‘M’ in the CAMEL acronym). After undergoing the process of applying for and becoming an LICU, perhaps the management of a credit union has access to management training and advice that credit unions of similar size and scope cannot access. For example, LICUs are able to access consulting services from the National Credit Union Association’s Office of Small Credit Union Initiatives. There are also important best practices sharing opportunities that may not be available to similar credit unions. An additional consideration is that the process of becoming an LICU calls on the management team to carefully consider their strategic priorities, and the realities of having more than 50.1% of their members as low-income households. Second, a designated LICU can accept non-member deposits, which may tend to buoy the bank’s balance sheet in challenging economic downturns. Future research might use either survey methods or qualitative interviews to determine whether there are indeed differences in the management training, field practices or the extent of non-member depositors in LICUs when compared to similar credit unions that do not hold this designation.

For the finding regarding the lower risk for what we have termed “dominant” CDFI banks (those that tend to overlap with other financial institutions with disparate regions of activity), we can hypothesize that there is some protective element conferred in the diversity of market exposure a dominant bank has both in its own portfolio, and those of the other banks operating in their overlapping markets. One managerial element might be that these banks tend to receive greater amounts of information about prevailing market trends than those who have less overlapping exposure. This finding would align with one of the cornerstone theories in finance, diversification, yet this finding is speculative at this point. Future research efforts should examine the portfolio quality of lending clients in both dominant banks (and credit unions), and their non-dominant peers. A sample of “dominant” loan portfolios could be examined for their delinquencies, and compared to a set of matched portfolios to determine any systematic differences.

Finally, this research has not included a measure for the term “M” in CAMEL models. We chose to exclude this measure for two reasons: first, there is not a generally –accepted measure for this element; and second, measuring managerial fitness usually requires some non-financial balance sheet approach, which was beyond the scope of this analysis. In the future, we might pair these financial measures with survey items that would allow us to discern differences in the management of various banks and credit unions. Rather than assert a management measure, we may be able to determine from a statistical analysis which elements were most associated with lowered default risks (e.g., years experience in finance of management team; level of education of management team; years tenure in management team).

Conclusions

In this evaluation, we applied measures of network connectedness (eigenvector centrality), and dominance (Bonacich centrality) to a logistic regression model measuring the likelihood of institutional failure among banks and credit unions. We had two aims in this research: first, to determine whether these methods could be applied as measures of systemic risks in financial institutions, and second, to determine whether CDFIs were more or less likely to be at risk for failure, given their connectedness and balance sheets, ceteris paribus.

This research was somewhat exploratory, given precious little scholarship examining systemic risks using institutional networks as a proxy measure. Our primary research hypothesis was that the greater degree of a depository institution's market interconnectedness in terms of mortgage markets, the greater the likelihood that the value of assets on its balance sheet would rise and fall with asset values in the mortgage market.

Our findings suggest promise for our first aim in this research. Our models report that network centrality does enhance risks of failure for banks that are more centrally connected in a mortgage market network. On the other hand, we found that there is less risk of failure specifically for CDFI banks that tend to dominate their markets (as opposed to simply being connected within those markets). Our findings for credit unions were less revealing, neither network centrality nor dominance were found to influence the likelihood of institutional failure. This finding suggests that in markets where CDFIs were able to capture relatively greater shares of the mortgage customers, their loans were less dangerous (likely to lead to failure). This finding suggests that CDFI dominance in markets was relatively protective, at least for the focal CDFI. While we feel the usage of these methods is promising, we are less sanguine about our findings regarding CDFIs specifically.

As exploratory work, the research has limitations. One prominent limitation is the capacity of computing models to perform the data-intensive calculations necessary to calculate all potential mortgage market adjacencies for such a large body of institutions, and over a decade. With more time or processing speed, researchers might be able perform these analyses. Nevertheless, we feel confident that our results are at least promising in terms of method, if not representative of all potential effects. Indeed, the number of observations (over

150,000 per dataset), and the significance of the measures (many over < .0001) suggest a robust model. We invite other scholars to improve and build on these methods of measuring systemic risks, and encourage regulatory agencies to consider the degree of market overlaps as an approach with potential.

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Appendix A

Data & Methods

A Historical Review of Institutional Credit Risk Assessment. 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 1960's (Altman E. I., 1968). Altman 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 these 5 weighted financial measures, given below. Specifically, Altman's model predicts a firm will fail within a given period (*e.g.,* 8 quarters) if its particular sum falls below a certain threshold.

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

X_1 = *(Current Assets - Current Liabilities)/Total Assets*
X_2 = *Retained Earnings/Total Assets* X_3 = *Net Interest Income/Total Assets*
X_4 = *1/Leverage*
X_5 = *"sales"/Total Assets*

Prior work examined the differences in descriptive statistics of financial ratios between distressed and healthy firms (Beaver, 1966). However, by leveraging advances in computer processing, Altman was able to study and formalize what was before largely practitioner intuition. The Z-score addressed not only the question of what financial measures are sufficient for a risk evaluation but also the question of what recommendation is to be given if a firm is healthy for some measures but distressed in others.

At least one limitation of Altman's initial 1968 model was its focus on manufacturing firms. 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, 2005; 1977; Altman, Haldeman & Narayan, 1977; Altman, Marco & Varetta, 1994; Altman & Narayan, 1997; Blum, 1974; Espahbodi, 1991; Killough, 1990; Taffler, 1984).

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). Though experience and theoretical investigations have shown it to be a resilient and robust means of assessment, it has not deterred the development of other risk scoring methodologies (Martin, 1977; Ohlson, 1980; Thomas, 2002). Models using logistic regression or non-parametric methods such as neural networks and recursive partitioning (Altman, Marco & Varetta, 1994; Keasey & McGuiness, 1990; Peat, 2008; Thomas, Edelman, & Crook, 2002; West, 1985), are among the more popular alternatives.

These models rely upon different statistical underpinnings and vary in their mathematical complexity. Yet on any given set of data, they are all relatively similar in terms of the quality of their predictions (Kolari, Glennon, Shin & Caputo, 2002; Thomas, Edelman & Crook, 2002). Consequently, data tends to be more important than method in risk measurement. In fact, without access to accurate and reliable data sources for both failure and healthy firms, the models are largely ineffectual or unreliable.

As a result, active research in the use of financial measures to assess firm health tends to focus on one of three areas. The first is identifying methods that marginally improve predictions with the existing data. The second is on how to incorporate nontraditional measures or data into existing frameworks. The last examines the differences in prediction between various models at the extremal points. The three need not be mutually exclusive.

While the analysis below stays strictly within the framework described above (*i.e*., its analysis is largely dependent upon the financial measures of the firm), other paradigms exist. One extensively developed approach based on option pricing theory determines institutional risk from stock exchange data (for example of these methods, see Black & Scholes, 1974; Broadie & Kaya, 2007). By looking exclusively at the market values of a firm's equity, volatility, pay offs in dividends, payoffs for interest, and debt structuring, these “Structural Models” are able to calculate a proximity to default measure of the firm being studied.

Such models are regarded by some as more sound than the Z-score and its derivatives, because the option-theoretic equations are grounded in the mathematics of financial economics rather than the outputs of statistical modeling (Charitou, 2008). However, because very few CDFIs are traded on any exchange, this approach was not pursued here.

Risk Model: Logistic Regression. As noted earlier, the use of logistic regression models is well developed in risk modeling of financial institutions (Altman, 1997; Martin, 1977; R.C., 1985). Strictly speaking Logit is the log probability of odds for an event, i.e.

$$\operatorname{logit}(p) = \log\left(\frac{p}{1-p}\right) = \log(p) - \log(1-p).$$

where p is the probability of an event occurring and consequently is a number between 0 and 1, while logistic regression is a regression on the logit, given a set of covariates.

$$\operatorname{logit}(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i}.$$

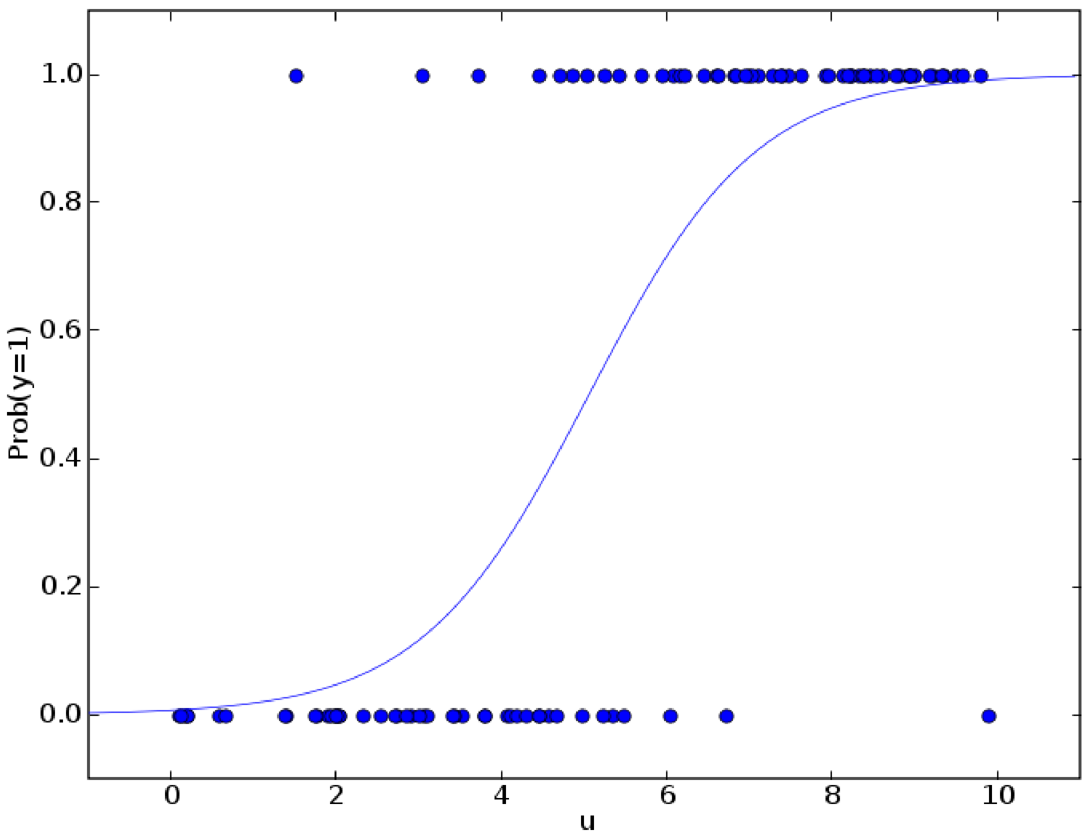
Where p_i represents the probability that an event occurs for observation i, $x_{j,i}$ is value of the covariate x_j for observation i, and β_js regression coefficient for covariate x_j.

If one were to solve for p_i, the result becomes

$$p_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i})}}.$$

Because in real life one typically observes the event itself rather than its underlying process, logistic regression graphically tends to resemble the curve in figure A-1.[14] In the present context, 1 is to be taken as failure as defined earlier, with 0 its absence.

Figure A-1



As a tool for analysis, Logistic regression's most useful feature is that predicted values never exceed 1 nor fall below 0, which can be interpreted as a probability for an event's occurence. Hence, it has been widely applied in the modelling of discrete outcomes, such as distressed firm failure. In fact, the use of Logit to monitor banks was first proposed in 1977 by

[14] Image taken from http://abel.ee.ucla.edu/cvxopt/examples/book/logreg.html

Daniel Martin and it has remained a staple of the credit risk and banking ever since the publication of this paper (See earlier citations, also Thomas, 2002).

Systemic Risks. The relationship between financial variables and bank risk has been a popular topic for modern research, spanning interest across disciplines from traditional economics, finance, public policy, and operations research. With the advent of greater computational resources available to researchers and practitioners, increasingly complex models of financial risk behavior have been adopted to measure firm risk. While traditional analysis has long emphasized the risk presented by the decisions of individual institutions, their loan officers and the assets on their balance sheets, the 2007 crisis has brought about greater interest in systemic risk across firms. Systemic risks generally refers either to the likelihood of a significant portion of the financial system being affected by either cascading failures or how interbank relationships and contagion may affect individual banks. For the purposes of this project, our interest is in the second question. Our interest is in the influence of the actions of other mortgage market actors on the financial fortunes of a focal financial unit (*i.e.,* depository CDFIs).

Firm Risk. 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 1960's (Altman E. I., 1968). Altman introduced a method of predicting corporate failure using a combination of financial ratios of the firm, which has become known on Altman's Z-score. 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, 2005; 1977;

Altman et al., 1977; Altman et al., 1994; Altman & Narayan, 1997; Blum, 1974; Espahbodi, 1991; Killough, 1990; Taffler, 1984).

In our previous logistic regression research, we have followed the research path of the model first developed by Martin (1977) and applied it to the CAMEL measures that bank regulators adopt, where CAMEL is an acronym that stands for capital, asset quality, management, earnings, and liability. Of these five values all but management are readily measurable through financial balance sheet ratios. In this approach, the risks that a financial institution faced were internally derived, institutionally held, and could be predicted using various quantitative methods. However, the 2007 financial crisis has prompted greater interest on whether or not to include an additional variable, Systemic risk. We discuss the importance of systemic risks to the fortunes of individual financial institutions, and discuss its measurement in the next section.

Interbank Systemic Risk. While the research on systemic risk is voluminous there is little agreement on the most appropriate approach to its assessment, because of issues of data availability. Nevertheless, there are recurrent themes in this literature that have attracted significant attention by researchers until recently. Specifically, these are interbank lending, tightening and correlated portfolios. We discuss each of these in this subsection and provide insight into the investigational choices we eventually made.

Approaches collectively categorized as *Interbank lending* refer to risks created by the borrowing performed between banks in order to cover unexpected demands of cash. Various analyses of systemic risk generally take interbank lending as a central if not crucial mechanism by which systemic risk cascades through the financial institutions. The overall argument is that firms that are unable to meet the liquidity demands because of a weakness in their assets are also unable to lend to other institutions that need liquidity. This in turn creates a demand for cash cascade, when the system is unable to meet these demands, institutional collapse is triggered (De Bandt & Hartmann, 2000; Furfine, 2003).

Correlated portfolios approaches look at systemic risk with respect to the way various firms hold similar assets that are correlated with one another. Because firm specific holdings are rarely public, research in this area generally looks at the way in which the performance of different financial institutions with similar distributions of asset classes move with one another with respect to return and volatility (Das et al., 2007, Duffie, 2011). The goal of this approach is measuring an implicit underlying correlative element that is characteristic of the group of firms and affects them all. This correlate is informed by each institution's separate individual qualities but not simply reducible to some combination of it.

Our approach adopts a networked view of interbank relations based on shared competitive links. This work is in part inspired by the recent approach of Hu et al. (2012) to model interbank systemic risk by looking at the various ties disparate firms hold with one another. The contribution of their model is that they considered how the network properties of interbank relations might be an additional source of interbank risk, specifically the centrality of different firms as "hubs".

