Do Community Development Financial Institutions Promote Economic Growth in Neighborhoods? A Multi-Metro Area Analysis of Home Values

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MPP Essay

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Public Policy

Presented June 9th, 2017
Commencement June 17th, 2017

Master of Public Policy essay of Caitlin McRae presented on June 9th, 2017

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Abstract

Adequate access to financial markets is crucial for healthy communities. Some communities within the United States have historically been excluded from financial markets due to factors of geographic isolation or racial discrimination. The mechanism behind households and individuals lacking access to financial products and services is due to credit rationing by conventional lenders stemming from production externalities of market information. Community Development Financial Institutions (CDFIs) provide a means to bridge the financial services gap between financial institutions and traditionally underserved populations. CDFIs are financial institutions that are primarily focused on providing access to financial services to populations that have been historically underserved by conventional financial institutions such as minority and low-and-moderate income individuals and communities. Many of the past studies on CDFIs have focused on the immediate outcomes of CDFI operations, with only a modest number analyzing potential broader community impacts. To answer the question of do CDFIs have a measurable community wide impact, specifically on home values in the communities they serve, this study used an array of multivariate regression estimators to analyze the relationship between CDFI lending activity and the level of CDFI lending with census tract median housing values, controlling for community socioeconomic and demographic variables. The study used transaction level data of certified CDFIs from the CDFI Fund merged with Census Bureau data on census tracts in Atlanta, Chicago, Dallas, Los Angeles, Minneapolis, New York, and Portland over the years of 2000-2014. Results of this study suggest that CDFIs target their transactions to worse off communities, and would need to provide loanable funds and investments of over $30,000,000 in a census tract over a five-year period to significantly raise the tract’s median housing value. To foster industry support of CDFIs and community reinvest efforts, this paper suggests that the Community Reinvestment Act (CRA) be updated to better meet community financing needs and increase collaboration between CDFIs and conventional lenders.

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LIST OF ACRONYMS

ACS – American Community Survey

CDFI – Community Development Financial Institution

CIIS – Community Investment Impact System

DID – Difference-in-Differences

FDIC – Federal Deposit Insurance Corporation

FHA – Fair Housing Act

MB – Marginal Benefit

NCUA – National Credit Union Authority

PMB – Private Marginal Benefit

PMC – Private Marginal Cost

SMB – Social Marginal Benefit

SMC – Social Marginal Cost

Introduction

From nation states to close-knit communities, the ability to obtain credit and have access to capital is necessary for functional societies. While less attention grabbing than an international capital crisis, neighborhoods and communities within the United States have historically struggled with accessing financial products and services and suffered the consequences. Some communities are geographically isolated from institutions that provide financial services, are made up of individuals that do not meet the underwriting criteria set out by conventional financial institutions[1], or are explicitly excluded due to racial discrimination. Community Development Financial Institutions (CDFIs) are organizations that offer a means to end exclusion from credit markets due to these reasons.

CDFIs are mission-driven financial institutions that provide, and even target, their financial products and services to low-and-moderate income (LMI) and minority individuals and neighborhoods to generate beneficial social returns as well as financial returns. Embodiment of these dual purposes is often called having a double-bottom line, and the primary characteristic distinguishing CDFIs from their conventional lending institution counterparts. CDFIs were first formed by community groups in the U.S. as a grass-roots effort to ameliorate the financial exclusion still rampant in many minority and urban neighborhoods during the mid-twentieth century. After a series of financial industry policy reforms, CDFIs gained official recognition and financial support from the federal government in the 1994 with the passing of the Riegle Community Development and Regulatory Improvement Act. With the resulting industry growth

[1] Conventional financial institutions are also often called mainstream or traditional financial institutions. For consistency, they will only be referred to as conventional financial institutions or conventional lenders in this paper.

from federal support, research on CDFIs has also increased. Studies have shown that generally CDFIs produce their desired outcomes of connecting underserved markets to needed financing and generating positive benefits to the borrower. However, little research has been conducted on the broader impact, or spill-over effects, received by the larger community that CDFI lending activity should create. The question remains: Do CDFIs have a measurable community wide impact on home values in the communities they serve?

To answer the question of whether CDFI lending activity has measurable neighborhood level impacts captured in home values, this study was conducted using the census tracts in the central counties of the metropolitan areas of Atlanta, Chicago, Dallas, Los Angeles, Minneapolis, New York, and Portland over the 2000-2014 time period. Matching CDFI transaction data with census tract socioeconomic and demographic variables, an array of multivariate regression estimators were used to analyze the relationship between the presence of CDFI lending activity and the level of CDFI lending activity on neighborhood value as capitalized in the tract median housing price. Results of this study suggest that CDFIs target their transactions to worse off communities, and would need to supply investments and loanable funds of over $30,000,000 in a census tract over a five-year period to realize a significant positive impact on the tract's median housing value.

The rest of this paper proceeds as follows: first, a presentation of the theoretical framework of market failures in credit markets, CDFIs as a potential solution to the market failures, a historical background of the development of the CDFI field in the U.S., and details of the current CDFI field; second, a literature review of the empirical studies conducted on CDFIs' roles in connecting communities to capital and the outcomes and impacts of CDFI operations; third, description of the data, variables, empirical models, analysis, and a presentation of the results of the study; and to conclude, a discussion of the methodological limitations of this study, and policy recommendations for sustaining the CDFI field.

Background

Theoretical Framework

Though markets are generally assumed to be mechanisms reliably facilitating socially efficient commerce, under certain conditions markets will fail to provide efficient economic outcomes. The under provision of LMI and minority borrowers' fair access to credit is an inefficient economic outcome caused by market failures that CDFIs are designed to correct for. Market failures that have caused financial exclusion of LMI and minority neighborhoods are due in large to information asymmetries and credit rationing, which have been perpetuated by racial discrimination, particularly in urban areas. Information asymmetries describes situations in which buyers and sellers in a market have differences in available information to base their decision-making in. In credit markets this primarily affects the ability for lenders to gauge the default or repayment risk of borrowers. This can lead to financial exclusion through credit rationing, neighborhood red-lining, and other spatial variation in access to credit and financial services, creating a feedback loop of perpetuating market inefficiencies and costly negative neighborhood effects.

Information Costs and Externalities

Information in credit markets is an imperfect public good. Public goods are characterized by being non-rivalrous—undiminished by consumption and non-excludable—available to all. While information is fully non-rivalrous, market actors are, in some instances, able to keep information they have from others. The characteristics of public goods can cause market failures of externalities to exist in markets. Externalities occur when costs or benefits from production or consumption in markets are not fully internalized by the party generating the costs or benefits, and other parties bear some of the costs or benefits without having caused them. Generation of market information in credit markets creates positive production externalities.

Producing and obtaining information on borrowers' default risk in credit markets can be costly, but is crucial for financial institutions as they make and price loans on this information. For home mortgages, credit market information refers to both information on borrower default risk, and information on the value of the housing unit. Conventional lenders rely on past financial history to create aggregate borrower profiles and economize on information costs. Information on borrowers' default risk comes from credit histories and scores derived from a record of past loan repayments. Without a credit history, extensive research would be required to create a risk profile of each potential borrower, an effort that lenders often deem too costly. The values of homes are determined by appraisals which are based on past sales prices of the house in question or similar ones nearby. Those past sales were likewise based on past financing based on appraisals of past sales with past financing based on past appraisals, and on, and on. Without past sales, determining the accurate value of a housing unit becomes difficult. By generating market information, loans create a positive information externality to future lenders and borrowers by lowering information costs for future transactions. However, where little information is available due to low housing sales or borrowers' lack of credit history, information deficits are created and can lead to market failures.

Problems with information externalities arise because conventional lenders bear the costs of obtaining market information, but are not able to necessarily internalize all the benefits of producing market information. The positive production externality associated with information will lead to an underproduction of the socially optimal level of information. Figure 1 shows the general model of a market failure due to a positive production externality. The optimal, socially efficient provision of a good, in this case market information, is represented by Q*. The good will be underprovided by the supplier because the private marginal cost of producing the good (PMC) exceeds the social marginal cost (SMC) of the production of the good, leading the private market provision of the good to be at a quantity of Q, an under-provision of the socially optimal level of the good. In the case of under provision of market information, production of market information becomes increasingly expensive, leading lenders to produce even less i.e. make fewer loans, increasing the under provision, and causing efficiency loss represented by the area of deadweight loss in the model.

