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Ana Patricia Muñoz and Kristin F. Butcher

Community Development Discussion Paper

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Abstract

We use a regression discontinuity design to investigate the effect of the Community Reinvestment Act on consumer credit outcomes using data from the Federal Reserve Bank of New York's Consumer Credit Panel database (Equifax data) for the years 2004 to 2012. A bank's activities in census tracts with median family incomes less than 80 percent of the metropolitan statistical area (MSA) median family income count toward a lending institution's compliance with CRA rules. Assuming census tracts with median incomes at 79.9 percent of the MSA median are the same as census tracts at 80 percent—except for CRA eligibility—discontinuous changes in consumer credit outcomes at that threshold 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. However, we do find evidence that CRA expanded broad measures of credit market activity: at the CRA threshold, there is a 9 percent increase in the total number of loans, an increase in the number of people covered by the Equifax data, and an increase in the fraction of individuals with a valid risk score. Despite expanded credit activity, which may increase consumers' risk for adverse outcomes, there is no significant increase in delinquencies at the CRA threshold.

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Access to credit is critical to a well-functioning economy. It allows consumers to smooth their consumption over good and bad times; it allows businesses to invest and expand; it allows individuals to become homeowners. Consumers and businesses in lower-income areas tend to have less access to credit than their higher-income counterparts. While it may make sense that lenders are more willing to lend to those in whom they have high confidence of their ability to repay, it is possible that, from a societal perspective, there is less access to credit in low-income areas than is optimal for economic growth. If there are “market failures” in low-income areas such that there are individuals who are “credit worthy” who nonetheless are not being served by lenders, then there is a role for policy intervention to increase lenders’ incentives to lend in those areas. The Community Reinvestment Act (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. Has it been effective in expanding access to credit in lower-income areas? If so, has that expansion been a good thing? Do the CRA’s incentives induce depository institutions to make bad loans that increase instability in LMI neighborhoods? The financial crisis of 2007 and the Great Recession that followed have made the last question especially salient. Many have questioned whether government policies to expand access to credit, including the CRA, exacerbated the housing bubble and crash and were drivers of the foreclosure crisis. Alternatively, the CRA may have given banks an incentive to develop lending products that were appropriate for LMI consumers, leading to better outcomes in their neighborhoods.

In this paper, we shed light on these questions using the Federal Reserve Bank of New York’s Consumer Credit Panel, a longitudinal database comprising individual credit records maintained by Equifax. This nationally representative 5 percent sample of individuals with consumer credit records allows us to examine a rich set of credit outcomes for consumers, including whether they have a mortgage and/or a foreclosure, their total number of trades (accounts), and the number of accounts in delinquency.

The main challenge in determining whether a policy like the CRA has had a salutary or adverse effect is that the targeted individuals—people with lower incomes—are likely to have different outcomes that those with higher incomes for reasons that have nothing to do with the policy under investigation. We need a way to compare individuals who are likely to be the same, with the sole exception being that one group is affected by the CRA and one group is not. In this study, we use a feature of the CRA eligibility rules to create just such comparisons. A census tract is considered low or moderate income, and lending in that census tract will count toward a depository institution's CRA lending, if the median family income in that census tract is less than 80 percent of the median family income in the metropolitan statistical area (MSA). This creates the ideal circumstances for what is known as a regression discontinuity design: we can examine whether there is a discontinuous change in consumers' outcomes for those in neighborhoods that are just below that 80 percent cutoff—which are thus in CRA-eligible areas—compared with those in neighborhoods at 80 percent or above, which are not in CRA-eligible areas. Assuming that people who are in neighborhoods where median family income is at 79% of the MSA's median family income are unlikely to be very different from people in neighborhoods at 80 percent, this comparison gives insight into the causal effect of the CRA on credit outcomes. Further, we can use this methodology to examine whether the effect of the CRA is different before and after the financial crisis.

We find evidence that the CRA expanded access to credit in LMI neighborhoods. Individuals in neighborhoods (census tracts) that barely meet the CRA eligibility requirement have 9 percent more accounts overall than do individuals in neighborhoods that are just over the eligibility threshold. We see no statistically meaningful increase in risk of foreclosure at the CRA eligibility threshold. Further, there is no evidence of an adverse *change* in foreclosures at the CRA eligibility threshold after the beginning of the financial crisis. These findings suggest that the CRA expanded access to credit for individuals in neighborhoods that were eligible and that this expanded access to credit did not result in worse credit outcomes after the financial crisis.

Background

The CRA was enacted in 1977 to encourage depository institutions to help meet the credit needs of their local communities, including LMI neighborhoods.[1] The CRA created an affirmative obligation for banks to provide credit in LMI communities without establishing minimum targets of lending or investment.[2] Institutions that are regulated by the federal government are affected by CRA rules.[3] The CRA is enforced through regulators' periodic examination of banks' records, and an institution's CRA rating is taken into account when an institution applies for deposit facilities, including for mergers and acquisitions. Thus, an institution's CRA compliance has an effect on its future business options. [4]

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[5] 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 reform, the spatial emphasis of CRA was modified including in the evaluation loans to LMI *borrowers* regardless of the economic

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[1] 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).

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

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

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

[5] Public disclosure began in 1990.

status of their neighborhoods (Friedman and Squires 2005). In 2005, a new category of small banks was created, "intermediate small" institutions, that are subject to a lending 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 (FDIC) supervises banks with state charters that are not members of the FRS, and the Office of the Comptroller of the Currency (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 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.[6] Thus, if a bank has a deposit-taking ATM in a wealthy census tract in Boston, all other census tracts in the metropolitan area of Boston will count as part of that bank's assessment area.

Regulators evaluate the compliance of large institutions through tests of their lending, investments, and banking services.[7] 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

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[6] See Regulation BB, implementation of the CRA, section 228.41, assessment area delineation, as amended effective January 1, 2010.

[7] Large institutions are defined as those with $250 million or more in assets. Small banks are assessed on lending activities. In 2005, a new category of "intermediate small" banks was created. Banks in this category are assessed on their lending activities and a community development test. More information on examination procedures is available at the CRA examination overview page on the Federal Financial Institutions Examination Council website, http://www.ffiec.gov/cra/exam_overview.htm.

the median for their MSA, regardless of their neighborhoods' LMI status (Friedman and Squires 2005).[8] 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.[9] Banks get credit for services provided to LMI borrowers which could affect the number of trades/accounts available in LMI tracts.

Neighborhoods' income status is determined by decennial census data. As stated earlier, a census tract is considered LMI, and loans in that area count toward a positive CRA assessment for the bank, if the median family income in that census tract is less than 80 percent of the median family income in the MSA. If a census tract is not in a metropolitan area, then it will be considered LMI if the median family income is less than 80 percent of the median family income among all families that are outside of metropolitan areas. In 2004, based on the 2000 census, a list of census tracts that were designated LMI was released by the Federal Financial Institutions Examination Council (FFIEC). This 2004 list governed which census tracts were designated LMI through 2012, when the list was updated to reflect information from the 2010 census.