Though Hu et. al. define their network in terms of interbank lending, we define ties based on the overlap two firms have with respect to a region in which they do mortgage origination. We do so because bank failures affect other financial institutions by undermining the stability of asset holdings they all share. Therefore firms that overlap in their mortgage lending can affect one another in this way (Duffie, 2011). In the next section we provide a brief overview of the network literature, and provide a direction toward the properties that we applied in our analysis.

Network Centrality. A broad overview of centrality measures is summarized in Bonacich (1987), and a general overview of network theories and analysis is found in Jackson (2010), including those used in this analysis.

Both eigenvector centrality and Bonacich centrality measures are similar calculations but there are differences between the two that make us consider the utility of both in this analysis. Eigenvector centrality captures how "in the middle" of things any particular point is in a network. As a measure, eigenvector centrality is scaled between 0 to 1, as such it is context specific to the network being studied. Bonacich centrality is similar because it incorporates how connected various individuals are, but it differs from eigenvector centrality in that it attempts to measure how dominated or dominating a firm is based on where it is connected. In practice this means bonacich centrality varies across the real line and so takes on negative and positive values. Consequently, negative Bonacich centrality indicates how dominated a firm is by its neighbors, while a positive score indicates how dominating it is to its neighbors.

Calculating both measures is found through a matrix calculation. Given any graph one characterize it in its entirety by using an adjacency matrix, **A**. Where each entry a_{ij} in the matrix indicates whether or not node i is connected to node j. In the simplest networks this value is simply 0 or 1, indicating the existence or absence of a tie, respectively. If one wanted to weigh the strength of the connection, a_{ij} can be any positive real number. Finally, while in many situations the existence of a tie is reciprocal, such as roads between geographic points. In other contexts, the tie may not be reciprocal and metaphorically, some roads can be one way. In this work, some may be unidirectional. Situations where the reciprocity is assumed are called undirected networks while networks where it is not are called directed. Fortunately, the calculation remains the same whether one is dealing with the undirected or directed case.

Eigenvector centrality is calculated by solving the following matrix equation for a network's adjacency graph **A**.

$$\boldsymbol{A}\boldsymbol{x} = \gamma \mathbf{x}$$

The Bonacich centrality□is calculated by solving the matrix equation, were a is a normalization factor which can be defaulted to be one, ***I*** is the identity matrix, and **1** is a matrix of one's.

$$\boldsymbol{C}(a, \gamma) = a(\boldsymbol{I} - \gamma \boldsymbol{A})^{-\mathbf{1}} \boldsymbol{A}\mathbf{1}$$

Adjacency and Centrality Measures*.* In this model, our primary interest in the influence of overlapping mortgage markets on the risks faced by individual financial institutions. We applied density overlap measures to define edge types (*i.e.,* boundaries) between banks based on intersections of loan applications received. The edge type is generated between two firms if they both received an application for a mortgage loan in the same region. Because these measures of connections between firms do not account for the degree or importance of connection, we need to assign weight and directionality to these ties. We explain our approach in the following subsection.

Centrality Measures. We will define a value E_{ij} that is a measure for the effects of bank i on bank j. For the purposes of discussion we define E_{ij} in terms of total applications received.

First let bank K_{ic} be the importance of county c to bank **i** defined as *Total Applications received by bank i from c/Total Applications Received by Bank i for all counties*.

Thus K_{ic} measures how important county c is to bank i in terms of the applications it receives. It measures how much of its business is generated in county c.

Now let P_{cj} be the importance of bank **j** to the county c's lending business as *Total Applications Received by bank j in count c/Total Applications received in county c for all banks***.**

Thus, P_{cj} is a measure for how much of county c's loan applications are meant for bank j. It measures how important firm j is to the loan applications that are generated in county c.

If we take the product of K_{ic} and P_{cj} then we get a measure for how bank i is affected by bank j because of its exposure to j's business activities within county c. Since banks often do business in multiple regions we sum this product across all counties to get a measure for how bank i is affected by bank j.

We now define $\mathbf{E_{ij}}$ as the *product of K_{ic} and P_{cj} summed over all counties*. Symbolically this is

$$E_{ij} = \sum_{All\ c} \left(K_{ic} P_{cj} \right)$$

Thus $\mathbf{E_{ij}}$ represents for our purposes how much i is affected by j. This in turn allows us to produce a weighted graph of the connections between firms.

Using this set of values we can calculate a number of measures for how banks and credit unions are affected by their neighbors. The first of these involves applications. One property of this definition for E_{ij} is that if we sum E_{ij} over all j, then it sums to 1, if we include E_{ii}. Thus the value 1 - E_{ii} is one simple measure for how affected each firm is due to its neighbors. We define this measure as T_Apps for total applications received.

Second, from our introduction we can calculate the eigenvector centrality for each firm based on the adjacency matrix generated of E_{ij}. Third, we can calculate the Bonacich centrality also from the adjacency matrix of E_{ij}. In our systemic risk regressions we use T-Apps, eigenvector centrality and Bonacich centrality.

Systemic Risk Measurement. We applied a logistic regression on a number of explanatory variables derived from a prior CAMEL model we developed and applied to CDFIs (Fairchild & Jia, 2008). In that model, and this one, we also included rural-urban commuting area (RUCA) codes for firm headquarters. These codes were developed by the University of Washington on a ten-point scale that measures the degree of urban to rural development for areas, with one being most urban and ten being most rural. To examine the influence of being an identified low-income serving depository institution, we added dummy variables for CDFIs, and in the case of credit unions, Low Income Credit Unions (LICUs). Lastly, we separated banks and credit unions because of their differences in business goals as well as regulatory settings.

The definitions for each of the model covariates are detailed in Table 1 below.

Table 1
Definitions of Regression Model Variables

Variable	Definition
NPA Over Assets	This is the percentage of assets held by a firm that are considered non-performing.
ROAA	This is the average return on equity, based on financial performance over a year.
CF	Cost of Funds, the interest rate paid by financial institutions to their depositors.
Reserves over Loans	This is the ratio of reserves held over loans assets as a percentage
Yield Cost Spread/ Yieldcostratio	The spread between average interest for borrowers and average interest paid to depositors.
OpRe/rOpExp	The Ratio of operational revenue over operational costs expressed as a percentage.
Equity Assets Ratio	The ratio of Equity over Assets.
RUCA_V2	The Rural urban Classical Codes for a firm
Liquidity_Ratio	The Ratio of liquid assets over short term obligations for a firm.
LN_TA	The natural log of firm assets.
CDFI Desig	A dummy variable for CDFI designation.
LICU Desig	A dummy variable for LICU designation.
LC: CDFI * LICU	*Interaction based on the designations*
EC1	The eigenvector centrality of a firm based on applications received.
BC	The Bonacich centrality of a firm based on applications received.
T_Apps	1 – E_{ii} for a firm where E_{ii} is defined from applications received.
Branch Poverty %	percentage of branches in high poverty areas.
Loan Poverty %	percentage of loans in high poverty areas.
T_Apps	1 – E_{ii} for a firm where E_{ii} is defined from applications received.
dependent variable (banks)	Failure within 24 months
dependent variable (banks)	Failure within 12 months

Key Variables in CAMEL Model analysis. The following figure below provides an extended discussion of key variables used in this analysis.

Figure 1

Key variables in CAMEL Models[15]

CAPITAL: * CDFI Asset Size: There are significant scale effects in all sectors of the CDFI industry. Larger sized CDFI's are more self-sufficient and will have in place more sophisticated systems, controls and procedures. * Unrestricted Net Asset Ratio: The net asset ratio represents an important indication of capital adequacy. Often the assets of CDFI's carry restrictions which limit their utility. Unrestricted net assets should be similar to total asset ratio. * Debt to Equity Ratio: The ratio of total debt to net assets provides additional insights to capital adequacy. The higher the ratio, the greater the risk. Applicants with high debt to net asset ratios will face less financial flexibility. * Debt Equivalency Ratio: Off balance sheet debt obligations may manifest as future liabilities. Thus, consideration of total debt equivalency is needed to clarify availability of capital. * Earnings Performance: Positive earnings year over year improve capital and allow CDFI's to deploy more capital and/or absorb additional losses.* Change in Net Assets: Net assets represent the CDFI's ability to deploy capital and/or absorb future losses.

ASSET QUALITY. * Loan Charge Offs: Over time CDFIs will experience non-performing loans that will need to be written off as uncollectible. Low loan charge-off rates reflect sound underwriting and strong asset quality. * Loan Loss Reserve Ratio: The loan loss reserve ratio represents the CDFI's internal assessment of loan portfolio risk. High levels of loan loss reserve ratio may indicate both conservative and prudent best practices, or indication of high loan portfolio risk. * Non-Performing Assets (90 Days Delinquent Loans): Defined as loans that are 90 days delinquent, non-performing assets provide additional insights on portfolio asset quality. A low ratio of non-performing assets / portfolio indicates strong asset quality. * Borrower Concentration: CDFIs tend to be concentrated regionally, and in some cases, CDFIs' carry portfolios that are concentrated in a limited number of sectors. Such concentration of credit risk may expose CDFI financial health to trends in specific sectors. CDFIs with portfolios that are concentrated in a limited number of borrowers are exposed to additional credit risk. * Asset Composition: The composition of a CDFI's assets provides insights into financial strength. CCFI's with assets other than loans receivable have additional sources of liquidity. * Loan Securitization: The security and collateral of the loans in the CDFI's portfolio also provide indications of financial health.

EARNINGS. * Net Margin: The surplus/(deficit) from operations / unrestricted revenue measured over the trailing 12 quarter period provides insights to the CDFI's ongoing liquidity position. Positive net margins improve capital adequacy and provide added cushion to protect against losses. * Impact Performance: Together with strong portfolio performance the ability of an organization to deploy funds available for financing will help the CDFI attract additional funding. * Self Sufficiency Ratio: Similar to the net margin analysis; the self-sufficiency ratio provides insights to financial health and the ability of the CDFI to contain cost. In this case, it is measured on an annual basis to provide insights to the CDFI ability to remain efficient at different revenue levels. * 3 Year Trending In Performance & Earnings Measures: By design, the LOGIT model blends three years over performance. Accordingly, positive or negative trends need to be assessed as a separate performance and earnings attribute. An organization exhibit a trend year over year should be considered for notching. * Other Relevant Attributes: There may be other project specific factors worthy of consideration under the management assessment process. To the extent these factors add to, or detract from, the strength of the project or highlight weaknesses, they can be documented under this category.

LIQUIDITY. * Cash and Cash Equivalents: Cash and cash equivalents are essential forms of liquidity and will allow the organization to remain in operation in challenging times. * Access to Grant Funding: The presence of undrawn committed funding facilities represents an important source of liquidity. As part of the analysis of liquidity, the maturities of outstanding debt obligations should be identified to assess refinancing risk to the Applicant. These risks will be exacerbated if there exist tightening credit conditions and/or the Applicant has failed to maintain covenant compliance with existing loan facilities. * Projected Debt Service Coverage: The analysis of liquidity should include a review of forecasted financial performance taking into account the Applicant's ability to meet its future principal and interest obligations. * Affiliate / Guarantor Support: The Applicant's relationship to affiliate entities can enhance or detract from financial health. Such relationships should be thoroughly reviewed to assess potential impacts to the CDFI. * Concentration of Funding Sources: High concentrations of funding sources poses a potential risk to the operational liquidity of the Applicant should such sources be terminated. The concentration of funding sources should be considered to account for this risk.

[15] Please note that the models used in this analysis do not measure managerial fitness, the "M" in the CAMEL acronym.

Figure 1

Control for Rural Locations: RUCA Codes. These codes were developed by the University of Washington on a ten-point scale that measures the degree of urban to rural development for areas, with one being most urban and ten being most rural. To examine the influence of being an identified low-income serving depository institution, we added dummy variables for CDFIs, and in the case of credit unions, Low-Income Credit Unions (LICUs). Lastly, we separated banks and credit unions because of their differences in business goals as well as regulatory settings.

Models. For each group, banks and credit unions, we ran three models. The first model includes CAMEL measures from institutional balance sheets, CDFI designations, and some local measures (*i.e.,.* RUCA codes). The second model includes the variables of the first model but also includes two of the centrality measures we used. For our analysis we used total applications received. The third model includes the variables of the second model but also includes interaction terms between CDFI with the centrality variables. Definitions for the specific variables used for the bank regression can be found in Table 1. In Table 2, we provide a list of the specifications of each of the regression models we tested on banks, and the variables used for the credit unions regressions are provided in Table 3.

Table 2
Bank Centrality Regression Model Variables

Model 1	Model 2	Model 3
NPAoverAssets	NPAoverAssets	NPAoverAssets
ReservesOverNPA	ReservesoverNPA	ReservesoverNPA
ROAA	ROAA	ROAA
LiquidityRatio	LiquidityRatio	LiquidityRatio
Yield_Cost_Ratio	YieldCostRatio	YieldCostRatio
Equity Assets Ratio	EA_Ratio	EA_Ratio
RUCA_V2	RUCA_V2	RUCA_V2
CDFI_Designation	CDFI_Designation	CDFI_Designation
	EC1	EC1
	BC	BC
	T_Apps	T_Apps
		CDFI_Designation*EC1
		CDFI_Designation*BC
		CDFI_Designa*T_Value

Table 3
Model Variables
Credit Union Centrality Regression

Model 1 (Base Case)	Model 2 (No Interactions)	Model 3 (Full Model)
NPAoverAssets	NPAoverAssets	NPAoverAssets
ROAA	ROAA	ROAA
ReservesOverLoans	ReservesOverLoans	ReservesOverLoans
Yield_Cost_Spread	Yield_Cost_Spread	Yield_Cost_Spread
OpRevOverOpExp	OpRevOverOpExp	OpRevOverOpExp
Gearing	Gearing	Gearing
CF	CF	CF
RUCA_V2	RUCA_V2	RUCA_V2
CDFI	CDFI	CDFI
LICU	LICU	LICU
LC	LC	LC
LN_TA	LN_TA	LN_TA
	EC1	EC1
	BC	BC
	T_Apps	CDFI*EC1
		CDFI*BC
		T_Apps
		CDFI*T_Apps

Data sources. Regulation C of the Home Mortgage Disclosure Act (1975) requires lending institutions to report public loan data. These data are compiled by the Federal Financial Institutions Examination Council (FFIEC) data for regulatory reasons, and for a small set of research analysis purposes. These products were acquired in a number of ways including directly from FFIEC, interlibrary loan from the University of Michigan, a generous gift from a colleague,[16] and ordered through the National Archives maintained by the University of Maryland.

[16] **Quinn Curtis, University of Virginia School of Law**

The data used to generate the adjacency graph comes from HMDA files on loans by institution from 2002 to 2011. However we did not calculate the entire adjacency matrix of every firm with every other firm. We calculated the 2000 to 4000 largest firms in both applications and loan origination values combined with all CDFI firms. We made this restriction for a couple of reasons. The first is a restriction of research scope to accommodate approximate peer institutions. Since CDFIs, even the largest, are capped at $4 billion dollars, firms in the range we specified are below $10 billion dollars. The second is a computational limitation. Generating the full adjacency matrix would require roughly two weeks of calculation for each year, which given our computational resources was past the time available. Even with this truncated selection the graph we generated had between 720,000 to 989,000 edges for any given year. Even given this substantial magnitude, these represent only a 5% sample of the complete adjacency graph. A full, comprehensive agency graph approximating all available data would take 20 weeks of processing time (or would require series or supercomputers). To give a sense of the magnitude, our sample included 147,000 bank observations and 170,000 credit union observations (i.*e*., financial measures per year per institution). Annual financial information on banks and credit unions were collected from the SNL Financial database. The SNL is a financial data provider that compiles publicly-available quarterly call reports on regulated depositories (*i.e.,* banks, credit unions). The coverage years we pulled from SNL for this analysis spanned the period from 2002 to 2011.