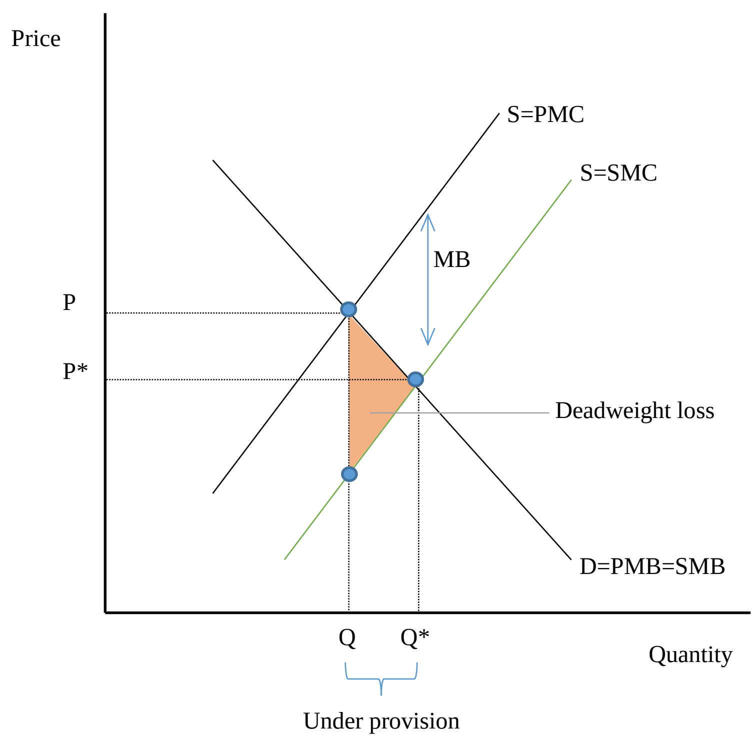

Figure 1 General Model of Positive Production Externality Reprinted from Gruber (2013)

Asymmetric Information and Credit Rationing

Additionally, the lack of readily available market information and the high cost of getting information produces an additional issue of information asymmetry, differences in market information between producers and consumers. Here, borrowers have a better understanding of their own default risk than do lenders. For potential borrowers in LMI areas, information asymmetries often lead to credit rationing. Conventional lenders are not willing to invest in determining the individual high and low risk borrowers of LMI areas because of the relative high cost of determining creditworthiness of borrowers lacking prior credit history to the relatively low value loans. This perception of average higher risk in low income areas may prevent sound borrowers from accessing credit and capital.

This inability or unwillingness by conventional lenders to differentiate high and low risk borrowers from one another in LMI neighborhoods underpins the model of credit rationing developed by Stiglitz and Weiss (1981). Asymmetric information leads to an excess of demand for loanable funds when there are different groups of borrowers with different levels of default risk all being charged the same rate on loans. Figure 2 shows the amount of profit a lender can expect at given interest rates in a market with unknown high and low risk borrowers and a perfectly elastic supply of credit. At low interest rates both high and low risk borrowers are in the market for loanable funds. However, to increase profit a lender will want to increase rates on loans. At some point, represented by r* in the model, the interest rate on loans will exceed what the low-risk borrowers are willing to pay, and they will leave the market. Through adverse selection their absence will leave higher risk borrowers alone in the market, decreasing the lender's profitability from the borrowers' increased probability of defaulting on the loan. Rates will be profitable for the lender between r_1 and r* when both types of borrowers are in the market, and when only high risk borrowers are in the market at rates greater than r_2. Rates between 0 and r_1 when both types of borrowers are in the market and rates between r* and r_2 when only high risk borrowers are in the market are unprofitable, resulting in no loans being made by the lender (Thomas, 2008).

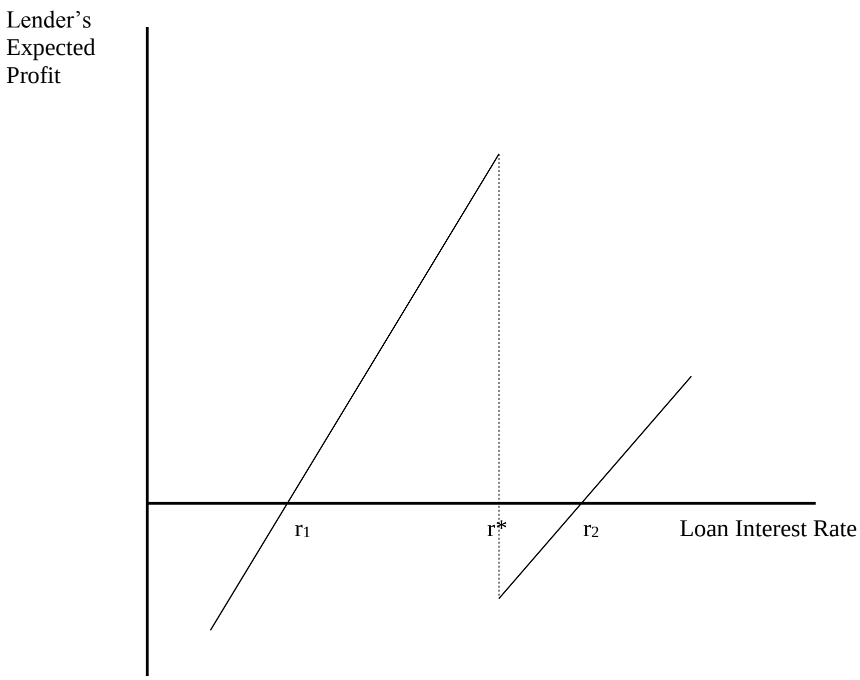

Figure 2 Loan Profit with Adverse Selection. Reprinted from Walsh (2003)

Even if loan seekers were willing and able to pay more than the market interest rate or put up more collateral than demanded by lenders, potential borrowers would still be denied the loan because of the increased risk those loans would add to the lender's portfolio resulting in lowered profitability. In the case of lending in LMI neighborhoods, conventional lending institutions may perceive the cost of obtaining information on borrowers and lending opportunities in LMI neighborhoods as too high and profitability too low, opting not to do business in those areas all together.

Racial Discrimination & Redlining

Historically, these mechanisms of market failures have been deeply trenched in racial discrimination. Racial discrimination, both formal and informal, limited access to credit markets for minority individuals through much of the 20th century, creating a barrier for minorities to establish and expand businesses and purchase homes. Financial institutions reasoned that the evaluation of minority loans would be a profitless endeavor because of a lack of cultural affinity between lender and borrower, and the perception of minorities being poorer as group, thus less credit worthy (Calomiris et al., 1994). Throughout much of the twentieth century few loans, if any, were made by financial institutions in black neighborhoods or even to black borrowers in white neighborhoods. Minority borrowers seeking mortgages were constrained to borrowing from the limited number of black financial institutions, or from an informal lender at potentially usurious rates (Immergluck, 2004).

Credit rationing by conventional lenders led to a practice called redlining. Often lenders would literally draw red lines around areas on maps, designating places to outright reject loan applications from. Numerous studies have shown that typically the residents of redlined neighborhoods were predominately African-American (MacInnes, 2002). Low lending history from past racial discrimination continues to cause problems for previously red-lined communities. Fewer resales data makes housing price appraisals more difficult to conduct and lending risker for financial institutions, leading to more credit rationing and perpetuating the lack of credit access into the future (Lang & Nakamura, 1992).

Neighborhood Effects

These externalities can aggregate and lead to significant societal costs by creating negative neighborhood effects. The value of any individual home is connected to the values of the surrounding homes and other properties. Individual home value, both at present and in the future, is less dependent on its own maintenance and improvements as much as it is on the value of all the other homes and built structures in the neighborhood. Negative externalities like poverty, blight, and high crime rates associated with neighborhood disinvestment are detrimental to the value of the surrounding immobile neighborhood structures. Housing values can even be greatly influenced by the home financing decisions of neighboring home-owners. Foreclosed and vacant houses, including those originating from predatory mortgages, have been shown to significantly reduce neighborhood home values via a contagion effect (Goldstein, 2007; Harding, Rosenblatt, & Yao, 2009; Immergluck & Smith, 2006).

Much like with the problem of information externalities, neighborhood externalities also become a self-reinforcing issue. Households and businesses in redlined neighborhoods with adequate resources often left the area, causing broader decline by taking their wealth and leaving vacant structures. Presently neighborhoods, particularly in central cities, are still dealing with the ramifications of past financial exclusion and area disinvestment. Once the mechanisms for disinvestment and abandonment take hold, reversal is a is formidable and often requires outside intervention.

CDFIs as a Market Intervention

Public goods will be underprovided by profit-maximizing private actors. Though society may benefit from LMI neighborhoods receiving access to financial capital, the private lending institutions may not, and thus will not willingly provide the socially optimal level of financing to LMI borrowers resulting in credit rationing, rational or discriminatory. Because of their organizational mission to create societal benefits, and with the additional aid of subsidies through outside funding to cover the costliness of obtaining market information, CDFIs act as a market correcting mechanism to meet the excess demand for loanable funds in LMI credit markets.

Conventional lenders will charge a higher interest rate and supply fewer loans compared to CDFIs due to higher information costs to conventional lenders and their subsequent credit rationing. By CDFIs offering a lower interest rate, borrowers with lower default risk that had dropped out of the market through adverse selection return, increasing the demand for CDFI loanable funds greater compared to conventional lenders' loanable funds. Through the increased provision of loans, the market information generating role of those loans, CDFIs fulfill a market intervention role of increasing the underproduction of the public goods of market information, and neighborhood investment. By facilitating this role CDFIs have the potential to begin reversing some of the detrimental neighborhood effects from the long history of financial exclusion experienced by individuals and communities in the U.S.