Based on the outcome of the review process, regulators give lending institutions a rating of either Outstanding, High Satisfactory, Low Satisfactory, Needs to Improve, or Substantial Noncompliance. According to the FFIEC database, of the 69,792 banks examined between 1990 and 2012, 15.3 percent were rated Outstanding, and 80.7

[8] If the person or census tract is not in a metropolitan area, then the median family income in non-metropolitan areas is used as the benchmark. [9] Examples of alternative delivery systems for services include proprietary and nonproprietary ATMs, loan production offices, banking by telephone or computer, and bank-at-work or by-mail programs.
[9] Examples of alternative delivery systems for services include proprietary and nonproprietary ATMs, loan production offices, banking by telephone or computer, and bank-at-work or by-mail programs.

percent were rated either High Satisfactory or Low Satisfactory. The vast majority of banks are in compliance with CRA rules.

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 maximizing profits will not supply the optimal amount of credit and there is an important role for government intervention. Theoretically, there are reasons to believe that credit markets bear many of the traits of markets that would be plagued by market failures: there is incomplete and asymmetric information, 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," where because individuals belong to a group that is statistically more likely to default and less likely to be able to pay back a loan, they end up being 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 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 that there are 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, p. 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 CRA had no real effect on the supply of credit, then there is little reason to suspect it would be part of the reason for the mortgage crisis and ensuing financial crisis.

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

Berry and Lee (2007) find that the CRA had very little effect on outcomes in Home Mortgage Disclosure Act (HMDA) data on loan applications for 1993 to 2003. However, they focus on pairs of census tracts that are geographically adjacent, as well as having median family incomes just above and below 80 percent of MSA median family income. Their sample size is small, and the results are imprecise.

Gabriel and Rosenthal (2009) find some evidence that CRA expanded home lending in the nonconforming loan sector (i.e. increased lending that did not conform to specific bank specifications for loans), but not in the conforming sector, and find the CRA had a small positive impact on home ownership. Finally, Bhutta (2011) uses HMDA data to examine mortgage originations in CRA-eligible neighborhoods and to CRA-eligible consumers. He focuses on two different periods: 1994–2002 and 2004–2006. The CRA may have had a different effect in these different periods both because of regulatory changes and changes in the economy. Bhutta also performs the analysis separately by metropolitan area size since there may be differences in regulatory enforcement (or in market forces that make it more or less likely that regulations have an impact) depending on area population. Bhutta finds that both mortgage originations and applications were higher in CRA-eligible neighborhoods in large metropolitan areas in the 1994–2002 period. Further, he finds that this increase was not simply among regulated institutions, suggesting that there might be a "crowding-in" rather than a "crowding-out" effect.[10] He finds little evidence that CRA affected housing-related credit outcomes in other areas or time periods.

The research presented here also uses a regression discontinuity design and exploits the rule that census tracts are CRA eligible if the median family income is less than 80 percent of the metropolitan statistical area median family income. Following Bhutta's findings, we will examine the effects separately for all areas and for large metropolitan areas (i.e., those with a population of at least 2 million), and we will also allow the results to differ by time period. This paper 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 Consumer Credit Panel Equifax data.

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:

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

[10] 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, than one lender's actions may provide the information necessary to makes it worthwhile for the nonregulated institutions to extend credit in those areas or to those individuals as well.

where Y_{int} is a given credit market outcome for individual *i* in neighborhood *n* at time *t.* LMI_n is a variable indicating whether the individual lives in an LMI neighborhood or not, X_{int} is a vector of individual and neighborhood characteristics that may vary over time, and e_{int} is the error term. The error term contains all the factors not explicitly included in the regression that affect Y. If we assume that the only things in the error term are random shocks that are not correlated with being in an LMI neighborhood, then this regression will tell us the causal effect of being in an LMI neighborhood has on credit outcomes. If we assume that we can control for all the factors that are different between LMI and non-LMI neighborhoods—except for CRA eligibility—then this will also tell us the effect of the CRA on consumer credit outcomes. These, however, are heroic assumptions and are not likely to match reality. There are many reasons why consumer credit outcomes may differ between LMI and non-LMI neighborhoods, and one is unlikely to be able to control for all of them.

Recognizing that individuals in LMI and non-LMI neighborhoods are likely to differ on many dimensions that will affect their credit outcomes, we exploit the fact that there is an inherent discontinuity in the way Banks get CRA credit based on the legislated definition of an LMI neighborhood. Neighborhoods will receive CRA credit if they are below the 80 percent threshold of the ratio of median family income in that census tract to median family income in the metropolitan statistical area (MSA). Thus, we define LMI as in equation (2):

(2) $LMI_{nc} = 1$ if $((medianfamilyincome_{nc} / medianfamilyincome_c) * 100) < 80.0$

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

where *n* indexes the census tract (or neighborhood) and *c* the metropolitan area. This is the source of the discontinuity: as relative median family income in the census tract passes from just below 80 percent to 80 percent or above, 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 relative median family income, or RMFI:

(3) $RMFI_{nc} = ((medianfamilyincome_{nc} / medianfamilyincome_{c} * 100) - 80)$

We scale the variable by the 80 percent threshold for ease of interpretation. When relative median family income is 0, LMI is 0, so in the analyses presented below we can center the data on 0.

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

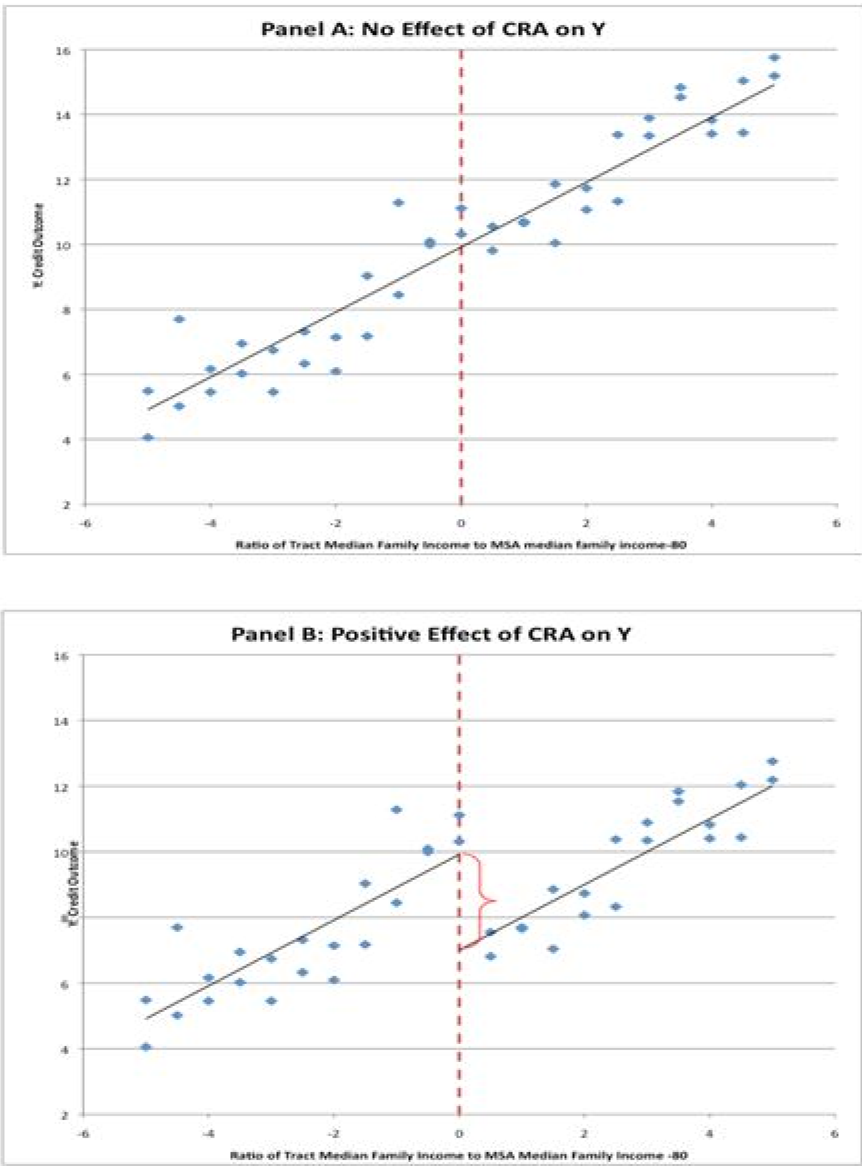
(4) $Y_{inct} = \beta_0 + \beta_1 LMI_{nc} + \beta_2 RMFI_{nc} + e_{inct}$

