Using Credit Reporting Agency Data To Assess the Link Between the Community Reinvestment Act and Consumer Credit Outcomes

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Abstract

We use a regression discontinuity design to investigate the effect of the Community Reinvestment Act (CRA) on consumer credit outcomes, using data from the Federal Reserve Bank of New York's Consumer Credit Panel database (hereafter, CCP/Equifax data) for the years 2004 to 2012. A bank's activities in census tracts with Median Family Incomes (MFIs) that are less than 80 percent of the metropolitan statistical area (MSA) MFI count toward a lending institution's compliance with CRA rules. Discontinuous changes in consumer credit outcomes at this threshold—assuming census tracts with MFIs at 79.9 percent of the MSA median are the same as census tracts at 80.0 percent, except for CRA eligibility—are evidence of the CRA's impact. We find no statistically significant effects of the CRA on mortgages or foreclosures, either before or after the financial crisis. We do, however, find evidence that the CRA expanded broad measures of credit market activity; at the CRA threshold, the total number of loans increased 9 percent, the number of people covered by the CCP/Equifax data increased, and the fraction of individuals with a valid risk score increased. Despite expanded credit activity, which may increase consumers' risk for adverse outcomes, delinquencies did not significantly increase, nor did credit risk score worsen at the CRA threshold.

Introduction

Access to credit is critical to a well-functioning economy. It enables consumers to smooth their consumption over good and bad times, businesses to invest and expand, and individuals to become homeowners. Consumers and businesses in lower-income areas tend to have less access to credit than their higher-income counterparts. Although it may make sense that lenders are more willing to lend to those whom they have high confidence will be able to repay the loan, it is possible that, from a societal perspective, access to credit is less in low-income areas than is optimal for economic growth. If market failures occur in low-income areas such that lenders do not serve individuals who are nonetheless "credit worthy," then policy intervention has a role in increasing lenders' incentives to lend in those areas. The Community Reinvestment Act[1] (CRA), enacted in 1977, is an example of such a policy. The goal of the CRA was to encourage depository institutions to help meet the credit needs of their local communities, including low- and moderate-income (LMI) neighborhoods.

Over the years, the CRA has attracted broad interest from researchers and policymakers. We seek to determine if it has been effective in expanding access to credit in lower-income areas.

Much of the research on the CRA has focused on mortgage lending. This article adds to the literature by examining broad measures of consumer credit market activity available in the Federal Reserve Bank of New York's Consumer Credit Panel (CCP). The longitudinal database, comprising individual credit records maintained by Equifax, is a nationally representative 5-percent sample of individuals with consumer credit records (hereafter, CCP/Equifax data). The database allows for us to examine a rich set of consumer credit outcomes, including mortgages and foreclosures, total number of trades (accounts), delinquencies, and credit risk scores.

The main challenge in determining whether a policy like the CRA has had a salutary or adverse effect is that people living in LMI areas who are the targets of the policy are likely to have different outcomes from people living in higher-income areas, for reasons that have nothing to do with the policy. We need a way to compare outcomes in areas that are likely to be the same, with the sole exception being that one group is affected by the CRA and one is not. In this study, we use a feature of the CRA eligibility rules to create only such comparisons. A census tract is considered LMI, and activity in that census tract will count toward a depository institution's CRA activities, if the MFI in that census tract is less than 80 percent of the Area Median Family Income (AMFI).[2] This creates the potential for using a regression discontinuity design; we can examine whether a discontinuous change in consumers' outcomes exists for those in neighborhoods that are slightly below that 80-percent cutoff—which are thus in CRA-eligible areas—compared with those in neighborhoods at or above 80 percent , which are not in CRA-eligible areas. If we assume that people in neighborhoods where MFI is at 79 percent of the AMFI are unlikely to be very different from people in neighborhoods where MFI is at 80 percent of AMFI, this comparison gives insight

[1] Pub. L. 95–128, 91 Stat. 1147, Title VIII.

[2] For census tracts in metropolitan areas, the AMFI is the median for the metropolitan area. For census tracts outside of metropolitan areas, the AMFI is the median for all tracts outside of metropolitan areas.

into the causal effect of the CRA on credit outcomes. Further, we can use this methodology to examine whether the effect of CRA eligibility is different before and after the financial crisis.[3]

We find evidence that the CRA expanded access to credit in LMI neighborhoods. Neighborhoods (census tracts) that barely meet the CRA-eligibility criteria have 9 percent more accounts overall than do neighborhoods that are immediately outside the eligibility threshold. Further, more people in the CCP/Equifax data are in neighborhoods that barely meet the CRA eligibility threshold, and the data are of higher quality with fewer missing values. We see no statistically meaningful increase in delinquencies, mortgages or risk of foreclosures, or changes in credit risk scores in census tracts at the CRA eligibility threshold. Additionally, no evidence emerges of an adverse *change* in foreclosures at the CRA eligibility threshold with the financial crisis in 2007.

The next section presents background on the CRA. The section that follows describes the CCP/Equifax data and presents summary statistics. We then discuss the regression discontinuity methodology. The subsequent section presents the results, followed by a discussion and conclusion section.

Background

The CRA was enacted in 1977 to encourage depository institutions to help meet the credit needs of their local communities, including LMI neighborhoods.[4] The CRA created an affirmative obligation for banks to provide credit in LMI communities without establishing minimum targets of lending or investment.[5] Institutions that are regulated by the federal government are affected by CRA rules.[6] The CRA is enforced through regulators' periodic examination of banks' records, and an institution's CRA rating is taken into account when it applies for deposit facilities, including for mergers and acquisitions. Thus, an institution's CRA compliance has an effect on its future business options.[7]

The CRA has gone through three major changes over the past three decades. In 1989, Congress required regulators to prepare a detailed written evaluation of lenders' CRA performance and mandated public disclosure[8] of CRA ratings and evaluation, making it easier for the public to observe whether banks were compliant. Further, regulatory changes in 1995 (effective in 1997) revised CRA examination of banks, establishing a three-pronged test for large institutions based on performance in the areas of lending, investments, and services, a change intended to make the examinations more objective. As part of the CRA reform, the spatial emphasis was modified to include in

[3] Note that CRA eligibility applies to both LMI individuals and individuals who live in LMI census tracts. In this study, we focus only on the latter because the CCP/Equifax data do not include information on family income, only on the current census tract.

[4] The CRA was enacted in response to claims of *redlining* practices: that is, banks' refusal to lend to potential borrowers living in low-income, minority communities (Barr, 2005).

[5] Congress argued that the CRA would be a reasonable quid pro quo for the federal benefits that banks receive, such as federal deposit insurance and the Federal Reserve's discount window (Bernanke, 2007).

[6] In addition, six states have enacted CRAs at the state level: Connecticut, Massachusetts, New York, Rhode Island, Washington, and West Virginia. Connecticut and Massachusetts have also enacted similar laws that apply to credit unions. Massachusetts is the only state that, since 2007, has also had CRA-like exams for residential mortgage lenders.

[7] In the 1980s, 8 of 40,000 applications were denied due to CRA concerns (Essene and Apgar, 2009).

[8] Public disclosure of CRA ratings and evaluations began in 1990.

the evaluation loans to LMI *borrowers* regardless of the economic status of their neighborhoods (Friedman and Squires, 2005). In 2005, a new category of small banks, *intermediate small institutions*, was created; they are subject to a lending test and a new community development test.

Enforcement: CRA Examinations

Three federal agencies are responsible for enforcing the CRA. The Board of Governors of the Federal Reserve System (FRS) supervises banks with state charters that are members of the FRS; the Federal Deposit Insurance Corporation, or FDIC, supervises banks with state charters that are not members of the FRS; and the Office of the Comptroller of the Currency, or OCC, supervises banks with charters from the federal government. All three regulators follow nearly identical rules to implement the CRA.