Table 6
Descriptive Statistics
Bank, CU Centrality Regressions

Variable	N (Banks)	N (CUs)	Mean (Banks)	Mean (CUs)	Std Dev (Banks)	Std Dev (CUs)
NPAoverAssets	146454	169914	1.29	0.01	2.51	0.02
Reserves/NPA	146190		905.57		8415.35	
Reserves/Loans		163746		0.28		3.32
ROAA	146436	152014	0.79	0.30	2.00	6.38
LiquidityRatio	146454		23.44		29.98	
YieldCostRatio	146433	152015	3.79	4.86	33.51	6.77
Oper Rev/Op Exp		151301		84.48		151.87
EA_Ratio	146419	169914	4.38	0.14	68.11	0.07
CF				0.00		0.02
EC1	17676	10436	0.20	0.20	0.14	0.15
BC	17681	10401	-0.45	-0.46	0.90	0.93
T_Apps	47037	31574	262.96	87.19	437.03	217.52
LN_TA		169914		9.46		1.96
RUCA_V2	148397	193858	4.20	2.05	3.51	2.20

Table 6 provides summary descriptive statistics for the variables used in the analyses. We do these analyses to determine whether there are differences that are important to note between banks and credit unions that are important prior to running our analysis. Tables 7 and 8 provide an initial test for multi-collinear predictors (bivariate correlations). The descriptive statistics and correlations reveal that there is substantial variance across measures (especially among banking institutions in this sample), and limited risks of multi-collinearity in these models (based on the bivariate correlations of the individual variable predictors).

Table 7
Correlations of Variables in Analysis
Bank Centrality Regressions

	2	3	4	5	6	7	8	9	10	11
1. Reserves/NPA	-0.06									
2. ROAA	-0.52	0.03								
3. YieldCostRatio	-0.24	0.01	0.35							
4. EA_Ratio	0.00	0.01	0.00	0.02						
5. LiquidityRatio	-0.10	0.02	0.06	-0.10	0.02					
6. CDFI_Desig.	0.08	-0.02	-0.06	0.12	0.02	0.04				
7. EC1	0.03	0.01	-0.04	-0.08	-0.10	-0.07	0.00			
8. BC	-0.04	0.00	0.03	0.00	-0.01	-0.03	-0.02	0.00		
9. T_Apps	-0.09	-0.03	0.08	0.04	0.04	-0.01	-0.15	-0.27	-0.01	
10. RUCA_V2	-0.06	-0.03	0.08	0.07	0.05	-0.01	-0.13	-0.23	-0.01	0.49

Table 8
Correlations of Variables in Analysis
Credit Union Centrality Regressions

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1) NPA over Assets														
2) ROAA	-0.33													
3) Reserves/Loans	0.03	-0.01												
4) Yield-Cost_Spread	0.16	0.09	0.06											
5) OpRev/OpExp	0.00	-0.08	0.00	0.00										
6) Gearing	-0.22	0.19	-0.02	-0.16	-0.02									
7) CF	-0.03	-0.03	-0.03	-0.30	0.00	0.14								
8) RUCA_V2	0.03	0.01	-0.01	0.04	0.00	0.01	0.01							
9) CDFI	0.18	0.00	0.01	0.19	0.00	-0.04	-0.02	0.15						
10) LICU	0.20	-0.01	0.02	0.22	0.00	-0.09	-0.03	0.10	0.72					
11) LC	0.19	0.00	0.01	0.19	0.00	-0.08	-0.01	0.09	0.87	0.83				
12) LN_TA	-0.10	0.05	-0.01	-0.33	-0.01	-0.03	0.12	-0.12	-0.22	-0.25	-0.21			
13) EC1	-0.08	-0.02	-0.01	-0.13	0.01	0.00	0.06	-0.14	-0.19	-0.18	-0.16	0.22		
14) BC	-0.01	-0.01	0.00	-0.02	0.00	0.03	0.05	0.01	-0.02	-0.01	-0.01	0.01	0.00	
15) T_Apps	0.02	0.03	0.01	0.03	0.00	-0.03	0.02	0.35	0.12	0.17	0.09	-0.04	-0.18	0.00

Bank Centrality. Table 4 provides the test of Bonacich and Eigenvector centrality in a Maximum Likelihood Estimation (MLE) logistic regression predicting risks of failure within two years. There are three models reported here. A first “original” model, excluding centrality measures; a second model that includes centrality measures but without interaction terms; and a third “full” model that provides results of everything in the prior models and the interaction terms for CDFIs .

In these models, the relative likelihood of an event occurring is expressed as an odd ratio of more than 1.00 or less than 1.00. Odds ratios above 1.00 indicate that an increase in that covariate results in a greater likelihood of the outcome of the dependent variable (in these models, failure within two years). Odds ratios below 1.00, including negative ratios, indicate that more of the covariate makes the outcome less likely. In the initial bank model, we have the expected finding that the balance sheet ratios contribute to the log odds of failure as we might anticipate (however, the magnitude of the log odds of failure for poor-quality (NPA over assets) is only .27). Interestingly, the CDFI designation has a log odds of -0.90, indicating that CDFIs were less likely to fail, at least in this dataset. The second model adds in the predictors for centrality. Only the eigenvector centrality measure was statistically significant and indicated heightened risks of failure with greater centrality in the network of banking institutions (log odds 1.5437). The coefficient for Bonacich centrality was insignificant in this model. In the third model, we find that the eigenvector centrality remains significant and expresses the strongest likelihood of any covariate. We also find an interaction term between Bonacich centrality and CDFis is significant (log odds of 0.52), even as the single Bonacich predictor remains insignificant. This suggests that for CDFIs, greater levels of dominance over the markets in which they operate was not associated with a higher likelihood of failure within 2 years. However, greater degrees of mortgage market overlap with other banks was associated with failure.

Table 4
Model Results
Bank Centrality Regressions

	Model 1 (Base Case)		Model 2 (No Interactions)		Model 3 (Full Model)	
Intercept	-2.3723	***	0.0682		0.0599	
NPAoverAssets	0.2651	***	0.2213	***	0.2252	***
ReservesoverNPA	-0.00004	*	-0.00478	***	-0.00467	***
ROAA	-0.1588	***	-0.1451	***	-0.1439	***
LiquidityRatio	-0.0484	***	-0.0518	***	-0.0522	***
YieldCostRatio	-0.3507	***	-0.9848	***	-0.9955	***
EA_Ratio	0.000027		-0.00014		-0.00016	
RUCA_V2	-0.1012	***	-0.0459		-0.0467	
CDFI_Designation	-0.8968	***	-1.1458	***	-0.8475	
EC1			1.5437	***	1.5231	***
BC			0.00913		-0.0449	
T_Apps			-0.00033		-0.00033	
CDFI_Designation*EC1					0.7799	
CDFI_Designation*BC					0.9201	***
CDFI_Designa*T_Apps					-0.00001	
Hosmer-Lemeshow Goodness of Fit Test						
Chi-Square	288.4042		15.6497		18.5204	
DF	8		8		8	
Pr > ChiSq	<.0001		0.0477		0.0176	

*** = <.0001, ** = < 0010, * = < .01

CU Centrality. The modeling approach for credit unions was virtually identical to that for banking institutions: A first “original” model, excluding centrality measures; a second model that includes centrality measures but without interaction terms; and a third “full” model that provides results of everything in the prior models and the interaction terms for CDFIs, LICUs, or both (institutions can have neither, either, or both designations).

The original, base case credit union model shows the expected influence of the credit union balance sheet measures, and with a clear, strong influence of poor performing loans (NPA over assets, log odds 6.91, < .0001). In this model, being a rural credit union (log odds -0.0269, < .0001) and being a designated low income serving credit union (LICU) were associated with less risks of failure (log odds -1.94, < .0001). This model also showed a protective effect for size (log of net assets, log odds -0.4034, < .0001). In the second and third models, only the following three covariates remained significant (NPA over assets, Return on Average Assets (ROAA), Size (log of net assets). These results suggests that neither eigenvector centrality (mortgage market connectedness) or Bonacich centrality (mortgage market dominance) were predictors of risks for credit unions.

Table 5
Model Results
Credit Union Centrality Regressions

	Model 1 (Base Case)		Model 2 (No Interactions)		Model 3 (Full Model)	
Intercept	1.0625	***	3.981		4.1052	
NPAoverAssets	6.9159	***	26.4975	***	26.662	***
ROAA	-0.062	***	-0.2246	***	-0.2226	***
ReservesOverLoans	-0.0192	*	-8.4744		-8.6374	
Yield_Cost_Spread	0.00505	***	0.1685		0.1802	
	0.00022	*				
OpRevOverOpExp	8		-0.00003		-0.00003	
Gearing	-4.0994	***	-5.4573		-5.7626	
CF	1.9668		-30.1713		-22.4953	
RUCA_V2	-0.0269	***	-0.7602		-0.7896	
CDFI	-0.333	*	0.5943		-0.0308	
LICU	-1.9463	***	-1.3392		-1.348	
LC	1.0183	***	-4.3376		-4.6996	
LN_TA	-0.4034	***	-0.6797	***	-0.695	***
EC1			-0.0001		-0.0624	
BC			-0.1782		-0.247	
CDFI*EC1			0.000455		8.6237	
CDFI*BC					0.8437	
T_Apps					0.00043	
CDFI*T_Apps					0.00119	
Hosmer-Lemeshow Goodness of Fit Test						
Chi-Square	114.345		12.4293		10.6455	
DF	8		8		8	
Pr > ChiSq	<.0001		0.1331		0.2226	

*** = <.0001, ** = < 0010, * = < .01

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List of CDFI Financial Institutions Used in Analysis (403 CDFIs in total)

Credit Unions in Bold

Note: *this list includes non-certified CDFIs that were previously certified*

1st Choice Credit Union
A.L. Bratcher Federal Credit Union
Advance Bank
Alamosa
Albina Community Bancorp
Albina Community Bank
ALco Federal Credit Union
Aliquippa Regional Credit Union
Alpena Credit Union
Alternatives Federal Credit Union
American Metro Bancorp, Inc.
American Metro Bank
American State Bank
Appalachian Community Bank, F.S.B.
Appalachian Development Federal Credit Union
Appalachian Federal Credit Union
ASI Federal Credit Union
Atlantic City Federal Credit Union
Austin/West Garfield Federal Credit Union
Avondale Community Federal Credit Union
B.O.N.D. Community Federal Credit Union
Bank of Cherokee County
Bear Paw Credit Union
Bethel Baptist Federal Credit Union
Bethel Community Federal Credit Union
Bethex Federal Credit Union
Bethlehem Community Development Credit Union
Bexar County Teachers Federal Credit Union
Binghamton Housing Authority Residents
Birmignham Financial Federal Credit Union
Bitterroot Community Federal Credit Union
Border Federal Credit Union
Borinquen Federal Credit Union
Bradley Initiative Credit Union
Brewery Credit Union
Brewton Mill Federal Credit Union
Bridge Street AWME Church Federal Credit Union
Broadway Federal Bank, F. S. B.
Brookland Federal Credit Union
Brooklyn Cooperative Federal Credit Union
Brooklyn Ecumenical Federal Credit Union
Buffalo Cooperative Federal Credit Union
Butte Federal Credit Union
Camden Community Credit Union
Canaan Baptist Federal Credit Union
Capitol City Bancshares, Inc.
Capitol City Bank & Trust Company
Caribbean-American State Credit Union
Carter County Federal Credit Union
Carter Federal Credit Union
Carver Federal Savings Bank
Carver Financial Corporation
Caswell Credit Union
Central Bancshares of Kansas City, Inc.
Central Bank of Kansas City
Central Brooklyn Federal Credit Union
CFBanc Corporation
Chatham-Lee Credit Union
Chetco
Chicanos Por La Causa Federal Credit Union
Choctaw Federal Credit Union
Choices Federal Credit Union
Chowan Credit Union
Christian Hope Credit Union
Church Koinonia Federal Credit Union
Citizens Bancshares Corporation
Citizens Bank & Trust Company of Chicago
Citizens Choice Federal Credit Union
Citizens Financial Corporation
Citizens Savings Bank & Trust Company

Citizens Trust Bank
City First Bank of D.C., National Association
City First Enterprises, Inc.
City National Bancshares Corporation
City National Bank of New Jersey
College Heights Credit Union
College Station Community Federal Credit Union
Communicating Arts
Communities United Credit Union
Community Bank of the Bay
Community Capital Bank of Virginia
Community Choice Federal Credit Union
Community Commerce Bank
Community Credit Union of Southern Humbolt
Community Development Bank, FSB
Community First Guam Federal Credit
Community Plus Federal Credit Union
Community Trust Credit Union
Community Trust Federal Credit Union
Comunidad Latina Federal Credit Union
Comunidades
Consumer's Credit Union
Consumer's Federal Credit Union
Consumer's Federal Credit Union
Cooperativa de Ahorro y Credito Elec
Cooperativa de Ahorro y Credito Empleados
Cooperativa de Ahorro y Credito Nuestra
Cooperative Center Federal Credit Union
Cooperative Federal Credit Union
CoVantage Credit Union
Covenant Bancshares, Inc.
Covenant Bank
Covenant Savings Federal Credit Union
D. Edwards Wells Federal Credit Union
Dakotaland Federal Credit Union
Davis Bancorporation, Inc.
Demopolis Federal Credit Union
Denver Community Development Credit Union
District Government Employees
Eagle Louisiana Federal Credit Union
East Austin Community Federal Credit Union
East End Baptist Tabernacle Federal Credit
El Futuro Credit Union
Electrical Products Employees Federal Credit Union
Enterprise Community Federal Credit Union
Episcopal Community Federal Credit Union
Everyone's Federal Credit Union
Express Credit Union
Fairfax County Federal Credit Union
Faith Based Federal Credit Union
Faith Community United Credit Union, Inc.
Fallon County Federal Credit Union
Family Federal Credit Union
Father Burke Federal Credit Union
Federation of Greene County Employees (FOGCE)
Fidelis Federal Credit Union
First American Credit Union
First American International Bank
First American International Corp.
First Combined Community Federal Credit Union
First Community Credit Union
First Delta Federal Credit Union
First Hawaiian Homes Federal Credit Union
First Independence Bank
First Legacy Community Credit Union
First Midwest Acquisition Corporation
First National Bank
First National Bank
First National Bank
First National Security Company
First Peoples Community Federal Credit Union
Five Star Credit Union
Fort Gibson Bancshares, Inc.
Fort Gibson State Bank
Fort Randall Federal Credit Union
Foss Ave Baptist Church Federal Credit