One would expect consumer credit outcomes to increase with relative median family income – so β_2 is expected to be positive. 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 there is something special about the CRA designation itself as there is no other reason to expect a discontinuous change in the relationship between credit outcomes and RMFI at that threshold.[11] If there is no discontinuity, then β_1 will be estimated to be 0, implying no estimated effect of CRA on individuals' credit outcomes. If β_1 is estimated to be a positive number, then this indicates that there are higher outcomes in LMI neighborhoods than in those neighborhoods that are incrementally better off in terms of relative median family income.

Figure 1 uses simulated data to illustrate two cases that might arise when one tries to estimate equation (4). In both panel A and panel B, the y axis is the average of a given credit outcome in a census tract, and the horizontal axis shows the median family income in a given census tract relative to the MSA median family income, scaled so that 80 percent is at zero. Only those neighborhoods where the median family income is five percentage points above or below the 80 percent threshold are shown. The vertical line at zero marks the threshold of CRA eligibility: individuals in neighborhoods to the left of the vertical line are in CRA-eligible neighborhoods, and individuals in neighborhoods at and to the right of the vertical line are not in CRA-eligible neighborhoods.

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

Figure 1: Simulated regression discontinuity



The estimated coefficient on LMI, $\hat{\beta}_1$, is at the vertical line. In panel A, the estimated coefficient on LMI, $\hat{\beta}_1$, is zero, and CRA eligibility has no effect on credit outcome Y; the credit outcome changes smoothly as the neighborhoods go from being CRA eligible to ineligible. In panel B, the estimated coefficient is positive: there is a discontinuous break in the relationship between Y and RMFI at the vertical line showing the threshold of CRA eligibility. This indicates that being in an LMI neighborhood, and thus in a CRA-eligible neighborhood, increases the credit outcome Y, conditional on the RMFI in the census tract.

The assumption that must hold for a regression discontinuity design to give insight into the impact of the Community Reinvestment Act on consumers' credit outcomes is that nothing else that might affect credit outcomes changes discontinuously at the 80% median family income threshold. Earlier research using regression discontinuity to study effects of the CRA has established that there are no changes in demographic characteristics, for example, at this threshold, suggesting that the regression discontinuity design is valid (Berry and Lee 2007; Bhutta 2011; Gabriel and Rosenthal 2009; Johnson 2012).[12]

This is not to say that the regression discontinuity design is 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 say with some certainty that there is or is not an effect. In addition, the estimates may be sensitive to functional form. In the simulated example above, there is clearly a linear relationship between relative median family income and the credit outcome, Y, but in real data, those relationships may be nonlinear. This will be explored in the empirical work below. A regression discontinuity is a particular kind of nonlinearity in the relationship between income and credit outcomes; in practice, it can be difficult to distinguish between different kinds of nonlinearities, although we are able to do so in one test presented below.

Finally, this technique focuses on changes at the LMI threshold – and the neighborhoods just below the 80 percent relative median income cutoff are the relatively better-off LMI neighborhoods. It is possible that the CRA has a different effect

[12] There are few characteristics in the Equifax data to examine to make sure they change smoothly at the CRA threshold. We do know individuals' ages, and an examination of median age shows no discontinuous jump at the CRA eligibility threshold. Other research has examined education and race and found little evidence of a discontinuous change in either factor at the threshold. 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).

farther away from this threshold; this technique cannot tell us that. The implications of this will be discussed with the results below.

Data

The data are from the Federal Reserve Bank of New York's Consumer Credit Panel (CCP), which is a subset of credit data maintained by Equifax, one of the large credit reporting agencies. The CCP is a nationally representative longitudinal data set. The data begin in 1999; they report information on loan performance and consumer debt on a quarterly basis. The data are a 5 percent sample of all individual credit records that Equifax maintains. Although the data are anonymous, individuals can be tracked over time using a unique individual identification code. The sample is replenished to maintain the representativeness of the sample as new people enter the Equifax database.[13] It is important to keep in mind that this is not a data set that is representative of the entire US population; it is representative of individuals with a credit report. Thus, being in the data set itself may be considered an outcome of interest.

Limitations of the CCP Dataset

The data set contains richly detailed information on individuals' number and status of loans, and these can be tracked quarterly. However, the data contain very little information about the individuals themselves. We know the year of their birth and their geographic location each quarter, including the metropolitan area and census tract, but no other personal characteristics. Knowing the geographic information, however, makes it possible to merge the CCP data with information on each census tract's characteristics, including the ratio of tract median family income to MSA median family income.

It is important to keep in mind that the purpose of this data set is to keep track of individuals and their credit outcomes. If individuals move, their credit outcomes

[13] 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 work, we focus only on the primary individuals.

move with them. Indeed, individuals' location is mapped to the address associated with loan activity, and thus if one uses these data to look at moving behavior, there is more movement than previous research would indicate is plausible. Since we are using information on location in a census tract to determine if a set of outcomes are affected by the CRA, we need to think through the implications of this for our estimates.

Our methodology essentially asks, "On average, are consumer credit outcomes better or worse in census tracts that are just barely CRA eligible than in those that are just barely not?" Since it is unlikely that there is more movement or misreporting of addresses among those who are in neighborhoods with median family incomes at 79 percent of the metropolitan area median than among those in neighborhoods at 80 percent, the regression discontinuity methodology helps alleviate worries about the effect of that particular problem. However, if, for example, CRA eligibility increases foreclosures, and people who are foreclosed upon leave and go to a neighborhood where the median family income is very different from that of their original neighborhood, then this does pose a threat for this estimation strategy. We will discuss this issue further when we examine housing-related consumer credit outcomes in the results section.

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 from the FFIEC, which the FFIEC puts together from census data. The FFIEC creates LMI census tract designations using census information on RMFI in the census tracts, updated after each census. The LMI designations were updated in 2004 to reflect the 2000 census, and more recently in 2013 to reflect the 2010 census. It is important to note that in our final data set, being a LMI census tract is a fixed characteristic of each tract in the time period we analyze. This does not change between 2004 and 2012.