CDFI Community Development Organization Origins

The beginnings of CDFIs are deeply embedded in the larger context of the civil rights and community reinvestment movement of the mid-late 20th century. After the passing of the Civil Rights Act in 1968, and with it the Fair Housing Act (FHA), racial discrimination in home lending was formally prohibited. However, due to regulatory ineffectiveness, discriminatory lending practices by banks still occurred frequently, and most prevalently in neighborhoods located in urban areas. Difficulties with enforcement of the FHA stemmed from the difficulty of individual borrowers proving banks' actions as discriminatory in court. Inaction from bank regulators also led to the continuation of minority lenders being unjustly denied access to financing. The inability for individuals to obtain adequate legal recourse led to the formation of grassroots community groups to take collective action to address the ongoing racial discrimination. Black community organizations in cities like Milwaukee, Chicago, and Pittsburgh formed their own cooperative, community controlled banks and neighborhood housing reinvestment programs to counteract the effects of redlining and lending discrimination. Some community development corporations changed their organizational roles to those of CDFIs to focus on providing capital investments to neighborhoods. Community organizations began to confront banks directly about their discriminatory lending practices too, coercing meetings with bank leadership through various, unorthodox but attention-grabbing tactics. Community activists were also confronting local governments about redlining and lending discrimination, resulting in several cities and states enacting antiredlining ordinances and statutes prior to any national policy.

Community Reinvestment Policy Response

With the influence of the community organizations' advocacy and the intention of correcting for market failures, the Community Reinvestment Act (CRA) of 1977 was enacted by Congress to address the ongoing prevalence of financial exclusion. The CRA declared that banks have an obligation to provide for the credit needs of communities throughout their chartered area, including LMI areas. The banking regulatory agencies were directed to conduct examinations of CRA compliance of banks under their regulatory authority when the institutions seek a merger, acquisition, expansion in service provisions, or opening and closing branches. The CRA also gave community groups a channel of for community groups to file critical comments of a bank's operations. If a bank receives a failing rating of the CRA examination, its request for a merger, acquisition, etc. may be denied by the regulatory agency.

Two additional federal policies implemented during the Clinton administration in the early 1990s set the stage for the establishment of a formally recognized CDFI field. First, the

1994 Riegle Community Development and Regulatory Improvement Act formally designated and defined CDFIs, as well as create the CDFI Fund, a subsidiary of the U.S. Treasury Department, to facilitate and support their operations. The CDFI Act received bipartisan support from Congress because CDFIs embody a market-based rather than a regulatory approach to addressing sub-optimal and discriminatory lending practices. Second, due to growing criticism of the CRA being inconsistently enforced and ineffective in fulfilling its purpose, the CRA regulations were updated and strengthened 1995 to provide objective performance measures of banks meeting the credit needs of the communities in their service areas. An additional significant revision to the CRA in 1995 designated CDFIs as qualifying CRA investments and borrowers. This change to the CRA regulations created incentive for conventional banks to provide funding for CDFIs. The 1995 CRA revisions have shown to have led to an increase in funds directed to CDFIs from conventional financial institutions (Holyoke, 2004), and an increase in lending to minorities in LMI areas (Belsky, Schill & Yezer, 2001).

The Current CDFI Industry

Since being formally recognized and receiving support from the federal government, the CDFI industry has grown considerably. CDFIs currently exist in all fifty states of the U.S., and serve both rural and urban communities. Currently there are 1,049 certified institutions in operation. In 2015 these CDFIs originated loans or investments of over $3.6 billion. Over $806 million of financing was directed for home purchase and improvement, $895 million for residential real estate transactions, and $897 million to businesses and microenterprises which financed over 11,000 businesses (CDFI Fund, 2016).

Types of CDFIs, Clients, & Services

A CDFI is a relatively broad term for institutions than can take on a variety of forms. CDFIs can either be nonprofit or for profit lending institutions, though most are nonprofits. A CDFI can also refer to several types of financial institutions: banks, credit unions, loan funds, and venture capital funds. Like other conventional banks and credit unions, community development banks and credit unions are depository financial institutions subject to regulation from federal and state agencies and have their deposits insured by the Federal Deposit Insurance Corporation (FDIC) or the National Credit Union Authority (NCUA). Community development loan funds and venture capital funds are not subject to such regulation because they are not depository institutions, allowing them to finance higher risk projects. Community development loan funds account for just over half of certified CDFIs; community development credit unions account for nearly thirty percent of certified CDFIs; community development banks account for about twenty percent; and community development venture capital funds account for only about one percent of all certified CDFIs (CDFI Fund, 2016).

Beyond differing by institution type, CDFIs can also have a broad and diverse clientele base. CDFIs provide financial products and services to small business owners, affordable housing developers, commercial real-estate developers in LMI communities, community nonprofits, other CDFIs, and individuals. CDFIs also usually provide other extensive services to their clients besides loans that many conventional lenders do not. The range and scope of services vary by individual CDFI, but they include technical assistance such as: housing counseling, down payment and closing cost assistance on home purchases, foreclosure prevention, landlord training, credit counseling, credit repair programs, financial literacy programs, personal finance management programs, and foreclosure prevention counseling.

Sources of CDFI Funding

As mostly nonprofit institutions and providers of public goods and services, most CDFIs require subsidies, or outside funding to conduct their operations and fulfill their mission-driven roles. multiple funding sources exist for CDFIs, the most significant being the CDFI Fund. Contributing over $1 billion of funding to CDFIs since its inception in 1994, the CDFI Fund is the largest source of funding for CDFIs in the U.S. (CDFI Fund). The organizational mission of the CDFI Fund is to facilitate the development and increase the service capacity of CDFIs in underserved markets across the U.S. To achieve this end, The CDFI Fund provides certification, equity investments, capital grants, loans, and technical assistance to CDFIs. CDFIs receiving funding and certification from the CDFI Fund are required to meet certain criteria as well as report operational data back to The CDFI Fund annually. The criteria that the CDFI Fund requires for certification of a CDFI are: 1) have a primary mission of community development 2) serve one or more target markets[2] 3) provide development services to borrowers as well as financial services and 4) maintaining accountability to a target market (CDFI Organizational Structures). CDFIs receive significant funding from other sources as well. Other funding sources are conventional financial institutions, other CDFIs, foundations, state and local governments, individuals, and investment intermediaries interested in socially responsible investment opportunities. These sources provide both equity and debt financing to CDFIs, and debt financing is generally provided at below market rates.

[2] Target markets refer to low-income populations, often including minority, migrant, or rural populations, that lack sufficient access to financial products or services. The precise definition can be found in statute 13 C.F.R. § 1805.201(b)(3).

Literature Review

Roles of CDFIs in the market place

Several viewpoints exist as to the role that CDFIs play in the financial market: as financing gap-fillers, conventional lending intermediaries, or as a substitute to conventional lenders. CDFIs were initially created to facilitate the role of filling the financing gap that communities in both urban and rural settings faced. Some evidence suggests that gap filling role has evolved and CDFIs work with conventional lenders using their connections and knowledge of local market conditions to connect underserved populations to the higher level of capital a conventional lender cannot supply. CDFIs may also be seen as substitutes or competitors to conventional financial institutions. Each of these roles are given more detail below.

Filling the Gap

CDFIs provide services in rural communities that lack access to banking services as well as urban communities. CDFIs have stepped in to serve the financial transaction needs of rural communities when conventional financial institutions had exited the market providing a needed capital source to the community (Ralston & Beal, 1999). CDFIs have also provided the small dollar mortgages for the sometimes exceptionally inexpensive houses in rural areas that conventional lenders would not provide due to lack of profitability (Wolff & Ratcliffe, 2008). More than just in rural communities, there is modest evidence that CDFIs target home lending to areas with low levels of reported loans from conventional financial institutions (Swack et al., 2014). CDFIs have even provided critical financing to fund charter schools as conventional lenders were not willing to provide financing (Donovan, 2008).

Partners and Intermediaries

The 1995 revision to the CRA made partnerships with CDFIs more desirable for conventional banks. Partnerships with CDFIs help banks fulfill the updated-CRA's community lending and investment criteria. Tax credits[3] for certain types of community development focused investments also make partnerships with CDFIs appealing enough for conventional lenders to accept below market rates of return. Due to the modified regulatory and incentive structure over the last several decades, conventional lenders have transitioned from being the culprits of disinvestment to partners in in serving CDFIs' target markets. Research has shown partnerships between conventional lenders and CDFIs to be mutually beneficial, helping conventional institutions fulfil CRA obligations, connecting conventional lenders to new potential clientele by bridging information gaps, and leading to an increase in the lending capacity of CDFIs (Mclenighan & Tholin, 1997; Newberger et al., 2008). However, Smith et al (2008) note that the bank-CDFI partnership may be quite largely grounded in the expectation that the CDFI will refer clients to the bank in the future after they have established a sound credit history with the CDFI.