Union
Franklin National Bank of Minneapolis
Freedom First Federal Credit Union
Friendship Federal Credit Union
Froid Federal Credit Union
Gateway Community Federal Credit Union
Gateway Credit Union
GE Credit Union
Generations Community Credit Union
Genesee Co-Op Federal Credit Union
Georgia Power Northeast Credit Union
Glamour Community Federal Credit Union
Greater Kinston Credit Union
Guadalupe Credit Union
Guaranty Bancorp
Guaranty Bank & Trust Company
Guaranty Bank & Trust Company
Guaranty Bank & Trust Company
Guaranty Bank & Trust Company
Gubecoop
Guernsey Community Federal Credit Union
Harbor Bankshares Corporation
Harney County Federal Credit Union
HAWAII FIRST Federal Credit Union
Highland Community Bank
Highland Community Company
Hill District Federal Credit Union
Homesteaders Federal Credit Union
Hope Federal Credit Union
Hospitality Community Federal Credit Union
Howland - Enfield Federal Credit Union
Hudson Valley Holding Corp.
IBC Bancorp, Inc.
IBW Financial Corporation
Illinois-Service Federal Savings and Loan Association
Independent Employers Federal Credit Union
Industrial Bank
Industrial Credit Union of Whatcom County
Inter National Bank
International Bank of Chicago
JD Financial Group, Inc.
Ka'u Federal Credit Union
Kahuku Federal Credit Union
Kappa Alpha Federal Credit Union
KC Terminal Employees/Guadalupe Center
Kekaha Federal Credit Union
Kenworth Employees Credit Union
Kern Central Federal Credit Union
Kerr County Federal Credit Union
Kingsville Community Federal Credit Union
Ko-Am Federal Credit Union
Kootenai Valley Federal Credit Union
Kulia Ohana Federal Credit Union
Kunia Federal Credit Union
La Capitol Federal Credit Union
La Casa Federal Credit Union
La Fuerza Unida Community Development Federal Credit Union
Lac Courte Oreilles Federal Credit Union
Landmark Community Bank
Latino Community Credit Union
LCO Federal Credit Union
Legacy Bancorp, Inc.
Legacy Bank
Liberty Bank & Trust Company
Liberty County Teachers Federal Credit Union
Liberty Financial Services, Inc.
Lincoln County Credit Union
Little Haiti Edison Federal Credit Union
Louisville Community Development Bank
Louisville Development Bancorp, Incorporated
Lower East Side People's Federal Credit
M&F Bancorp, Inc.
Maine Highlands Federal Credit Union
Marion County Federal Credit Union
MariSol Federal Credit Union
Marvel City Federal Credit Union
Mechanics & Farmers Bank
Memphis First Corporation
Mendo Lake Credit Union
Metropolitan Community Credit Union

Mission Area Federal Credit Union
Missouri Family Federal Credit Union
Mission Community Bank
Mission Valley Bancorp
Mission Valley Bank
Mission-Valley Bancorp
Missouri Family Federal Credit Union
Molokai Community Federal Credit Union
Monroe Education Employees
Morgan City Federal Credit Union
Mt Zion Federal Credit Union
Native American Bancorporation Co.
Native American Bank, National Association
NCP Community Development Credit Union
Need Action Federal Credit Union
Neighborhood Bancorp
Neighborhood National Bank
Neighborhood Trust Federal Credit Union
New Community Federal Credit Union
New Convenant Dominion Federal Credit Union
New Generations Federal Credit Union
New Hope Community Development Federal
New Horizons Community Federal Credit Union
New Life Credit Union
New Pilgrim Federal Credit Union
New York National Bank
New York University Federal Credit Union
Newport News Neighborhood Federal Credit
Newrizons Federal Credit Union
NorState Federal Credit Union
North Dade Community Development
North Hawaii Community Federal Credit
North Milwaukee Bancshares, Inc.
North Milwaukee State Bank
North Side Community Federal Credit Union
Northcountry Cooperative Federal Credit
Northeast Community Federal Credit Union
Northeast Credit Union
Northland Area Federal Credit Union
Northwest Baptist Federal Credit Union
NRS Community Development Federal
Nuestro Banco
O.U.R. Federal Credit Union
OASIS Community Developoment Federal Credit Union
Old West Federal Credit Union
OneCalifornia Bank, FSB
OneUnited Bank
Onomea Federal Credit Union
Opportunities Credit Union
Our Mother of Mercy Parish Federal Credit
Pacific Crest Federal Credit Union
Pacific Global Bank
Pacoima Development Federal Credit Union
Pahranagat Valley Federal Credit Union
Pan American Bank
Park Midway Bank, National Association
Pelican State Credit Union
People for People Community Development
People's Community Partnership Federal Credit Union
People's First Choice Federal Credit Union
Perquimans Credit Union
PGB Holdings, Inc.
Phenix Pride Federal Credit Union
Philips County Self-Help
Potlatch N 1
Premier Bancorp, Inc.
Premier Bank
Prichard Federal Credit Union
Prince Kuhio
Progressive Neighborhood Federal Credit Union
Promise Credit Union
Pueblo Coop
Pyramid Credit Union (Pyramid Federal Credit Union)

Queens Cluster Federal Credit Union
Quitman County Federal Credit Union
Renaissance Community Development
Roberto Clemente Federal Credit Union
Rowan Iredell Area Credit Union
Saguache County Credit Union
Santa Cruz Community Credit Union
SCCB Financial Corporation
Schofield Federal Credit Union
Schools Workers Federal Credit Union
SCJ, Inc.
Seaway Bancshares, Inc.
Seaway Bank And Trust Company
Second Federal Savings and Loan Association of Chicago
Security State Bank of Wewoka, Oklahoma
Select Employees Federal Credit Union
Self-Help Credit Union
Self-Help Federal Credit Union
Sentinel Federal Credit Union
Settlers Federal Credit Union
Shelby/Bolivar County Federal Credit Union
Shiloh of Alexandria Federal Credit Union
ShoreBank
ShoreBank Corporation
ShoreBank Pacific
Shorebank Pacific Corporation
Shreveport Federal Credit Union
Sisseton Co-op Federal Credit Union
Sooner Southwest Bankshares,Inc.
South Carolina Community Bank
South Central People's Federal Credit Union
South East Community Credit Union
South End Federal Credit Union
South Side Community Federal Credit
Southern Bancorp Bank
Southern Bancorp Bank, National Association
Southern Bancorp, Inc.
Southern Chautauqua Federal Credit Union
Southside Credit Union
St Louis Community Credit Union
St Margaret's Credit Union
St. Charles Borromeo Federal Credit Union
St. James AME Federal Credit Union
St. Luke Credit Union
St. Philip's Church Federal Credit Union
Stevenson Federal Credit Union
Stillman Community Development Federal Credit Union
Suntide Federal Credit Union
T & P Federal Credit Union
Table Rock Federal Credit Union
The Carver State Bank
The Community's Bank
The Credit Union of Atlanta
The First National Bank of Davis
The Harbor Bank of Maryland
The Union Bank
The Union Credit Union
The United Federal Credit Union
Thurston Union of Low-Income People (TULIP)
Timber County Community
Toledo Urban Federal Credit Union
Tombstone Federal Credit Union
Tongass Federal Credit Union
Total Community Action Federal Credit Union
Tri State Bank of Memphis
Tri-County Credit Union
Tri-Valley Community Federal Credit Union
Triumph Baptist Federal Credit Union
Tulane Loyola
Tuscaloosa VA Federal Credit Union
Tuskegee Federal Credit Union
Twin States Federal Credit Union
Union Bancshares, Incorporated
Union Baptist Church Federal Credit Union
Union Credit Union
Union Settlement Federal Credit Union
United Bancshares, Inc.
United Bank of Philadelphia
United Federal Credit Union

United Singers Federal Credit Union
UNITEHERE Federal Credit Union
University Financial Corp, Inc.
University National Bank
UNO
Urban Financial Group, Inc.
USSCO Federal Credit Union
Valley Educators Credit Union
Valued Members Credit Union
Vernon/Commerce Credit Union
Victory Masonic Mutual Credit Union
Vigo County Federal Credit Union
Virginia Community Capital, Inc.
W.M. Employees Elkins Federal Credit Union
Wailuku Federal Credit Union
Waldo Community Development Federal Credit Union
Wendell Philipps CDCredit Union
Weslaco Catholic Federal Credit Union
West Texas
Winthrop Federal Credit Union
Wolf Point Federal Credit Union
Women's Southwest Federal Credit Union
Word of Life Federal Credit Union
Workers United Federal Credit Union
Yellowstone Federal Credit Union
Zion United Credit Union

Efficient performance among CDFIs: A Comparison of Community Development and Mainstream Financial Institutions Utilizing Data Envelope Analysis (DEA)

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Efficient performance among CDFIs: A Comparison of Community Development and Mainstream Financial Institutions Utilizing Data Envelope Analysis (DEA)

Abstract

In this evaluation study, we compare the operational performance of Community Development Financial Institutions (CDFIs), and what have been called "mainstream" financial institutions. We apply a method for evaluating efficiency that uses the primary inputs of performance of a set of institutions, and compares them to their outputs. This method is known as Data Envelope Analysis (DEA). We had two goals in this paper: We were interested in whether the performance of depository institutions in the CDFI industry lagged those of similar mainstream institutions; we also wanted to examine whether the tendency of CDFIs to serve lower-income, underserved consumers lowers their efficiency. Answers to these questions would provide some insights into another question: whether subsidies to CDFIs may lead to lending to low-income, underserved areas and consumers, and whether these subsidies are relatively risky investments. Although we find a few years where CDFIs were less efficient than mainstream institutions in a model that did not include environmental factors as inputs, we find that CDFIs had virtually the same level of performance, once these factors were entered into the model. In fact, we find in some years that CDFIs were more efficient than mainstream institutions. We feel that this method can be used as a framework to compare CDFIs and Mainstream financial institutions.

Introduction

How operationally efficient are Community Development Financial Institutions (CDFIs), when compared to financial institutions of similar size and scope? That is, when we examine the investments in funds, materials and labor that flow into CDFIs, do they tend to process, or transform these funds in a fashion that is more or less efficient than comparable financial institutions? The question is at first a challenging one, given the niches CDFIs operate within, and the missions and services provided by CDFIs relative to what some might term Mainstream Financial Institutions (MFIs). The vast majority of CDFIs have an explicit emphasis serving the financial needs on lower-income, underserved consumers and their communities. In this analysis, we apply a method used for decades to examine efficiency in industrial analysis: Data Envelopment Analysis (DEA). This method has been used in firms across a broad range of fields, including financial institutions. We use this method to attempt to compare the relative efficiency of community development and mainstream subgroups. DEA methods have been used to examine similar questions in a broad range of industries, including depository banks. To our knowledge, this will be one of the first applications of these methods to examine the efficient operational performance of CDFIs and to compare this performance to MFIs.

Motivation for this evaluation. We were interested in whether the performance of depository institutions in the CDFI industry lagged those of similar mainstream institutions; we also wanted to examine whether the tendency of CDFIs to serve lower-income, underserved consumers lowers their operational efficiency. We feel that answers to these questions would provide some insights into another question: whether the subsidies provided to CDFIs may lead to lending to low-income, underserved areas and consumers, and whether these subsidies are finding their ways into the relatively inefficient financial intermediaries.

The structural approach we take to examining firm performance is common in the field of strategic management. The most prominent of these comes from Michael Porter, who proposed five structural forces that determine the performance potential of firms competing in a given industry: the threat of substitute products or services, the threat of established rivals, the threat of new entrants, the bargaining power of suppliers, and the bargaining power of customers (Porter, 1980). Each of the forces determine prices, costs and investment requirements, which drive long-term profitability and hence, industry attractiveness. Essentially, the five forces of industry structure affect overall industry performance, and therefore the performance of firms within the industry. In structural approaches like the one we take in this analysis, the competitive forces of an industry are key to explaining performance variation across firms.

Methodological Approach. Our primary method used in this analysis is a comparison of CDFIs and MFIs using a well-developed statistical modeling process: Data Envelope Analysis (DEA). As with the prior analysis, the statistical analysis that follows is limited to regulated CDFIs. We limit our analysis to regulated CDFIs because of their requirement to regularly provide performance data in a systematic fashion. We feel that this method can be used as a framework to compare the performance of CDFIs and Mainstream financial institutions. One primary benefit of this choice of statistical modeling is that this method allows an evaluation of whether CDFIs are less efficient than what are termed “mainstream” financial institutions. At the same time, our use of this method in evaluation has benefits beyond comparisons across these groups. For example, by measuring the efficiency of a group of firms, like CDFIs, we can better gauge whether they face greater potential risks in the event of unforeseen environmental shocks or market downturn. Berger & Meister (1997) have noted that relatively inefficient banks are more vulnerable from a risk perspective. They found that less efficient, high-cost banks were more prone to failure. If we are able to evaluate the relative efficiency of a group of banks like CDFIs, regulators and policy makers might be better prepared to respond with policies that could help prevent systematic failure. These methods might also be used to locate potentially vulnerable individual firms in a diagnostic fashion. For example, this method could be used to identify poorly performing CDFIs and provide insight into the areas that might improve their operations, bringing their performance in line with the efficiency levels of the industry, or to levels that might be "protective" from an institutional failure standpoint.

In this specific analysis, we were interested in evaluating what some call "the efficient frontier" for the CDFI cohort, along with a comparable group of MFI peer depository institutions (*i.e.*, credit unions and banks of similar asset sizes). By "efficient frontier" we mean the expected performance standard for an expected level of risk faced by a set of firms. The efficient frontier is a concept used in modern financial theory. A combination of inputs into a firm, (a portfolio of inputs) is referred to as "efficient" if it has the best possible expected level of return for its recognized level of risk. For a manufacturing firm, these inputs could be natural resources, labor, utilities, technology, and of course level of financial investments. The resulting outputs might be furniture, lumber or iron ore. In financial institutions, the inputs are overwhelmingly financial in nature, and the labor input generally includes management, staffing and perhaps technology.

In addition to examining the level of output commensurate with the level of risks, DEA allows for statistical comparison within and across a group of similar firms, like CDFIs. Our primary plan in this evaluation is to use the DEA method to gain insight into whether there is a gap in the mean efficiency of CDFIs and MFIs ("Are CDFIs less efficient than mainstream institutions?"). Given the unique nature of CDFIs' missions to serve lower-income consumers and relatively uncertain markets, along with the additional work spent in technical assistance, our assumption going into the evaluation was that CDFIs would likely be less efficient in terms of their ability to convert a portfolio of financial inputs into outputs.

On the other hand, we recognized *a priori* that CDFIs often receive a considerable amount of their income from restricted and unrestricted federal, state, local and private foundation grants. Grant funding may be used to subsidize loan activities. CDFIs are able to have a lower costs of funds through grants, which may offset the additional expense and risks of the markets in which they operate. This produced a counter-hypothesis in which this subsidy contribution might lead CDFIs to be equally, or even more efficient than MFIs.

