Mission-driven Lenders*

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Abstract

The U.S. government created the Community Development Financial Institution (CDFI) certification to promote greater credit access in distressed communities. In this paper, we provide a systematic analysis of CDFIs and provide insights into why CDFIs are growing and how they are different from other lenders. Consistent with their mission-driven requirement, we document that CDFIs have expanded in counties with a greater reliance on government-subsidized business lending, higher unemployment rates, and a larger minority population. Within the universe of depository institutions, credit unions and minority depository institutions (MDIs) are more likely to become certified CDFIs as well as institutions with relatively low levels of cash and high leverage. After becoming certified, CDFIs tend to grow faster and lend more, which suggests that the resources available to CDFIs alleviate institution-level financial constraints. In our final analysis, we analyze the cost of CDFI lending using a novel loan-level dataset.

Keywords: CDFIs, community development, small business lending

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1 Introduction

To promote more credit access and expand economic opportunity in underserved communities, the U.S. government created in 1994 the Community Development Financial Institution (CDFI) certification that allows a financial institution access to government funding sources. This designation can be applied to both depository institutions such as banks and credit unions as well as unregulated financial institutions such as loan funds. Regardless of institution type, the key requirement for a CDFI is to be "mission-driven." As of July 2023, there exist nearly 1,500 CDFIs that manage portfolios of loans in excess of $100 billion. Despite their significant growth and nearly 30-year history, there is relatively little research on CDFIs. In this paper, we attempt to fill in this gap in the literature through a systematic analysis of CDFIs.

We aim to provide insights into the following two questions: why are CDFIs growing and how are they different from other lenders? To do so, we gather and rely on a few novel sources of data regarding CDFIs. These sources include historical lists of CDFIs to measure CDFI certification over time and a loan-level database of CDFI activity to understand their lending. We further augment these sources through manual linking to well-known datasets (e.g., Call Reports).

In terms of geographic expansion since 2000, we find that CDFIs tended to enter counties with a larger presence of government-subsidized business lending, higher unemployment rates, and a larger minority population. Taken together, these findings are consistent with the stated mission of the CDFI program to expand credit access in particular to underserved minority communities.

Within counties in which CDFIs already had an established presence, small business lending from CDFIs grew more relative to conventional small business lending provided by banks. We find that the same county-specific factors are also associated with this growth as in the geographic expansion analysis. However, in the case of small business lending we also find that CDFIs grew more in counties with higher rates of poverty.

Next, we explore the institution-level characteristics associated with becoming a CDFI. Here we focus on depository institutions given that we have detailed financial data on them regardless of CDFI status. We find that two types of depository institution were more likely to become certified CDFIs: credit unions and minority depository institutions (MDIs). These findings make intuitive sense given that both credit unions and MDIs are endowed with objectives akin to the mission-driven requirement to become a certified CDFI. Further, we find that depository institutions with relatively low levels of cash and high leverage were more likely to become CDFIs. This result is consistent with the key benefit of becoming a CDFI: access to government financial resources offered through various CDFI award programs.

Further, we perform a regression analysis similar in form to a difference-in-differences framework to understand if and how depository institutions change after becoming certified as a CDFI. We find that CDFIs tend to grow faster and lend more afterwards relative to non-CDFIs, which suggests that the resources available to CDFIs alleviate institution-level financial constraints. Becoming certified as a CDFI, however, is not an exogenous event and hence the interpretation of our results is not be causal. Nonetheless, our findings shed light on the factors and outcomes associated with becoming a CDFI. For example, we also find that banks that become CDFIs are less profitable thereafter. This result seemingly contradicts the profit-maximizing nature of banks. However, our short-term profitability measures may be missing longer-term value created through being a CDFI. It may also be reverse causlity: banks with declining profitability are more likely to pursue CDFI certification. Finally, CDFI banks may simply focus less on profitability than larger publicly-traded banks, which is consistent with the mission-driven aspect of the CDFI program to serve lower-income people and communities.

Finally, we analyze the cost of CDFI lending by directly comparing CDFI loans to those made through the U.S. Small Business Administration (SBA) 7a program. To be clear, there are many differences between loans made through SBA programs and those from CDFIs including the underwriting process and post-lending role of the lender. This comparison, however, is relevant because SBA loans are similarly intended for the most credit-constrained small businesses that cannot obtain conventional loans elsewhere (see, e.g., Gong and Rosen, 2022). We find that interest rates on CDFI business loans are 1.7 p.p. to 4.3 p.p. higher than standard SBA 7a loans. The fact that CDFI loans are more expensive is not surprising on its own given that SBA loans are government-subsidized. However, the quantitative magnitude provides a sense of how much more expensive CDFI loans are compared to a similar (and therefore substitutable) source of financing.

Our study contributes first and foremost to the nascent literature on CDFIs. Kovner and Lerner (2015) study the venture capital funds that became CDFIs, which are a relatively small set of the CDFI universe. Carpenter (2022) and Office of the Comptroller of the Currency (2019) provide overviews of CDFIs in terms of their history and how they tend to operate. Swack, Hangen, and Northrup (2015) analyze loan-level CDFI data through 2012. Combined with census tract data, they provide evidence that CDFIs promote economic revitalization and community development through the provision of credit, capital, and financial services to underserved populations and communities. We document similar findings in our county-level analysis of CDFI entry and growth in the subsequent time period (2010–2019). McCall and Hoyman (2023) analyze how CDFIs and the CDFI program are evaluated. Swack, Hangen, and Northrup (2016) consider the impact of fintech growth on the CDFIs while Hangen and Swack (2020) discuss the positive role that CDFIs can play in the disbursement of paycheck protection program loans.

Our study also contributes the literature that explore financial institutions with similar stated objectives to CDFIs. Berger, Feldman, Langford, and Roman (2022) and Vatsa (2021) study minority-owned banks. In our analysis, we document the significant overlap between minority-owned banks and CDFIs. We also show that credit unions, which are non-profits by design, have been more likely to become CDFIs in the recent period. In this sense, we contribute to the understanding of credit unions, which have been studied in several papers including Cororaton (2019); Shahidinejad (2022); Van Rijn, Zeng, and Hueth (2023); Li and van Rijn (2022).

2 Data

We utilize numerous datasets in this study including a few that are unique to the academic literature. First off, we gather historical lists of CDFIs through 2022 to establish which institutions are CDFIs and the year in which they became certified. Further, we manually review the names and locations of the CDFIs in order to assign their associated RSSD ID values if available. RSSD ID is the unique identifier assigned to a financial institution by the Federal Reserve and they are generated for both banks and credit unions. Once matched, we can gather information from sources that cover such depository institutions as described below.

Second, we obtained a CDFI investment-level dataset from the CDFI Fund. Each investment observation includes the location of the borrower and the terms of the investment. However, this dataset does not indicate which specific institution provided the loan nor does it provide the name of the borrowers. Nonetheless, this dataset allows us to measure and aggregate CDFI lending flows and is also useful for studying the cost of CDFI financing. An important caveat is that not all CDFIs report their investment-level activity to the CDFI Fund and hence the data are not fully representative of the universe of CDFIs.

We gather financial information for depository institutions from the standard sources. For commercial banks, these data are from the FFIEC Call Reports. For credit unions, these data are from the National Credit Union Administration (NCUA).

To measure the flow of financing to small businesses from commercial banks, we rely on the data provided through the Community Reinvestment Act (CRA). These small business financing flows are available at the institution-county-year for the set of banks that are required to report them.

We gather data on the loans made through the U.S. Small Business Administration (SBA) 7a program from the SBA website.[1] This loan-level dataset provides a relevant comparison to CDFI loans given that SBA loans are intended for the most credit-constrained small businesses (see, e.g., Gong and Rosen, 2022).

Finally, we gather U.S. county-level data from a few different sources. GDP data are from the Bureau of Economic Analysis, unemployment rate data are from the Bureau of Labor Statistics, and demographic information on poverty and racial composition from the Census.

3 Empirical Analysis

In this section, we explore CDFIs and CDFI lending along the following dimensions. First, we document the growth in CDFIs with a particular focus on where they are growing. Next, we explore the factors influencing CDFI growth from the institution perspective. Specifically, we analyze the characteristics of depository CDFIs before and after their decision to become

[1] https://data.sba.gov/dataset/7-a-504-foia

certified. Finally, we characterize CDFI lending using our loan-level datasets. In particular, we compare the pricing of CDFI loans relative to those made through the government-subsidized SBA programs.

3.1 The CDFI Program and Aggregate CDFI Growth

Established in 1994 under the Community Development and Regulatory Improvement Act, the Community Development Financial Institutions program (CDFI program) is tasked with the mission to create economic opportunity and provide resources on the most distressed and underserved communities in the nation. Historically, individuals and families in these communities are often unable to access personal and business financial services from traditional, mainstream financial sectors. Moreover, in recent years, large banks have both gone through consolidation and tightened their lending standards, which made it even more challenging for individuals and small business to gain access to capital. Those barriers to accessing financial services and capital have led to increased need for alternative and reliable resources of financing.

The program is managed by the CDFI Fund, a division of the U.S. Department of Treasury. The CDFI Fund uses its resources to invest in and builds the capacity of community-based financial institutions including CDFIs. The following quote from their website summarizes their role nicely:

> By offering tailored resources and innovative programs that invest federal dollars alongside private sector capital, the CDFI Fund serves mission-driven financial institutions that take a market-based approach to supporting economically disadvantaged communities. These mission-driven organizations are encouraged to apply for CDFI Certification and participate in CDFI Fund programs that inject new sources of capital into neighborhoods that lack access to financing.[2]

CDFIs can include regulated institutions such as credit unions and community banks, and non-regulated institutions like loan funds and venture capital funds. For an organization or financial institution to be eligible for the financial assistance through the CDFI program, it must be certified as specialized organization that provide financial services in low-income

[2] https://www.cdfifund.gov/

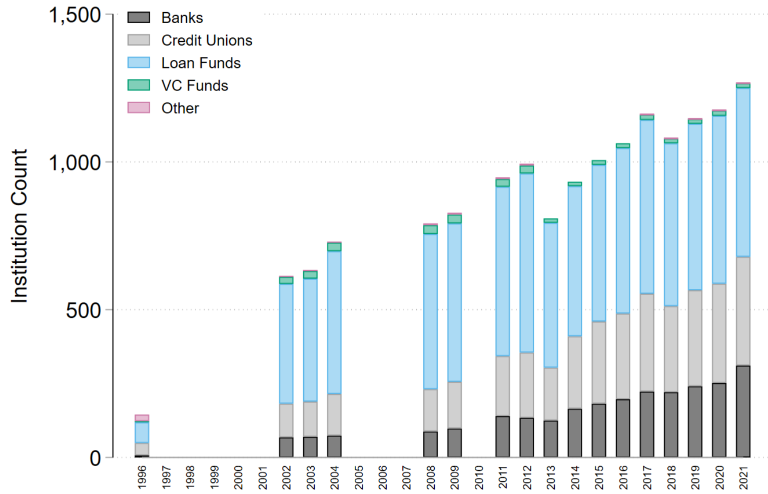


Figure 1. Counts of CDFIs Over Time
This figure shows the number of certified CDFIs by type in each year according to the CDFI Fund. Gaps in the bars represent years in which we do not have a historical list. See Section 2 for details about our data sources.

communities and to people who lack access to financing. The CDFI certification is both a designation given by the CDFI fund and the U.S. Department of the Treasury's recognition.