The CCP/Equifax data contain about 409 million quarterly observations from 2004 to the second quarter of 2012. When we turn to the regression discontinuity analysis described earlier, we keep all individuals who are in census tracts that have median family incomes between 75 percent and 85 percent of the MSA median. Recall that the CRA cutoff is at 80% of the MSA median family income, so this focuses our analysis on neighborhoods that have median family incomes quite close to the cutoff. Within that narrow band, there are less likely to be nonlinearities in the relationship between RMFI and the consumer credit outcomes of interest that might adversely affect the regression discontinuity estimates.[14]

Summary statistics on consumer credit outcomes

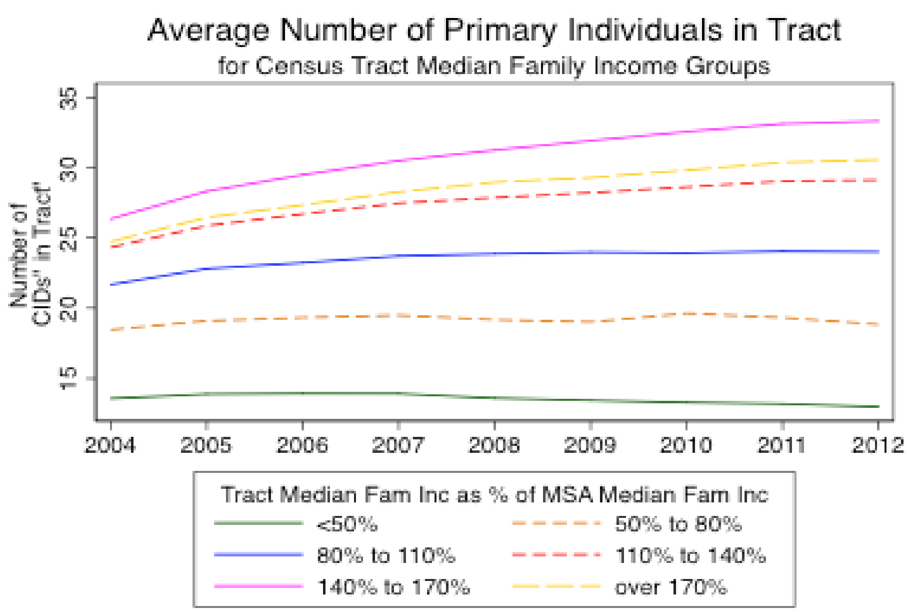
Prior to undertaking the regression discontinuity analysis, we present some summary statistics describing how consumer credit outcomes changed over time by median family income relative to the MSA median, which is helpful to know as groundwork for considering the impact of the CRA on consumer credit outcomes. For this analysis, we use consumers who are 18–85 years old. We take a 10 percent random subset of the individuals in this data set.[15] We then aggregate that by relative median family income in a census tract and by year. We present outcomes by year and by six categories of RMFI: less than 50 percent of MSA median, 50–80 percent of the median, 80–110 percent of the median, 110–140 percent of the median, 140–170 of the median, and over 170 percent of the median.

Figure 2 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 vertical axis shows the average number of people in each census tract in the CCP data. The horizontal axis shows the year. The outcomes for the six RMFI categories are represented by the six different lines in the graph. For the top three RMFI categories, those above 110 percent of the MSA median family income, the average number of primary individuals in the data set ranges between 25 and 35. For the lowest income census tracts, those with median family incomes less than 50 percent of the MSA median, there are, on average, fewer than 15 primary individuals in the census tract.

[14] 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.
[15] Since the data set contains repeated observations on individuals, we take a 10% random subset of the individuals, not the observations.

Since census tracts are constructed (at least originally) to have similar-sized total populations, and lower-income neighborhoods tend to have a lower adult-to-child ratio, it is possible that this result is driven by demographic differences across these neighborhoods. 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 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. 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 -ineligible tracts, allowing us to see whether CRA has an effect on individuals' presence in the credit data. As credit report data begin to be used for purposes other than to determine one's risk of defaulting on a loan—for example, many employers are beginning to request credit reports as part of the employment screening process—being in the data may be an important outcome in and of itself.

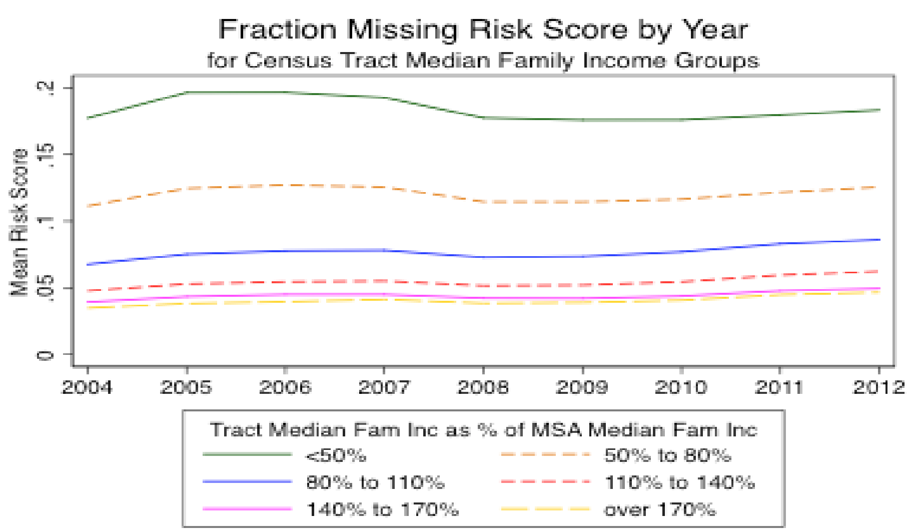
Figure 2



Source: NY Fed/Equifax. Note: CID refers to primary individuals in the CCP/Equifax dataset

Figure 3 provides further evidence of how the thickness of the data varies by median family income. The CCP/Equifax data are turned into a risk score by FICO and other credit score organizations.[16] Although the precise methodology they use to arrive at credit scores is proprietary, it is known to use information collected on outstanding credit activity to predict the probability of being more than 60 days late on a loan. The credit scoring organization must have a certain amount of information about an individual—which means Equifax has to have provided at least that much information—in order to produce a credit or risk score. Since not all individuals' information is equally easy to find, there are some individuals who 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. Figure 3 shows the fraction of individuals in a census tract that are missing their risk score. [17] For census tracts in the highest three categories of RMFI (at or above 110 percent of the MSA median) around 5 percent or fewer are missing risk scores. For those in census tracts with median family income less than 50 percent of the MSA median, between 15 and 20 percent of the individuals are missing risk scores.