Data & Methods

In this section, we provide a brief overview of our methods in completing this evaluation (a more detailed evaluation is provided in Appendix B of this paper). Going into our project, we recognized that the range of variables necessary to perform a DEA efficiency evaluation of the type we envisioned meant that we would have to create a unique and comprehensive dataset that was not available from one source. In this first subsection, we provide a brief on Data Envelope Analysis (DEA) statistical modeling process we used. In the second subsection, we briefly review the multiple data sources that were considered, queried, ultimately selected, cleaned and compiled to create the eventual dataset in our research. Finally in this section, we discuss the methods we used, providing a brief review of the DEA techniques.

DEA is known by scholars as a “non-parametric frontier analysis.” It is called “non-parametric” because it makes no assumptions about how the inputs are used or altered to generate the outputs. Instead this method projects where a firm's inputs ought to place it in terms of the overall productivity described by the data, and then scores it by how far a firm’s actual output is from that point. Measuring industrial productivity in this fashion has been used for decades. These methods were originally applied within the engineering context. In addition to providing a total efficiency score, these methods allow for an analysis that would reveal the combination of operating practices that could provide an optimum set of outputs.

In recent years, an increasing number of scholars have examined the efficiency of what may be termed mainstream financial institutions (MFIs) using DEA methods (See the bibliography for examples of research using these types of approaches, including Barr and colleagues, 2002; Luo, 2003; Yeh, 1996). Although there are certainly a growing number of scholars and practitioners using these methods, there are differences in the approaches used by scholars applying DEA methods to financial institutions. Recognizing the benefits of each of these approaches, we provide analyses below using each of the two prevailing approaches in the field to determine whether the results produce contradictory findings (see Data and Methods Appendix B for more details on each of these approaches).

Data sources. Because of the unique nature of our evaluation, data for this analysis was collected from several sources (see Data and Methods Appendix B for more information about the data sources used in this evaluation). To facilitate apples-to-apples comparisons, this evaluation was limited to depository institutions (that is, credit unions and banks). We did not examine CDFI loan funds because there would not be a comparison set of non-CDFI loan funds to use in this evaluation (a list of the credit unions and banks used in this analysis is in Data and Methods Appendix B). Loan funds make up a substantial proportion of the number of institutions that are CDFIs. Although CDFIs credit unions and banks hold the majority of the assets under management in CDFIs.

In our evaluation, we recognized that credit union and banking institutions' performance may differ considerably based on the local conditions in their chartered service area. To further add controls for local conditions, indicators of the socio-economic context of the bank's chartered and headquartered area, was gathered from the Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS), including the level of poverty and unemployment in a financial institution's service area (see Data and Methods Appendix B for more information about the data sources used in this evaluation).

Analytical process. Our resulting dataset included a large set of variables available for analysis**,** and we grounded our variable list based on our knowledge of the field. The resulting variable list composed of a set of 10 variables of interest follows. These variables are reviewed in Table 1 below.

Table 1

Input and Output Variables used in DEA Analysis

Name of variable	Symbol	Definition
Firm input variables		
Cost of Funds	COF	The average interest rate paid by a financial institution to its depositors
Equity Ratio	EA Ratio	The ratio of a depository's equity over its assets as a percentage by year
Assets	Assets	The total value of all assets held by the firm in a given year
Firm output variables		
Performing Assets	PA Ratio	The percentage of assets held by a firm, that are currently performing at year's end
Return on Average Assets	ROAA	The return on average assets for a firm in a given fiscal year
Value of Originated Loans	Total Value	The weighted average for the total value of loans approved by a firm in the counties it operated within a given fiscal year
Number of Applications Received	Applications	The weighted average for the total number of loan applications received by a firm in the counties it operated within a given fiscal year
Non-firm Inputs		
Median Income	HHINCMED	The weighted average of the median income of the counties a firm had operated within a given fiscal year
Poverty Percentage	Poverty %	The weighted average of the percentage of poverty of the counties a firm had operated within a given fiscal year
Unemployment Percentage	Unemployment %	The weighted average of the percentage of unemployment a firm had operated within a given fiscal year

We ran three analyses using the variables described above, with each analysis focused on the fiscal years from 2002 to 2011. However, across analyses the mix of variables differed. The initial analysis ignored loan origination and environmental conditions and looked simply at firm profitability with risk management; we call this the *Base Case DEA*. The second analysis included the variables of the first, but also included environmental inputs and loan applicant output. This model evaluated a firm's ability to attract loan applicants, and is we call it the

Production Approach DEA. The third analysis was identical to the second analysis except instead of loan applicant data, it included the value of loans originated. It examined the value generated by a firm while also managing profitability and risk; we call this the *Intermediation Approach DEA*. Each of these approaches provides a slightly different view of the operational efficiency of firms, and we believe there is value in the cumulative results rather than a single, specific model. Thus, the full list of variables included in each model can be found in as found in table 2. After running the models initially, we separated firms by whether or not they were CDFIs. The results were then plotted to allow for group comparisons.

Table 2

DEA Models Used in Analyses

Type of analysis	Variables Used
Base case DEA (w/o environmental factors)	
Input variables	Cost of Funds, Equity Asset Ratio, Total Assets
Environmental Inputs	N/A
Output variables	Return on average assets, Performing Assets
Production Approach DEA	
Input variables	Cost of Funds, Equity Asset Ratio, Total Assets
Environmental Inputs	Unemployment percentage, Poverty percentage, Median income
Output variables	Return on average assets, Performing Assets, Number of Applicants Received
Intermediation Approach DEA	
Input variables	Cost of Funds, Equity Asset Ratio, Total Assets
Environmental Inputs	Unemployment percentage, Poverty percentage, Median income
Output variables	Return on average assets, Performing Assets, Value of Originated Loans

Results

Our primary research question focused on whether CDFIs had typically lower efficiency ratios than MFIs. If we found that indeed, CDFIs were less efficient, then this would raise questions about the value of the subsidies CDFIs receive, at least in terms of the performance of these firms vis-a-via MFIs. Such a finding would also raise question about the risk of failure of CDFIs relative to MFIs. Table 5 provides the results of a test for differences in the mean DEA efficiency scores between CDFI and MFI groups. Table 3 provides the results of a test of differences for each of our three DEA models (*i.e.,* Base, Production Approach, Intermediation Approach), and in each year from 2002-2011. This provides a total of 30 year/model combinations in which we might find statistically significant differences in means. As the shaded areas of the table indicate, there were only 7 year/model combinations that resulted in a significant mean differences between CDFIs and MFIs (2004, 2005 *Base Case* and *Production Approach* DEA), and in 2007 across all three models. Put differently, we can only discern a difference in performance in 23.3% of the years across these periods.

The directionality of these differences also reveals some provocative findings. In 2004, the mean efficiency of MFIs was considerably higher than CDFIs in the base case model. Likewise, the production approach model also showed greater efficiency for MFIs. What is noteworthy is that in both models, the relative efficiency of groups reversed in 2005. *That is, in both of these models the mean efficiency of CDFIs was greater in 2005.*

In the midst of the financial crisis, 2007, was a year that produced statistically significant differences in efficiency across the two groups. *However, in 2007 it was the CDFIs that had higher mean efficiencies, and this difference was found across all models.* Taken together, the results in Table 5 indicate that the in majority of tested model/year periods, CDFIs and MFIs had mean efficiency ratios that were not statistically different (23/30, 76.6%). *Further, in four of the seven periods in which there was a difference, CDFIs showed higher mean efficiencies.*

Table 3

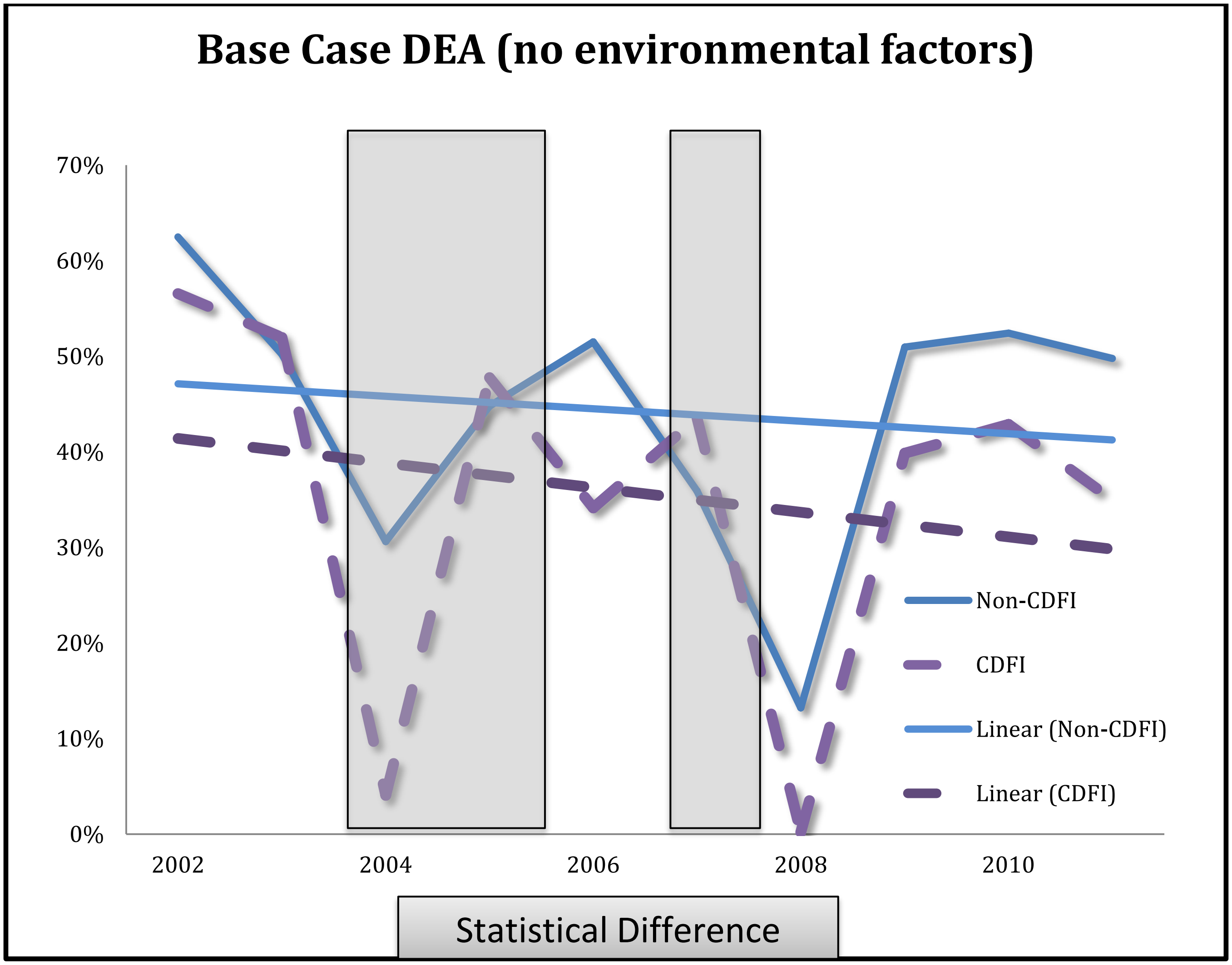
Kolmogorov-Smirnov Test for Differences Between Groups

Year	K-S Test P-value Base Case DEA	Significance	K-S Test P-value Production DEA	Significance	K-S Test P-value Intermediation DEA	Significance
2002	0.19891	SAME	0.50155	SAME	0.8453	SAME
2003	0.20608	SAME	0.39089	SAME	0.25312	SAME
2004	0.006412	Different	0.023558	Different	0.074408	SAME
2005	0.020958	Different	0.045916	Different	0.090796	SAME
2006	0.13936	SAME	0.62727	SAME	0.5658	SAME
2007	0.0071	Different	0.0181	Different	0.0196	Different
2008	0.0644	SAME	0.5561	SAME	0.6261	SAME
2009	0.1652	SAME	0.4598	SAME	0.3704	SAME
2010	0.1986	SAME	0.1514	SAME	0.2246	SAME
2011	0.2689	SAME	0.1511	SAME	0.136	SAME

Visual Representation of DEA Models. We felt that a statistical analysis alone failed to effectively communicate the differences between CDFIs and MFIs, particularly in those case which were identified, the statistical analysis did not show how large these differences might actually be across groups. To address this, Figures 1, 2 and 3 provide a visual representation of the data in Table 1 (the shaded areas are the periods where the mean differences are statistically significant). What is clear from immediate visual inspection is that the mean efficiency of both CDFIs and MFIs shows considerable year-to-year variability. Second, with a few exceptions, the mean efficiencies of CDFIs and MFIs are virtually indistinguishable. The base DEA model (without environmental factors) shows the most visual gaps between the two, but their relative positions are frequently reversed. Third, the first period, 2002, was the highest mean efficiency for both CDFIs and MFIs and across all models. In the base and production approach models, the trend lines show that mean efficiency was declining over time, and at a slightly faster rate for CDFIs. The intermediation approach model shows a flat trend over time.

Figure 1 (Base DEA without environmental factors) shows the two groups' mean efficiency scores moving together, and the shaded areas show periods of statistically significant differences between groups. Prior to financial crisis, 2004 was a particularly poor year for efficiency among depository CDFIs. *What is noticeable is that this was the worst year of efficiency for CDFIs over the full decade.* Our review of CDFI appropriations shows considerable variance over the research period. In 2004, the CDFI Fund's total appropriation fell to $61 million from $75 million in the 2003, and continued to decline to $54.5 million in 2007 and then began to increase in 2008 to $91 million. These declines were considerable from the 2001 levels of $118 million, and may have affected the industry's efficiencies during that period. It is remarkable that CDFIs continued to perform at competitive efficiencies when one of their prominent sources of funds was variable and declining.