We report the number of certified CDFI institutions over time in Figure 1. The total number has been growing steadily over the past 25 years. As of 2021, there are over 1300 CDFIs. This number was around 600 back in 2002 and only about 200 in 1996. In past 10 years, roughly 100-200 CDFIs are added each year.

In terms of composition, CDFIs are mostly comprise of loan funds. These institutions are unregulated and hence we do not have access to detailed information about their financials. Therefore, our institution-level analysis (e.g., Section 3.4) focuses on depository CDFIs for which we have detailed financial data given their regulatory reporting requirements. Nonetheless, we are able to capture lending activity by loan fund CDFIs in our loan-level dataset. Based on CDFI Fund reports and conversations with industry participants, we understand that loan funds are typically much smaller than depository CDFIs and hence their share of aggregate CDFI lending is relatively small as well. For example, the 2019 CDFI Annual Certification and Data Collection Report reports that loan funds

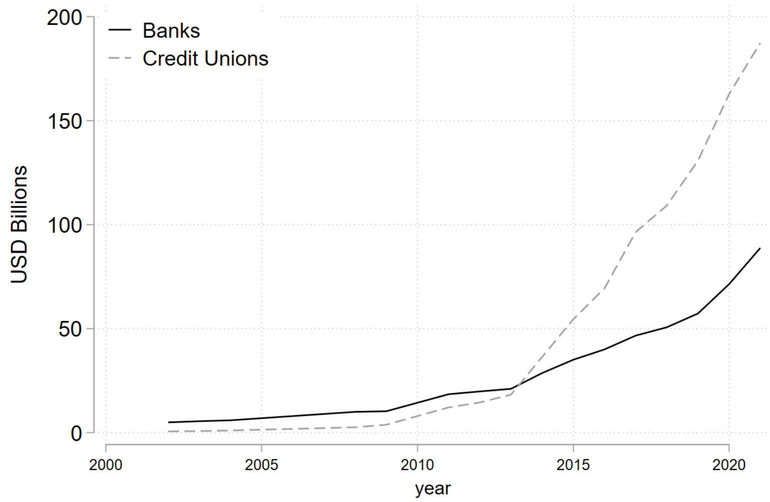


Figure 2. Assets of Depository CDFIs Over Time
This figure shows the aggregated assets of certified CDFIs that are depository institutions. See Section 2 for details about our data sources.

represent 50.6% of CDFI institutions but only 11.1% of aggregate CDFI investments.[3]

In Figure 2, we report the total size of depository CDFIs over time separated by banks and credit unions. Depository CDFIs are growing in count across both types (banks and CUs) as seen in Figure 1. In Figure 2, we see that assets of CDFI depository institutions is over $200 billion as of 2020, with about $150 billion from CUs and $70 billion for banks. The growth rate in assets associated with credit union CDFIs is clearly higher than for banks, which is a fact that can also be seen when looking at the growth in the number of institutions.

To provide additional context for the growth in credit union CDFIs, we report their size relative to all credit unions in Figure 3. Here we can see that around 8% of all credit union assets are held by credit union CDFIs by the end of our sample. This figure is around 6% by institution count. In sum, CDFIs represent a non-trivial share of the credit union sector.

Why do institutions want to be certified as a CDFI? An key benefit and perhaps the most important is that CDFIs have access to financial resources through the CDFI Fund. Through certification, CDFIs are qualified to apply for technical and financial assistance awards through a variety of programs , as well as various trading opportunities provided by

[3]https://www.cdfifund.gov/sites/cdfi/files/2021-01/ACR-Public-Report-Final-10292020-508Compliant.pdf

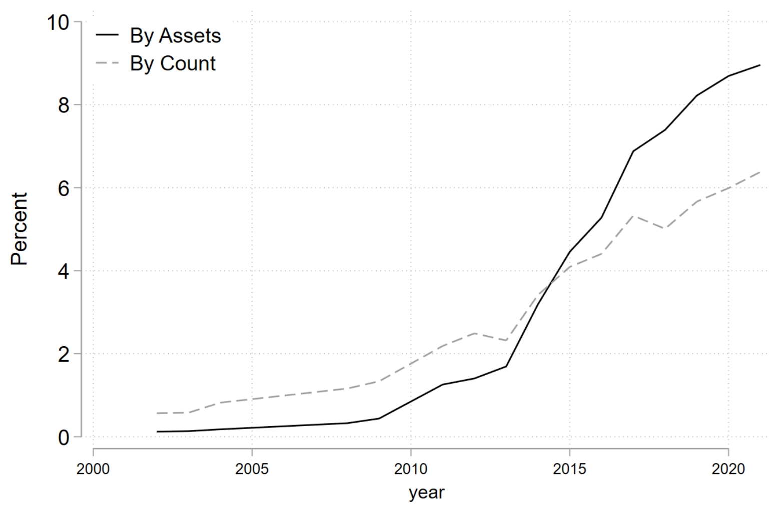


Figure 3. Relative Size of Credit Union CDFIs Over Time
This figure shows the relative size of certified CDFIs that are credit unions in terms of counts and assets. See Section 2 for details about our data sources.

the CDFI fund. It is reported in 2020 that CDFIs can apply to receive financial assistance awards of up to $2 million to sustain or expand their products and services. These awards enable CDFIs to finance a wide range of activities and can be used for capital reserves, daily operation, lending capital, and/or development services.

In Figure 4, we report the aggregate amount of financial awards that have been provided to CDFIs over time. Importantly, the underlying sample only includes awards for the CDFI-specific programs: CDFI-FA and CDFI-TA.[4] "FA" stands for financial assistance and "TA" is technical assistance. Since 2010, the CDFI Fund provided CDFIs with around $150 million per year on average through these programs. The cumulative award amounts are around $2 billion and 3,000 total awards since 2000.[5]

[4] Given that our sample stops in 2019, the numbers in Figure 4 do not include awards made through the CDFI-RRP, the Rapid Response Program, which was created for the COVID-19 pandemic in 2020. This program ultimately provided around $8.6 billion in awards to CDFIs, which is larger than aggregate amounts given through the other two CDFI programs combined.

[5] The aggregate figures are much larger if we include the CDFI-RRP and New Markets Tax Credit (NMTC) programs through 2022. After including these programs and data through 2022, there have been around $24 billion in awards to CDFIs that we can link to the certified lists. We need to link institutions that received NMTC awards to our CDFI lists because there are many non-CDFIs that receive them. In fact, we calculate that nearly 90% of NMTC awards go to non-CDFIs.

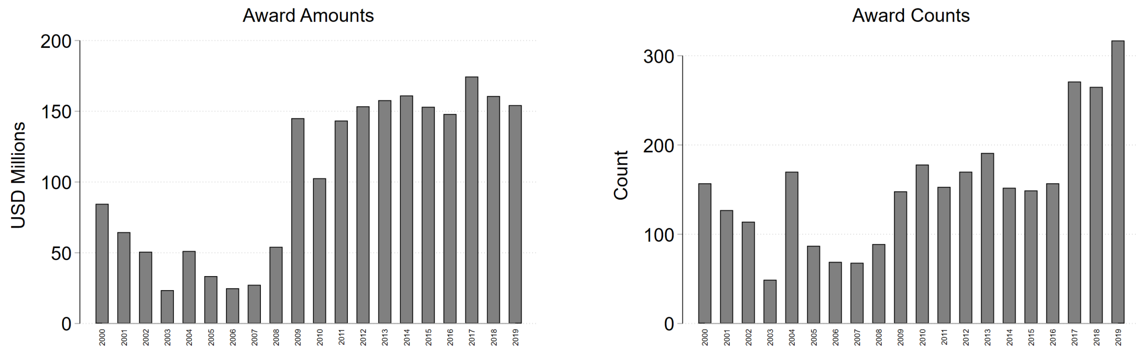


Figure 4. CDFI Fund Awards Over Time
This figure shows the aggregate amount and number of awards distributed by the CDFI Fund through it's CDFI-specific programs. See Section 2 for details about our data sources.

3.2 CDFI Growth Across Counties

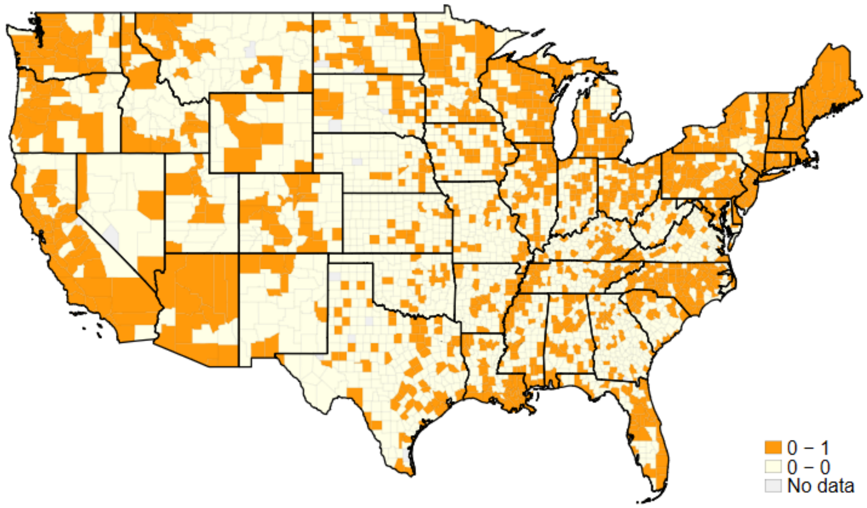
Now that we have documented the aggregate growth in CDFIs, we explore where they are growing. Currently, there are certified CDFIs in all 50 states, the District of Columbia, Guam, and Puerto Rico. In Figure 5, we visualize CDFI presence at the county level. We define CDFI presence if a depository CDFI has a branch or if we observe a CDFI loan in the county during the given year. The latter condition is based on our CDFI loan-level data and allows us to capture the presence of loan funds.