Conventional lender-CDFI partnerships can take several forms. For example, some CDFIs partner with conventional lenders to provide a complementary subordinate mortgage covering a portion of the value of the home, lowering the borrower's overall interest rate and repayment risk taken on by the conventional lender (Benjamin et al., 2004). Other CDFIs and conventional lenders have also worked in tangent to fund purchase and renovation of vacant single-family homes and development of new rental units (Patterson & Silverman, 2007). Even partnerships between CDFIs and investment vehicles such as insurance companies, large

[3] Examples of such tax credits are the Low-Income Housing Tax Credit and New Markets Tax Credit.

commercial banks, and public pensions, with the CDFI acting in an intermediary role have been facilitated. One such partnership consisted of investor groups exchanging patient capital for socially responsible investment opportunities has shown to bear positive returns for investors and rural communities in New England (Steiger, Hebb, & Hagerman,2008). Another program consisting of a partnership between Fannie Mae, the Ford Foundation, and an established CDFI in North Carolina provided affordable mortgages to underserved borrowers (Stegman, Quercia, & Davis, 2007).

Substitutes and Competitors

Another view is that CDFIs act as alternatives to, or competition for conventional lenders. Large CDFIs may be competitors to conventional lenders for the tax credits that makes partnerships with smaller CDFIs appealing (Rubin, 2007). Also, community development banks and credit unions are more likely than community development loan funds to compete with small niche banks for depositors and borrowers because of the regulations disallowing depository institutions such as banks and credit unions from taking on as much risk in their investment portfolios (Smith et al., 2008). Some CDFIs see themselves as a necessary alternative to conventional lenders, representing a way for communities to express their preference for local control of capital (Benjamin, Rubin, & Zielenbach, 2004), while their private sector advocates tend to see CDFIs as unfairly receiving government funding.

CDFI Research

While still a burgeoning field of the community development scene, a growing number of studies have been conducted on CDFIs. Though most are conducted or contracted by the CDFI Fund or CDFIs themselves, academic interest in CDFIs have been growing as well. Many studies on CDFIs focus on their associated outcomes and impacts, as does much of the research on community development programs. In common nomenclature, these concepts may be somewhat interchangeable or synonymous. However, in community development research outcomes and impacts are distinct from each other. Here, outcomes are the direct effects of CDFI activities while impacts are the indirect, purported effects of CDFI activities.

Outcomes

Most research on CDFIs measure the more direct outcomes of their operations. Attribution of outcomes to CDFIs can be difficult, particularly in instances where the CDFI worked in conjunction with another organization such as a conventional lender to finance a project. However, research has connected CDFI activity to beneficial outcomes for neighborhoods, community organizations, and individuals. The literature tends to agree that CDFIs achieve their objective of providing financial products and services to underserved markets of LMI and minority borrowers. CDFIs direct the majority of their mortgage loans to LMI and minority neighborhoods, and more so than conventional lenders (Wolff & Ratcliffe, 2008; Campen & Callahan, 200; Swack, Hangen, & Northrup, 2014; Quercia et al, 2001). These findings are important in conjunction with Greer and Gonzales' (2017) findings that while lending patterns of conventional lenders continue to reinforce path dependent flows of credit to mostly white, middle income areas, CDFIs' pattern of lending focus on minority and LMI neighborhoods.

Services of CDFIs have been found to yield greater benefits to their lower income and less educated clients (Kolodinsky, Stewart, & Bullard, 2006). The underwriting flexibility that CDFIs provide can lead to an increase in financing available for traditionally LMI populations (Quercia et al, 2001). This flexibility has been associated to increased refinancing loans and business lending in CDFI lending areas in Washington D.C. (Holyoke, 2004) A CDFI in San

Francisco specializing in providing financial counseling and refinancing services to borrowers in the early stages of delinquency has led to lower than average redelinquency rates and over 80 percent of borrowers receiving counseling to avoid foreclosure (Gorey & Collins, 2007). A program run by a CDFI in Chicago to acquire foreclosed and vacant properties has had success in selling the rehabilitated units to new homeowners (Wolff & Ratcliffe, 2008). Other first-time homeowners attributed to CDFI financing and counseling have experienced real home equity gains and increased wealth (Stegman, Quercia, & Davis, 2007). CDFIs financial support of other community development organizations has also been critical to their existence in periods of declining funds from government sources (Liou & Stroh, 1998). In the CDFI Fund's 2016 year in review report, CDFIs receiving funding from the CDFI Fund were credited with financing over 33,000 affordable housing units and 11,000 businesses in fiscal year 2015.

Impacts

The beneficial outcomes of CDFI lending activity are generally believed to also lead to wider community impacts. Community development frameworks suggest that gains for individuals within a community translate into collective gains for the community (DeFillippis, 2004). Fewer studies have been conducted that examine the impact of CDFIs compared to outcomes of CDFIs because of the reduced feasibility of the analysis required. Impacts are difficult to measure due to the increasingly diffuse nature of benefits from CDFI intervention the further out from the initial transaction, increasing the analytical rigor necessary to make a causality claim. Regardless of these challenges, a few studies have focused on measuring impacts of CDFI activity, with mixed results. CDFIs focused on business development have shown to create modest employment growth in targeted communities (Caskey & Hollister, 2001; CEI, 2006). A qualitative study suggested that membership and degree of connectedness in community development credit unions have shown to have a positive impact in members' lives including improvements in income, housing, employment, optimism about the future of the community, and a variety of other quality of life measures (Kolodinsky, Stewart, & Bullard, 2006; Ralston & Beal, 1999). However, an impact analysis of Chicago's South Shore Bank, the first CDFI in America, did not show any results for the effectiveness in achieving neighborhood revitalization (Etsy, 1995).

Literature Gap

Though conducting robust impact analyses are difficult and subject to many pitfalls, they remain a worthwhile exercise, and when done well provide important evaluative information. With the intention of community development programs being the accrual of benefits to the community, research focused on just the production of outcomes lacks a broader evaluation of the community development mission CDFIs aim to achieve. To date, research on the impact of CDFIs have been few and small in scale. Porteous & Narain (2008) note that, "The evidence that increased financial intermediation at a local microlevel—such as a census tract—leads to positive social outcomes at that level has not yet been demonstrated" (p. 97).

This study aims to fill the research gap that Porteous & Narain (2008) describe by attempting to measure the impact of CDFI lending activity on neighborhood home values, since increased neighborhood home values show an increase in the area wealth and potential economic vitality. The main research question this study seeks to answer is: Do CDFI lending activities have a measurable impact on the communities they operate in? More specifically, does the presence of lending activity have measurable impact on neighborhoods' housing value? If so, does the volume of lending activity vary the level of impact on neighborhoods' housing values? By correcting market failures in the credit markets of communities, and generating positive production externalities and spillover effects, CDFI lending activity theoretically should create positive returns for the locations of their financing activity. The proceeding section describes the data and research design used to test these hypotheses.

Data & Methods

Geographies & Units of Analysis

The geographies of this study neighborhoods within the central counties of the metropolitan areas of Atlanta, Chicago, Dallas, Los Angeles, Minneapolis, New York, and Portland. These cities were chosen to create a cross-section of major metropolitan areas spanning the Eastern, Southern, Midwestern, and Western regions of the United States. The unit of observation is the census tract. Census tracts are small, relatively stable areas that have a population size that can range from 1,200 – 8,000, but tend to have about 4,000 inhabitants (Census Bureau). Census tracts provide a useful approximation of neighborhoods. While individuals don't conceptualize their communities or neighborhoods by their census tracts, using census tracts and smaller census bureau statistical areas as a neighborhood equivalents have been utilized in several studies of community development initiatives (Hanka et al., 2015; Kim, 2000; Hipp & Singh, 2014; Swack et al, 2014). While other, smaller geographic units may be more desirable, census tracts are small enough to approximate neighborhoods and capture differences in housing values as well utilize other data aggregated by census tract.

A portion of the analysis was conducted using a restricted sample of the LMI census tracts[4] of the seven metropolitan areas.[5] Designation of LMI tracts are based on the median

[4] LMI tract definition from HMDA and CRA regulations. In this analysis, a tract was determined to be LMI by dividing the 2005-2009 census tract median household income for a tract by the 2005 metropolitan area median household income obtained from the 2005 ACS. While using the metropolitan area household median income from 2000 would have been preferred, 2005 was the earliest year available.

[5] Summary statistics table for both the full and LMI sample can be found in the appendix.

income of the tract being at or below 80% of the area median income. This variable was calculated using the area median household income from the American Community Survey (ACS) data of the corresponding time period. If a census tract was ever an LMI tract during the period of analysis it was included in the restricted LMI sample.

Data Sources

Data pertaining to CDFIs were gathered from the CDFI Fund's Community Investment Impact System (CIIS) database. The CIIS is a web-based data collection system the CDFI Fund uses to evaluate grant-recipient CDFIs' operations. This database consists of both institution level data as well as transaction level data. The institution level data describes characteristics of the individual CDFI such as the location of the CDFI to the zip code level, the size of the institution, size of assets, outstanding liabilities, sources of capital, among other relevant financial variables. The transaction level data contains information on each financial transaction that an institution makes including the census tract of the location of the financing, the dollar amount of the transaction, terms of the loan, and borrower characteristics. All CDFIs receiving funding from the CDFI Fund are required to annually report financial and operational information through the CIIS. This detailed data has been gathered via the CIIS since its implementation in 2004, and is publicly available on the CDFI Fund's website.