Examiners review lenders' activities in lenders' assessment areas. Assessment areas consist of metropolitan statistical areas (MSAs), metropolitan divisions, or contiguous political subdivisions in which the institution has its main office, branches, or deposit-taking ATMs, as well as surrounding geographies in which the institution originated or purchased a substantial portion of its loans.[9]

Regulators evaluate the compliance of large institutions through tests of their lending, investments, and banking services.[10] Under the lending test, regulators look at the volume of each type of loan made or purchased by the institution within its assessment area. Examiners analyze the loans' geographic and income distribution, looking at the share of consumer and mortgage loans made in LMI geographies and the share of loans made to LMI borrowers whose median income is less than 80 percent of the median for their MSA, regardless of their neighborhoods' LMI status (Friedman and Squires, 2005). Examiners take into account mortgages, small business loans, and community development lending.

Under the investment test, examiners review the degree to which investments serve LMI areas or individuals. The service test determines whether the institution provides adequate services to LMI borrowers and in LMI areas by looking at the distribution of the institution's branches, its record of opening and closing branch offices, and the accessibility and use of alternative systems for delivering retail banking services.[11] Although much of the research on the CRA focuses on mortgage lending, keep in mind that large institutions get CRA credit for services provided to LMI borrowers and borrowers in LMI areas. There are reasons to think that the CRA may have effects beyond mortgage lending.

Based on the outcome of the review process, regulators give lending institutions a rating of "Outstanding," "High Satisfactory," "Low Satisfactory," "Needs to Improve," or "Substantial Noncompliance." According to the Federal Financial Institutions Examination Council (FFIEC) database, of the 69,792 banks examined between 1990 and 2012, 15.3 percent were rated Outstanding and 80.7 percent were rated either High Satisfactory or Low Satisfactory. The vast majority of banks were in compliance with CRA rules.

[9] Pub. L. 95–128, 91 Stat. 1147, Title VIII, § 228.41, assessment area delineation, as amended effective January 1, 2010.

[10] Large institutions are defined as those with $250 million or more in assets. Small banks are assessed on lending activities. More information on examination procedures is available at the CRA examination overview page on the Federal Financial Institutions Examination Council (FFIEC) website, http://www.ffiec.gov/cra/exam_overview.htm.

[11] Examples of alternative delivery systems for services include proprietary and nonproprietary ATMs, loan production offices, banking by telephone or computer, and bank-at-work programs.

Effects of the CRA

The effect of the CRA on neighborhoods, consumers, and banks has been a topic of controversy. If the credit market is fraught with market failures, then private banks that seek to maximize profits will not supply the optimal amount of credit; thus, government intervention has an important role to play.[12] Theoretically, it is reasonable to believe that credit markets bear many of the traits of markets that would be plagued by market failures; information is incomplete and asymmetric, for example, about consumers' ability to pay back a loan. If information is difficult to gather and analyze, then banks may end up using rules of thumb about the likelihood of a consumer being able to pay back a loan, and those practices may result in "statistical discrimination," whereby, because individuals belong to a race or ethnic group, for example, that is statistically more likely to default and less likely to be able to pay back a loan, they are less likely to get a loan, despite the fact that if their own circumstances were fully understood, they would be deemed creditworthy. Proponents of the CRA and other interventions argue that these policies help to address these market failures and lead to better economic outcomes. Critics say government intervention in the credit markets, including (but not limited to) the CRA, played a major role in the financial crisis (see, for example, Leibowitz, 2008). These critics suggest that government policies, like the CRA, gave banks an incentive to adopt unsafe lending practices in the name of extending credit to underserved communities. Criticism from another perspective suggests that the CRA has had little impact on access to credit because bank lending may simply crowd out lending that would have taken place through other institutions, resulting in little overall increase in lending to LMI neighborhoods and consumers. These two streams of criticism suggest two important and basic questions for research to answer; first, does the CRA actually expand access to credit, and second, if so, does it do so in a way that contributed to the financial crisis that preceded the Great Recession?

Empirical research on the second question suggests that the CRA had little to do with the subprime crisis. Kroszner (2009: 11), for example, writes—

> Two key points emerge from all of our analysis of the available data. First, only a small portion of subprime mortgage originations are related to the CRA. Second, CRA-related loans appear to perform comparably to other types of subprime loans. Taken together … we believe that the available evidence runs counter to the contention that the CRA contributed in any substantive way to the current mortgage crisis.

Of course, if the CRA had no real effect on the supply of credit, then it would be unlikely to have been part of the reason for the mortgage crisis and ensuing financial crisis.

The few papers that attempt to empirically examine the effect of the CRA on housing outcomes show mixed results. In particular, three papers use similar methodology to this article: Berry and Lee (2007), Gabriel and Rosenthal (2009), and Bhutta (2011). All three papers used a regression discontinuity design to examine the effect of the CRA on homeownership, mortgage applications, and mortgage originations, respectively, for example.

Berry and Lee (2007) found that the CRA had very little effect on outcomes in Home Mortgage Disclosure Act (HMDA) data on loan applications for the 1993-to-2003 period. However, they

[12] See Barr (2005) for a discussion of the credit market failures the CRA was designed to address.

focused on pairs of census tracts that are geographically adjacent, as well as having MFIs slightly less or more than 80 percent of AMFI. Their sample was is relatively small, and the estimated impacts have large standard errors and are statistically insignificant.

Gabriel and Rosenthal (2009) found some evidence that the CRA expanded home lending in the nonconforming[13] loan sector, but not in the conforming sector, and that the CRA had a small positive impact on homeownership. Finally, Bhutta (2011) used HMDA data to examine mortgage originations in CRA-eligible neighborhoods and to CRA-eligible consumers. He focuses on two different periods: 1994 to 2002 and 2004 to 2006. The CRA may have had a different effect in these different periods because of both regulatory changes and changes in the economy. Bhutta also performed the analysis separately by metropolitan area size, because regulatory enforcement (or market forces that make it more or less likely that regulations have an impact) may differ depending on area population. Bhutta found that mortgage originations and applications were both higher in CRA-eligible neighborhoods in large metropolitan areas during the 1994-to-2002 period. Further, he found that this increase was not simply among regulated institutions, suggesting that the effect might be one of "crowding in" rather than "crowding out."[14] He found little evidence that the CRA affected housing-related credit outcomes in other areas or time periods.

In this article, we build on this prior research and similarly use a regression discontinuity design to measure the CRA's effects. Following Bhutta's findings, we focus on the effects in large metropolitan areas (that is, metropolitan areas with a population of at least 2 million) and allow the results to differ by time period.[15] This article adds to the existing research by shifting the focus from outcomes solely in the home lending market to the broader set of consumer credit outcomes available in the CCP/Equifax data.

Data and Descriptive Statistics

The CCP/Equifax data contains data beginning in 1999; the database reports information on loan performance and consumer debt on a quarterly basis. Although the data are anonymous, individuals can be tracked over time using a unique individual identification code. CCP/Equifax is updated every quarter adding individuals who have entered the credit report database using the same randomized sampling methods to maintain the representativeness of the sample as new people enter the Equifax database.[16] Keep in mind that this data set is not representative of the entire U.S. population; it is representative of individuals with a credit report. Thus, simply being in the data set may be an outcome of interest.

[13] *Nonconforming* loans are those that either do not conform to the Fannie Mae or Freddie Mac guidelines, typically because the dollar amount is more than the purchasing limit—so-called *jumbo* loans—or because they do not conform to loan-to-value guidelines.

[14] A *crowd-in* effect can happen in the following manner: if one lender is induced by regulation to make loans to individuals or areas that nonregulated lenders have been reluctant to serve, due to lack of sufficient information for wise lending decisions, then one lender's actions may provide the information necessary to make it worthwhile for the nonregulated institutions to extend credit in those areas or to those individuals as well.

[15] Appendix exhibit A-2 provides results for all metropolitan areas regardless of population for completeness.

[16] One can get information not only on those in the 5-percent sample (primary individuals), but also on individuals with credit reports who share a household with a primary individual. In this article, we focus only on the primary individuals.

Limitations of the CCP/Equifax Data Set

The data set contains richly detailed information on individuals' credit records and the status of their loans, which can be tracked quarterly. However, the data contain very little information about the actual individuals; we know the years of their birth and their geographic locations each quarter, including the metropolitan area and census tract, but no other personal characteristics.[17] Knowing the geographic information, however, makes it possible to merge the CCP/Equifax data with information on each census tract's characteristics, including the ratio of tract MFI to AMFI.