Figure 3



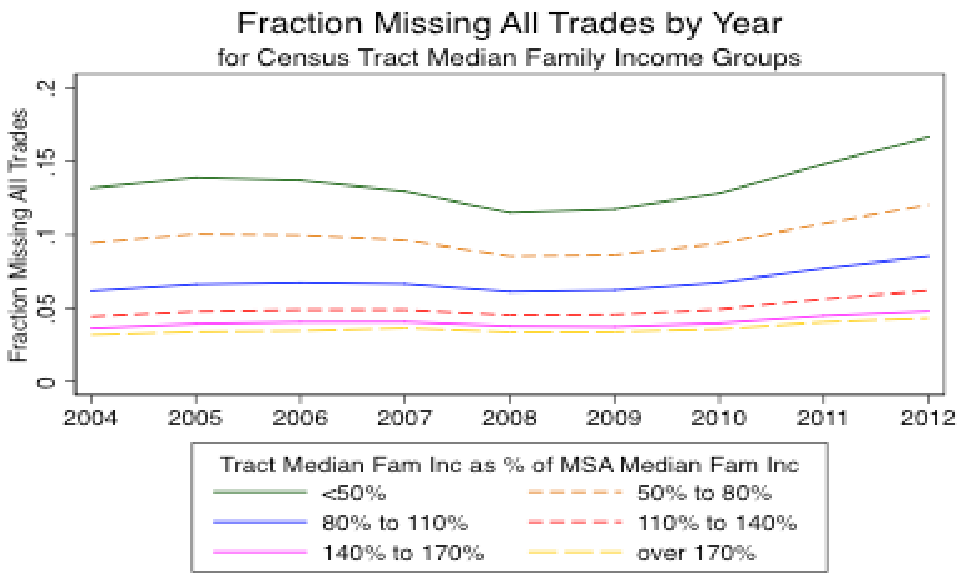
Source: NY Fed/Equifax

[16] 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.

[17] 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.

The final piece of evidence on the thickness of the data by median family income category is presented in Figure 4: this figure gives information on the fraction of individuals missing all trades in the data. The first piece of information on credit activity in the CCP/Equifax data is the total number of trades. “Trade” is defined as activity associated with an account (e.g., an auto loan, a mortgage, a student loan, etc.), and “all trades” is an aggregate measure of all the different types of activity captured in the CCP/Equifax data. For some individuals, this piece of information is missing. This means that at some point these individuals had enough of the right type of economic activity to get in the Equifax database, and then they are followed for 10 years as part of the panel. However, in some years, they cannot be found or they do not have enough activity to enter into the database, resulting in a “missing” for “all trades.” Figure 4 shows that, again, for those census tracts with median family incomes above 110 percent of the MSA median, missing values for all trades is relatively rare, generally lower than 5 percent. However, as median family income falls, the incidence of missing data on all trades increases. In neighborhoods below 50 percent of median family income, the incidence is around 15 percent. It is important to keep in mind then, that median family income is correlated with being in the CCP/Equifax data at all and with the amount of actual information about one’s economic activities that is in the data set. In what follows, we will look at these as outcomes and examine whether a neighborhood being eligible for the Community Reinvestment Act has an effect on these margins, as well as on other measured outcomes.

Figure 4



Source: NY Fed/Equifax

Figures 5 through 9 present information on additional credit outcomes monitored by Equifax. Figure 5 shows the average number of trades/accounts (from the all-trades information) by RFMI and by year. In all years, there are more trades on average in census tracts with higher relative median family incomes. In addition, one can see the stark decline in economic activity after 2008, with the beginning of the Great Recession. Figure 6 shows the average high credit (credit limit) for a bank card (credit card). Again, higher median family income in a census tract is associated with higher credit limits. In addition, the collapse of consumer credit at the beginning of the Great Recession is clear in this figure. Consumer credit appears to have begun to expand again after 2010 for those in census tracts with median family incomes above 140 percent of the MSA median.

Figure 5

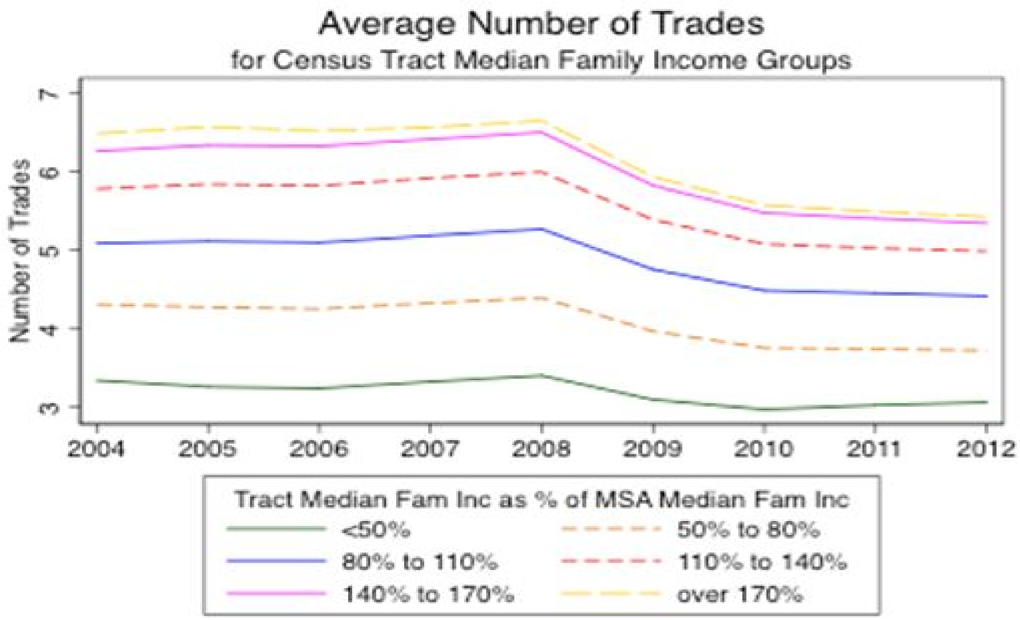
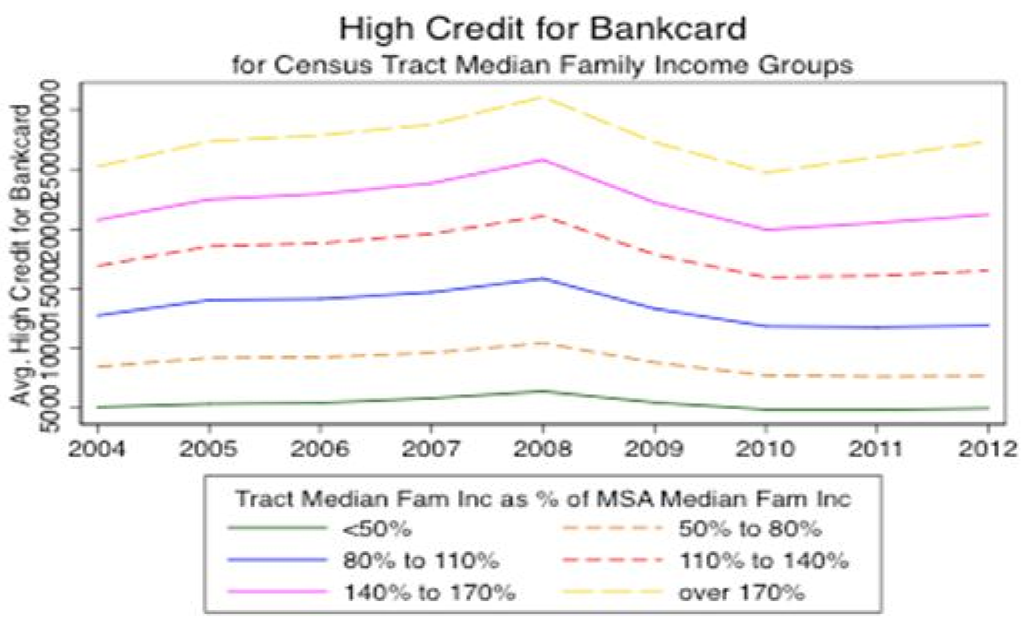