All other data were gathered from the U.S. Census Bureau through their American FactFinder web application. Census tract housing valuation and control variables were gathered from the 2000 census to provide a baseline of neighborhood characteristics before the measured CDFI activity were implemented. Subsequent data were taken from the 2005-2009 and 2010-

2014 ACS 5-year estimates.[6] The data for the CDFI transactions were aggregated over the years to match the ACS 5-year estimate period.

Census tract boundaries often change over time between the decennial censuses to account for changes in population, and changed over the study's 2000-2014 period of analysis. To control for the census tract boundary differences between the 2000 and 2010 censuses, data associated with the 2010 census tract boundaries were cross-walked to their associated 2000 census tract boundaries using Brown University's Longitudinal Tract Data Base, developed by Logan, Xu and Stults (2014). All data denominated in dollars were adjusted to real values, adjusting for inflation using the U.S. Bureau of Labor Statistics Consumer Price Index Inflation Calculator. The relevant variables are all denoted in 2009 dollars.

Dependent Variable: Housing Valuation

The dependent variable is the median single-family housing unit price of the census tract. The housing price data obtained from the Census Bureau are based on self-reported values. Though the Census Bureau data are based on self-reports that tend to be consistently overestimated, there is not significant evidence to suggest that the overvaluation is related to any particular neighborhood characteristics, and thus will not bias coefficients for neighborhood characteristics (Goodman, & Ittner, 1992; Kiel & Zabel 1999), and are considered to be reasonable for usage as proxies of neighborhood home values (Hipp & Singh, 2014; Guierra, Hartley, & Hurst, 2010; Harris, 1999; Kim, 2000). Guierra, Hartley, & Hurst (2010) even found

[6] The data to construct these estimates were collected over a 60 month period. Non-overlapping periods were utilized to avoid the same microdata being used to construct temporally different census tract estimates. Other than the decennial census data, the ACS data estimates are the only ones produced by the Census Bureau at the census tract level, and were chosen for their more frequent occurrences. More details about the multiyear estimates can be found at https://www.census.gov/programs-surveys/acs/guidance/estimates.html

census data housing price appreciations to be similar to Case-Shiller repeated sales data and Zillow's hedonic housing value index data.

In this analysis, single-family housing values are utilized to capture community gains in neighborhood quality. Studies analyzing the impact of community development initiatives have used sale prices of single-family houses because evidence suggests neighborhood externalities are capitalized into property values (Galster et al., 2004; Grieson & White, 1986; Palmquist, 1992; Etsy, 1995). While the CDFI industry in large tends to focus on employment and housing outcomes, CDFIs can potentially impact many neighborhood quality indicators. However, a measure with an increased permanency, such as the gains capitalized in physical infrastructure, offers a better measure of the impact of CDFI activity due to the generally diffuse nature of other potential impacts of interest (Immergluck, 2006). For example, benefits to neighborhood employment levels are less constrained to the physical, geographical area of the investment than that of community gains in the structural characteristics of the neighborhood. Individuals that have experienced beneficial employment gains could leave the neighborhood and take those gains with them or even have initially resided in a different neighborhood.

Independent Variable of Interest: CDFI Activity

The main independent variable is the CDFI transaction activity. CDFI transactions that were included in the analysis had an indicated purpose of either business financing, home purchase loan, home improvement loan, commercial real estate financing, multi-family housing construction financing, single family housing construction financing, real estate rehabilitation financing, multi-family housing rehabilitation financing, and single family housing rehabilitation financing.[7] All transactions that were reported in each year for a census tract were aggregated by both the number of transactions and the dollar amount of the transactions. They were then aggregated over the five-year periods to temporally match the CDFI data to the Census Bureau data. In the models, CDFI activity is operationalized as a dichotomous variable denoting whether a census tract received any of the prior listed financing, and as a continuous variable of the dollar amount (in thousands) of the financing that the census tract received during the period.

Socioeconomic & Demographic Controls

Neighborhood socioeconomic and demographic characteristic variables were included in the analysis as controls. The socioeconomic and demographic control variables consist of the median income, unemployment rate, poverty level, population density, and the percent of the population that are recent residents. In the past, the non-white population has shown to have a negative correlation with owner occupied housing values and appreciation rates (Hipp & Singh, 2014; Harris, 1999; Kim, 2000; Meyers, 2004). This has been attributed to lower accessibility to other neighborhoods and perceived socioeconomic status. However, recently there has been evidence to suggest the negative relationship has dissipated, and that more racially homogenous minority neighborhoods increase area housing values (Hipp & Singh, 2014). The models include both a variable for the percent of the census tract population that are non-white and the square of the variable to account for these changing negative and positive relationships with the housing value. Median income is expected to have a positive relationship with the neighborhood housing value. Areas comprised of individuals with higher incomes should have the housing stock to match. The unemployment rate and poverty level are both expected to have negative relationships with the housing value. Residents without a steady or adequate income will likely

[7] Transaction purpose types that were not included were consumer loans, micro enterprise loans, and those categorized as “other”

not be able to reside in areas with high housing values. Population density can both represent higher demand for limited housing stock and signal desirability of living in the area, both would presumably lead areas of higher population density to also increase housing values.

Housing Characteristic Controls

Several variables of the census tract housing characteristics were included in the analysis as controls for neighborhood differences of a structural nature. These controls are: median age of housing units, vacancy rates, percent renter occupancy, and number of housing units. Age of the housing unit has shown to have a non-linear relationship with housing price and have either a positive or negative correlation depending on the extent of the agedness of the unit (Hanka et al., 2015). Initially age implies depreciation of the housing unit, however at some point increasing age of a unit comes to be seen as vintage, and more desirable (Hipp & Singh, 2014). Vacancy rates have been noted to have a negative effect on housing value (Shlay & Whitman, 2004; Han, 2013). High vacancy rates represent low demand for housing, blight, or potential financing issues. The number of housing units is expected to be positively correlated with the housing value; the larger the number of housing units the less demand for each individual unit. Higher proportions of renter occupancy is expected to lower the housing price. The more housing units occupied by renters, the more unstable or transient the population seems. Residents who have recently moved into the tract are expected lower prices. High turnover shows residential instability and should lower housing values (Hipp & Singh, 2014).

Analysis & Results

The analysis proceeds in three parts. To begin, baseline pooled regression models are presented, followed by a series of panel regressions models of both random and fixed effects specifications, and the analysis concludes with several specifications of a difference-in differences (DID) estimator.

Empirical Models

The empirical models of the analysis are as follows:

Pooled Regression Models 1-2 :

$$y_i = \beta_1 CDFI_i + \beta_k S_{k,i} + \beta_j H_{j,i} + \varepsilon_i$$

Panel Regression Random Effects Models 3-4:

$$y_{it} = \beta_1 CDFI_{it} + \beta_k S_{k,it} + \beta_j H_{j,it} + \beta_3 Period0509 + \beta_4 Period1014 + \varepsilon_{it}$$

Panel Regression Time Demeaned Fixed Effects Models 5-6:

$$(y_{it} - \bar{y}_i) = \beta_1(CDFI_{it} - \overline{CDFI}_i) + \beta_k(S_{k,it} - \bar{S}_i) + \beta_j(H_{j,it} - \bar{H}_i) + \beta_3 Period0509 + \beta_4 Period1014 + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

Panel Regression County Fixed Effects Models 7-10:

$$y_{it} = \beta_1 CDFI_{it} + \beta_k S_{k,it} + \beta_j H_{j,it} + \beta_c Co_{c,it} + \beta_3 Period0509 + \beta_4 Period1014 + \varepsilon_{it}$$

Difference-in-Differences Models 11-13:

$$y_{it} = \beta_0 + \beta_1 CDFIgroup_i + \beta_2 CDFItreat_{it} + \beta_3 Period0509 + \beta_4 Period1014 + \beta_k S_{k,it} + \beta_j H_{j,it} + \beta_c Co_{c,it} + \varepsilon_{it}$$

Where i subscripts individual census tracts; t subscripts the time period of observation and:

y_i is the median single-unit housing value in tract i

$\beta_1 CDFI_i$ is the independent variable of interest, either a dummy variable representing CDFI lending activity in the tract or a continuous variable of the total dollar amount of the aggregated CDFI loans during the period of observation

$\beta_k S_{k,i}$ is a set of socioeconomic and demographic control variables for k=1 to k variables

$\beta_j H_{j,i}$ is a set of housing characteristic control variables for j=1 to j variables

$\beta_c Co_{c,i}$ is a set of county level fixed effects from c=1 to c-1 counties

$\beta_1 CDFIgroup_i$ is a dummy variable where a 1 denotes tract i received CDFI financing over the period of study and a 0 if no CDFI financing was received over the period of study

$\beta_2 CDFItreat_{it}$ is a dummy variable where a 1 denotes that tract i received CDFI financing during period t and 0 if no CDFI financing was received during period t

$\beta_3 Period0509$ is a dummy variable for the 2005-2009 period of observation

$\beta_4 Period1014$ is a dummy variable for the 2010-2014 period of observation

ε_i is a random error term

What follows are the results of the statistical analysis. With each step, specifications of the estimation models are modified to incorporate robustness measures to eliminate sources of potential bias. One source of bias to the standard errors was addressed from the onset of analysis, and each model incorporates robust standard errors to control for heteroskedasticity[8]. The analysis was a highly iterative process, and the procession of the results section reflects that.