For this analysis, we use information from the first quarter of 2004 through the second quarter of 2012 (the latest information available when the project began). We merge the CCP/Equifax data with information on census tract characteristics that the FFIEC puts together from census or American Community Survey data. The FFIEC creates LMI census tract designations using census information on the relative Median Family Income (RMFI) in the census tracts, updated after each census.[18] The LMI designations were updated in 2004 to reflect the 2000 census. Note that in our final data set, being an LMI census tract is a fixed characteristic of each tract in the time period we analyze. The LMI designation does not change between 2004 and 2012.

The CCP/Equifax data contain about 409 million quarterly observations from the first quarter of 2004 through the second quarter of 2012. In the regression discontinuity analysis, we keep all individuals who are in census tracts that have MFIs between 75 and 85 percent of the AMFI. Recall that the CRA cutoff is at 80 percent of the AMFI, so this focuses our analysis on neighborhoods that have MFIs close to the cutoff. Within that narrow band, nonlinearities are less likely in the relationship between RMFI and the consumer credit outcomes of interest that might adversely affect the regression discontinuity estimates.[19] We aggregate the individual-level data to census tract-level for each quarter.

Summary Statistics on Consumer Credit Outcomes

In this section, we present summary statistics describing how consumer credit outcomes changed over time by MFI, relative to the AMFI, which is helpful to know as groundwork for considering the impact of the CRA on consumer credit outcomes. We focus on a 10-percent random subset of the individuals who are 18 to 85 years old.[20] We present outcomes by year and by six categories of RMFI: less than 50 percent, 50 to 80 percent, 80 to 110 percent, 110 to 140 percent, 140 to 170 percent, and more than 170 percent of AMFI.

Exhibit 1 shows how the average number of primary individuals—that is, individuals represented in the CCP/Equifax data—in a census tract varies by RMFI. The average number of primary

[17] If individuals move, their credit outcomes move with them. An individual's location is mapped to the address associated with current loan activity, which could cause problems for our estimation strategy if credit activity induces geographic mobility. Two points mitigate our concerns about this strategy. First, our estimation strategy is valid if mobility across census tracts generally differ with different income levels; it is only if differential mobility occurs right at the CRA threshold that our estimates could be affected. Second, research using census data examining whether mobility at the CRA threshold differs finds no evidence of this (Johnson, 2012).

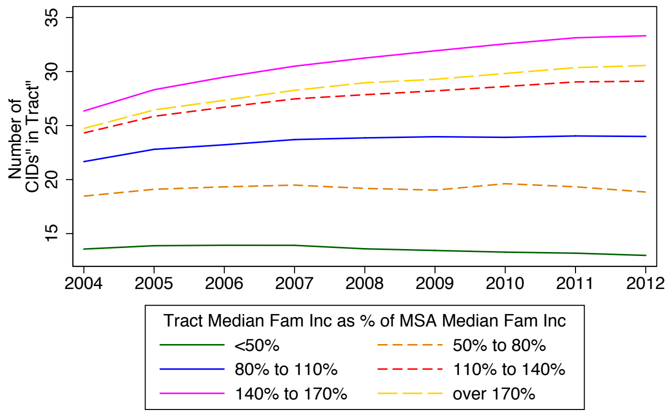
[18] Until 2012, the FFIEC classifications were updated every 10 years using the decennial census data. Starting in 2012, classifications have been updated every 5 years using the American Community Survey.

[19] When we examine whether the estimates are robust to nonlinear specifications, we find they are when we limit the analysis to this narrow band of RMFI.

[20] Because the data set contains repeated observations on individuals, we take a 10-percent random subset of the individuals, not the observations.

Exhibit 1

Average Number of Primary Individuals in Tract



CID = primary individuals in the data set. MSA = metropolitan statistical area.
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax data

individuals in the data set for the top three RMFI categories—those above 110 percent of AMFI—ranges between 25 and 35. On average, fewer than 15 primary individuals are in in the lowest-income census tracts (those with MFIs less than 50 percent of AMFI). Because census tracts were originally constructed to have similar-sized total populations, and lower-income neighborhoods tend to have a lower adult-to-child ratios, this result is possibly driven by demographic differences across these neighborhoods.[21] On the other hand, an individual must have a certain amount and type of economic activity connected to him or her in order to be included in the CCP/Equifax data. It makes sense that census tracts with higher income levels would be more likely to have more people with the type of economic activity that Equifax monitors and thus be more likely to be in the CCP/Equifax data.[22] When we turn to the regression discontinuity analysis, the methodology will implicitly control for differences in the adult-to-child ratio across CRA-eligible and CRA-ineligible tracts, enabling us to see whether the CRA has an effect on individuals' presence in the credit data. As credit report data are used for purposes other than to determine one's risk of defaulting on a loan—for example, many employers request credit reports as part of the employment screening process—simply being in the data may be an important outcome.

The top-line information on credit activity in the CCP/Equifax data is the total number of trades. A *trade* is defined as activity associated with an account (for example, an automobile loan, a mortgage, or a student loan), and *all trades* is an aggregate measure of all the different types of activity captured in the CCP/Equifax data. Exhibit 2 shows how the all trades measure changes over time; the decline in all trades is stark with the beginning of the Great Recession, consistent with the decline in overall economic activity during a recession. Exhibit 2 also shows the average number of trades or accounts (from the all trades information) by RMFI by year. In all years, trades, on average, are more numerous

[21] In exhibit 4, we examine whether the fraction of adults in a census tract changes abruptly at the CRA-eligibility threshold and find that it does not.

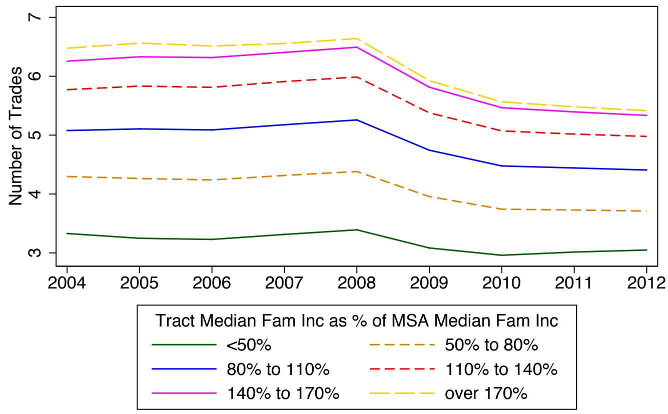
[22] We also find that the fraction missing the top line information on "all trades" is lower in the higher-income census tracts (Muñoz and Butcher, 2013).

in census tracts with higher RMFIs. Further, in results not shown, we find the fraction of individuals missing information on all trades is higher in lower-income census tracts as well. In census tracts with MFIs above 110 percent of AMFI, missing values for all trades are relatively rare, generally less than 5 percent. However, as MFI falls, the incidence of missing data on all trades increases. In neighborhoods below 50 percent of AMFI, the incidence is about 15 percent (Muñoz and Butcher, 2013).

Exhibit 3 provides further evidence on how the data vary by MFI and over time. The CCP/Equifax data are turned into a risk score by FICO and other credit score organizations.[23] Although the precise

Exhibit 2

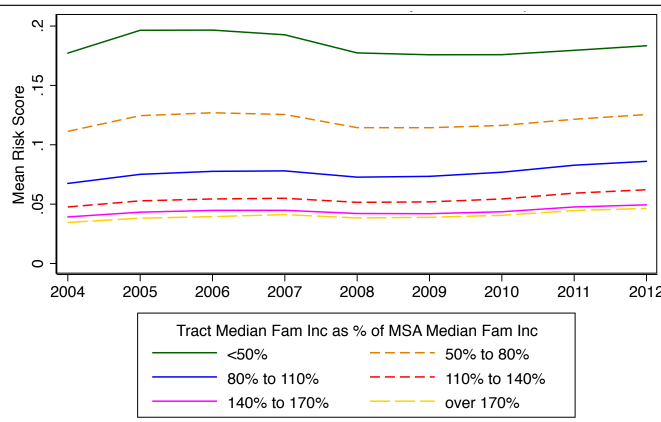
Average Number of Trades



MSA = metropolitan statistical area.
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax data

Exhibit 3

Fraction Missing Risk Score by Year



MSA = metropolitan statistical area.
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax data

[23] The risk score in the CCP/Equifax data is not the official FICO score, but it has the same range and behaves in a similar way.

methodology used to arrive at credit scores is proprietary, it is known to use information collected on outstanding credit activity to predict the probability that an individual would be more than 60 days late on a loan. Because not all individuals' information is equally easy to find, some individuals have patchier records in the CCP/Equifax data than others. For example, some individuals have missing risk scores, presumably indicating that not enough information was available for them for the methodology to produce a reliable risk score.[24] Exhibit 3 shows the fraction of individuals in a census tract who are missing their risk scores.[25] For census tracts in the highest three categories of RMFI (at or above 110 percent of AMFI), about 5 percent or fewer are missing risk scores. For those in census tracts with MFIs less than 50 percent of AMFI, between 15 and 20 percent of the individuals are missing risk scores.