A visual comparison between the map from 2000 and the map from 2019 in Figure 5 indicates that CDFIs have expanded their geographic footprint substantially since 2000. In 2000, only about 38% of U.S. counties have CDFI presence. By 2019, 60% counties have CDFI presence. This growth can be attributed both to preexisting depository institutions choosing to become certified CDFIs and the creation of new CDFI loan funds. For the sake of brevity in our ensuing discussion, we refer to the introduction of CDFI presence as "CDFI entry" regardless of how it was obtained.

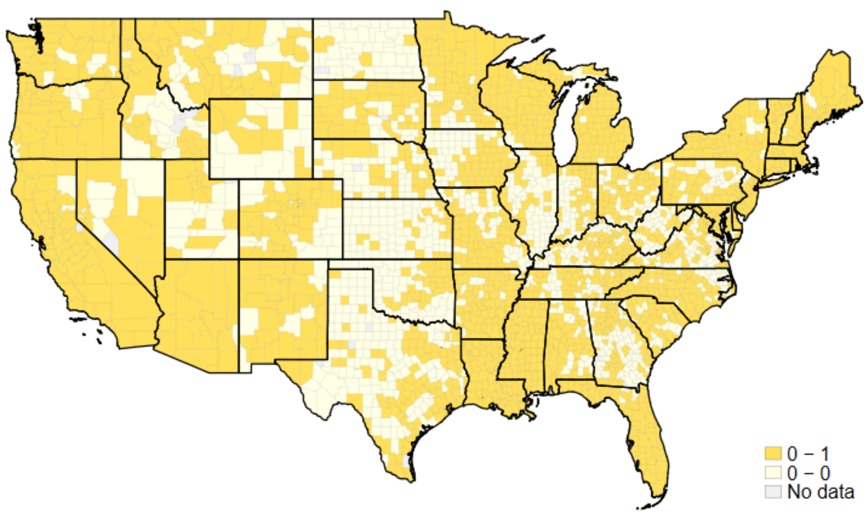
Next, we formally explore the characteristics of the counties that CDFIs entered through the following panel regression:

$$\text{CDFI Presence}_{c,t} = \beta' X_{c,t-1} + \nu_c + \nu_t + \epsilon_{c,t}. \tag{1}$$

The dependent variable is an indicator for whether there is CDFI presence in county c in



Panel A: CDFI Presence in 2000



Panel B: CDFI Presence in 2019

Figure 5. CDFI Presence Across Counties in the U.S.
This figure shows the counties in which CDFIs have a presence. We define CDFI presence if a depository CDFI has a branch or if we observe a CDFI loan in the county during the given year.

year t. The explanatory variables include county-level characteristics from year $t-1$ that capture features of the credit market, economy, and demographics.

The results from this regression analysis are presented in Table 1. The first key insight we gain is that CDFIs were more likely to enter counties in which government-subsidized loans made through the U.S. Small Business Administration (SBA) 7(a) program were more prevalent. We capture this aspect of local credit markets through the ratio of SBA loans under $1 million to loans reported through Community Reinvestment Act (CRA) disclosures. Given that government-subsidized SBA loans are intended for credit-constrained small business (see, e.g., Gong and Rosen, 2022), we expect that CDFIs would be more likely to enter markets that rely more on this source of financing. The reason is that the targets of CDFI business investments are also credit-constrained by design. The positive coefficient estimates are consistent with the view that CDFI financing can be a substitute for SBA loans.

We find that CDFIs are more likely to enter a county if the local banking market is more competitive as measured by a deposit-based Herfindahl-Hirschman Index (HHI). This result may seem contradictory to the mission of CDFIs as one might expect them to enter "underserved" areas. However, CDFIs may be entering counties to serve specific communities that are not being sufficiently reached by the banks already present.

In terms of local economic factors, we find that CDFIs are more likey to enter counties with higher GDP per capita and higher unemployment rates in general. These results are only obtained, however, without the inclusion of county fixed effects. Once we include county fixed effects, we see that CDFIs are more likely to enter counties when unemployment rates are relatively low, which suggest that CDFI entry may also be driven by greater investment opportunities and demand for credit stemming from a robust local economy.

Finally, we find that CDFIs are more likely to enter counties whose population is more diverse. We capture this feature using the fraction of residents that are not categorized as white. We only include this measure in our specifications without county fixed effects because the time variation in this measure is minimal at the county level. This result is in line with the stated mission of CDFIs to serve underserved communities, which are often minority communities. In this respect, our findings are consistent with Swack et al. (2015) that analyzes CDFI activity and census tract data through 2012.

Table 1. CDFI Entry into New Counties

This table shows the coefficient estimates from estimating the regression specification (1) in which the dependent variable is an indicator for whether there is CDFI presence in county c in year t. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
A. Credit Market				
SBA/CRA Ratio	17.968***	3.000**	20.403***	1.194
	(1.690)	(1.365)	(1.730)	(1.373)
Deposit HHI	-0.687***	-0.134***	-0.678***	-0.104***
	(0.010)	(0.030)	(0.010)	(0.029)
B. Real Variables				
GDP per capita	0.044***	0.039***	0.049***	-0.046***
	(0.004)	(0.009)	(0.004)	(0.010)
Unemployment Rate	0.767***	-1.038***	2.296***	-0.538***
	(0.089)	(0.084)	(0.111)	(0.145)
C. Demographic Variables				
Poverty	-0.004***		-0.006***	
	(0.000)		(0.000)	
Non-White	0.595***		0.559***	
	(0.015)		(0.015)	
County FEs	No	Yes	No	Yes
Year FEs	No	No	Yes	Yes
Adj. R^2	0.12	0.51	0.13	0.51
N	54,774	54,774	54,774	54,774

3.3 CDFI Growth Within Counties

In the previous section, we analyzed the counties that CDFIs entered. Next, we turn our attention to the factors associated with CDFI lending growth *within* a given county that already has CDFI presence. To do so, we run the following panel regression:

$$(\text{CDFI Business Loans}_{c,t}/\text{CRA Loans}_{c,t}) = \beta' X_{c,t-1} + \nu_c + \nu_t + \epsilon_{c,t}. \tag{2}$$

This specification is identical to (1) except that the dependent variable is now a measure of CDFI lending intensity. We proxy for this intensity using the ratio of CDFI business loans reported in the CRA loans in county c in year t. The numerator is computed using our CDFI loan-level database. The denominator only captures loans from banks large enough to be required to report its small business lending data through the CRA (roughly $1 billion in assets).

For this analysis, it is important to focus on counties in which CDFIs are already present. To do so, we restrict our sample to the period from 2010 onward and the set of counties in which CDFIs had a non-zero presence beforehand.

The results from this within-county panel regression analysis are presented in Table 2. The first key insight is that, similar to Table 1, CDFI lending intensity is higher in counties in which borrowers rely more on SBA financing. This result disappears, however, when we include county fixed effects suggesting that CDFIs were growing more in counties with higher degrees of SBA lending in general, not responding to greater SBA lending within a given county. The coefficient estimates on the deposit-based HHI tell a similar story: CDFIs grew more on a relative basis in counties with more a concentrated banking sector. This result makes sense given that non-CDFI banks can fulfill their CRA-based requirements by financing CDFIs that lend in the same area.

The results in Table 2 also tell us that the relative share of lending grew more in counties with weaker economic conditions as measured by lower GDP per capita. This finding holds with the inclusion of both county and year fixed effects, meaning that the share of CDFI lending grew within a given county when GDP per capita declined.

Finally, we observed a similar outcome to the results in Table 1 in the sense that CDFI lending grew more in counties with higher rates of poverty and more diverse populations.

3.4 CDFI Characteristics

In the previous sections, we explored the factors associated with CDFI growth. Now we turn our attention to the CDFI institutions themselves. This institution-level analysis will focus on depository CDFIs given that we have detailed financial data for them due to their regulatory reporting requirements.

We present summary statistics for depository institutions in Table 3 according to their

Table 2. CDFI Growth within Counties with CDFI Presence

This table shows the coefficient estimates from estimating the regression specification (2) in which the dependent variable is the ratio of CDFI loans to CRA loans in county c in year t. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
A. Credit Market				
SBA/CRA Ratio	261.859***	-85.599	266.027***	-95.105
	(63.821)	(65.026)	(64.834)	(66.417)
Deposit HHI	2.928***	0.640	2.904***	0.608
	(0.307)	(1.013)	(0.309)	(1.013)
B. Real Variables				
GDP per capita	-0.669***	-0.888***	-0.648***	-0.858***
	(0.068)	(0.247)	(0.067)	(0.243)
Unemployment Rate	-17.480***	-16.242***	-15.792***	-24.050***
	(1.751)	(1.490)	(2.416)	(3.388)
C. Demographic Variables				
Poverty	0.127***		0.127***	
	(0.010)		(0.010)	
Non-White	4.463***		4.392***	
	(0.413)		(0.407)	
County FEs	No	Yes	No	Yes
Year FEs	No	No	Yes	Yes
Adj. R^2	0.11	0.63	0.11	0.63
N	13,176	13,176	13,176	13,176

institution type and CDFI status. We separate credit unions and banks given that these institutions are different in a few key ways. For example, credit unions are non-profits and member-owned, which are features that seem related to the idea of being mission-driven. It is therefore not surprising to see that the relative rate of CDFI status is higher.