Pooled Regression Models

The results of the initial pooled regressions suggest CDFIs having a positive impact on the neighborhoods they serve. Both the measure of the CDFI transaction presence in the tract and the dollar amount of CDFI loans in the tract are statistically significant ($p<0.01$ for both variables) and positively correlated with the tract median housing value. The pooled regressions suggest that for every thousand dollars of CDFI financing in the tract the median housing price would increase by $5.62, and tracts that received any CDFI financing in a period have a housing value $10,012 higher than tracts that did not. Most of the socioeconomic and demographic controls are statistically significant and have the expected positive or negative relationship with

[8] White test results showed significant heteroskedasticity in the pooled regression. Though, likelihood ratio tests for heteroskedasticity were unable to be run in the panel regressions because of the large number of panels, robust standard errors were still used in these specifications to avoid risk of biased standard errors from heteroskedasticity.

the dependent variable, though most of the housing control variables are counter to their expected relationship.

Table 1 Pooled Regression Models

	(1)	(2)
Variables	Presence	Dollar
CDFI Activity in Tract	10,012***	
	(2,044)	
CDFI Dollar Amount		5.621***
		(0.900)
Sociodemographic Controls		
Median Household Income	5.195***	5.191***
	(0.0526)	(0.0526)
Unemployment Rate	-234.5	-180.7
	(212.1)	(210.3)
% Population Under Poverty Level	-1,409***	-1,428***
	(131.3)	(131.3)
% Minority Residents	161.2	177.9
	(109.0)	(109.0)
% Minority Residents^2	-1.808*	-1.921*
	(0.989)	(0.990)
Population Density	1.193***	1.193***
	(0.0690)	(0.0689)
% Population that Moved During the Period	-3,294***	-3,335***
	(90.90)	(90.13)
Housing Characteristic Controls		
Housing Units	-7.514***	-7.348***
	(0.746)	(0.743)
% Renter Occupied Housing Units	2,468***	2,449***
	(63.80)	(63.80)
% Vacant Housing Units	851.7***	857.0***
	(192.5)	(192.1)
Median Structure Age	2,391***	2,334***
	(253.8)	(253.8)
Median Structure Age^2	-5.228	-4.412
	(3.185)	(3.181)
Constant	-152,769***	-150,428***
	(8,846)	(8,844)
Observations	28,865	28,865
R^2	0.488	0.488

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel Regression Models

To build upon the pooled regression, panel regression specifications are utilized to control for time factors. Inclusion of a linear time trend variable in each model is used to control for potential time effects. Models 3 & 4 are random effects models. Models 5 & 6 have included census tract fixed effects, while Models 7-10 utilize less restrictive county level fixed effects.

Fixed effects models were used to control for non-time variant unobserved factors in each census tract and later for each county. Additionally, Models 9 & 10 are estimates derived from a restricted sample of just the LMI census tracts in the seven metro areas.

The estimates of the panel regressions in Table 3 contain a few unexpected results. In Model 3 the coefficient on CDFI loan presence actually becomes negative. In Model 5 and Model 6, with the included census tract fixed effects, both the coefficients on the CDFI variables are negative, though only the program variable is statistically significant. However, use of demeaned census tract fixed effects may not be optimal in this study. There are only three time periods allowing for a smaller chance of observing adequate within census tract variation. Since counties are the next smallest areal units, county fixed effects are incorporated in subsequent model specifications. With the county level fixed effects, the results of the dollar amount of the loans in the tract is continues to lack statistical significance, and the coefficient on the presence of the CDFI activity variable remains negative and statistically significant.

Selection bias may be causing the coefficient on the CDFI activity dummy variable to be negative in these models. Since CDFIs generally target their products and services to underserved areas, I excluded the higher income census tracts that would generally not have, or necessarily benefit from, any CDFI lending activity within them anyway. Each of the proceeding models are derived from the sample restricted to just the LMI census tracts of the seven metropolitan areas. The results of Models 9 & 10, of the LMI sample, do not estimate a significant relationship between the CDFI variables and neighborhood housing value, though the relationship between the CDFI activity variable and the tract median housing value continues to be negative.

Table 2 Panel Regression Models

Variable	(3) RE Presence	(4) RE Dollar	(5) FE Presence	(6) FE Dollar	(7) County FE Presence	(8) County FE Dollar	(9) LMI Co. FE Presence	(10) LMI Co. FE Dollar
CDFI Activity in Tract	-8,643***		-9,220***		-11,220***		-8,621***	
	(1,439)		(1,352)		(1,355)		(2,190)	
CDFI Dollar Amount		0.0369		-1.230		-0.948		0.186
		(0.750)		(0.823)		(0.694)		(0.699)
Sociodemographic Controls								
Median Income	3.843***	3.848***	1.811***	1.807***	3.422***	3.425***	1.881***	1.882***
	(0.0628)	(0.0629)	(0.0898)	(0.0898)	(0.0569)	(0.0569)	(0.164)	(0.164)
Unemployment Rate	-1,495***	-1,530***	-1,172***	-1,199***	-1,429***	-1,461***	-1,244***	-1,276***
	(184.4)	(184.8)	(177.9)	(177.7)	(190.6)	(190.7)	(234.2)	(234.0)
percent of population under poverty level	-1,098***	-1,099***	-1,409***	-1,413***	-424.1***	-427.1***	-843.8***	-841.6***
	(118.6)	(118.6)	(133.0)	(133.2)	(110.5)	(110.7)	(156.2)	(156.2)
% minority residents	-1,299***	-1,268***	-1,252***	-1,210***	-2,571***	-2,554***	-2,720***	-2,720***
	(107.2)	(107.3)	(143.6)	(143.6)	(104.0)	(104.1)	(209.9)	(210.0)
% minority residents^2	9.777***	9.475***	13.21***	12.89***	15.42***	15.18***	17.68***	17.65***
	(0.895)	(0.896)	(1.020)	(1.021)	(0.844)	(0.845)	(1.528)	(1.529)
Population Density	1.392***	1.390***	0.929**	0.920**	-0.161	-0.153	0.0461	0.0525
	(0.0846)	(0.0845)	(0.422)	(0.420)	(0.101)	(0.101)	(0.112)	(0.112)
% population that moved during the period	-358.2***	-372.3***	-494.9***	-499.5***	-574.5***	-589.6***	14.80	-1.206
	(84.09)	(84.01)	(88.14)	(87.98)	(86.63)	(86.64)	(165.7)	(165.7)
Housing Characteristic Controls								
Housing Units	-11.39***	-11.56***	-13.10***	-13.38***	-3.757***	-4.044***	-9.842***	-10.13***
	(0.990)	(0.987)	(1.791)	(1.789)	(0.734)	(0.735)	(1.525)	(1.528)
% renter occupied housing units	2,095***	2,088***	349.2***	342.8***	1,572***	1,565***	1,375***	1,368***
	(76.06)	(76.02)	(112.9)	(113.1)	(63.95)	(63.99)	(88.97)	(88.88)
% vacant housing units	-925.0***	-912.7***	-1,697***	-1,690***	279.8	289.6	-1,055***	-1,055***
	(184.5)	(184.8)	(174.6)	(174.7)	(180.0)	(180.3)	(191.1)	(190.8)
median structure age	708.7***	762.1***	-2,892***	-2,845***	-1,347***	-1,291***	-3,319***	-3,236***
	(238.5)	(239.0)	(297.0)	(297.5)	(223.4)	(223.8)	(395.0)	(393.4)
median structure age^2	12.36***	11.55***	43.17***	42.45***	26.35***	25.50***	42.76***	41.60***
	(2.890)	(2.897)	(3.191)	(3.196)	(2.625)	(2.630)	(4.446)	(4.419)
2005-2009 Time Dummy	141,603***	139,933***	138,449***	136,839***	147,168***	145,221***	140,090***	138,129***
	(2,045)	(2,021)	(2,415)	(2,391)	(2,072)	(2,058)	(3,101)	(3,076)
2010-2014 Time Dummy	80,551***	77,786***	76,571***	73,877***	89,341***	86,064***	87,022***	83,559***
	(2,387)	(2,337)	(3,097)	(3,058)	(2,406)	(2,375)	(3,496)	(3,430)
Constant	-66,489***	-67,090***	221,955***	221,752***	188,251***	187,978***	313,179***	312,887***
	(9,757)	(9,750)	(13,672)	(13,674)	(10,713)	(10,724)	(18,404)	(18,385)
Observations	28,865	28,865	28,865	28,865	28,865	28,865	11,706	11,706
Number of geoid	10,597	10,597	10,597	10,597	10,597	10,597	4,540	4,540
R-squared			0.540	0.539				

Robust standard errors in parentheses
County Fixed Effects not displayed to save space
*** p<0.01, ** p<0.05, * p<0.1

Difference-in-Differences Models

Impact analysis of community development programs have been strongly recommended to have a counterfactual to better measure the effect of the intervention by estimating what would have happened in the absence of the program (Hollister & Hill, 1995; Immergluck, 2006). A DID estimator is one method of doing this. Use of a DID model can estimate the counterfactual case, and the impact of CDFI activity by comparing the differences in the trajectory of the median housing value over the period study between census tracts that received CDFI financing during the period of study—the treatment group, and census tracts that did not receive CDFI financing during the period of study—the control group. This method produces the average treatment effect of the treated, specifically the average impact of CDFI activity on the median housing value for the census tracts that receive financing.