Figure 6



Source: NY Fed/Equifax

Figures 7 and 8 show how housing-related credit outcomes vary with tract-level median family income and over time. Figure 7 shows the fraction of individuals (in the CCP/Equifax data) in a census tract with any type of mortgage. Mortgage categories include first mortgages, second home mortgages, home equity lines, and the like, and all these categories are combined in this measure. This is best thought of as a measure of the stock of mortgages, since mortgages of all ages are combined. One can see that throughout this period, the fraction of individuals with a mortgage was strongly related to median family income, and there is a decline in fraction of individuals with mortgages after 2008, particularly in the three highest income categories. Figure 8 shows the fraction of individuals in a census tract with a foreclosure on their record. Again, this is measured as a fraction of the individuals in the CCP/Equifax data, not the universe of foreclosures. This figure should also be thought of as based on a stock measure, since foreclosures remain part of an individual's credit records for seven years. The figure shows the steep rise in foreclosures after the financial crisis in 2007.

Figure 7

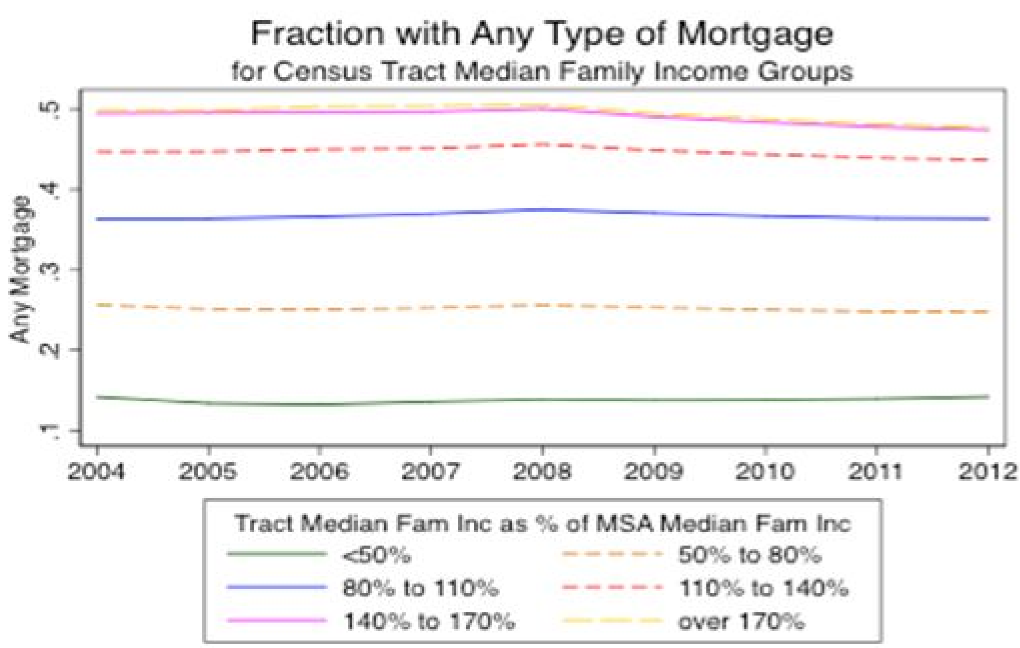
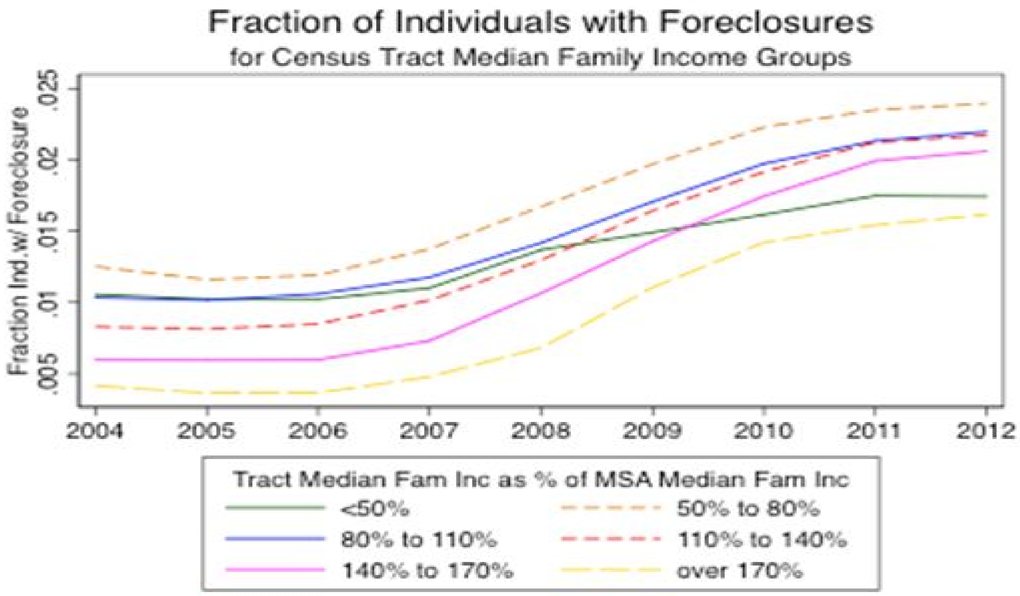


Figure 8



Source: NY Fed/Equifax

Of course, in order to have a foreclosure, one must have had a mortgage in the first place, so the levels of foreclosure by median family income are not monotonically related to those income levels, and the rise in the fraction of individuals with a foreclosure is steepest for those whose income is 140–170 percent of the median family income for their census tract and lowest for those whose income is less than 50 percent of the median family income for their census tract. Although the largest *increase* in the fraction of individuals with a foreclosure on record is for census tracts in the 140–170 percent RMFI range, well above the CRA eligibility cutoff, the neighborhoods with the highest fraction of individuals with foreclosures are in the 50–80 percent RMFI range – neighborhoods that are CRA eligible.