Comparing the CDFI and non-CDFI columns within each institution type helps to provide expectations about what we will find in a regression analysis later in this section. First off, we note that credit union CDFIs are larger than non-CDFIs, while the opposite is true for banks. We explore these differences further in simple histograms plotted in Figure

Table 3. Institution-Level Averages

This table shows institution-level averages for credit unions and non-large banks according to their CDFI status. Each variable is first averaged across time within a given institution and then these values are averaged over the institutions within each group. An institution is considered within the CDFI category if it was ever certified during our sample period. The underlying annual data cover the period 2010 through 2019 and we only include banks that never exceeded $10 billion in assets. See Section 2 for details about our data sources.

	Credit Unions		Banks	
	CDFI	Non-CDFI	CDFI	Non-CDFI
Assets, Millions of USD	231.8	177.1	293.3	420.3
Loans / Assets, %	62.8	52.0	64.1	62.1
RE Loans / Total Loans, %	33.5	28.1	72.0	69.9
Consumer Loans / Total Loans, %	66.3	71.7	5.9	5.6
C&I Loans / Total Loans, %	0.6	0.3	12.7	12.6
Cash / Assets, %	12.1	12.9	9.2	10.1
Liabilities / Assets, %	89.3	86.6	89.2	88.2
Net Interest Margin, %	3.4	3.0	3.9	3.5
Return on Assets, %	0.5	0.2	0.7	0.7
Return on Equity, %	5.6	2.3	6.8	6.3
Cost of Debt, %	0.6	0.6	0.7	0.8
Is Minority Depository Insitution, %			28.6	2.2
N	464	6,298	168	7,314

6. Here we find that non-CDFI institutions do in fact tend to be a bit smaller given the greater mass at the left tail of the distributions. But for banks there is a larger right tail as well even within our sample that focuses on banks under $10 billion.

The next key area we observe a difference between CDFIs and non-CDFIs is leverage. Both credit union CDFIs and bank CDFIs appear to have higher leverage on average than their non-CDFI counterparts. Similarly, we observe that CDFIs tend to have lower cash-to-assets ratios across both types of institutions. Given that an important benefit of being a CDFI is access to financial resources, we would have expect that institutions with less cash would be more likely to pursue CDFI certification. We will test this hypothesis later in this section.

The final pair of summary statistics that we highlight are the rates of minority depository institution (MDI) status across banks by CDFI status. Bank CDFIs have a much higher rate of being an MDI at almost 30% compared to around 2% for non-CDFI banks.

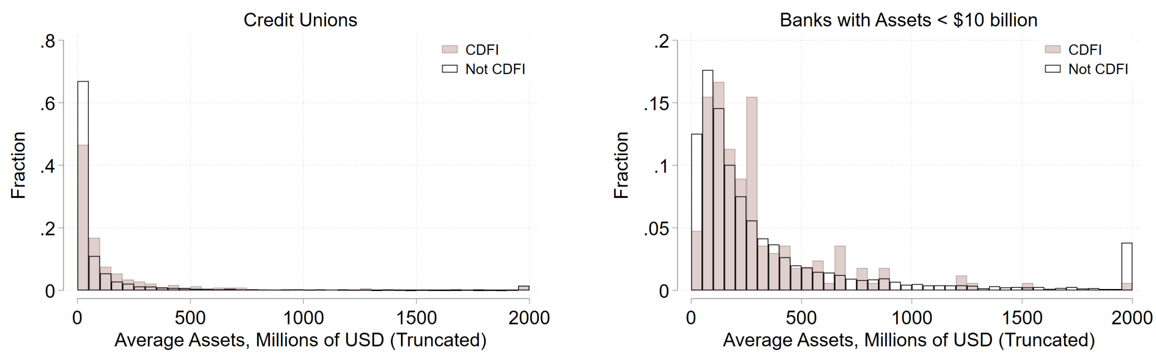


Figure 6. Asset Size Distribution by Institution Type and CDFI Status
Average asset values are truncated for visual purposes and each bar represents an increment of $50 million. The underlying sample is the same as used in Table 3.

This is another finding that we would have expected given the mission-driven requirement of being a CDFI.

To formally explore the factors that influence a depository institution's decision to become certified as a CDFI, we run the following regression:

$$\text{CDFI Certification}_{i,c,t+1} = \beta' X_{i,t} + \nu_c + \epsilon_{i,c,t}. \tag{3}$$

The dependent variable is an indicator for whether institution i headquartered in county c became certified as a CDFI between year t and year $t+1$. For any given year t, we only include in the sample the institutions that are not currently CDFIs. We do so because our goal is to understand the factors that influence an institution's decision to *become* a CDFI. For explanatory variables, we include indicator variables to capture whether the institution is a credit union or a minority depository institution (MDI). We also include measures of the institution's cash holdings (Cash/Assets), leverage (Liabilities/Assets), and profitability (return on assets, denoted "ROA") as of time t.

The results from this regression analysis are presented in Table 4. The first several columns report results from cross-sectional regressions for a given year. For example, the "2011" column refers to the case in which the dependent variable reflects whether depository institutions that are *not* CDFIs as of 2011 become certified in 2012.[6] In these specifications,

[6]We exclude the years 2010, 2013, and 2014 from this analysis given that we do not have historical CDFI lists for 2010 or 2014 (see, e.g., Figure 1). As a result, we cannot precisely determine which year an institution

Table 4. Predicting CDFI Certification

This table shows the coefficient estimates from estimating the regression specification (3) in which the dependent variable is an indicator for whether institution i headquartered in county c became certified as a CDFI between year t and year $t+1$. The first several columns report results from cross-sectional regressions for a given year. The "All Years" columns report results from panel regressions that include all of the years from the individual-year columns. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

	(1) 2011	(2) 2012	(3) 2013	(4) 2014	(5) 2015	(6) 2016	(7) 2017	(8) 2018	(9) All Years	(10) All Years
Is Credit Union	0.003***	0.005***	0.011***	0.007***	0.005***	0.009***	0.007***	0.006***	0.007***	
	(3.80)	(3.16)	(5.17)	(4.10)	(3.40)	(4.29)	(4.64)	(3.56)	(11.14)	
Is MDI Bank	-0.004	0.018	0.012	0.017	0.005	0.024	0.012	0.009	0.011***	
	(-1.46)	(1.50)	(1.19)	(1.42)	(0.60)	(1.43)	(0.96)	(0.54)	(2.75)	
Cash/Assets	0.002	-0.004	-0.006	-0.005	0.003	0.001	-0.007	-0.019***	-0.004	-0.007
	(0.25)	(-0.82)	(-0.70)	(-0.67)	(0.54)	(0.07)	(-1.15)	(-2.94)	(-1.64)	(-1.57)
Liabilities/Assets	0.008	0.026***	0.044***	0.031***	0.027***	0.040***	0.030***	0.029***	0.029***	-0.016
	(1.01)	(3.44)	(2.96)	(2.65)	(3.47)	(3.13)	(3.31)	(2.98)	(7.66)	(-1.12)
ROA	-0.003	0.009	0.195**	0.144**	0.252***	0.122	0.129**	0.093	0.107***	-0.106**
	(-0.04)	(0.11)	(2.41)	(1.98)	(3.13)	(0.95)	(2.10)	(1.24)	(3.56)	(-2.48)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
County-Year FE	No	No	No	No	No	No	No	No	Yes	Yes
Institution FE	No	No	No	No	No	No	No	No	No	Yes
R^2	0.088	0.137	0.206	0.177	0.183	0.197	0.136	0.173	0.175	0.397
N	12,386	12,151	12,441	11,760	11,123	10,583	10,046	9,530	90,020	89,658

we include county-level fixed effects based on the institution's headquarters to control for local economic conditions. The "All Years" columns report results from panel regressions that include all of the years from the individual-year columns. In these specifications, we include county-year fixed effects to control for time-varying local economic conditions. Additionally, we run one specification with institutional fixed effects to control for all time-invariant and potentially unobservable factors at the institution level.

There are a few takeaways from this regression analysis. First, we confirm that credit unions are more likely to become CDFIs given the positive and significant coefficient estimate on the credit union indicator. the observation that CDFI certification is relatively more common among credit unions by the end of our sample (see, e.g., Table 3). We also observe this relatively higher growth rate in the aggregate assets of CDFI credit unions (Figure 2). Overall, this result is consistent with the community-oriented nature of credit unions, which are non-profits by design, relative to profit-maximizing commercial banks (Cororaton, 2019).

became a CDFI in these periods.

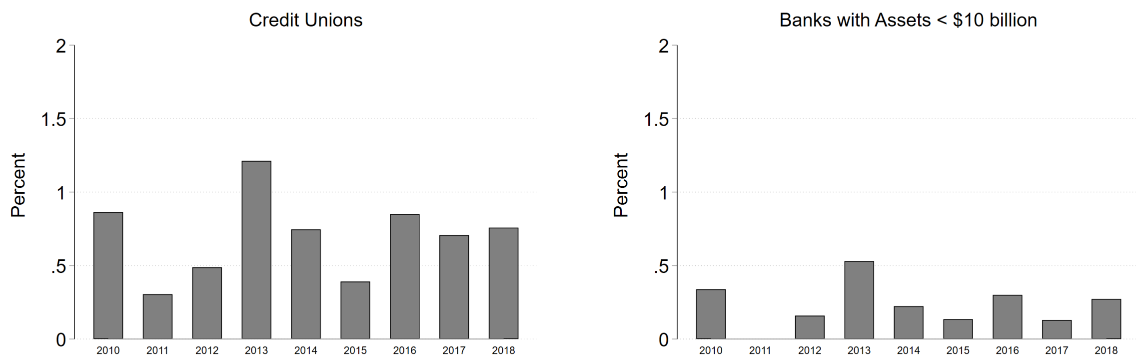


Figure 7. Rate of New CDFI Certification by Institution Type
Each bar represents the percent of non-CDFI institutions that became certified as a CDFI in the subsequent year. Gaps in the bars represent years in which we do not have a historical list. The underlying sample is the same as used in Table 3.

In general, credit unions are more likely to become certified as a CDFI in any given year with an average rate around 0.6% during the period 2010 through 2018 (Figure 7). In contrast, the new rate of CDFIs is around 0.2% on average for banks during the same period. Noticeably larger values in 2010 and 2014 are due in part to the fact that we do not have historical CDFI lists for neither 2009 nor 2013 as shown in Figure 1. As a result, the rate of new CDFIs in 2010 and 2014 are overstated because they include CDFIs certified in the 2009 and 2013, respectively. Given this issue with the data, we will exclude these years from our ensuing regression analysis.