Keep in mind then, that MFI is correlated with being in the CCP/Equifax data at all and with the amount of actual information in the data set about one's economic activities. In the sections that follow, we will look at these as outcomes and examine whether a neighborhood being eligible for the CRA has an effect on these margins, as well as on other consumer credit outcomes.

Methodology

We would like to estimate the causal effect of the CRA on consumer credit outcomes. By *causal effect*, we mean those changes in consumer credit outcomes that are due to CRA regulations. A starting point is the following linear regression.

$$Y_{\text{int}} = \beta_0 + \beta_1 LMI_n + X_{\text{int}}\beta_2 + e_{\text{int}} \ , \qquad (1)$$

where Y_{int} is a given credit market outcome for individual *i* in neighborhood *n* at time *t*. $\boldsymbol{LMI_n}$ is a variable indicating whether the individual lives in an LMI neighborhood or not, $\boldsymbol{X_{\text{int}}}$ is a vector of individual and neighborhood characteristics that may vary over time, and $\boldsymbol{e_{\text{int}}}$ is the error term. The error term contains all the factors not explicitly included in the regression that affect $\boldsymbol{Y}$. If these factors are correlated with whether one lives in an LMI neighborhood, then the estimated impact of $\boldsymbol{LMI}$ on consumer credit outcomes from equation (1) will be biased and will pick up many differences between consumers in LMI and non-LMI neighborhoods that have nothing to do with CRA.

Because individuals in LMI and non-LMI neighborhoods are likely to differ on many dimensions that will affect their credit outcomes, to estimate the causal effect of CRA on consumer credit outcomes, we exploit the discontinuity in the way banks get CRA credit, based on the legislated definition of an LMI neighborhood. Neighborhoods will be deemed LMI, and banks will receive CRA credit for activities in that neighborhood, if they are below the 80-percent threshold on the ratio of MFI in that census tract to AMFI in the MSA. Thus, we define LMI as in equation 2.

[24] This finding is consistent with the results on missing information on all trades discussed previously (Muñoz and Butcher, 2013).

[25] The denominator here, and in all the other fraction outcomes, is the number of individuals in the CCP/Equifax data in the census tract, not a measure of the tract population from the census.

$$LMI_{nc} = 1 \text{ if } ((medianfamilyincome_{nc} / medianfamilyincome_{c}) * 100) < 80.0\,, \tag{2}$$

$$LMI_{nc} = 0 \text{ if } ((medianfamilyincome_{nc} / medianfamilyincome_{c}) * 100) \geq 80.0\,,$$

where *n* indexes the census tract (or neighborhood) and *c* the metropolitan area. This equation is the source of the discontinuity; as RMFI in the census tract passes from slightly less than 80 percent to 80 percent or more, its designation flips from LMI to not LMI (or from 1 to 0 in our data categories).

We also define a scaled version of the census tract's RMFI.

$$\mathbf{RMFI}_{nc} = ((medianfamilyincome_{nc} / medianfamilyincome_{c} * 100) - 80)\,. \tag{3}$$

We scale the variable by the 80-percent threshold for ease of interpretation. When RMFI is 0, LMI is 0, so in the following analyses, we can center the data on 0.

Using the variables LMI and RMFI, we have the following regression equation.

$$Y_{inct} = \beta_0 + \beta_1 LMI_{nc} + \beta_2 RMFI_{nc} + e_{inct}\,. \tag{4}$$

One would expect consumer credit outcomes to increase with RMFI—so β_2 is expected to be positive (for good outcomes). The question posed in this study is whether the response of credit outcomes to income right at the LMI boundary is discontinuous, which would suggest something special about the CRA designation, as no other reason exists to expect a discontinuous change in the relationship between credit outcomes and RMFI at that threshold.[26] If no discontinuity exists, then β_1 will be estimated to be 0, implying no estimated effect of the CRA on individuals' credit outcomes. If β_1 is estimated to be a positive (negative) number, then this indicates that outcomes in LMI neighborhoods are better (worse) than in neighborhoods that are incrementally better off in terms of RMFI.

The assumption that must hold for a regression discontinuity design to give insight into the impact of the CRA on consumers' credit outcomes is that nothing else that might affect credit outcomes changes discontinuously at the 80-percent RMFI threshold. Exhibit 4 examines whether observable characteristics change at the LMI threshold, holding constant RMFI. We use the same sample restrictions as in the main analysis using the consumer credit data.[27] Columns 1 through 5 use tract-level data from the 2000 census to examine whether a discontinuous change occurs in tract characteristics at the LMI threshold for the following:[28] population, fraction of the population that is more than 25 years old, fraction of the population with a college degree, fraction of the population that reports being Hispanic, and fraction of the population that reports being African-American (non-Hispanic). No change in these tract-level characteristics is statistically significant at the LMI threshold. Previous research using regression discontinuity to study effects of the CRA has also presented evidence that the regression discontinuity design is valid by examining characteristics at the CRA eligibility threshold (Berry

[26] In the regression discontinuity framework, the continuous variable—in our case, RMFI—is referred to as the "running variable."

[27] We focus on census tracts with MFIs between 75 and 85 percent of AMFI; further, we focus on large MSAs with populations greater than 2 million.

[28] The data are from the 2000 census, with one observation per census tract.

Exhibit 4

Estimated Regression Coefficients for Census Tract Characteristics

	(1) Population	(2) Fraction of Population Older Than 25	(3) Fraction of Population College Degree	(4) Fraction of Population Hispanic	(5) Fraction of Population African-American	(6) Median Age in Tract
LMI tract	145.7	0.00387	0.000638	0.00150	– 0.0110	0.058
(Standard error)	(171.8)	(0.00615)	(0.00365)	(0.0123)	(0.0171)	(0.3934)
p-value	0.397	0.530	0.861	0.903	0.521	0.884
RMFI	60.43	0.00291	0.00204	– 0.00647	– 0.00615	0.111
(Standard error)	(29.51)	(0.00106)	(0.000627)	(0.00212)	(0.00295)	(0.0681)
p-value	0.0407	0.00598	0.00116	0.00226	0.0368	0.102
Observations	2,518	2,518	2,518	2,518	2,518	85,221
R-squared	0.137	0.193	0.236	0.555	0.203	0.1981

LMI = low- and moderate-income. RMFI = relative Median Family Income.

Notes: The regressions in columns 1 through 5 use census tract-level data, available from the Federal Financial Institutions Examination Council from 2009 (based on the 2000 census and revisions made to LMI tract definitions in 2004). Columns 1 through 5 are estimated including metropolitan statistical area (MSA) fixed effects. Observations are at the tract level, with one observation per census tract. Columns 1 through 5 include census tracts where the Median Family Income (MFI) is between 75 and 85 percent of the MSA median; only large MSAs are included. Column 6 reports results of a regression using Consumer Credit Panel/Equifax data, and the same specification used for the main results in exhibit 5. The outcome is median age in the census tract. Column 6 includes census tracts where MFI is between 75 and 85 percent of the MSA median; only large MSA are included. Column 6 includes MSA fixed effects and quarter fixed effects. In Column 6, standard errors clustered at the census tract level.

and Lee, 2007;[29] Bhutta, 2011; Gabriel and Rosenthal, 2009; Johnson, 2012[30]).[31] The last column of exhibit 4 uses median age in the census tract in the CCP/Equifax data, which similarly shows no discontinuous change in median age at the CRA threshold.[32]

Although the regression discontinuity design is rigorous and has the potential to establish causal relationships, it is not without drawbacks. It is a "data hungry" methodology; it needs a large number of observations in order to get an estimate that is precise enough to be able to determine an effect with some certainty.[33]

[29] Berry and Lee (2007) show no discontinuity at the CRA threshold in percent female, percent Black, percent Hispanic, percent Asian, or income.