Figure 1


Base Case DEA (no environmental factors)
70%
60%
50%
40%
30%
20%
10%
0%
2002
2004
2006
2008
2010
Non-CDFI
CDFI
Linear (Non-CDFI)
Linear (CDFI)
Statistical Difference

Similar to the prior graphical chart, Figure 2 (Production Approach with environmental inputs) shows the two groups' mean efficiency scores moving together, and the shaded areas show periods of statistically significant differences. Also similarly, 2004 was a particularly poor year. *One difference in a comparison with the prior model is that the gaps between groups have tightened considerably. This suggests that once we control for the relatively lower income, underserved markets in which CDFIs operate, we find that their performance is virtually the same as MFIs.*

Figure 2

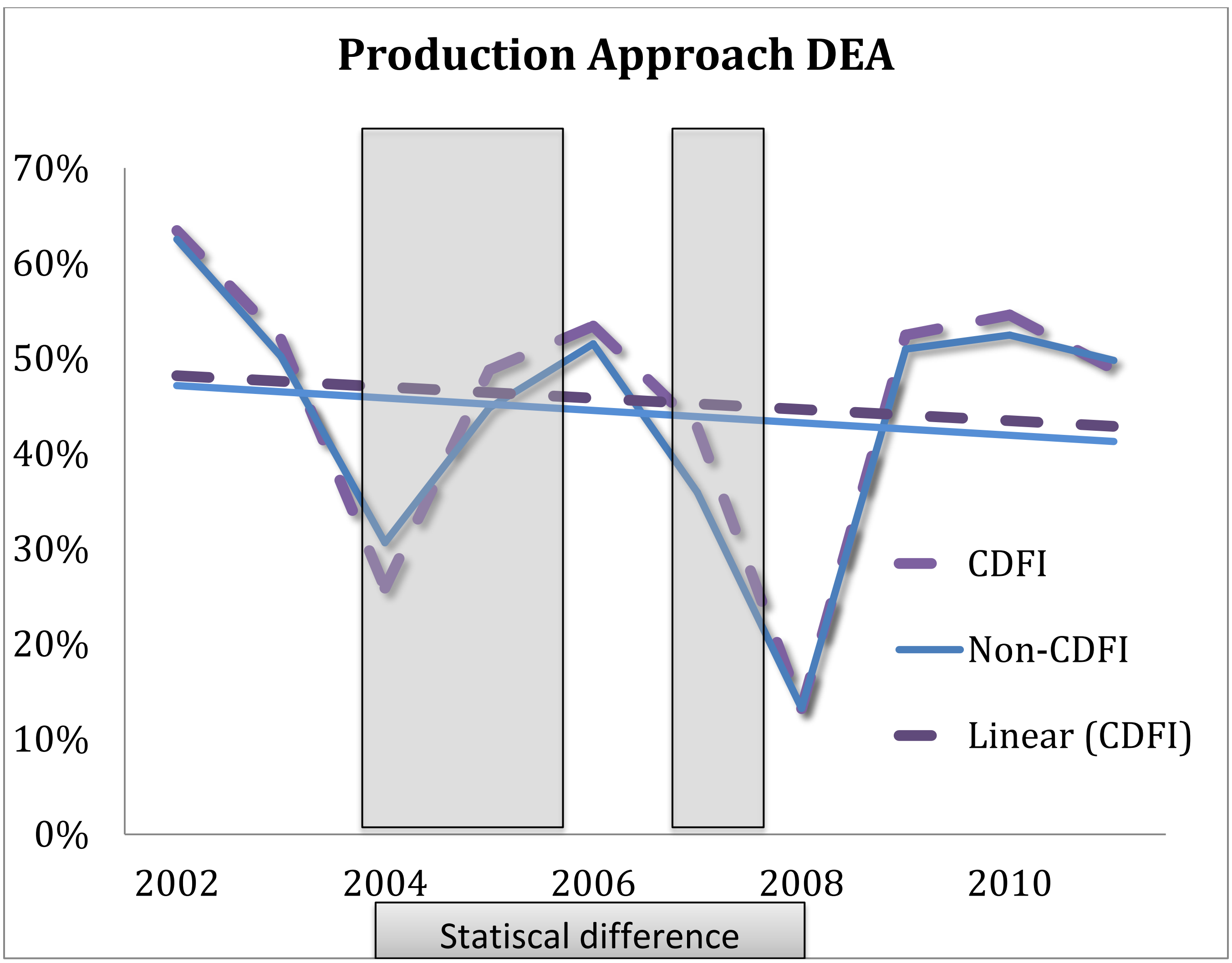
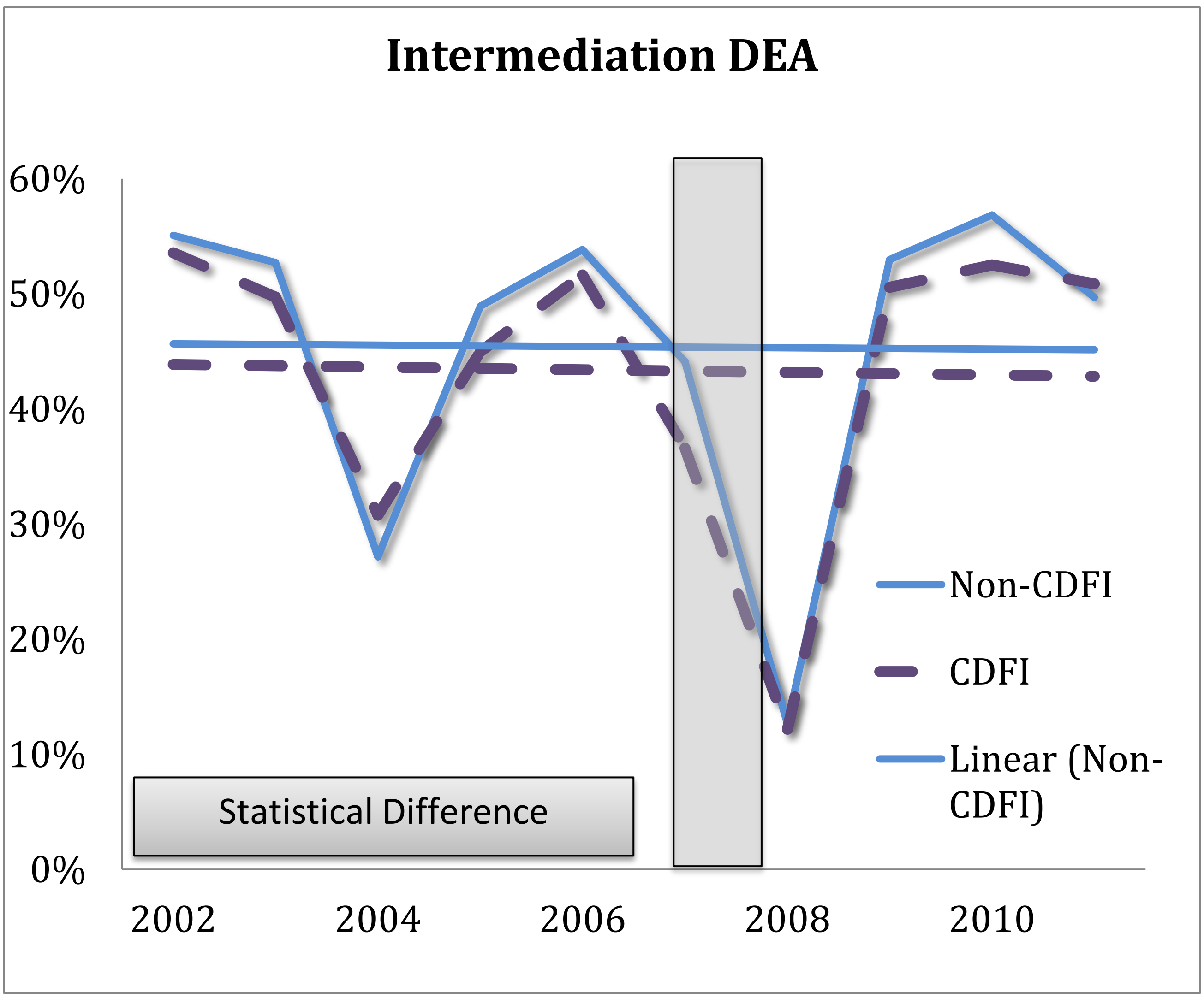


Figure 3 provides a graphical representation of the results from the Intermediation model with environmental factors. This graphic differs from the prior two in a couple of ways. First, 2004 was not a statistically significant year of poor relative performance among CDFIs, and second, the trend over time is flatter than the prior models. Past research has shown that different DEA models frequently produce contrasting findings. *Our analyses show that across models, efficiency was quite variable, was generally declining over time, and the efficiency of CDFIs was virtually indistinguishable from those of MFIs.*

Figure 3



Conclusions

Our primary interest in this research was to compare the performance of a set of CDFIs with a set of similar sized MFI peers (credit unions and banks), with an eye toward determining whether there were differences in efficient performance across groups. Using a decades-old, well-established operational efficiency analysis method, Data Envelopment Analysis (DEA), we found that CDFIs are no more inefficient than their similar-sized MFI peers. We also found that mean efficiency showed considerable volatility over the decade analyzed, and was generally declining over time. In fact, in some years, we found that CDFIs were more efficient than MFIs.

Limitations of This Analysis. We feel very confident about the value of this model. However, there are some limitations based on our sample and use of performance variables. First, the model is based on financial performance measures and therefore does not directly measure inputs that could not be found in financial statements or government datasets. So, for example, these models don't capture measures of branch locations, drive-by-traffic flow or consumer sentiment about a bank or credit union in this analysis. One particularly important area of interest might be the input of various technological enhancements on performance, which we discuss in more detail below in our discussion of future research opportunities. All of these could have material influence on a financial institution's performance. Second, our DEA model can only be applied to other depository institutions at this point (that is, banks and credit unions). Thus, these results may reflect firm behavior that is true of regulated financial institutions, and not relatively unregulated institutions like CDFI loan or equity funds. In short, although our model may capture some general idiosyncrasies of the CDFI industry, it ignores any evaluation of non-regulated CDFIs (which may be either more or less efficient). Finally, these results may be true of financial institutions with similar net asset sizes (loan funds tend to be much smaller than credit union or bank CDFIs).

Future research opportunities. One limitation of structural approaches like the one undertaken here is the constraint of input and output variables available for scaled, statistical analysis. By taking a structural approach to the question of firm efficiency, we have chosen to be less focused on the resources a given firm or group of firms may posses that can provide competitive advantage. One prominent example of a limitation in this regard is these models exclude the input of technological investments. During the period of this analysis, there have been two trends that have likely influenced the efficiency of the industry. The first factor is the general decline in branch banking over time. There is a declining stock of bank branches, and particularly in the areas that have higher proportions of low-income consumers (*e.g.,* rural areas). This has been coupled with a greater application of technological platforms that would lower the overhead and transaction costs in retail banking: online banking, mobile banking platforms, telephone banking, Automatic Teller Machines (ATMs), computerized credit-scoring models and loan approval systems. There is not an even distribution of these investments across the industry, and especially among lower-income consumers. CDFIs have typically engaged in what can be termed "high-touch" retail banking practices, and may have reliance on technology. This in turn may suggest a greater reliance of CDFIs on subsidy to perform these relatively costly banking services. Future research should examine the input of technological platforms and investments on the overall efficiency levels in the CDFI industry to determine whether there are important differences between CDFI and MFI institutions and across CDFI financial intermediaries. This could be done using survey methods with a sample of CDFIs and matched MFI institutions.

A second area for future research is in the responses of individual or groups of CDFIs to declines in the appropriations from the CDFI Fund. The aggregate declines are discussed above. However, there is likely variance in those declines across the CDFI industry with some CDFIs potentially not declining, or even increasing their access to funds over the period. Using survey methods, the concentration of funds from various philanthropic or government sources over the study period might add insight into the degree to which CDFIs are vulnerable to swings in these sources of funds, how quickly they are able to respond when these funds begin to decline, and whether there are "best practices" among CDFIs during periods when funding sources are challenged.

We noted earlier in this paper that DEA models also allow for diagnostic use by evaluators. That is, these models can be used to assist in locating underperforming CDFIs and to provide advice on how they might become more efficient. Such an analysis was beyond the scope of this evaluation. Future research should take a deeper emphasis on ferretting out relative differences within subgroups of CDFIs. Are there firms that have especially noteworthy efficiencies, at both the high- and low end of the efficiency scale? Using these methods, future research can provide actionable, strategic data that may help raise the efficiency of CDFIs overall, to identify best-in-performance firms, and to assist those that may be laggards. These methods might be particularly useful to industry associations, regulatory agencies and policymakers.

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Appendix B

Data & Methods

Going into our project, we recognized that the range of variables necessary to perform a DEA analysis of the type envisioned meant that we would have to create a unique and comprehensive dataset that was not available from one source. In this first subsection, we provide a brief on Data Envelope Analysis (DEA). In the second subsection, we review the multiple datasources that were considered, queried, selected, cleaned and compiled to create the eventual dataset in our research. Finally in this section, we discuss the methods we used, providing a brief review of the DEA techniques.

A brief on Data Envelopment Analysis (DEA). DEA assumes that firms within an industry take inputs and transform them into outputs. From this set of inputs and outputs, it estimates a production frontier and assigns efficiency scores for a firm relative to its proximity to that frontier. For a review of how DEA has been used in the study of financial institutions and a comparison with other methods of analysis see Berger & Mester (1997). DEA is a non-parametric frontier analysis frequently used for assessing efficiency across multiple production units. It is non-parametric because it makes no assumptions about how the inputs are used or altered to generate the outputs. Instead it projects where a firm's inputs ought to place it in terms of the production frontier described by the data, and then scores it by how far actual output is from that point.

Despite a sizable and growing body of literature examining the question of performance and efficiency within the financial industry, there is no consensus for a single universally-accepted method of its assessment. Broadly speaking, most of the research can roughly be described as variations of frontier analysis. Frontier analyses attempt to measure the distance of individuals and groups of firms from their best possible performance outcomes, based on the resources and inputs they had available. These methods were originally applied within the engineering context, and have historically provided a quantitative measurement of a firm's efficient use of the inputs they have in producing their resulting outputs. In a prescriptive sense, these methods allow for an analysis that would reveal the combination of operating practices utilizing a given a set of resources that will provide an optimum set of outputs. One avenue for frequent scholarly and practical discussion in the use of these analyses is agreement about the optimum outputs and appropriate inputs for inclusion. In recent years, an increasing number of scholars have examined the efficiency of MFIs using DEA methods (Barr et al, 2002; Luo, 2003; Yeh, 1996).

A Brief on Data Envelopment Analysis (DEA). DEA is frequently used for assessing efficiency across firms (Cooper, 1999). It makes no assumptions about how the inputs are used or altered to generate the outputs. Instead it projects where a firm's inputs ought to place it in terms of the production frontier described by the data, and then scores it by how far actual output is from that point.[17]

To provide a simplistic example, in the table below we provide data on three firms with one input and one output. The firms listed can be evaluated by comparing the ratio of their respective outputs over their respective inputs. Since firm A has output 5 and input 1 and firm B has output 8 and input 2, firm A is more efficient than firm B (5/1 = 5 **>** 8/2 = 4). Firm C is obviously less efficient than both A and B.

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[17] (Cooper W., 1999) and (Ramanathan, 2003) provide similar examples to the one given. This discussion is based on chapters 1, 2, 3 of Ramanathan and 2, 3, 4 of Cooper.

Firm	Input	Output	Output/Input
A	**1**	**5**	**5**
B	**2**	**8**	**4**
C	**3.5**	**7**	**2**

X_1 = (Current Assets - Current Liabilities)/Total Assets X_2 = Retained Earnings/Total Assets X_3 = Net Interest Income/Total Assets X_4 = 1/Leverage X_5 = "sales"/Total Assets

Table 1: Single input, Single output example

The most efficient firm is the one whose position on the graph draws the steepest line between it and the origin.

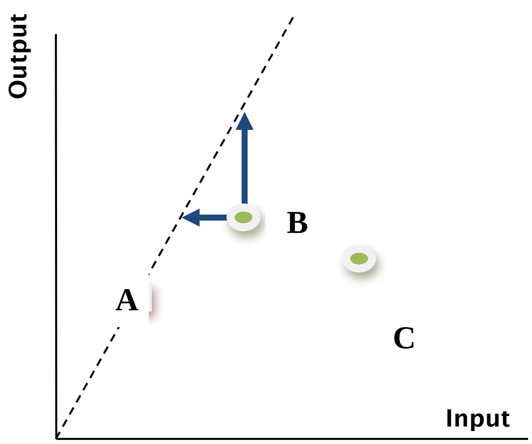

Image 1: Single input, Single output graph

Here, the square dot, representing firm A, is the most efficient of all the points given. If one were to now score the efficiency of all the points, the simplest way would be to simply take the ratio of their slopes relative to steepest one.