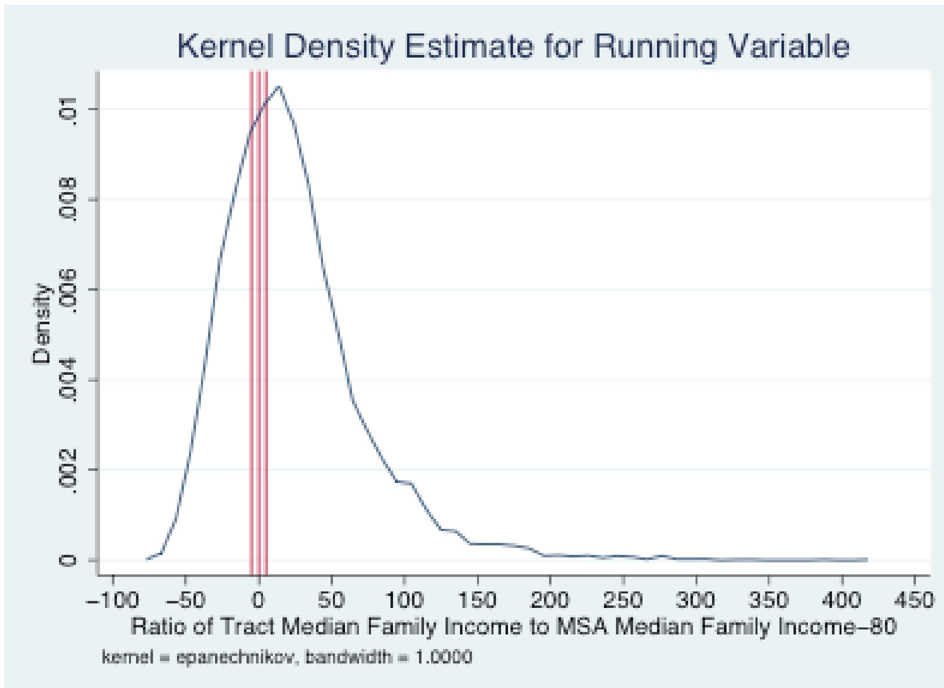
These summary statistics cannot tell us whether additional mortgages were "induced" by the CRA, or if they were, if those mortgages were more at risk of foreclosure. With the above overview of the CCP data and how (a subset) of consumer credit outcomes vary over time and by RMFI, we now turn to our regression discontinuity analysis of the effect of the CRA on consumer credit outcomes.

Results

For our main results, we follow Bhutta (2011) and focus on the large metropolitan areas, those with populations of at least 2 million, although in a later analysis we also show results for all areas. To create the analysis data set, we use all the individuals in the data set who lived in census tracts (from 2004 through the second quarter of 2012) where the median family income was between 75 percent and 85 percent of the MSA median family income.[18] Focusing on this narrow range of median family incomes allow us to model the relationship between consumer credit outcomes and relative median family income as linear.[19] We then aggregate consumer credit outcomes to the current census tract of residence and keep only those that are in the large metropolitan areas. [20] Figure 9 shows a kernel density estimate for census tract RMFI in the large metropolitan areas. Because we scale RMFI by subtracting 80, the vertical line at 0 shows census tracts where the RMFI is precisely 80 percent of the MSA median. The left vertical line is where RMFI is at 75 percent (–5 in the scaled RMFI) and the right vertical line is where RMFI is at 85 percent (+5 in scaled RMFI). Our main analysis data set consists of the 85,221 quarterly census tract observations that fall within this range.

[18] Recall that RMFI is based on information from the 2000 census and does not vary within a census tract over time during 2004–2012.
[19] With this range of relative median family incomes, the coefficient on the LMI threshold variable is not sensitive functional form of the relationship between Y and RMFI. This will be discussed further as we discuss the results. [20] There are 42 metropolitan areas included in the analysis.
[20] There are 42 metropolitan areas included in the analysis.

Figure 9



Equation (4) allows us to hold RMFI constant and ask whether there is a discontinuous jump in the relationship between the consumer credit outcome in question, Y, and being in a neighborhood that just barely passes into CRA eligibility by virtue of median family income being less than 80 percent of the MSA median family income. The LMI variable is equal to 1 if the RMFI is less than 80 percent and equal to 0 otherwise, as discussed earlier.

(4) $$Y_{inct} = \beta_0 + \beta_1 LMI_{nc} + \beta_2 RMFI_{nc} + e_{inct}$$

For most of the results below, we will present coefficients from regressions in the form of a table at the end of the report. The regression equation (4) is parsimonious, but our overall regression discontinuity design will allow us to include additional controls and 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.

(5)

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

Presenting the results in table format will allow for easy comparison across different specifications.

The essence of the discontinuity analysis

To illustrate the essence of the discontinuity analysis prior to considering more formal results, consider Figure 10. Across the bottom axis is RMFI, which ranges from 75 percent to 85 percent of the (large) MSA median family income, scaled so that 80 percent is centered on 0. Each dot represents the natural log of the sum of all trades/accounts[21] averaged across census tracts at the same (using a 0.5 percentage-point bandwidth) RMFI. [22] All dots to the left of the vertical line represent census tracts that have median family incomes less than 80 percent of the MSA median and thus are CRA eligible. All dots to the right are census tracts with median family incomes above the threshold and thus are not CRA eligible. We have then graphed the best-fitting line through the set of dots to the left of the vertical line and to the right of the vertical line. If CRA had no effect on the volume of trades/accounts in a neighborhood, we would expect the fitted line to go straight through the vertical line denoting the CRA threshold. Instead, there is a jump at the threshold such that neighborhoods that are (just barely) CRA eligible have about 0.08 higher log sum of trades, which translates to about an 8 percent higher volume of total trades. Assuming that nothing else changes at this

[21] Many of the outcomes are "count" data: we are counting up the number of times we find a given outcome in a census tract. Taking the log of the data transforms it to fit normality assumptions. In addition, the coefficient estimates (multiplied by 100) can be interpreted approximately as percentages which makes comparing the size of coefficients across outcomes easier.

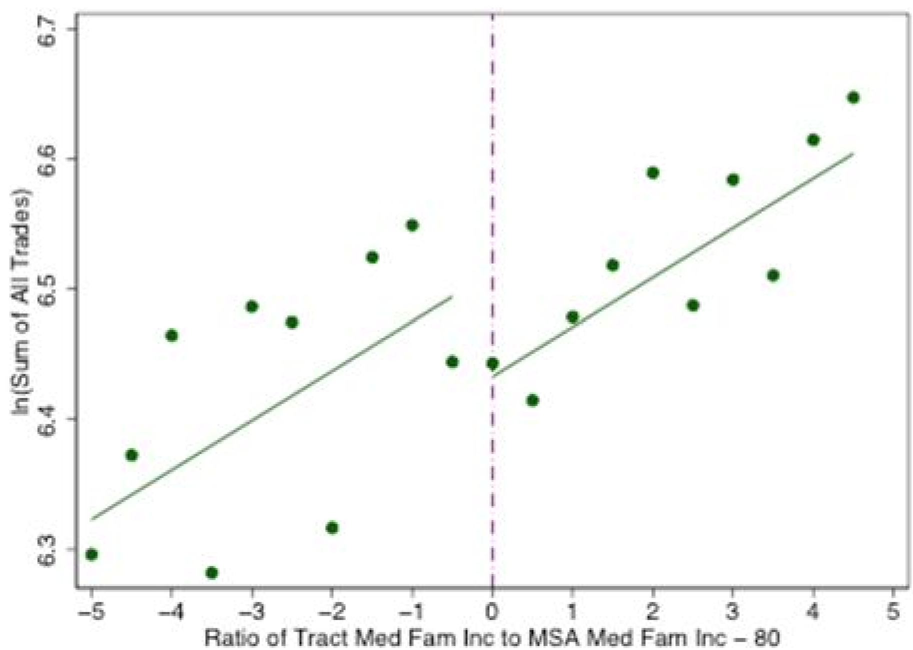
[22] So all tracts with median family incomes from 79 percent to 79.5 percent are averaged together, etc.

threshold besides CRA eligibility, this estimate suggests that CRA eligibility gains a neighborhood about an 8 percent higher volume of consumer credit trades/accounts.