[30] Johnson's (2012) undergraduate honors thesis at Wellesley College examined evidence of an impact of the CRA on demographic characteristics of a neighborhood. As Johnson points out, changes in credit outcomes in a neighborhood could generate changes in neighborhood demographic and real estate characteristics. However, Johnson's findings indicate no statistically significant difference at the threshold in mobility rates or home values; she found some evidence for a change in college education and commute times.

[31] Note that, under these conditions, a regression discontinuity design is similar to a randomized controlled trial and can give sound insight into the causal effects of the CRA on credit outcomes (Lee, 2008).

[32] Appendix exhibit A-1 investigates the robustness of results to alternative specifications. Columns 3 and 4 show the results with and without controlling for median age in the census tract. The results are robust; in the main results, we include median age as a control.

[33] We need enough data around the threshold to allow for this estimation strategy. In results not shown, we estimated a kernel density function and showed good support in the data in the 75- to 85-percent range of AMI (Muñoz and Butcher, 2013: 24).

Finally, this technique focuses on changes at the LMI threshold—and the neighborhoods slightly below the 80-percent RMFI cutoff are the relatively better-off LMI neighborhoods. It is possible that the CRA has a different effect farther away from this threshold; this technique cannot tell us that.

Results

Our main results focus on data that are aggregated from the individual level to the census tract level for the years 2004 to 2012. We restrict the sample to census tracts between 75 and 85 percent of AMFI and model the relationship between credit outcomes and RMFI as linear.[34,35] We further restrict our analysis to large metropolitan areas, those with at least 2 million people (Bhutta, 2011).[36,37] Our main analysis data set consists of the 85,221 quarterly census-tract observations that fall within this range.

Equation 4 enables us to hold RMFI constant and ask whether a discontinuous jump occurs in the relationship between each consumer credit outcome in question, Y, and being in a neighborhood that barely passes into CRA eligibility. Our regression discontinuity design will also enable us to test whether the relationship between the consumer credit outcomes and LMI is different before and after the financial crisis, as in equation 5. Estimates of β_4 in equation 5 will show whether the discontinuous jump at the LMI threshold is significantly different after the financial crisis.

$$Y_{inct} = \beta_0 + \beta_1 LMI_{nc} + \beta_2 RMFI_{nc} + \beta_3 PostCrisis_t + \beta_4 LMI_{nc} * PostCrisis_t + \beta_5 RMFI_{nc} * PostCrisis_t + e_{inct} \quad (5)$$

The Regression Estimates of the Discontinuity at the LMI Threshold

Exhibit 5 presents the results of estimating the regression discontinuity for different consumer credit outcomes[38] and enables us to see whether the size of the jump at the CRA threshold is statistically different from 0. We control for MSA fixed effects, quarter effects, and median age in the census tract, and we cluster the standard errors at the census tract.[39] The results in column 1 of exhibit 5 hold constant MSA fixed effect, quarter effects, and median age in the census tract. The estimated jump in all trades at the CRA eligibility threshold is about 9 percent, which is statistically significantly different from 0 at the 10-percent level, suggesting that the CRA has expanded access to credit in LMI neighborhoods.

[34] Regression discontinuity estimates can be sensitive to functional form. We tested different functional forms, including allowing the slope to differ on either side of the discontinuity, and a cubic in RMFI. When the data are limited to RMFIs within 5 points of the cutoff, a linear functional form fits the data, and the results are robust to other choices of functional form.
[35] Recall that RMFI is based on information from the 2000 census and does not vary within a census tract from 2004 to 2012.
[36] Results that include other areas are in appendix exhibit A-2. We find no statistically significant effects at the CRA threshold in this sample.
[37] The analysis includes 42 metropolitan areas.
[38] Appendix exhibit A-1 shows that the results for the sum of all trades are robust to various functional form assumptions about the relationship between the sum of all trades and RMFI and to the inclusion of different controls.
[39] We cluster the standard errors at the census tract-level, as tracts may have systematically correlated shocks in their consumer credit outcomes. This sample includes 2,509 different census tracts. Results are robust to clustering standard errors at the MSA level.

Exhibit 5

Estimated Regression Coefficients for Selected Consumer Credit Outcomes: Large Metropolitan Areas

	(1) log(Sum of All Trades)	(2) log(Number of People in Tract)	(3) Fraction Missing Risk Score	(4) log(Sum of Mortgages)	(5) log(Sum of Auto Loans)	(6) log(Sum of Delinquencies)	(7) Average Risk Score
LMI tract	0.0899	0.0714	– 0.00526	0.0275	0.0604	0.0566	1.742
(Standard error)	(0.0466)	(0.0426)	(0.00261)	(0.0478)	(0.0456)	(0.0478)	(1.775)
p-value	0.0539	0.0938	0.0443	0.565	0.185	0.236	0.327
RMFI	0.0376	0.0262	– 0.00230	0.0356	0.0338	0.0158	1.429
(Standard error)	(0.00814)	(0.00751)	(0.000447)	(0.00855)	(0.00805)	(0.00832)	(0.306)
p-value	0.0000	0.000487	0.0000	0.0000	0.0000	0.0570	0.0000
Standard errors clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Median age in census tract	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,203	85,221	85,221	84,924	85,021	84,940	85,207
R-squared	0.207	0.204	0.223	0.354	0.396	0.219	0.447

LMI = low- and moderate-income. MSA = metropolitan statistical area. RMFI = relative Median Family Income.

Notes: The dependent variable is the indicated consumer credit outcome in a census tract in a given quarter. LMI tract is a dummy variable equal to 1 if the Median Family Income (MFI) in the census tract is less than 80 percent of the Area Median Family Income (AMFI), indicating the census tract is eligible for the Community Reinvestment Act, and 0 otherwise. RMFI is MFI in the census tract divided by AMFI, multiplied by 100 to obtain the percentage, then scaled by subtracting 80, so that at RMFI = 0, LMI turns from 1 to 0. All regressions include a constant. Standard errors are in parentheses and are clustered at the census tract level; the clusters numbered 2,509.

In columns 2 through 7 of exhibit 5, we examine additional consumer credit outcomes: the log of the number of individuals in the CCP/Equifax data in each census tract in each quarter, the fraction of individuals in a census tract in a quarter who are missing their risk scores, the log of the sum of mortgages in a census tract in a quarter, the log of the sum of auto loans in a census tract in a quarter, the log of the sum of delinquent loans in a census tract in a quarter, and finally the average credit risk score in a census tract in a quarter. Although other credit outcomes are available in the CCP/Equifax data, we believe these measures capture a broad set of interesting outcomes.

The estimates in column 2 of exhibit 5 indicate that 7 percent more individuals are represented in the CCP/Equifax data set in census tracts that are only barely eligible for the CRA than are in census tracts that are only barely ineligible. Recall from the discussion of exhibit 1 that more individuals in the CCP/Equifax data are in higher-income census tracts, possibly because those tracts have a higher adult-to-child ratio, leading to more people with credit records, or possibly because more of the types of economic activities that generate a credit market footprint are in higher-income neighborhoods. The regression discontinuity methodology controls for potential differences in demographic makeup of the tracts, adult-to-child ratios should not differ significantly between tracts that are barely below and above the CRA threshold (and, as presented in exhibit 4, no direct evidence was found of a change in the fraction of the population that is more than 25 years old). A marginally statistically significant 7-percent discontinuous jump emerged in the data at the eligibility threshold, suggesting that CRA eligibility has expanded credit market activity in these areas.