In the numerical example above, firm A has an efficiency of 1, firm B has an efficiency of 4/5 = 0.8, and firm C has an efficiency of 2/5 = 0.4.

One may also describe how these inefficiencies might be improved, either by lowering input relative to the output, or raising output relative to the input. For firm B, to match the efficiency of firm A, it has to either raise its production by 2 units or lower its input by 0.4. These two options are represented graphically in the chart by the blue arrows from firm B pointing to different regions on firm A's efficiency frontier.

To further illustrate the degree of complexity in DEA modeling, we provide an example based on the slightly more complex case of one input and two outputs.

Table 2: Single Input, Multiple Output example

Firm	Input	Output 1	Output 2	Output 1/Input	Output 2/Input
A	**1**	**5**	**2**	**5**	**2**
B	**1.5**	**6**	**4**	**4**	**2.67**
C	**3**	**7**	**15**	**2.33**	**5**
D	**2**	**8**	**7**	**4**	**3.5**
E	**1.2**	**4**	**4**	**3.33**	**3.33**
F	**1**	**1.7**	**3**	**1.7**	**3**

We provide this example to illustrate that in this case, comparing relative efficiencies of the different firms is more difficult. If we plot the output/input ratios on a graph we get the following picture:

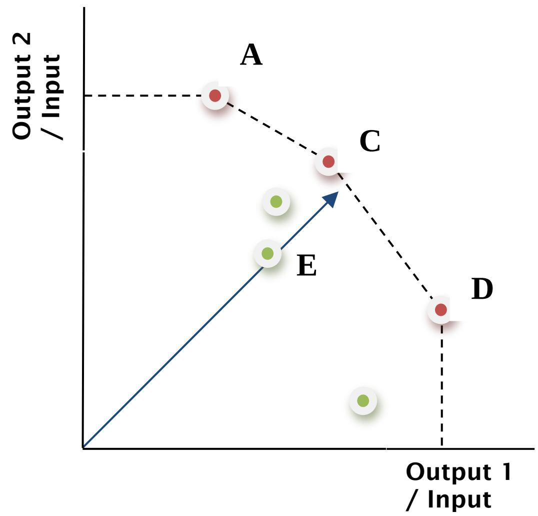

Image 2: Single input, multiple output graph

The points representing firms A, C, and D effectively constitute a production frontier, which envelops (hence the E in DEA) all the other points. Consequently, a natural measure for firm efficiency is how near or far a firm is from the production frontier. Like before, one may also specify how an efficient firm operates more efficiently, by either lowering certain inputs or increasing specific outputs. As we discussed earlier, DEA assumes that firms within an industry take inputs and transform them into outputs. From this set of inputs and outputs, it estimates a measure of optimum efficiency given the risk profile for a set of firms, and assigns efficiency scores for an individual firm relative to its proximity to that frontier. For a review of how DEA has been used in the study of financial institutions and a comparison with other methods of analysis see Berger & Mester (1997).

Although there are a growing number of scholars and practitioners using these methods, there are differences in the approaches used by scholars applying DEA methods to financial institutions. For example, some scholars take the view that financial institutions are producers of loans and deposit accounts, and these scholars tend to measure output using measures like the number of accounts or transactions serviced. This has been called the *Production Approach* (Sherman & Gold, 1985; Sherman & Ladino, 1995). On the other hand, some scholars have taken the view that the output of banks is better measured in terms of the value of the loans that they originate. This has been called the *Intermediation Approach* (Yue, 1992). Recognizing the benefits of each of these approaches, we provide analyses below using each of these approaches to determine whether the results produce contradictory findings.

Data sources. Data for this analysis was collected from several sources. Annual financial information on banks and credit unions were collected from the SNL Financial database. The SNL is a financial data provider that compiles publicly-available quarterly call reports on regulated depositories (*i.e.,* banks, credit unions). The coverage years we initially pulled from SNL spanned the period from 1997 to 2012. These data provide some of the inputs and outputs in the eventual DEA model.

Banking institutions performance may differ considerably based on the local conditions in their chartered service area. To provide some measure of statistical control in our analysis, we also included in our model Home Mortgage Disclosure Act (HMDA files). Regulation C of the HMDA (1975), requires lending institutions to report public loan data. These data are compiled by the Federal Financial Institutions Examination Council (FFIEC) data for regulatory reasons, and for a small set of research analysis purposes. These products were acquired in a number of ways including directly from FFIEC, interlibrary loan from the University of Michigan, a generous gift from a colleague,[18] and ordered through the National Archives maintained by the University of Maryland. Cumulatively, the data we acquired from both long form application (LARS) files and firm transmittal sheet data (TS) data spanned a 20-year period from 1991 to 2011.

To further add controls for local conditions, indicators of the socio-economic context of the bank's chartered and headquartered area, was gathered from the Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS). These data covered the period between 1997 and 2011.

[18] Quinn Curtis, University of Virginia School of Law

After collecting a robust set of input and output indicators for depository financial institutions, we needed to distinguish CDFIs from MFIs found in our dataset. Using a list of certified CDFIs provided by the CDFI Fund, the National Federation of Community Development Credit Unions, and the National Community Investment Fund we were able to create a matching algorithm, which selected CDFIs based on names or charter number, and cross-referenced these with SNL identification numbers.

Another use for the HMDA data involved the output of loans by institution. We created an index based on the volume of loan activity generated by each financial institution in a given year, and for each county in which they received an application. We ran descriptive statistics on these data, and to avoid outliers, we removed loan requests whose amounts were further than 1.5 times the inner quartile distance from the median. We then merged into these firm-county-year files and combined with the socio-economic indicators for each county in each year. Finally, these data were matched to the firm-level call report financial data from SNL.

Because SNL uses a different identification numbering system than the FFIEC and Thrifts and Savings files do not include charter numbers for the institutions that are covered, the names from both files had to be matched. Because of the interest in this research of controlling for local market conditions, we matched firms by name, geographic location, and parent firm, if applicable. Several rounds of iteration were used to control for quality. Also, because SNL does not gather data on firms that are not regulated depositories, this eliminated from analysis those firms that are purely mortgage originators. We then calculated a weighted average of the firm's loan activities and operating environments for a given year weighted by the number of loans they approved for a given county. We chose to weight by this number because it allows for an examination of the areas a firm is most active in generating loan volume. These data were then matched with the lists of CDFIs to generate our final data set.

Analytical process. Our resulting dataset included a surfeit of variables available for analysis**,** and some researchers have been known to use data reduction techniques that have statistical methods impose a set of variables based on iterations using all potential variable combinations. We felt that this “all in” approach was atheoretical, and for our analysis, we grounded our variable list based on our knowledge of the field. The resulting variable list, composed of a set of 10 variables of interest follows. These variables are reviewed in Table 1 below.

Table 1

Input and Output Variables used in DEA Analysis

Name of variable	Symbol	Definition
Firm input variables		
Cost of Funds	COF	The average interest rate paid by a financial institution to its depositors
Equity Ratio	EA Ratio	The ratio of a depository's equity over its assets as a percentage by year
Assets	Assets	The total value of all assets held by the firm in a given year
Firm output variables		
Performing Assets	PA Ratio	The percentage of assets held by a firm, that are currently performing at year's end
Return on Average Assets	ROAA	The return on average assets for a firm in a given fiscal year
Value of Originated Loans	Total Value	The weighted average for the total value of loans approved by a firm in the counties it operated within a given fiscal year
Number of Applications Received	Applications	The weighted average for the total number of loan applications received by a firm in the counties it operated within a given fiscal year
Non-firm Inputs		
Median Income	HHINCMED	The weighted average of the median income of the counties a firm had operated within a given fiscal year
Poverty Percentage	Poverty %	The weighted average of the percentage of poverty of the counties a firm had operated within a given fiscal year
Unemployment Percentage	Unemployment %	The weighted average of the percentage of unemployment a firm had operated within a given fiscal year

To examine the impact of loan originations, and local socioeconomic conditions separately, we ran three analyses using the variables described above. Each analysis focused on the fiscal years from 2002 to 2011. However, the mix of variables differed. The initial analysis ignored loan origination and environmental conditions and looked simply at firm profitability with risk management (*base case DEA*). The second analysis included the variables of the first, but also included environmental inputs and loan applicant output. This model examined a firm's ability to attract loan applicants (*Production Approach DEA*). The third analysis was identical to the second analysis except instead of loan applicant data, it included the value of loans originated. It examined the value generated by a firm while also managing profitability and risk (*Intermediation Approach DEA*).

Thus, in terms of specifications across the analyses, the variables were included as found in Table 2 (entries with missing data were excluded from the analysis).

Table 2

DEA Models Used in Analyses

Type of analysis	Variables Used
Base case DEA (w/o environmental factors)	
Input variables	Cost of Funds, Equity Asset Ratio, Total Assets
Environmental Inputs	N/A
Output variables	Return on average assets, Performing Assets
Production Approach DEA	
Input variables	Cost of Funds, Equity Asset Ratio, Total Assets
Environmental Inputs	Unemployment percentage, Poverty percentage, Median income
Output variables	Return on average assets, Performing Assets, Number of Applicants Received
Intermediation Approach DEA	
Input variables	Cost of Funds, Equity Asset Ratio, Total Assets
Environmental Inputs	Unemployment percentage, Poverty percentage, Median income
Output variables	Return on average assets, Performing Assets, Value of Originated Loans

While were mainly interested in the variable return to scale for each firm, we also ran a constant return to scale to examine how close various firms are to their maximum scale efficiency. Then, we separated firms by whether or not they were CDFIs. The results were then plotted to allow for group comparisons.

Table 3 provides means and standard deviations for the variables used in the analysis, but only for TFIs (Traditional Financial Institutions). Table 4 provides these same data from CDFIs. Lastly, we tested hypotheses for whether or not CDFIs are more or less efficient than peer institutions by these three DEA models (since DEA measures are not necessarily normally distributed we used the non-parametric Kolmogorov-Smirnov statistic, which reports quintile distances, to test for differences between CDFIs and non-CDFI firms).

Table 3

Descriptive Statistics of Variables used in Analyses (Non CDFIs)

Symbol	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Frequency	5641	5812	6206	6166	6042	6029	6018	5935	5844	5740
COF	2.72	2.01	1.76	2.24	3.08	3.55	2.88	2.05	1.46	1.10
(std)	(0.66)	(0.61)	(0.60)	(0.72)	(0.84)	(0.85)	(0.68)	(0.59)	(0.51)	(0.66)
EA Ratio	10.26	10.27	10.47	10.57	11.00	11.22	10.55	10.07	10.21	10.60
(std)	(3.39)	(3.45)	(3.51)	(3.68)	(3.87)	(3.95)	(3.66)	(3.47)	(3.38)	(3.39)
Assets ($s M)	1.37E+06	1.55E+06	1.85E+06	1.92E+06	1.58E+06	1.58E+06	1.78E+06	1.33E+06	1.25E+06	1.39E+06
(std)	(1.73E+07)	(1.88E+07)	(2.44E+07)	(2.40E+07)	(2.67E+07)	(2.98E+07)	(3.51E+07)	(2.31E+07)	(2.23E+07)	(2.51E+07)
PA Ratio	99.38	99.39	99.44	99.43	99.39	99.00	98.06	97.07	96.84	97.11
(std)	(0.91)	(0.90)	(0.82)	(0.82)	(0.94)	(1.50)	(2.86)	(3.91)	(4.25)	(0.91)
ROAA	1.02	0.98	0.96	0.97	0.92	0.73	0.08	-0.20	0.12	0.43
(std)	(0.69)	(0.88)	(0.76)	(0.85)	(0.84)	(0.94)	(3.17)	(1.74)	(1.50)	(0.69)
Total Value ($s)	16147	19935	11324	11551	9581	9484	10596	14595	12610	11301
(std)	(45967)	(53608)	(33283)	(36395)	(27057)	(25864)	(44051)	(40270)	(35546)	(45967)
Applications	188.57	219.25	133.86	130.12	117.11	111.18	108.04	139.95	121.66	109.90
(std)	(411.81)	(460.27)	(281.39)	(317.03)	(265.72)	(256.58)	(219.27)	(288.76)	(254.13)	(411.81)
HHINCMED ($s)	44793	45401	45923	47532	49288	51370	53276	51393	50910	54066
(std)	(8964)	(8633)	(8595)	(9295)	(9637)	(9955)	(10497)	(10456)	(10108)	(8964)
Poverty %	11.07	11.48	12.03	12.67	12.84	12.59	12.78	13.91	14.77	14.33
(std)	(3.61)	(3.41)	(3.39)	(4.00)	(3.84)	(3.75)	(3.64)	(3.90)	(3.96)	(3.61)
Unemployment %	5.58	5.83	5.45	5.09	4.62	4.62	5.65	8.97	9.22	8.50
(std)	(0.91)	(0.90)	(0.82)	(0.82)	(0.94)	(1.50)	(2.86)	(3.91)	(4.25)	(0.91)

Table 4

Descriptive Statistics of Variables used in Analyses (CDFIs)

Symbol	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
					Means					
Frequency	62	66	69	72	77	78	79	83	75	70
COF	2.49	1.85	1.61	2.13	2.88	3.31	2.80	2.11	1.47	1.12
(std)	(0.60)	(0.53)	(0.46)	(0.60)	(0.80)	(0.82)	(0.74)	(0.67)	(0.54)	(0.47)
EA Ratio	10.05	10.06	10.30	10.15	10.07	10.32	9.21	9.03	9.20	9.90
(std)	(3.31)	(3.01)	(3.47)	(3.27)	(3.11)	(3.32)	(2.76)	(3.00)	(3.25)	(3.73)
Assets ($s M)	1.71E+05	1.80E+05	1.95E+05	2.23E+05	2.37E+05	2.50E+05	2.76E+05	2.90E+05	2.86E+05	2.97E+05
(std)	(2.05E+05)	(2.23E+05)	(2.39E+05)	(3.01E+05)	(3.33E+05)	(3.51E+05)	(4.02E+05)	(4.07E+05)	(3.60E+05)	(3.51E+05)
PA Ratio	98.95	98.85	98.99	98.84	98.73	98.42	97.00	95.74	95.37	95.29
(std)	(1.20)	(1.20)	(1.46)	(1.31)	(1.29)	(1.49)	(2.57)	(4.61)	(4.17)	(5.27)
ROAA	0.89	0.90	1.08	0.86	0.88	0.74	-0.23	-0.35	-0.04	0.21
(std)	(0.99)	(1.12)	(0.85)	(1.02)	(0.77)	(1.04)	(2.03)	(1.64)	(1.23)	(1.20)
Total Value ($s)	8330	9978	8158	7317	7024	5236	6313	6529	5415	4908
(std)	(22804)	(28351)	(21346)	(18489)	(18046)	(13315)	(14496)	(17375)	(11753)	(6787)
Applications	90.33	101.92	78.30	72.96	70.56	69.95	75.99	76.56	66.86	57.94
(std)	(134.58)	(158.72)	(130.05)	(126.56)	(127.67)	(122.97)	(132.60)	(109.59)	(99.41)	(76.17)
HHINCMED ($s)	42076	42268	43639	45640	46858	49119	50454	49650	48634	52576
(std)	(7477)	(6747)	(8069)	(8778)	(9600)	(9810)	(8982)	(10624)	(8531)	(9465)
Poverty %	13.64	14.22	14.37	15.42	15.86	15.47	15.46	16.18	17.38	16.57
(std)	(4.30)	(3.99)	(4.07)	(4.88)	(4.73)	(4.54)	(4.17)	(4.39)	(4.31)	(4.25)
Unemployment %	6.10	6.49	5.95	5.54	4.77	4.83	5.83	9.11	9.42	8.99
(std)	(1.29)	(1.33)	(1.20)	(1.13)	(1.02)	(1.08)	(1.27)	(1.93)	(1.87)	(1.86)