Second, MDI banks were not much more likely to become CDFIs during the period 2011 through 2019. This result seemingly contradicts an observation from Table 3 that nearly 30 percent of CDFI banks are MDIs compared to around 2 percent for non-CDFI banks. However, one can reconcile the regression results with the summary statistics by noticing that the MDI bank CDFIs had already become certified as CDFIs in the early 2000s (see Figure 8). As a consequence, our regression results do not capture the relevance of being an MDI bank in becoming a CDFI. Instead, they imply that MDI banks that didn't already elect to become a certified CDFI by 2010 are not much more likely to do so than non-MDI banks, all else equal.

Third, we find that cash holdings and leverage are factors associated with becoming a CDFI. Specifically, depository institutions with less cash and higher leverage were more

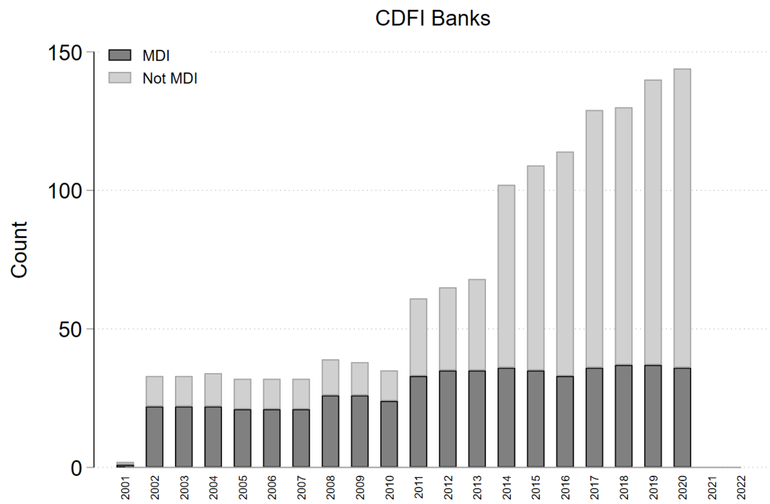


Figure 8. Bank CDFIs Over Time by MDI Status
This figure shows the number of certified CDFIs that are banks within each year by their MDI status. See Section 2 for details about our data sources.

likely to become certified CDFIs. This finding makes intuitive sense given that a clear benefit of becoming a CDFI is access to government grants (see, e.g., Figure 4), which should be more valuable to cash-constrained and over-levered institutions, all else equal.

The finding regarding cash ratios and leverage is most cleanly observed in the "All Years" specifications. The coefficient on the cash ratio, however, is only negative for later years, suggesting that this factor gained importance during our sample. This statement, however, assumes that relative cash holdings are a causal factor in becoming a CDFI, which is not supported directly by the regression results in Table 4. Cash ratios may themselves only be associated with the "true" underlying causal factors. This same concern can be raised about the other significant variables identified in the results.

The cash ratio and leverage results continue to hold even in the specification in which we include institution-level fixed effects (see the last column of Table 4), although the leverage coefficient is only significant with a p-value around 13%. This finding suggest that *time-varying* institution-level factors are relevant for the decision to become a certified CDFI. The signs on the coefficient estimates from this specification are the same as institution-level fixed effects, which imply that the any given institution is more likely to become a CDFI when its cash levels decline or its leverage increases.

Finally, it seems that profitability as proxied by ROA is relevant in the decision to become a CDFI except only in a time-varying sense. The coefficient estimate on this variable is only statistically significant in the specification with institution-level fixed effects. In this case, the coefficient estimate is negative, implying that a given institution is less likely to become a CDFI when its profitability increases.

3.5 Before and After CDFI Certification

In this section, we perform a regression analysis to understand if and how depository institutions change after becoming certified as a CDFI. Becoming certified as a CDFI is not an exogenous event and hence the interpretation of our results will not be causal. However, our findings will shed light on the factors and outcomes associated with becoming a CDFI.

Our regression specification is similar in form to a difference-in-differences analysis. We also follow a multiple-event "cohort" approach when constructing the underlying dataset in the spirit of Gormley and Matsa (2011). Using this approach, we estimate institutions' responses to the incentives of the CDFI program by comparing the changes in the treated (i.e., certified) and control (i.e., non-certified) institutions. For each calendar year, we construct a cohort including institution-year observations for CDFIs certified in that year and non-CDFI institutions. Within each cohort, the differential responses are measured in the three years around the given certification year. Importantly, the underlying sample of credit unions and banks is the same as used in our CDFI-level analysis in section 3.4 in which we exclude banks over \$10 billion dollars.

For ease of explanation, we first describe the case that only considers CDFIs certified in a single year: 2012. In this case, our regression specification is:

$$y_{i,t} = \sum_{\tau \neq -1} \left[\gamma_\tau \left(\mathbb{I}_{t=2012+\tau} \times BecameCDFI_{2012,i} \right) \right] + \nu_{2012,i} + \nu_{2012,t} + \epsilon_{i,t}. \tag{4}$$

The dependent variable is an outcome for institution i in year t (e.g., the asset growth rate). The key explanatory variable is an indicator variable for whether an institution became a CDFI in 2012 ($BecameCDFI_{2012,i}$). Functionally, it acts a "treated" dummy for institutions with a "treatment" year of 2012. We refer to 2012 as the "cohort" year, and our full analysis will include multiple cohorts.

The γ_τ coefficients are relative-period-specific coefficients that capture the average difference in the dependent variable between institutions that became CDFIs in the given cohort year of 2012 versus those that did not. We do not include a coefficient for the year before certification ($\tau = -1$) so that this period acts as the relative baseline. We include institution fixed effects to control for time invariant differences across institutions and year fixed effects to control for common time trends.

When estimating (4), the composition of the underlying sample is important. We include all of the yearly observations for all institutions that became CDFIs in 2012 (i.e., the cohort year) to represent the "treated" group. For the "control" group, we include the yearly observations for institutions in our sample during which they are not certified CDFIs. In this way, there are two types of institutions captured in our control group. The first are institutions that never became CDFIs. The second type are institutions that became CDFIs later than 2012. If an institution became a CDFI in 2013, however, only its observations through 2012 are included in the regression sample.

Our analysis considers CDFIs designated between 2012 and 2016. We focus on this period so that we have three years of data before and after the cohort year. Specifically, we "stack" the datasets compiled for each cohort year Y before estimating the panel regression. This generic specification can be written as follows:

$$y_{Y,i,t} = \sum_{\tau \neq -1} \left[\gamma_\tau \left(\mathbb{I}_{t=Y+\tau} \times BecameCDFI_{Y,i}\right)\right] + \nu_{Y,i} + \nu_{Y,t} + \epsilon_{Y,i,t}; \quad Y \in [2012, ..., 2016] \quad (5)$$

where $y_{Y,i,t}$ represents the outcome for institution i in year t within cohort Y. Note that a given institution-year observation can appear in multiple cohorts and therefore can be represented in the regression sample multiple times as well.

As a final note, we run the analysis separately for credit unions and banks. We split the sample before estimating given the differences observed across credit unions and banks in our CDFI status predictive analyses described in section 3.4.

In our first set of results, we examine total asset growth rates (Figure 9). We find that asset growth rates accelerated for institutions after becoming certified as a CDFI. In contrast, asset growth rates were relatively lower than non-CDFIs before certification. These results are similar across credit unions and banks. In sum, they are consistent with the notion that institutions are able to grow faster after becoming a CDFI given the additional financial resources available to them (see section 3.1). Moreover, they also suggest that CDFIs may have been hampered in their growth prior to becoming certified. Either interpretation suggests that the resources available to CDFIs alleviate institution-level financial constraints.

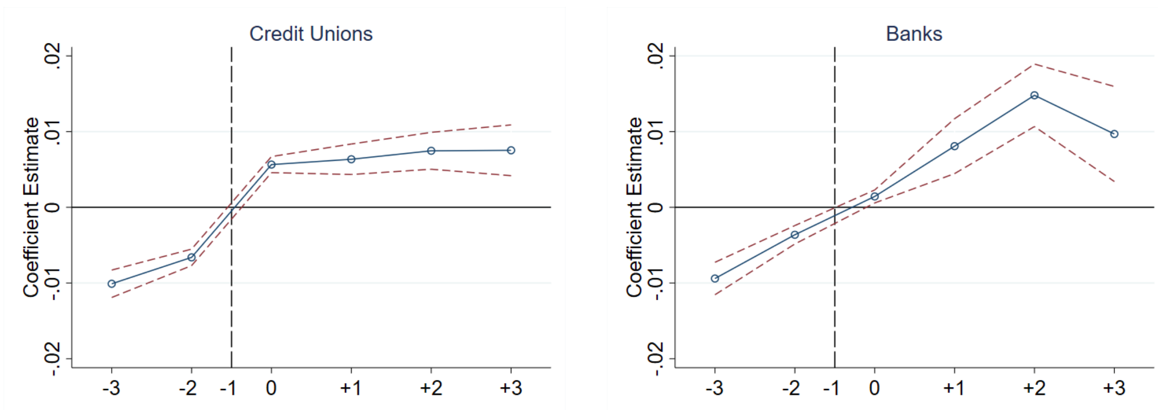
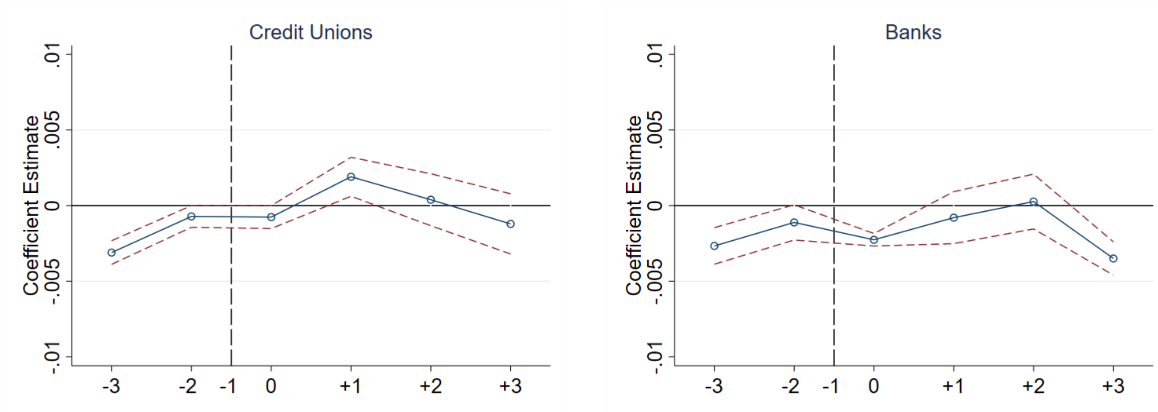