Column 3 of exhibit 5 presents coefficient estimates for the fraction of individuals in a census tract or quarter who are missing a risk score. As discussed previously, in order to generate a risk score for an individual, the scoring companies need to have enough information about a person's interaction with the credit markets to predict his or her risk of default. Thus, a missing risk score is an indication that an individual has a relatively thin record (or that the person's activities were difficult to track for some reason). We see a statistically significant discontinuous -0.0053 jump in the fraction of individuals who are missing their risk scores at the CRA eligibility threshold. The mean of the fraction that represents missing risk scores is about 9.5 percent. The coefficient indicates that going from non-LMI to LMI status (controlling for RMFI) reduces this by about 0.5 percentage point, or by about 5 percent of the mean. We take the results for these three outcomes—total number of trades, the number of individuals in the CCP/Equifax data, and the fraction of individuals with a missing risk score—to show that, in general, more credit market activity is present among individuals who live in areas that barely meet the criteria for CRA eligibility.

In columns 4 through 7 of exhibit 5, we examine some specific credit outcomes: the sum of all mortgages, sum of automobile loans, sum of delinquencies, and the average credit risk score. The results[40] in column 4 indicate that the estimated size of the jump in mortgages at the CRA eligibility threshold is about 2.75 percent, but although this estimate is positive it is not statistically different from 0. Recall from the background section that Bhutta (2011) found a statistically significant 4-percent increase in mortgage originations using a regression discontinuity methodology and focusing on a similar sample from large metropolitan areas.

Why the difference in results? First, note that our 95-percent confidence interval ranges from -6.6 percent to 12.1 percent, which includes Bhutta's estimate. In addition, the measures and the time periods of the two studies differ substantially. Our measure should be thought of as a measure of the stock of mortgages—the number of existing mortgages—in a given census tract in a given quarter, whereas Bhutta's measure is a measure of mortgage originations or flows—new mortgages in census tract in a given year.[41] In any given time period, no reason exists to think that the effect on the stock of mortgages and the flow of mortgages will be the same. In addition, our study begins in 2004, during the housing boom, when many mortgages were being extended and thus being on the correct side of the CRA threshold may not have been a determining factor in lending institutions' decisions to extend credit for housing. It may not be surprising that we do not find a statistically significant effect at the CRA threshold for mortgages during this period.

Column 5 of exhibit 5 presents evidence for the log of the sum of auto loans in a census tract in a quarter. The coefficient on LMI indicates that about 6 percent more automobile loans are made in areas that cross the threshold of CRA eligibility, but—as with the estimate for mortgages—although it is positive, this coefficient is not statistically different from 0.

[40] The sample size varies across the columns because not all census tracts have all outcomes. For example, not all census tracts have mortgages in the CCP/Equifax data in all quarters and, because we are taking the log of the sum of mortgages and the log of 0 is undefined, the sample size is different for mortgage outcomes and for the number of people in a census tract.
[41] HMDA data used by Bhutta reports the number of new mortgages issued in a given year.

The results so far suggest that the CRA expands some types of credit market activities in LMI neighborhoods. If credit activity increases, does the CRA put more consumers at risk of undesirable outcomes? Column 6 presents evidence for one adverse outcome: delinquencies. The dependent variable is calculated as the log of the sum of all delinquencies in a census tract in a quarter. Delinquencies are defined as the total number of trades on record minus the total number of trades that are defined by Equifax as being current (that is, not more than 30 days past due). Thus, the sum of delinquencies in a neighborhood can be higher if more people have a single delinquency, a single person has many delinquencies, or both. As the number of people and the number of trades in a census tract increase, the risk of a delinquency will increase, and we know from the results in columns 1 and 2 that both of these variables are higher at the CRA threshold. However, the evidence in column 6 shows that the total number of delinquencies in a census tract at the CRA threshold did not have a statistically significant change.

Finally, column 7 of exhibit 5 presents estimates for the impact of CRA eligibility on the average risk score in a census tract in a quarter. A higher credit risk score indicates that the individual is considered more likely to pay back a loan. It is unclear how the CRA, if it were to increase credit supply in a neighborhood, might affect risk scores. If the CRA encourages lenders to make loans to individuals with poor credit histories, drawing more marginal borrowers into to the credit market, then one might expect the coefficient on LMI to be negative. On the other hand, if CRA encourages lenders to *find* individuals who are no riskier than other customers but who happen to live in a CRA-eligible neighborhood, then individuals' credit scores may not be affected. Finally, it is possible that the CRA could improve individual credit scores if it made appropriate loans available to relatively low-income individuals such that they were able to keep up with the payments and establish healthy credit records.

The estimate in column 7 of exhibit 5 is inconclusive; the point estimate is a positive 1.74, but it is not statistically different from 0. The 95-percent confidence around the point estimate ranges from –1.74 to 5.22. Because the mean of the average risk score in a census tract and year is 671.5, the range of estimates implies that we can rule out large changes in average credit risk score at the CRA threshold.

In sum, the results from exhibit 5 suggest that CRA eligibility expanded LMI neighborhoods' access to credit markets in the 2004-to-2012 period. Census tracts that barely qualify for CRA eligibility by virtue of having RMFI slightly below 80 percent of the AMFI have 9 percent more total trades, 7 percent more people in the CCP/Equifax data, and are 0.5 percentage points less likely to have missing risk score information (about a 5-percent reduction) compared with census tracts that have slightly *higher* RMFI.

In the next section, we look more closely at housing-related credit outcomes and examine whether the effect of the CRA was different before and after the beginning of the financial crisis and Great Recession.

Housing Outcomes Before and After the Financial Crisis

Exhibit 6 uses the same basic regression discontinuity framework to investigate the impact of the CRA on housing-related consumer credit outcomes: mortgages and foreclosures. Because the financial crisis arguably began with the bursting of the housing bubble, and because government

Exhibit 6

Estimated Regression Coefficients for Housing-Related Consumer Credit Outcomes, Before and After the Financial Crisis: Large Metropolitan Areas

	(1) log(Sum of Mortgages)	(2) log(Sum of Mortgages)	(3) log(Sum of Foreclosures)	(4) log(Sum of Foreclosures)	(5) log(Sum of Foreclosures in Past 2 Years)	(6) log(Sum of Foreclosures in Past 2 Years)	(7) Fraction Foreclosures	(8) Fraction Foreclosures
LMI tract	0.0275	0.0399	0.00231	0.0335	0.00798	0.0336	0.00110	– 0.00551
(Standard error)	(0.0478)	(0.0482)	(0.0402)	(0.0508)	(0.0290)	(0.0393)	(0.00297)	(0.00393)
p-value	0.565	0.408	0.954	0.510	0.783	0.393	0.710	0.161
LMI * Post 2007		– 0.0191		– 0.0450		– 0.0336		0.0102
(Standard error)		(0.0175)		(0.0519)		(0.0485)		(0.00470)
p-value		0.275		0.387		0.488		0.0296
RMFI	0.0356	0.0362	0.00774	0.0122	0.00685	0.00954	– 0.000840	– 0.00129
(Standard error)	(0.00855)	(0.00850)	(0.00700)	(0.00878)	(0.00519)	(0.00694)	(0.000476)	(0.000612)
p-value	0.0000	0.0000	0.269	0.167	0.187	0.169	0.0780	0.0352
RMFI * Post 2007		– 0.000998		– 0.00636		– 0.00352		0.000697
(Standard error)		(0.00307)		(0.00914)		(0.00866)		(0.000733)
p-value		0.745		0.487		0.684		0.342
Standard errors clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Median age in census tract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,924	84,924	66,576	66,576	45,180	45,180	84,924	84,924
R-squared	0.354	0.354	0.292	0.292	0.225	0.225	0.225	0.226

LMI = low- and moderate-income. MSA = metropolitan statistical area. RMFI = relative Median Family Income.

Notes: The dependent variable is the indicated consumer credit outcome in a census tract in a given quarter. In each of the paired columns (1 and 2, 3 and 4, and so on), the first set of results is from estimating equations as in column 4 of exhibits 4 and 5, and the second set comes from estimating equation 5. LMI is a dummy variable equal to 1 if the Median Family Income (MFI) in the census tract is less than 80 percent of the Area Median Family Income (AMFI), indicating the census tract is eligible for the Community Reinvestment Act, and 0 otherwise. RMFI is MFI in the census tract divided by AMFI, multiplied by 100 obtain the percentage, then scaled by subtracting 80, so that at RMFI = 0, LMI turns from 1 to 0. Post2007 is an indicator that equals 1 if the observation is from 2007 or later, 0 otherwise. It interacts with both LMI and RMFI. The postcrisis main effect on the outcome is controlled for with the quarter indicators. All regressions include a constant. Standard errors are in parentheses and are clustered at the census tract level.

interventions in the credit markets related to housing have come in for particular criticism as exacerbating (or creating) the financial crisis, it is worthwhile to examine whether the estimated impact that living in a CRA-eligible neighborhood has on housing outcomes differs before and after the financial crisis. Exhibit 6 presents two sets of results for each housing outcome. The first set of results is from estimating equations, as in exhibit 5. The second set comes from estimating equation 5, enabling interactions between the LMI indicator and an indicator variable for the postcrisis period (as well as an interaction between RMFI and the postcrisis indicator).