In addition to the classical OLS assumptions, the parallel trends assumption is important for DID models. The parallel trends assumption implies that the average change of the control group can be taken to represent the counterfactual change of the treatment group because both groups are subject to the same broad trends over time. Analyzing pre-treatment trends are often utilized to test if the parallel trends assumption hold. However, due to the inability to analyze pre-treatment trends, this analysis is constrained to deductively conclude that the assumption likely holds through use of the LMI tract restricted sample. The CDFI variable as the treatment effect is still represented as both a dummy treatment variable and as a continuous, dosage treatment variable based on the dollar amount of CDFI lending in the tract.

Table 3 shows the results of the initial DID estimates. The results for Model 12 shows the CDFI activity variable in dollars continues to be positive, though much smaller in magnitude, and statistically non-significant. The negative overall effect of the CDFI program dummy is still prevalent and statistically significant (p<0.01) as shown in Model 11. The coefficient on the variable suggests that on average census tracts in the treatment group would have a median housing value $7,841 higher if the CDFI had not made any transactions in the tract.

Table 3 DID Models

	(11)	(12)
Variables	Presence	Dollar
CDFI Activity Treatment Effect	-7,841***	
	(2,698)	
CDFI Dollar Treatment Effect		0.687
		(0.684)
CDFI Treatment Group	-4,785*	-8,662***
	(2,895)	(2,689)
Sociodemographic Controls		
Median Income	0.713***	0.723***
	(0.229)	(0.229)
Unemployment Rate	-1,471***	-1,499***
	(257.0)	(256.9)
% Population Under Poverty Level	-1,019***	-1,009***
	(176.6)	(176.6)
% Minority Residents	-2,232***	-2,216***
	(305.5)	(304.7)
% Minority Residents^2	13.14***	13.06***
	(2.189)	(2.184)
Population Density	0.0423	0.0487
	(0.121)	(0.122)
% Population that Moved During the Period	-145.6	-162.4
	(240.7)	(240.4)
Housing Characteristic Controls		
Housing Units	-9.738***	-9.819***
	(1.739)	(1.742)
% Renter Occupied Housing Units	1,172***	1,165***
	(96.85)	(96.73)
% Vacant Housing Units	-1,152***	-1,148***
	(211.7)	(211.4)
Median Structure Age	-2,736***	-2,667***
	(484.5)	(482.7)
Median Structure Age^2	35.71***	34.87***
	(5.420)	(5.395)
2005-2009 Time Dummy	142,700***	140,304***
	(3,679)	(3,630)
2010-2014 Time Dummy	87,627***	83,699***
	(4,073)	(3,946)
Constant	351,926***	352,335***
	(22,159)	(22,158)
Observations	8,929	8,929
Number of geoid	4,394	4,394

Robust standard errors in parentheses
County Fixed Effects not displayed to save space
Low and Moderate Income Tract Sample
*** p<0.01, ** p<0.05, * p<0.1

Another possible scenario may be that the dollar effect of CDFI financing in communities may have a non-linear relationship with the housing value in the community. There may exist a sort of investment threshold that needs to take place within a neighborhood before positive effects can be accrued to the neighborhood. Immergluck (2006) noted that these two possibilities should be addressed when analyzing CDFI lending. To incorporate these possible factors, an additional DID model with a quadratic term for CDFI loan amount is specified. The results of the model estimates are described by Model 13 in Table 4.

Even though the average treatment effect of the CDFI program is still negative, Model 13 suggests that the dollar value of the CDFI activity does at a point have a positive relationship with the median tract housing value. The inflection point where the estimated dollar value of CDFI transactions in a tract changing from a negative to a positive relationship with the median housing value is at $6,038,780. Though, the inflection point is determined to not be significantly different from zero (p<=0.332).

Table 4 Quadratic DID Model

Variables	(13) Dollar
CDFI Dollar Treatment Effect	-0.820
	(1.151)
CDFI Dollar Treatment Effect²	6.79e-05**
	(3.09e-05)
CDFI Treatment Group	-8,264***
	(2,698)
Sociodemographic Controls	
Median Income	0.725***
	(0.229)
Unemployment Rate	-1,487***
	(256.1)
% Population Under Poverty Level	-1,007***
	(176.6)
% Minority Residents	-2,226***
	(304.8)
% Minority Residents²	13.15***
	(2.185)
Population Density	0.0470
	(0.122)
% Population that Moved During the Period	-159.3
	(240.5)
Housing Characteristic Controls	
Housing Units	-9.758***
	(1.745)

table 4 continued	
% Renter Occupied Housing Units	1,167***
	(96.74)
% Vacant Housing Units	-1,155***
	(211.3)
Median Structure Age	-2,679***
	(483.2)
Median Structure²	35.01***
	(5.401)
2005-2009 Time Dummy	140,499***
	(3,626)
2010-2014 Time Dummy	84,175***
	(3,945)
Constant	352,359***
	(22,161)
Observations	8,929
Number of geoid	4,394

Robust standard errors in parentheses
County Fixed Effects not displayed to save space
*** p<0.01, ** p<0.05, * p<0.1

The Figure 4 graphs[9] provide further context to the relationship. The graph on the right shows the range of the levels of CDFI dollars that census tracts in the LMI sample have received, and their relationship with the median housing value holding the control variables at their averages. The graph on left is a close up of the right-side graph, displaying the lower range of CDFI lending amount and centers around the estimated inflection point. The graph on the left illustrates why the inflection point was not statistically significant. As the CDFI transaction dollar amount increases, the associated confidence intervals broaden as well. From this, the failure for the null hypothesis to be rejected can be observed visually. At each point, the bounds of the confidence interval contain the median housing value associated with zero dollars of CDFI activity suggesting negative or otherwise, the relationship between median housing value and low levels of CDFI financing is not statistically significant. However, at increasingly large CDFI transaction amounts, the relationship is positive and statistically significant. The right-side graph shows, and a t-test confirms, that at $30,000,000 in CDFI transactions the effect on the median housing value becomes significantly different from $0 of CDFI transactions. However, this value

[9] The graphs were generated using STATA's margins and marginsplot commands.

is on the higher end of the spectrum of the dollar amount of CDFI transactions in the LMI sample of census tracts. The median total dollar amount of financing in treatment group census tracts during a period of receipt is $272,686, well below the threshold of tract level positive returns.

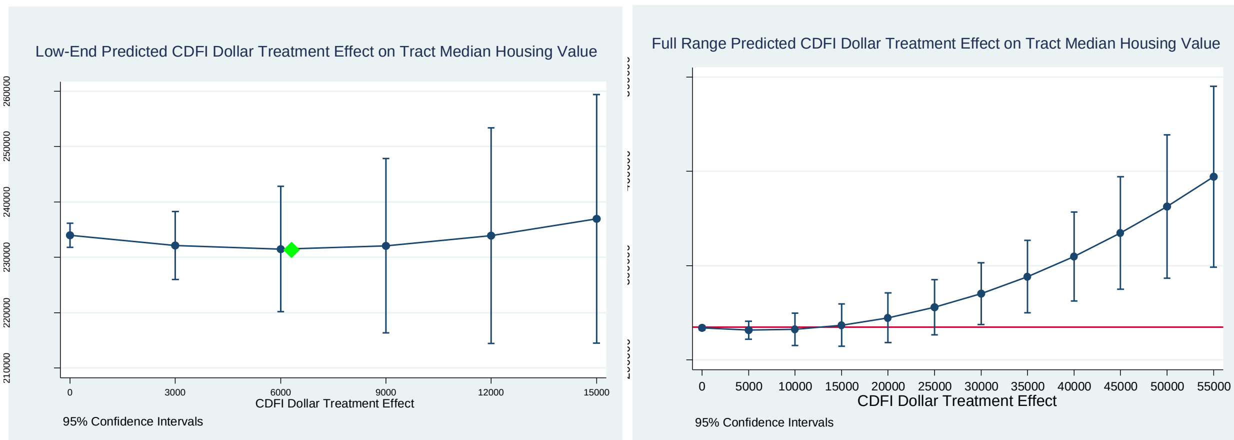

Figure 4 Graphs of the predicted marginal effects of CDFI dollar treatment

Discussion

Interpretation of Results

The results of the analysis have several, potentially significant implications. The first is that as Immergluck (2006) suggested, there may be a threshold to CDFI lending impacts. There may be a level of CDFI loanable funds that a census tract would need receive before realizing neighborhood effects in the form of a higher median housing value. An implication of this may be that only very large CDFIs that can provide huge amounts of financing within a census tract will produce positive neighborhood effects capitalized in housing prices for the census tract.