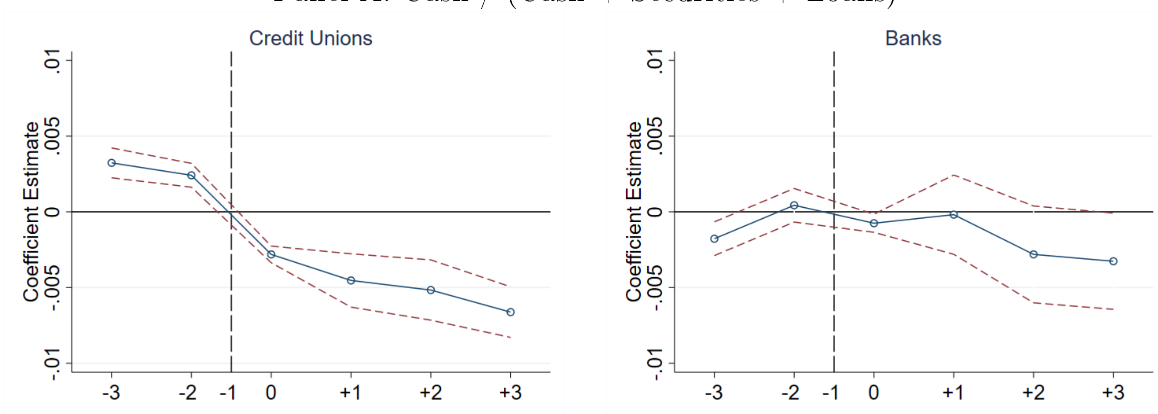
Figure 9. Asset Growth Rates
This figure shows the γ_τ coefficient estimates from estimating the regression specification (5) in which the dependent variable is the difference in log assets for institution i between year $t-1$ and year t. The index τ captures the period relative to the cohort year Y. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

Next we turn our attention to the composition of assets before and after becoming a CDFI. In Figure 10, we report the results pertaining to the changes in balance sheet ratios for cash, securities, and loans. CDFIs appear to increase their lending activity relative to non-CDFIs. We infer this outcome given that the average change in the share of loan assets is greater for CDFIs starting in the certification year. Credit union CDFIs achieve this outcome by relatively reducing their securities holdings while bank CDFIs do so through a combined reduction of cash and securities. Overall, this result is not surprising because CDFI certification is contingent upon a minimum deployment ratio whereas non-CDFI lenders are not subjected to this requirement.

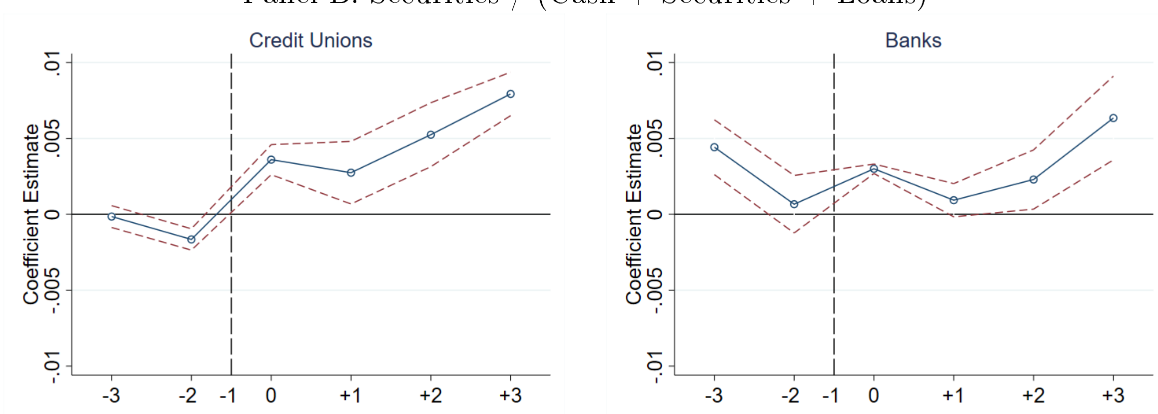
Given that CDFIs increase their lending relative to non-CDFIs, we next explore whether this is achieve through specific types of lending. In Figure 11, we report results pertaining to the changes in portfolio ratios across loans backed by real estate (RE); loans to individuals for personal personal expenditures (Consumer); and commercial and industrial loans (C&I).



Panel A: Cash / (Cash + Securities + Loans)



Panel B: Securities / (Cash + Securities + Loans)



Panel C: Loans / (Cash + Securities + Loans)

Figure 10. Change in Balance Sheet Ratios
This figure shows the γ_τ coefficient estimates from estimating the regression specification (5) in which the dependent variable is the change in balance sheet ratio for institution i between year $t-1$ and year t. The index τ captures the period relative to the cohort year Y. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

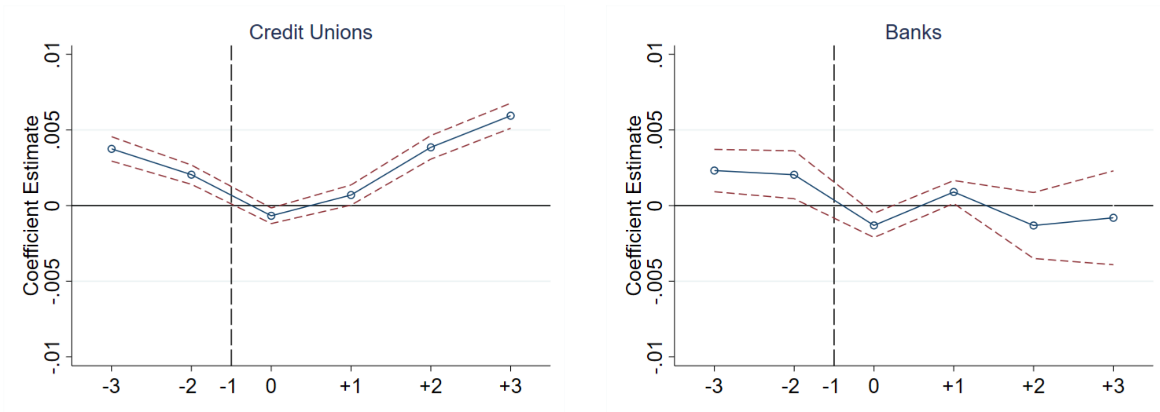
Only credit union CDFIs appear to alter their lending mix towards RE loans and away from Consumer loans relative to non-CDFI credit unions. This outcome represents a continuation of the trends observed in the pre-CDFI period.

Bank CDFIs appear to relatively shrink their C&I lending in the period before becoming a CDFI. However, after being certified, bank CDFIs appear to adjust their loan portfolio consistently with non-CDFI banks. This result is inferred from the γ_τ estimates being close to zero across loan categories from relative period $\tau = 0$ and onward. This result is in contrast to the post-CDFI shift in lending composition among credit unions.

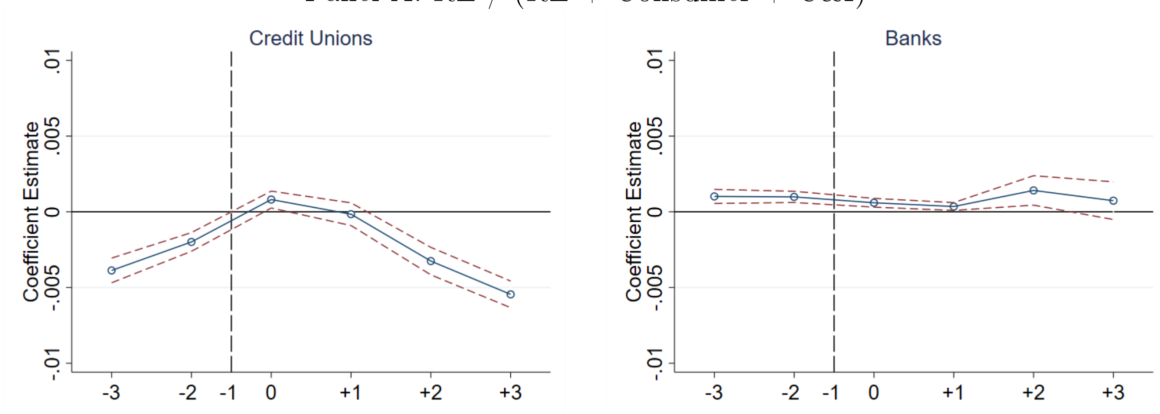
Given that credit union CDFIs appear to shift the composition of their lending after being certified, we ask whether there are subsequent changes in interest-related ratios. This question is natural as different loan types may yield different levels of average interest income if there are differences in the underlying riskiness of the loans. We report these results in Figure 12. We find that credit unions that became CDFIs had lower net interest margins on average prior to becoming a CDFI (see Panel A). These lower margins were due to the combination of both lower interest income (Panel B) and higher interest expenses (Panel C). The corresponding magnitudes are economically significant. For example, the average net interest margins are roughly 3% meaning that an increase of 0.1 p.p. to 0.2 p.p. represents a 3%-6% increase compared to the average level. After becoming a CDFI, the credit union CDFIs appear to become more similar to their non-CDFI peers along interest-related ratios. These findings are consistent with credit union CDFIs increasing the riskiness of their loan portfolio while simultaneously reducing their cost of debt.