Table 5

Kolmogorov-Smirnov Test for Differences Between Groups

Year	K-S Test P-value Base Case DEA	Significance	K-S Test P-value Production DEA	Significance	K-S Test P-value Intermediation DEA	Significance
2002	0.19891	SAME	0.50155	SAME	0.8453	SAME
2003	0.20608	SAME	0.39089	SAME	0.25312	SAME
2004	0.006412	Different	0.023558	Different	0.074408	SAME
2005	0.020958	Different	0.045916	Different	0.090796	SAME
2006	0.13936	SAME	0.62727	SAME	0.5658	SAME
2007	0.0071	Different	0.0181	Different	0.0196	Different
2008	0.0644	SAME	0.5561	SAME	0.6261	SAME
2009	0.1652	SAME	0.4598	SAME	0.3704	SAME
2010	0.1986	SAME	0.1514	SAME	0.2246	SAME
2011	0.2689	SAME	0.1511	SAME	0.136	SAME

List of CDFI Financial Institutions Used in Analysis (403 CDFIs in total)

Credit Unions in Bold

1st Choice Credit Union
A.L. Bratcher Federal Credit Union
Advance Bank
Alamosa
Albina Community Bancorp
Albina Community Bank
ALco Federal Credit Union
Aliquippa Regional Credit Union
Alpena Credit Union
Alternatives Federal Credit Union
American Metro Bancorp, Inc.
American Metro Bank
American State Bank
Appalachian Community Bank, F.S.B.
Appalachian Development Federal Credit Union
Appalachian Federal Credit Union
ASI Federal Credit Union
Atlantic City Federal Credit Union
Austin/West Garfield Federal Credit Union
Avondale Community Federal Credit Union
B.O.N.D. Community Federal Credit Union
Bank of Cherokee County
Bear Paw Credit Union
Bethel Baptist Federal Credit Union
Bethel Community Federal Credit Union
Bethex Federal Credit Union
Bethlehem Community Development Credit Union
Bexar County Teachers Federal Credit Union
Binghamton Housing Authority Residents
Birmignham Financial Federal Credit Union
Bitterroot Community Federal Credit Union
Border Federal Credit Union
Borinquen Federal Credit Union
Bradley Initiative Credit Union
Brewery Credit Union
Brewton Mill Federal Credit Union
Bridge Street AWME Church Federal Credit Union
Broadway Federal Bank, F. S. B.
Brookland Federal Credit Union
Brooklyn Cooperative Federal Credit Union
Brooklyn Ecumenical Federal Credit Union
Buffalo Cooperative Federal Credit Union
Butte Federal Credit Union
Camden Community Credit Union
Canaan Baptist Federal Credit Union
Capitol City Bancshares, Inc.
Capitol City Bank & Trust Company
Caribbean-American State Credit Union
Carter County Federal Credit Union
Carter Federal Credit Union
Carver Federal Savings Bank
Carver Financial Corporation
Caswell Credit Union
Central Bancshares of Kansas City, Inc.
Central Bank of Kansas City
Central Brooklyn Federal Credit Union
CFBanc Corporation
Chatham-Lee Credit Union
Chetco
Chicanos Por La Causa Federal Credit Union
Choctaw Federal Credit Union
Choices Federal Credit Union
Chowan Credit Union
Christian Hope Credit Union
Church Koinonia Federal Credit Union
Citizens Bancshares Corporation
Citizens Bank & Trust Company of Chicago
Citizens Choice Federal Credit Union
Citizens Financial Corporation
Citizens Savings Bank & Trust Company
Citizens Trust Bank

City First Bank of D.C., National Association
City First Enterprises, Inc.
City National Bancshares Corporation
City National Bank of New Jersey
College Heights Credit Union
College Station Community Federal Credit Union
Communicating Arts
Communities United Credit Union
Community Bank of the Bay
Community Capital Bank of Virginia
Community Choice Federal Credit Union
Community Commerce Bank
Community Credit Union of Southern Humbolt
Community Development Bank, FSB
Community First Guam Federal Credit
Community Plus Federal Credit Union
Community Trust Credit Union
Community Trust Federal Credit Union
Comunidad Latina Federal Credit Union
Comunidades
Consumer's Credit Union
Consumer's Federal Credit Union
Consumer's Federal Credit Union
Cooperativa de Ahorro y Credito Elec
Cooperativa de Ahorro y Credito Empleados
Cooperativa de Ahorro y Credito Nuestra
Cooperative Center Federal Credit Union
Cooperative Federal Credit Union
CoVantage Credit Union
Covenant Bancshares, Inc.
Covenant Bank
Covenant Savings Federal Credit Union
D. Edwards Wells Federal Credit Union
Dakotaland Federal Credit Union
Davis Bancorporation, Inc.
Demopolis Federal Credit Union
Denver Community Development Credit Union
District Government Employees
Eagle Louisiana Federal Credit Union
East Austin Community Federal Credit Union
East End Baptist Tabernacle Federal Credit
El Futuro Credit Union
Electrical Products Employees Federal Credit Union
Enterprise Community Federal Credit Union
Episcopal Community Federal Credit Union
Everyone's Federal Credit Union
Express Credit Union
Fairfax County Federal Credit Union
Faith Based Federal Credit Union
Faith Community United Credit Union, Inc.
Fallon County Federal Credit Union
Family Federal Credit Union
Father Burke Federal Credit Union
Federation of Greene County Employees (FOGCE)
Fidelis Federal Credit Union
First American Credit Union
First American International Bank
First American International Corp.
First Combined Community Federal Credit Union
First Community Credit Union
First Delta Federal Credit Union
First Hawaiian Homes Federal Credit Union
First Independence Bank
First Legacy Community Credit Union
First Midwest Acquisition Corporation
First National Bank
First National Bank
First National Bank
First National Security Company
First Peoples Community Federal Credit Union
Five Star Credit Union
Fort Gibson Bancshares, Inc.
Fort Gibson State Bank
Fort Randall Federal Credit Union
Foss Ave Baptist Church Federal Credit Union

Franklin National Bank of Minneapolis
Freedom First Federal Credit Union
Friendship Federal Credit Union
Froid Federal Credit Union
Gateway Community Federal Credit Union
Gateway Credit Union
GE Credit Union
Generations Community Credit Union
Genesee Co-Op Federal Credit Union
Georgia Power Northeast Credit Union
Glamour Community Federal Credit Union
Greater Kinston Credit Union
Guadalupe Credit Union
Guaranty Bancorp
Guaranty Bank & Trust Company
Guaranty Bank & Trust Company
Guaranty Bank & Trust Company
Guaranty Bank & Trust Company
Gubecoop
Guernsey Community Federal Credit Union
Harbor Bankshares Corporation
Harney County Federal Credit Union
HAWAII FIRST Federal Credit Union
Highland Community Bank
Highland Community Company
Hill District Federal Credit Union
Homesteaders Federal Credit Union
Hope Federal Credit Union
Hospitality Community Federal Credit Union
Howland - Enfield Federal Credit Union
Hudson Valley Holding Corp.
IBC Bancorp, Inc.
IBW Financial Corporation
Illinois-Service Federal Savings and Loan Association
Independent Employers Federal Credit Union
Industrial Bank
Industrial Credit Union of Whatcom County
Inter National Bank
International Bank of Chicago
JD Financial Group, Inc.
Ka'u Federal Credit Union
Kahuku Federal Credit Union
Kappa Alpha Federal Credit Union
KC Terminal Employees/Guadalupe Center
Kekaha Federal Credit Union
Kenworth Employees Credit Union
Kern Central Federal Credit Union
Kerr County Federal Credit Union
Kingsville Community Federal Credit Union
Ko-Am Federal Credit Union
Kootenai Valley Federal Credit Union
Kulia Ohana Federal Credit Union
Kunia Federal Credit Union
La Capitol Federal Credit Union
La Casa Federal Credit Union
La Fuerza Unida Community Development Federal Credit Union
Lac Courte Oreilles Federal Credit Union
Landmark Community Bank
Latino Community Credit Union
LCO Federal Credit Union
Legacy Bancorp, Inc.
Legacy Bank
Liberty Bank & Trust Company
Liberty County Teachers Federal Credit Union
Liberty Financial Services, Inc.
Lincoln County Credit Union
Little Haiti Edison Federal Credit Union
Louisville Community Development Bank
Louisville Development Bancorp, Incorporated
Lower East Side People's Federal Credit
M&F Bancorp, Inc.
Maine Highlands Federal Credit Union
Marion County Federal Credit Union
MariSol Federal Credit Union
Marvel City Federal Credit Union
Mechanics & Farmers Bank
Memphis First Corporation
Mendo Lake Credit Union
Metropolitan Community Credit Union
Mission Area Federal Credit Union

Missouri Family Federal Credit Union
Mission Community Bank
Mission Valley Bancorp
Mission Valley Bank
Mission-Valley Bancorp
Missouri Family Federal Credit Union
Molokai Community Federal Credit Union
Monroe Education Employees
Morgan City Federal Credit Union
Mt Zion Federal Credit Union
Native American Bancorporation Co.
Native American Bank, National Association
NCP Community Development Credit Union
Need Action Federal Credit Union
Neighborhood Bancorp
Neighborhood National Bank
Neighborhood Trust Federal Credit Union
New Community Federal Credit Union
New Convenant Dominion Federal Credit Union
New Generations Federal Credit Union
New Hope Community Development Federal
New Horizons Community Federal Credit Union
New Life Credit Union
New Pilgrim Federal Credit Union
New York National Bank
New York University Federal Credit Union
Newport News Neighborhood Federal Credit
Newrizons Federal Credit Union
NorState Federal Credit Union
North Dade Community Development
North Hawaii Community Federal Credit
North Milwaukee Bancshares, Inc.
North Milwaukee State Bank
North Side Community Federal Credit Union
Northcountry Cooperative Federal Credit
Northeast Community Federal Credit Union
Northeast Credit Union
Northland Area Federal Credit Union
Northwest Baptist Federal Credit Union
NRS Community Development Federal
Nuestro Banco
O.U.R. Federal Credit Union
OASIS Community Developoment Federal Credit Union
Old West Federal Credit Union
OneCalifornia Bank, FSB
OneUnited Bank
Onomea Federal Credit Union
Opportunities Credit Union
Our Mother of Mercy Parish Federal Credit
Pacific Crest Federal Credit Union
Pacific Global Bank
Pacoima Development Federal Credit Union
Pahranagat Valley Federal Credit Union
Pan American Bank
Park Midway Bank, National Association
Pelican State Credit Union
People for People Community Development
People's Community Partnership Federal Credit Union
People's First Choice Federal Credit Union
Perquimans Credit Union
PGB Holdings, Inc.
Phenix Pride Federal Credit Union
Philips County Self-Help
Potlatch N 1
Premier Bancorp, Inc.
Premier Bank
Prichard Federal Credit Union
Prince Kuhio
Progressive Neighborhood Federal Credit Union
Promise Credit Union
Pueblo Coop
Pyramid Credit Union (Pyramid Federal Credit Union)
Queens Cluster Federal Credit Union

Quitman County Federal Credit Union
Renaissance Community Development
Roberto Clemente Federal Credit Union
Rowan Iredell Area Credit Union
Saguache County Credit Union
Santa Cruz Community Credit Union
SCCB Financial Corporation
Schofield Federal Credit Union
Schools Workers Federal Credit Union
SCJ, Inc.
Seaway Bancshares, Inc.
Seaway Bank And Trust Company
Second Federal Savings and Loan Association of Chicago
Security State Bank of Wewoka, Oklahoma
Select Employees Federal Credit Union
Self-Help Credit Union
Self-Help Federal Credit Union
Sentinel Federal Credit Union
Settlers Federal Credit Union
Shelby/Bolivar County Federal Credit Union
Shiloh of Alexandria Federal Credit Union
ShoreBank
ShoreBank Corporation
ShoreBank Pacific
Shorebank Pacific Corporation
Shreveport Federal Credit Union
Sisseton Co-op Federal Credit Union
Sooner Southwest Bankshares,Inc.
South Carolina Community Bank
South Central People's Federal Credit Union
South East Community Credit Union
South End Federal Credit Union
South Side Community Federal Credit
Southern Bancorp Bank
Southern Bancorp Bank, National Association
Southern Bancorp, Inc.
Southern Chautauqua Federal Credit Union
Southside Credit Union
St Louis Community Credit Union
St Margaret's Credit Union
St. Charles Borromeo Federal Credit Union
St. James AME Federal Credit Union
St. Luke Credit Union
St. Philip's Church Federal Credit Union
Stevenson Federal Credit Union
Stillman Community Development Federal Credit Union
Suntide Federal Credit Union
T & P Federal Credit Union
Table Rock Federal Credit Union
The Carver State Bank
The Community's Bank
The Credit Union of Atlanta
The First National Bank of Davis
The Harbor Bank of Maryland
The Union Bank
The Union Credit Union
The United Federal Credit Union
Thurston Union of Low-Income People (TULIP)
Timber County Community
Toledo Urban Federal Credit Union
Tombstone Federal Credit Union
Tongass Federal Credit Union
Total Community Action Federal Credit Union
Tri State Bank of Memphis
Tri-County Credit Union
Tri-Valley Community Federal Credit Union
Triumph Baptist Federal Credit Union
Tulane Loyola
Tuscaloosa VA Federal Credit Union
Tuskegee Federal Credit Union
Twin States Federal Credit Union
Union Bancshares, Incorporated
Union Baptist Church Federal Credit Union
Union Credit Union
Union Settlement Federal Credit Union
United Bancshares, Inc.
United Bank of Philadelphia
United Federal Credit Union
United Singers Federal Credit Union

UNITEHERE Federal Credit Union
University Financial Corp, Inc.
University National Bank
UNO
Urban Financial Group, Inc.
USSCO Federal Credit Union
Valley Educators Credit Union
Valued Members Credit Union
Vernon/Commerce Credit Union
Victory Masonic Mutual Credit Union
Vigo County Federal Credit Union
Virginia Community Capital, Inc.
W.M. Employees Elkins Federal Credit Union
Wailuku Federal Credit Union
Waldo Community Development Federal Credit Union
Wendell Philipps CDCredit Union
Weslaco Catholic Federal Credit Union
West Texas
Winthrop Federal Credit Union
Wolf Point Federal Credit Union
Women's Southwest Federal Credit Union
Word of Life Federal Credit Union
Workers United Federal Credit Union
Yellowstone Federal Credit Union
Zion United Credit Union