A second implication of these results is that CDFIs seem to either target activity to tracts with lower home value growth, or cause lower home value growth. If CDFIs can or are deliberately holding down home value growth it may be to curb neighborhood gentrification. Gentrification can transform the place for by removing the previous community and replacing them with a new group (Hollister & Hill, 1995; Immergluck, 2006), so even if the place improves, the people do not. Management for a CDFI in Chicago has previously claimed that their operations had held intentionally held housing prices down to make the houses more affordable and add lending security to the CDFI, though this claim is noted to be fairly dubious (Etsy, 1995). The more likely explanation is that CDFIs target the bulk of their products and services to the worse off LMI neighborhoods experiencing low growth in home values. It may be that CDFIs are facilitating a safety net role and more aggressively target their financing activity to buoy declining neighborhoods. This would cause a problem of simultaneity bias, creating an endogeneity problem, biasing the analysis, and makes robust inferences from the results inadvisable.

Methodological Limitations

Outside of the possibility of an endogeneity problem, the study has a number of limitations that should be noted. Several significant methodological weaknesses plague the analysis, and may be further biasing the estimates. The data measurements in this research are a primary concern. The data from the Census Bureau that are constructed from 5-year estimates increase the difficulty of measuring precise changes. Additionally, the CIIS data on CDFI transactions only include CDFIs that have received grant funding from the CDFI Fund. This results in the exclusion of certified CDFIs that have not received grant funding from the CDFI Fund as well as non-certified CDFIs. Only CDFIs that have received an award from the CDFI

Fund within the past three years are required to report detailed data to the fund, though many continue beyond the required time. This can lead to CDFI activity arbitrarily coming in and out of the dataset depending on which years they were funded and result the appearance of CDFI lending activity disappearing from a neighborhood over the period of analysis, even though in actuality the neighborhood still received financing. The lack of accuracy and precision in the measurements of variables undermine confidence in the models producing robust estimates.

There are also important control variables that were not included in any of the models that may be causing omitted variable bias. Crime, particularly violent crime, has shown to substantially lower neighborhood housing values (Lynch & Rasmussen, 2001). The quality of local public schools has also shown to impact area housing prices (Jud & Watts, 1981). Measures of existing conventional lending to the census tracts, for institutions fulfilling their CRA requirements without CDFI partnership, is an important missing variable in these models as well. Inclusion of these variables would likely have provided more accurate estimates, but data of these measures are not broadly available.

Aspects of the empirical models used in this analysis could also be improved upon. None of the regression models had controls for spatial correlation or spatial lag,[10] which has been noted to be of concern with neighborhood level analysis (Kingsley, Coulton & Pettit, 2014). The ability to fully incorporate fixed effects in most of the model specifications may also offer a means for analytical improvement. Meyers (2004) notes that even when neighborhood characteristics are controlled for as thoroughly as possible, random effects estimators are likely to be biased and inconsistent. Changes of raw dollar values may be misleading as well, and

[10] This in part was due to limited software capability to create a correlation matrix with the large number of census tracts in the analysis.

percent changes should be included for context in analyses using housing prices as a dependent variable (Hanka et al, 2015). A longer period of analysis with more time periods would increase the ability to fixed effects and percent changes, however the nature of the inconsistent reporting of CDFI transaction data may make this infeasible. Additionally, Census tracts may be too large of a unit to analyze CDFIs' impact on neighborhood effects. Assets of CDFIs are typically on par with a small community bank making the likelihood of measurable impact in each area quite low (Hollister, 2007). Smaller units of analysis such as census blocks, or block groups may be better suited to this type of analysis in measuring neighborhood effects.

Conclusion

While the question of broader neighborhood impacts may not have been settled with this study, other research has still shown strong evidence for the efficacy of CDFIs as a means to foster access to credit markets for underserved groups. Considering their beneficial roles in connecting individuals and communities to capital, the continued operational capacity of CDFIs should be supported, and perhaps even increased. The vast majority of CDFIs are dependent on outside funding, and volatility in the supply of funding poses challenges to conducting their operations. The CDFI Fund budget is subject to volatility, varying greatly from one administration to another (Smith et al., 2008). Foundations have cut back on grants and investing to CDFIs. Banks have cut back on their equity investments to CDFIs, instead offering near market rate term loans. Continued consolidation of the banking industry also limits sources of CDFI capital as the number of potential sources of funding from conventional financial institutions decreases (Smith et al., 2008). CDFIs are also quite vulnerable to market forces. During the Recession, a number of community development credit unions were forced to merge or liquidate (Rosenthal, 2012), and a large portion of microenterprise and venture capital focused CDFIs, ones exposed to higher risk, are defunct and no longer operating (Bates, 2000).

The relatively small size and scope of the CDFI industry limits the ability for these institutions to correct for all the credit market failures within the U.S. Despite the considerable growth since its inception, the CDFI industry remains quite small relative to the size of conventional lenders. A difference of the dollar amount loaned for housing endeavors between the two groups is in the hundreds of billions (Swack et al, 2014). O'Connor (1999) notes that targeted community-based programs are often undermined by broader economic policies favoring deregulated markets leading toward capital flight in LMI neighborhoods. A sentiment shared by Taibi (1994) who suggested that CDFIs are just a more efficient way of delivering social services to the poor, not a way of challenging the financial structure that marginalized them in the first place.

Policy Recommendations

While increasing the budget of the CDFI Fund may be the best method of supporting the operational capacity of CDFIs, there are other potentially more feasible policy options available that can be implemented. To increase the capacity of the CDFI industry several modifications should be made to the CRA. The requirements of the CRA should be expanded beyond just banks and apply to other financial institutions. The financial market has evolved since the initial implementation of the CRA, and while several revisions to the law have been made, the CRA still only applies to banks. Other financial institutions also engage in mortgage originations, small business lending, and other consumer financing and are not required to comply with ensuring they invest in the full-range of their service areas, including LMI and minority areas. At a minimum, the CRA should be expanded to apply to all institutions that generate mortgages and individual loans, such as mortgage-brokers, finance companies, and even some insurance companies. Details of the CRA examinations for these institutions would need to be further thought out, but the federal agency that could take regulatory charge of CRA examinations for these financial institutions would most sensibly be the Consumer Financial Protection Bureau (CFPB). The CFPB already currently has jurisdiction of conducting CRA examinations and maintains channels for monitoring and prosecuting discriminatory financial behavior. An expanded CRA would channel financing from financial institutions to LMI areas on their own to comply with regulations, but also increase the opportunity for CDFIs to partner with other financial institutions to bring financing to underserved markets.

An additional change to the CRA that could foster conventional lender-CDFI partnerships is a CRA tradeable obligation scheme as proposed by Klausner (2009). Based on the same principle of pollution abatement cap and trade schemes, a CRA tradeable obligation scheme would assign financial institutions quotas of CRA obligations for lending, investment, and other services based on the needs of the community and the expected cost of meeting those needs. Financial institutions that find these provisions to be too costly can pay other financial institutions that can more cost-effectively provide those products and services to provide some, or all of their CRA obligations. Under this scheme, CDFIs can receive payment from conventional lenders to provide the products and services that their organizational missions already lead them to do, or engage in a partnership with conventional lenders, assisting them with fulfilling their own CRA obligation. Through these modifications to the CRA, CDFIs can expand their partnerships with conventional lenders, or their funding from conventional lenders to support their operations and continue to connect underserved markets to adequate financial products and services.

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Appendix

Appendix Table Summary Statistics

	Full Sample					LMI Sample				
Variables	N	mean	sd	min	max	N	mean	sd	min	max
Median Housing Value	33,456	319,127	182,109	9,500	1239382	14,672	259,2010	159,250	9,500	1144322
CDFI Financing	35,337	0.196	0.397	0	1	15,804	0.251	0.433	0	1
CDFI Financing Dollars	35,337	159.6	1,034	0	52,735	15,804	251.75	1,379	0	5,2734
Median Household Income	34,932	63,130	30,746	2,266	247,000	15,448	39,124	13,359	2,266	215,200
Unemployment Rate	34,915	7.574	5.783	0	100	15,433	10.185	6.938	0	100
Poverty Rate	34,926	15.46	170.6	0	100	15448	26.29	254.68	0	100
% Minority	35,114	48.82	32.45	0	100	15591	69.88	27.80	0	100
Population Density	35,254	15,912	23,911	0	232,212	15725	23,767	27,688	0	232,212
% Population Moved in Period	34,925	12.94	316.9	0	59,200	15446	11.04	476.34	0	59,200
Housing Units	35,281	1,785	1,129	0	25,345	15752	1,569	953.34	0	12,799
% Renter Occupied Housing Units	35,113	40.61	27.03	0	100	15590	59.66	22.87	0	100
% Vacant Housing Units	35,047	7.176	7.137	0	100	15529	9.102	7.741	0	100
Median Structure Age	30,055	40.64	15.17	0	73	12370	44.71	13.81	0	73
Census Tracts	11,779					5268				