We also observe in Figure 12 that bank CDFIs do not experience a relative change in their net interest margins relative to non-CDFI banks. In other words, any differences in lending that may occur around CDFI certification do not lead to different margins on average. Similar to credit unions, bank CDFIs appear to increase their interest income ratios after becoming a CDFI. Unlike credit unions, however, bank CDFIs also increase their interest expense ratios. These two effects work in the same direction and therefore the net interest margins are similar across time

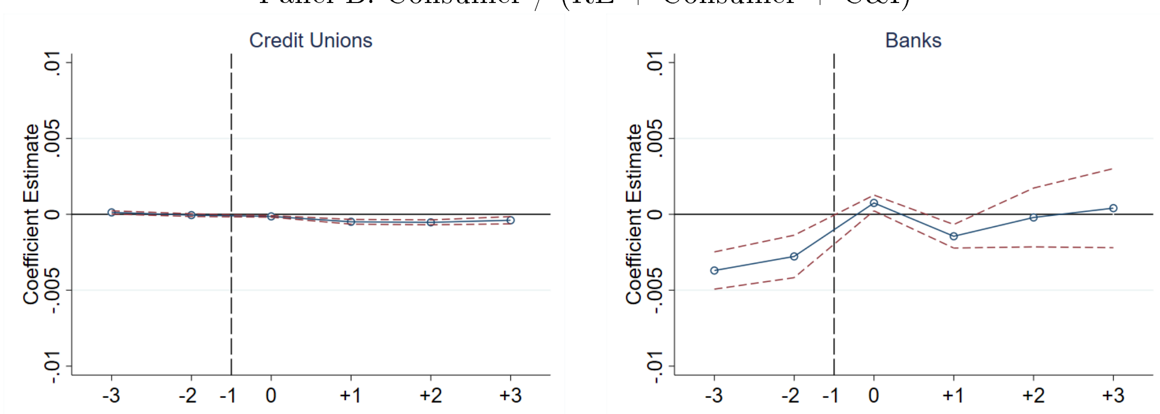
In Figure 13, we explore whether the overall return on assets (ROA) ratios were different across CDFIs and non-CDFIs. We might expect similar findings as shown in Figure 12 for net interest margin given that this measure is similar to ROA. The former is net interest



Panel A: RE / (RE + Consumer + C&I)

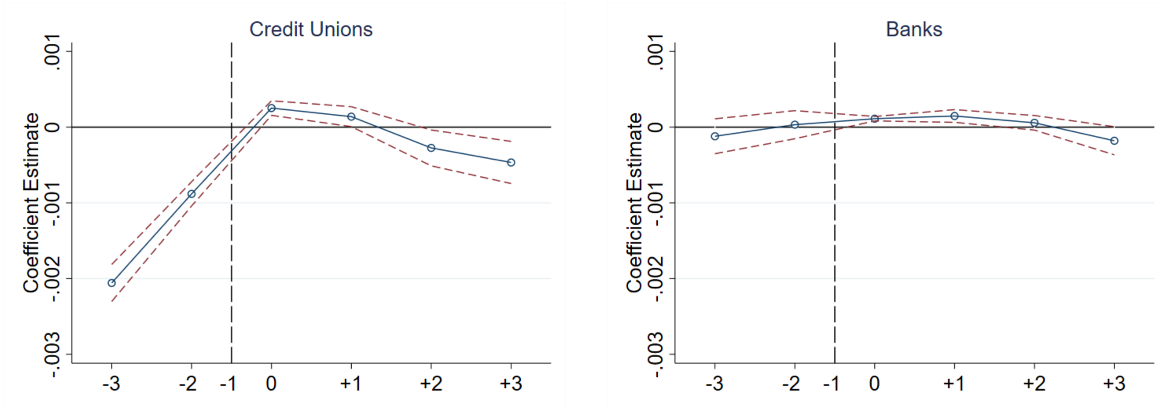


Panel B: Consumer / (RE + Consumer + C&I)

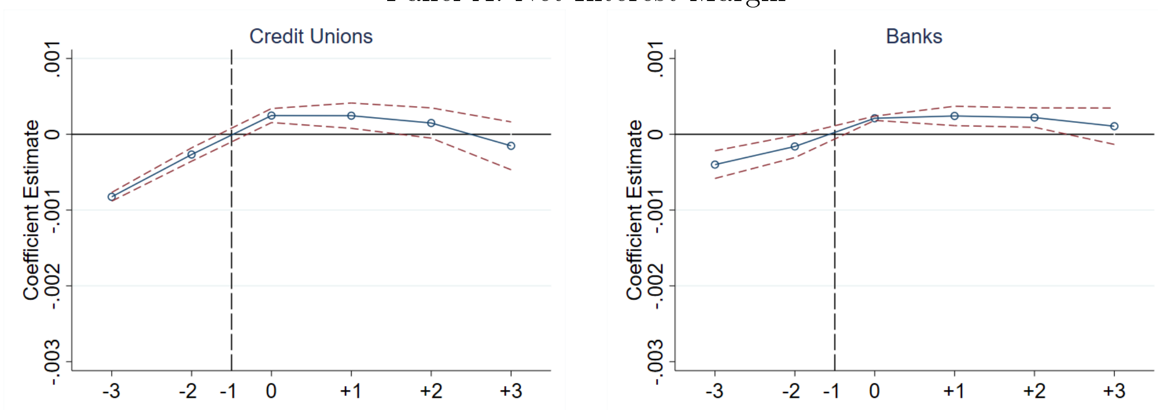


Panel C: C&I / (RE + Consumer + C&I)

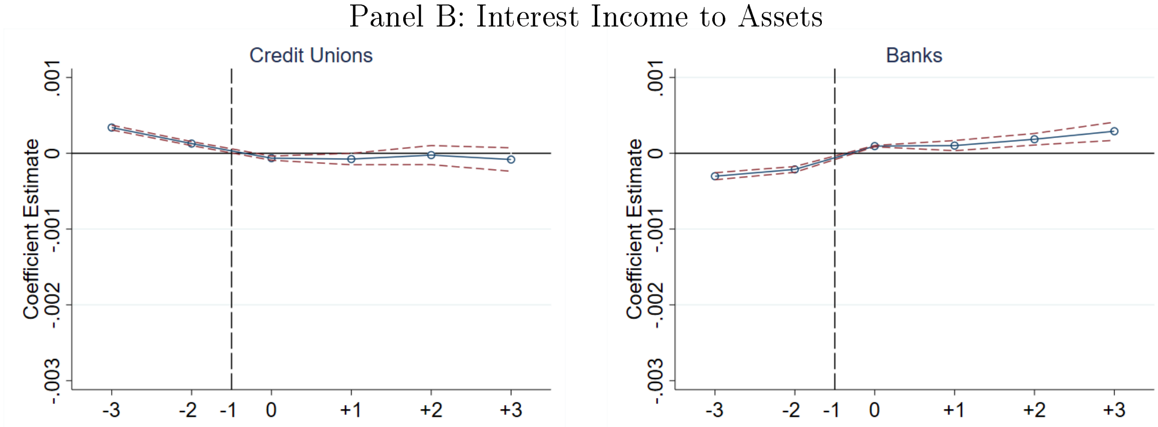
Figure 11. Change in Loan Portfolio Composition Ratios
This figure shows the γ_τ coefficient estimates from estimating the regression specification (5) in which the dependent variable is the change in loan portfolio ratio for institution i between year $t-1$ and year t. The index τ captures the period relative to the cohort year Y. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.



Panel A: Net Interest Margin



Panel B: Interest Income to Assets



Panel C: Interest Expense to Assets

Figure 12. Loan Profitability
This figure shows the γ_τ coefficient estimates from estimating the regression specification (5) in which the dependent variable is the interest-related ratio for institution i during year t. The index τ captures the period relative to the cohort year Y. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

income divided by last year's assets while the latter uses total net income.

Interestingly, we find that ROA declined for CDFI banks after certification relative to non-CDFI banks (right panel of 13). This result seemingly contradicts the profit-maximizing nature of banks.[7] However, our short-term profitability measures may be missing longer-term value created through being a CDFI. Given that most banks in our sample are small and therefore do not have publicly traded equity, we cannot directly infer changes in banks' market values. It may also be reverse causlity: banks with declining profitability are more likely to pursue CDFI certification. Finally, CDFI banks may simply focus less on profitability than larger publicly-traded banks, which is consistent with the mission-driven aspect of the CDFI program to serve lower-income people and communities.

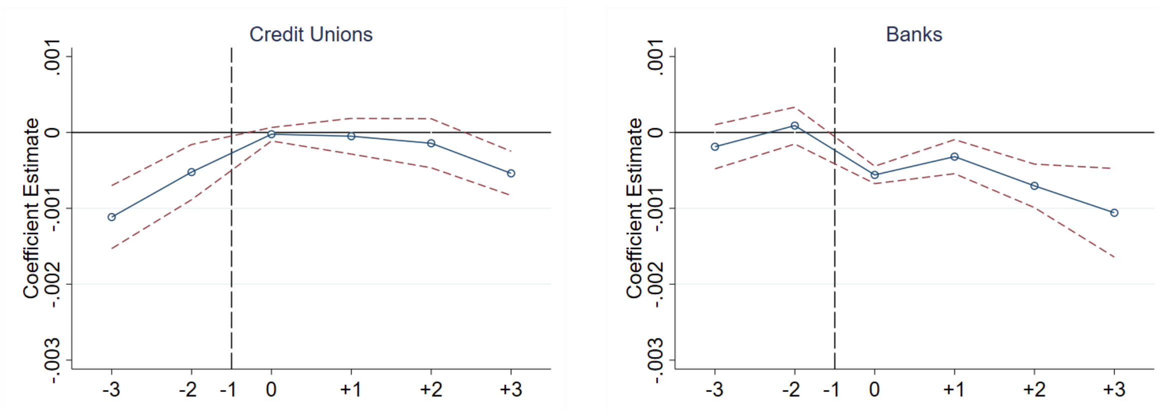


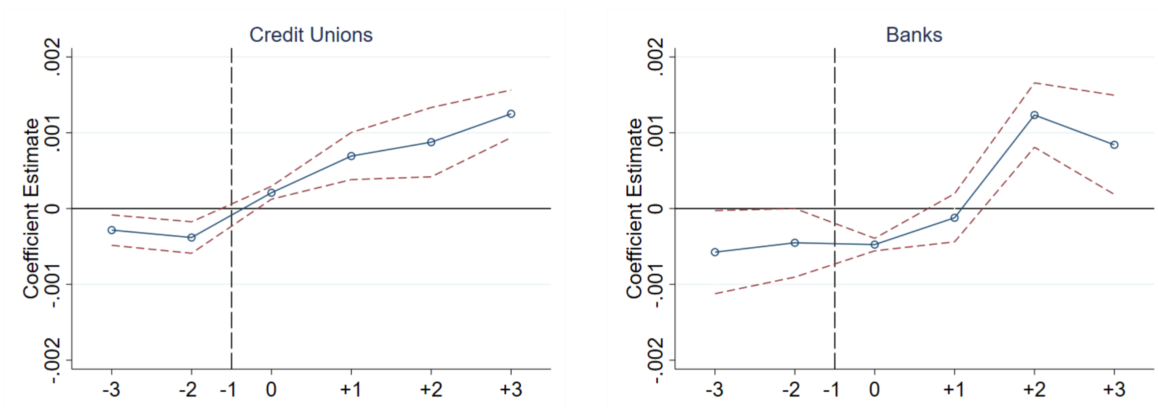
Figure 13. Return on Assets
This figure shows the γ_τ coefficient estimates from estimating the regression specification (5) in which the dependent variable is the return on assets ratio for institution i during year t. The index τ captures the period relative to the cohort year Y. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