We will focus on the estimates of β_1 and β_4 : β_1 tells us whether a discontinuous jump occurred at the CRA threshold prior to the crisis, and β_4 tells us whether the jump at the LMI threshold is *different* after the crisis begins. If the estimate of β_4 is not statistically different from 0, then the data indicate that the jump is not statistically different in the two time periods. The estimated size of the jump at the CRA threshold in the postcrisis period is given by adding the estimates of β_1 and β_4 .[42] As in the previously stated results, we control for quarter, for metropolitan area, and for median age in the census tract.

The housing outcomes we examine are the log of the sum of mortgages in the census tract in a quarter, the log of the sum of foreclosures in a quarter, the log of the sum of foreclosures within the past 2 years, and the foreclosure rate. Recall that the sum of mortgages in a census tract in a year is a measure of the stock of mortgages among individuals in that tract. Foreclosures are similarly a stock, but an individual would be coded as having a foreclosure on his or her record if a foreclosure had occurred in the past 7 years. Also, the CCP/Equifax data have a measure of foreclosures initiated in the past 2 years, so these can be thought of as a stock of recently initiated foreclosures. Finally, the foreclosure rate measure is the stock of foreclosures initiated in the past 7 years divided by the stock of mortgages on record. Given that the CRA may increase mortgages, and one needs to have a mortgage in order to be at risk of foreclosure, we are interested in whether the fraction of foreclosures is affected by CRA eligibility. However, getting the timing right for these measures, especially in terms of what we would have expected to change (and when) after the financial crisis, is difficult. Perhaps we should investigate only newly initiated foreclosures and whether that changed in 2007. However, if outcomes were worse earlier in LMI neighborhoods, limiting to newly initiated foreclosures might miss that. We think the measures we have chosen are a sensible starting point. We consider all the years from 2007 to 2012 to be postcrisis years, so if housing outcomes got relatively worse on average during that period in neighborhoods that are at the CRA eligibility threshold, our measures should pick that up.

Columns 1 and 2 of exhibit 6 show the results for the log of the sum of mortgages. No change was statistically significant in mortgages at the CRA threshold (results in column 1 are a repetition of exhibit 5, column 4). In column 2, we see that the interaction between LMI and the postcrisis period is negative but not statistically different from 0. In the discontinuity at the CRA eligibility threshold after the financial crisis, the change is not statistically significant. Overall, no evidence of a change in mortgage stock is present in the 2004-to-2012 period due to CRA eligibility.

Columns 3 and 4 present results for the log of the sum of foreclosures in a census tract in a quarter. Column 3 indicates CRA eligibility has no statistically meaningful relationship with the

[42] Any year after 2006 (2007 and later) is a postcrisis year.

stock of foreclosures. Column 4 also indicates no statistically meaningful change in the relationship between the precrisis and postcrisis years. Results using the log of the sum of foreclosures in the past 2 years follow a similar pattern. Finally, the estimated impact of CRA eligibility on foreclosure rate (column 7) is a small, imprecisely estimated, positive number (a coefficient of 0.0011, and the mean of the dependent variable is 0.051) for all time periods combined. When we allow the effect of CRA eligibility to differ by precrisis and postcrisis period (column 8), we see an estimated change in the size of the jump at the CRA threshold. The coefficient on LMI is negative but not statistically different from 0 for the precrisis period. The interaction term between LMI and the postcrisis period is positive and statistically different from 0, indicating a statistically meaningful change in the size of the jump, and that change was toward a higher fraction of foreclosures in CRA-eligible neighborhoods in the postcrisis period. However, the estimated size of the jump in the postcrisis period is small, 0.005,[43] and is not statistically different from 0.[44] Thus, no evidence exists that being in a CRA-eligible neighborhood affected the housing market either beneficially or adversely in the 2004-to-2012 period.[45]

Discussion and Conclusions

The research presented here uses CCP/Equifax credit data to examine the effect of the CRA on consumer credit outcomes. These data enable us to expand on previous research by focusing on a broad set of consumer credit outcomes for which little prior evidence of the CRA's impacts exists. Using a regression discontinuity design, we find evidence that the CRA expanded consumers' credit market footprint: a 9-percent increase in all trades, or accounts, at the CRA threshold. Also, the number of people who have a record in the CCP/Equifax data at the CRA threshold increased 7 percent, and the incidence of individuals missing a risk score—a likely indication of a thin record of activity in the CCP/Equifax data—at the CRA threshold decreased 0.5 percentage point (around 5 percent of the mean). These results suggest that the CRA is having an effect on consumer credit market activity. As credit reports are becoming broadly used—for example, by employers as a screening method during the hiring process—it is possible that even having a presence in the

[43] To see the size of the jump in the postcrisis period, one must add the coefficient on LMI (-0.0055) and the coefficient on the LMI*postcrisis interaction term (0.0102), to get 0.0047. Although this number is positive, it is not statistically significantly different from 0.

[44] The regression in column 8, and in the rest of the table, restricts the effects of the other variables in the regression—the MSA codes and the median age in the census tract—to be the same in the precrisis and postcrisis era. To ensure that this is not somehow affecting the coefficient on LMI, we also ran the regressions separately for the precrisis and postcrisis periods. When we do this, the coefficients (p-values) for LMI pre- and post-2007 are -0.0055 (0.141) and 0.0047 (0.177), respectively, which are very similar to the estimates in column 8.

[45] If CRA generated mortgages that were more likely to be foreclosed on, which then generated additional mobility to neighborhoods with RMFIs farther away from the CRA eligibility thresholds, our methodology would not pick up the increased foreclosure activity because we are measuring whether, in a tract in a given quarter, more people in the CCP/Equifax data have a foreclosure on their records. Evidence against this potential problem is that direct measures of mobility at the CRA threshold are no different (Johnson, 2012) and that we find more people in the CCP/Equifax data at the CRA threshold. Nonetheless, future research might fruitfully use the CCP/Equifax data to track individuals over time and examine whether those who are initially observed in neighborhoods at the CRA threshold have different long-term outcomes. Similarly, using the panel data during long periods to examine whether changes in the LMI designation that occur with releases of new census or American Community Survey data generate changes in outcomes for individuals may shed new light on these issues.

credit report data is an outcome with potential implications for individuals' well-being. We find no evidence that adverse outcomes, such as loan delinquencies, poor credit risk scores, or foreclosures, increase at the CRA threshold.

Although we find broad evidence of the CRA's impact on consumers' interactions with credit markets, we do not necessarily see these effects where one might have expected them. For example, because mortgages are an important piece of what regulators consider in assessing compliance with the CRA, one might expect to see an impact on housing-related outcomes. Indeed, much of the research on the CRA has focused on its impact on housing market outcomes. That research finds that the estimated impacts are sensitive to the sample's geographic area and time period, and the time frame we examine is one in which many mortgages were being extended by many types of lending institutions not subject to the CRA, so perhaps it is unsurprising that we find no effect on the stock of mortgages at the CRA eligibility threshold. However, we also find no adverse effects; we find no evidence of a significant jump in foreclosures at the CRA threshold, whether we focus on the time period before or the period during and after the financial crisis.

Our finding of a change in broad measures of consumer credit market activity at the CRA threshold suggests a role for CRA beyond the housing market. This finding does, of course, beg the question of what the mechanism might be. Large institutions, at least, are examined for CRA compliance in terms of services extended in LMI neighborhoods. Our results are consistent with institutions proffering expanded services in areas at the CRA eligibility threshold, leading to more overall credit market activity.