For our final set of results in this section, we consider the changes in leverage associated with becoming a CDFI (Figure 14). We find that leverage increases as measured by total liabilities over assets. Recall that total assets increase faster for CDFIs (Figure 9) meaning that total liabilities grow even faster. This result tells us that, despite CDFIs tending to have higher initial levels of leverage before certification (Table 4), they continue to increase

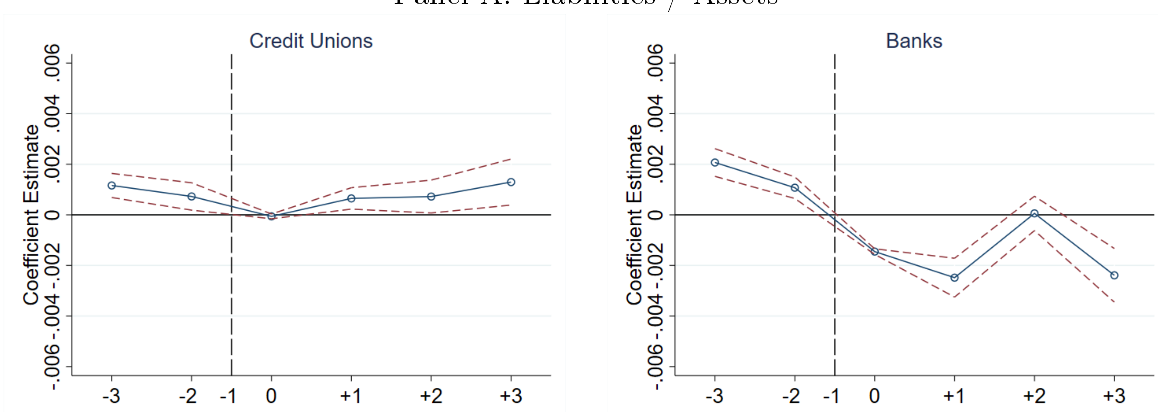
[7]This result also seemingly contradicts the similar values seen across the same groups for net interest margin in Figure 12. These differences in results, however, simply tells us that there must be a differences across net non-interest income measures.

leverage afterwards as well.

In the bottom panel of Figure 14, we see that the broad source of the greater growth in liabilities for CDFIs after certification is different across credit unions and banks. For credit union CDFIs, they appear to increase their relative share of deposits in their liability structure. This result is consistent with the notion that credit union CDFIs are better able to attract deposits, which represent membership interests for credit unions. For bank CDFIs, however, they appear to rely more on non-deposit financing.



Panel A: Liabilities / Assets



Panel B: Deposits / Liabilities

Figure 14. Change in Leverage Ratios
This figure shows the γ_τ coefficient estimates from estimating the regression specification (5) in which the dependent variable is the change in a liability-related ratio for institution i between year $t-1$ and year t. The index τ captures the period relative to the cohort year Y. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

3.6 CDFI Loan-Level Analysis

Our loan-level data for CDFI activity provides a unique opportunity to study the characteristics of their investments. In this section, we focus on the business lending that CDFIs provide. We do so because of the ability to compare such lending against SBA lending, which is also available at the loan level. Comparing CDFI to SBA lending also makes intuitive sense as the fundamental goals of the two programs are similar: to expand credit access. CDFI and SBA loans are similarly intended for the most credit-constrained small businesses that cannot obtain conventional loans elsewhere (see, e.g., Gong and Rosen, 2022). However, we acknowledge that there are many differences between loans made through SBA programs and those from CDFIs including the underwriting process and post-lending role of the lender.

In Table 5, we provide an initial set of summary statistics for both CDFI and SBA loans. These figures help provide a sense for the types of loans made through each program. A typical CDFI loan is for around \$60 thousand with a maturity of 4 years and an interest rate around 7 percent. These numbers are similar to the typical SBA 7a "express" loan, which is for around \$50 thousand and also around a 7 percent interest rate. Standard SBA 7a loans, however, are generally for much larger amounts.

We are particularly interested in understanding the relative difference in the cost of CDFI loans versus SBA. Here our loan-level datasets are particularly useful because they allow us to control for loan-level features in addition to local and time-varying economic conditions. We run the following loan-level regression:

$$\text{Interest Rate}_{l,c,k,t} = \beta' X_{l,t} + \nu_{c,t} + \nu_{k,t} + \epsilon_{l,c,k,t}. \tag{6}$$

The dependent variable is the interest rate for loan l whose borrower is in industry k located in county c during year t. For explanatory variables, we include several features of the loan including the type of loan (e.g., CDFI business) and loan amount, among others. Depending on the specification, we also control for a combination of fixed effects along the dimensions of county, year, and industry.

The results from this regression analysis are presented in Table 6. We focus on the results in column (4), which is our benchmark specification with county-year fixed effects as well as industry-year fixed effects. Including these narrow sets of fixed effects is important

Table 5. CDFI and SBA Loan-Level Summary Statistics

	Mean	SD	P5	P25	P50	P75	P95	N
CDFI - Bus Loans								
Amount (thd)	198.3	599.0	3.3	25.0	63.2	150.0	750.0	70,189
Real Amount (thd)	220.6	663.0	3.7	28.6	70.6	170.2	819.0	70,189
Maturity (year)	4.6	4.2	0.5	1.3	4.0	5.1	15.0	70,189
Interest Rate	7.2	2.8	3.5	5.3	6.8	8.5	12.0	70,189
Num of Jobs	12.1	42.0	0.0	1.0	2.5	8.0	46.0	70,189
CDFI - Microbusiness Loans								
Amount (thd)	7.0	9.0	1.5	2.2	3.5	7.0	27.0	271,856
Real Amount (thd)	7.7	10.1	1.6	2.4	3.9	7.6	30.6	271,856
Maturity (year)	1.2	1.3	0.5	0.5	0.5	1.5	5.0	271,856
Interest Rate	15.4	4.3	6.0	13.5	18.0	18.0	18.0	271,856
Num of Jobs	1.5	3.1	0.0	1.0	1.0	1.3	4.0	271,856
SBA Express 7a Loans								
Amount (thd)	75.9	89.3	10.0	25.0	50.0	100.0	257.3	262,227
Real Amount (thd)	87.1	104.1	10.8	26.5	54.0	110.6	310.7	262,227
Maturity (year)	6.8	2.8	2.5	5.0	7.0	7.0	10.0	262,227
Interest Rate	7.1	1.8	4.5	5.8	6.8	8.4	10.3	262,227
Num of Jobs	6.6	13.4	0.0	0.0	3.0	7.0	26.0	262,227
SBA Standard 7a Loans								
Amount (thd)	742.0	846.9	72.0	201.5	443.0	930.0	2500.0	209,997
Real Amount (thd)	844.2	959.8	80.9	233.9	503.3	1060.0	2849.3	209,997
Maturity (year)	14.3	7.3	5.2	10.0	10.0	25.0	25.0	209,997
Interest Rate	6.1	1.0	4.8	5.5	6.0	6.8	8.0	209,997
Num of Jobs	15.3	25.2	0.0	3.0	7.0	17.0	55.0	209,997

to control for unobservable and time-varying factors at both the county and industry levels. Our key findings are the coefficient estimates on the indicator variables that capture the source of the loan. We leave out the indicator variable for a standard SBA 7a loan, which means that the coefficient values for the other indicators represent the relative difference in

Table 6. CDFI vs SBA Loan Interest Rates

This table shows the coefficient estimates from estimating the regression specification (6) in which the dependent variable is the interest rate for loan l whose borrower is in industry k located in county c during year t. Our sample covers the period 2010 through 2019 because SBA loan interest rates are not available earlier. See Section 2 for details about our data sources. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate the significance level at the 10%, 5%, and 1% level, respectively.

	(1) interest rate	(2) interest rate	(3) interest rate	(4) interest rate
is CDFI Bus Loan	1.052***	0.106***	1.619***	1.739***
	(0.011)	(0.011)	(0.013)	(0.013)
is CDFI Mirco Bus Loan	9.321***	7.948***	4.215***	4.308***
	(0.009)	(0.012)	(0.015)	(0.015)
is SBA Express 7a	0.981***	0.178***	0.762***	0.781***
	(0.004)	(0.006)	(0.006)	(0.006)
Amount(mil)		-0.036***	-0.210***	-0.202***
		(0.006)	(0.006)	(0.006)
Maturity (year)		-0.093***	-0.031***	-0.032***
		(0.001)	(0.000)	(0.000)
Num of Jobs		-0.010***	-0.006***	-0.006***
		(0.000)	(0.000)	(0.000)
Industry FEs	No	No	Yes	No
County FEs	No	No	Yes	No
Year FEs	No	No	Yes	No
Industry-by-Year FEs	No	No	No	Yes
County-by-Year FEs	No	No	No	Yes
Adj. R^2	0.68	0.68	0.88	0.89
N	814,269	814,269	814,141	809,600

the average interest rate to to a standard SBA 7a loan.

We find that the interest rates on CDFI business loans are on average 1.7 p.p. to 4.3 p.p. higher than standard SBA 7a loans. The fact that CDFI loans are more expensive is not surprising on its own given that SBA loans are government-subsidized. What is interesting, however, is the quantitative magnitude as it tells us how much more expensive CDFI loans are compared to a similar (and therefore substitutable) source of financing.

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