Finally, keep in mind that the regression discontinuity methodology does have drawbacks. In particular, it only tells us what happens right at the threshold where we cross over from CRA eligibility to CRA ineligibility. If the CRA gives regulated lending institutions an incentive to extend credit to individuals in the highest-income neighborhoods among the CRA-eligible neighborhoods, then the effects could be large at the threshold but zero elsewhere. On the other hand, the CRA could drive institutions to create products that are appropriate for LMI consumers (loans that receive CRA credit), many of whom can be found in neighborhoods with MFIs at 80 percent, 81 percent, and so on of the AMFI. This would tend to erode any differences between neighborhoods right below and above the thresholds. In short, the fact that the CRA eligibility threshold in our broad measures of consumer credit market activity jumps suggests an effect of the CRA, but the magnitudes should be interpreted with caution.

Appendix

Exhibit A-1 shows that results for the log(sum of all trades) are robust to the inclusion of controls for metropolitan statistical area fixed effects, quarter fixed effects, and median age in the census tract. Further, the point estimates are similar when we allow for a cubic in relative Median Family Income (RMFI). Column 5 shows results when we use a cubic model. The coefficient on low- and moderate-income (LMI)—the estimate of the break at the Community Reinvestment Act (CRA) eligibility threshold—is still very similar to the coefficient in column 4 (9-percent increase in trades versus an 8-percent increase for columns 4 and 5, respectively). The coefficients in columns 4 and 5 are not statistically different from one another; however, the estimated break at the LMI threshold

Exhibit A-1

Estimated Regression Coefficients for log(Sum of All Trades in Census Tract): Large Metropolitan Areas

	(1)	(2)	(3)	(4)	(5)	(6)
LMI tract	0.0803	0.0803	0.0900	0.0899	0.0799	0.0910
(Standard error)	(0.00931)	(0.0515)	(0.0466)	(0.0466)	(0.0622)	(0.0467)
p-value	0.000	0.119	0.0535	0.0539	0.200	0.0516
RMFI	0.0380	0.0380	0.0378	0.0376	Cubic in RMFI	0.0469
(Standard error)	(0.00160)	(0.00896)	(0.00811)	(0.00814)		(0.0123)
p-value	0.000	0.000	0.000	0.000		0.000139
LMI * RMFI						– 0.0181
(Standard error)						(0.0163)
p-value						0.267
Standard errors clustered	No	Yes	Yes	Yes	Yes	Yes
Quarter indicators	No	No	Yes	Yes	Yes	Yes
MSA fixed effects	No	No	Yes	Yes	Yes	Yes
Median age in census tract	No	No	No	Yes	Yes	Yes
Observations	85,203	85,203	85,203	85,203	85,203	85,203
R-squared	0.013	0.013	0.207	0.207	0.207	0.207

LMI = low- and moderate-income. MSA = metropolitan statistical area. RMFI = relative Median Family Income.
Notes: The dependent variable is the natural log of the sum of all consumer credit trades in a census tract in a given quarter. The sample includes metropolitan areas with populations of 2 million or more. LMI is a dummy variable equal to 1 if the Median Family Income (MFI) in the census tract is less than 80 percent of the Area Median Family Income (AMFI), indicating the census tract is eligible for the Community Reinvestment Act, and 0 otherwise. RMFI is MFI in the census tract divided by AMFI, multiplied by 100 to obtain the percentage, then scaled by subtracting 80, so that at RMFI = 0, LMI turns from 1 to 0. All regressions include a constant. Standard errors are in parentheses and are clustered at the census tract level where indicated; the clusters numbered 2,509.

in column 5 is not statistically different from 0. Although the coefficients for the cubic in RMFI are not shown in the table, the estimates suggest that a linear relationship fits the data as well as the cubic.

Another possible way in which the relationship between RMFI and the *Y* variable may differ from linear is that the relationship may be different on either side of the LMI threshold. For example, it is possible that the relationship between the Median Family Income and the total number of trades is steeper in lower-income census tracts than in higher-income tracts. If that is the case, then the data may indicate a jump at the threshold, not because of the effect of the CRA but because of a naturally occurring difference in the linear relationship between RMFI and *Y* on either side of the threshold.

Column 6 allows for this possibility. We have interacted the continuous variable RMFI with the dummy variable LMI, which allows for the coefficient on RMFI to take on a different value when LMI = 1 and when LMI = 0. If the coefficient on this interaction term is statistically different from 0, it suggests a different slope to the relationship between RMFI and Y on either side of the threshold. However, this coefficient is not statistically different from 0 (*p*-value = 0.267). Further, the coefficient on LMI still indicates about 9 percent more trades or accounts in census tracts that are

CRA eligible. Columns 5 and 6 suggest that the simple linear relationship between log(sum of all trades) and RMFI does not violate the assumptions under which a regression discontinuity design provides an unbiased estimate of the effect of the CRA on consumer credit outcomes. We use the specification in column 4 of exhibit A-1 to investigate the relationship between CRA eligibility and consumer credit outcomes going forward.[46]

Other Geographic Areas

Like Bhutta (2011), we focused on large metropolitan areas (those with populations of 2 million or more) for our research. Bhutta's research found statistically significant effects of CRA eligibility on mortgage originations in these larger areas but not in others. Bhutta argued that CRA enforcement activities may be greater in larger cities and thus one may see a greater effect there. It is also plausible that the differences in lenders' responses to the CRA are driven by something other than enforcement. For example, if lenders have to do more outreach to potential borrowers in order to fulfill their responsibilities under the CRA, it is likely less costly to do that in more densely populated areas.

For completeness, we repeat the preceding analysis for all areas, not only those in large metropolitan areas. The results, which are presented in exhibit A-2, follow closely the outcomes presented in exhibit 5. Our results are similar to those of Bhutta (2011); we find no statistically significant jumps in credit outcomes at the CRA threshold when we consider all areas combined, despite the fact that the sample size is considerably larger.

Two studies, to our knowledge, find an impact at the CRA threshold when focusing on large metropolitan areas. Although investigating why the CRA has a different effect depending on the size of the metropolitan area is beyond the scope of this particular project, the question deserves further attention.

[46] For the other outcomes in exhibit 5, we have performed the same robustness checks and linearity, combined with the narrow 75- to 85-percent band, seems to fit the data and return results that are not sensitive to functional form.

Exhibit A-2

Estimated Regression Coefficients for Selected Consumer Credit Outcomes: All Areas

	(1) log(Sum of All Trades)	(2) log(Number of People in Tract)	(3) Fraction Missing Risk Score	(4) log(Sum of Mortgages)	(5) log(Sum of Foreclosures)	(6) Fraction Foreclosures	(7) Average Risk Score
LMI tract	0.0349	0.0252	– 0.0018	0.0197	0.0312	0.0029	– 0.2268
(Standard error)	(0.0293)	(0.0275)	(0.0018)	(0.0319)	(0.0245)	(0.0019)	(1.0876)
p-value	0.233	0.358	0.311	0.537	0.203	0.121	0.835
RMFI	0.0254	0.0166	– 0.0020	0.0306	0.0093	– 0.0004	1.2028
(Standard error)	(0.0050)	(0.0047)	(0.0003)	(0.0055)	(0.0042)	(0.0003)	(0.1884)
p-value	0.0000	0.0000	0.0000	0.0000	0.0280	0.142	0.0000
Standard errors clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Median age in census tract	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	240,554	240,679	240,679	239,697	179,529	239,697	0.4568
R-squared	0.2399	0.2074	0.2139	0.3104	0.2709	0.1694	0.447

LMI = low- and moderate-income. MSA = metropolitan statistical area. RMFI = relative Median Family Income.
Notes: The dependent variable is the indicated consumer credit outcome in a census tract in a given quarter. The sample includes all areas. LMI is a dummy variable equal to 1 if the Median Family Income (MFI) in the census tract is less than 80 percent of the Area Median Family Income (AMFI), indicating the census tract is eligible for the Community Reinvestment Act, and 0 otherwise. RMFI is MFI in the census tract divided by AMFI, multiplied by 100 to obtain the percentage, then scaled by subtracting 80, so that at RMFI = 0, LMI turns from 1 to 0. All regressions include a constant. Standard errors are in parentheses and are clustered at the census tract level; the clusters numbered 7,088.

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