The same information appears in Table 1. The regression results in Table 1 allow us to see whether the size of the jump at the CRA threshold is statistically different from zero and how the results change when we control for other variables. The results in column 1 of Table 1 correspond to Figure 10. The results show that, holding constant RMFI, the estimated jump at the CRA eligibility threshold is 8 percent. The estimated continuous response of trades to income suggests that a one-unit (one percentage point) increase in RMFI increases the number of trades by 3.8 percent (holding constant LMI). Column 1 indicates that both of these coefficients are statistically different from zero at a 1 percent (or more stringent) level of significance. Column 2 clusters the standard errors at the census tract level. [23] Here, the standard error rises such that the coefficient on LMI is no longer statistically different from zero at conventional levels. Column 3 adds controls for each of the quarters from the first quarter of 2004 to the second quarter of 2012 with an indicator variable. These will control for economic forces that vary over time, but affect all census tracts in similar ways. Additionally, this column adds fixed effects for each of the metropolitan areas. These will hold constant idiosyncratic factors for each metropolitan area that do not vary over time. The coefficients on LMI and RMFI are now identified by variation across census tracts within each metropolitan area. When these controls are added, the coefficients on LMI and RMFI are very similar to those in column 2. Similarly, when a control for median age in the census tract is added in column 4, the coefficients remain stable.

[23] Census tracts may have some systematically correlated elements in shocks to their consumer credit outcomes. Standard errors in column 2 are robust to these common shocks. There are 2,509 different census tracts included in this sample.

Figure 10



If the coefficient on LMI changed significantly when we added the controls, we would be concerned, as it would indicate that something else was changing, in addition to CRA eligibility, as we crossed the threshold from LMI to non-LMI neighborhoods. For example, if the coefficient on LMI changed substantially when we controlled for median age in the census tract, then we would be concerned that being in an LMI neighborhood was somehow correlated with age, which is expected to have its own independent effect on consumer credit outcomes. The fact that the results do not change much when we control for other observable characteristics about the time period or area suggests that the regression discontinuity methodology is yielding an unbiased estimate of the effect of CRA eligibility on the number of trades. Although controlling for other characteristics does not affect the *coefficients* on LMI and RMFI, it does reduce the standard errors. This is because MSA fixed effects and year indicators help explain the variation in the total number of trades. Thus, when these are held constant, the estimated coefficient on LMI is statistically significant at the 10 percent level (p-value = 0.0539), with the standard errors clustered at the census tract level.[24]

Columns 5 and 6 provide some robustness checks. As discussed in the methodology section, one of the questions when using regression discontinuity methodology is how to model the relationship between the running variable, which here is RMFI, and the consumer credit outcome variable (the Y variable), which here is the log(sum of all trades). In columns 1–4 of Table 1, that relationship is modeled linearly. Column 5 shows results when we use a cubic model. When we do that, the coefficient on LMI—the estimate of the break at the CRA eligibility threshold—is still very similar to 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 in column (5) is not statistically different from zero. 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. [25]

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 there is a steeper relationship between median family income and the total number of trades 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 there is a naturally occurring difference in the linear relationship between RMFI and Y on either side of the threshold.

Column 6 allows for this possibility. Here we have interacted the continuous variable RMFI with the dummy variable LMI, which allows the coefficient on RMFI to

[24] If we cluster the standard errors at the level of the 42 metropolitan areas included in these regressions, then the standard error on LMI is 0.0470, and the p-value associated with the coefficient is 0.063 (and, of course, the coefficient is the same).

[26] Of course, it is possible that the relationship between RMFI and other consumer credit outcomes is non-linear. We have performed the same robustness checks for other outcomes and linearity, combined with the narrow 75%-85% band, seems to fit the data and return results that are not sensitive to functional form.

take on a different value when LMI = 1 and when LMI = 0. If the coefficient on this interaction term is statistically different from zero, it suggests there is a different slope to the relationship between RMFI and Y on either side of the threshold. However, this coefficient is not statistically different from zero (p-value = 0.267). Further, the coefficient on LMI still indicates that there are about 9 percent more trades/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 will provide an unbiased estimate of the effect of the CRA on consumer credit outcomes. We will use the specification in column 4 of Table 1 to investigate the relationship between CRA eligibility and consumer credit outcomes going forward.[26]

Successful expansion of access to credit

The estimates in Table 1 suggest that by virtue of being just within the CRA eligibility threshold, consumers in LMI neighborhoods have about 9 percent more total consumer credit trades on their records. This suggests that the CRA has indeed expanded access to credit in LMI neighborhoods.

In Table 2, we examine a larger set of consumer credit outcomes. For reference, the first column repeats the results for all trades. In addition, we examine the log of the number of individuals in the Equifax data in each census tract in each quarter, the fraction of individuals in a census tract in a quarter that 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 risk score in a census tract in a quarter. Although there are other credit outcomes available in the Equifax/CCP data, we believe these outcomes are the most broad and interesting.

[26] Of course, it is possible that the relationship between RMFI and other consumer credit outcomes is non-linear. We have performed the same robustness checks for other outcomes and linearity, combined with the narrow 75%-85% band, seems to fit the data and return results that are not sensitive to functional form.

The estimates in column 2 of Table 2 indicate that there are 7 percent more individuals represented in the CCP/Equifax data set in census tracts that are just barely eligible for the CRA than there are in census tracts that are just barely ineligible. Recall from the discussion of Figure 2 that there are more individuals in the CCP/Equifax data in higher-income census tracts, possibly because there is a higher adult-to-child ratio in those tracts, leading to more people with credit records, or possibly due to there being more of the types of economic activities that generate a credit market footprint in higher-income neighborhoods. The regression discontinuity methodology controls for potential differences in demographic makeup of the tracts in that there should not be any significant difference between tracts that are just barely below and above the CRA threshold. Thus, the fact that there is a 7 percent discontinuous jump in presence in the data at the eligibility threshold is further evidence that CRA eligibility has expanded credit market activity in these areas.

Column 3 presents coefficient estimates for the fraction of individuals in a census tract/quarter who are missing a risk score. 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). Here we see that there is 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 are missing risk scores is about 9.5 percent. The coefficient indicates that going from non-LMI to LMI status (controlling for relative median income) reduces this by about half a 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 Equifax data, and the fraction of individuals with a missing risk score—to show that in general, there is more credit market activity among individuals who live in areas that are CRA eligible.

In columns 4–7 of Table 2, we examine some specific credit outcomes. The results in column 4[27] indicate that the estimated size of the jump in mortgages at the CRA eligibility threshold is about 2.75 percent. Although this estimate is positive, it is not statistically different from zero. Recall from the background section that Bhutta (2011) finds 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, it is important to note that our 95% confidence interval ranges from -6.6 percent to 12.1 percent which includes Bhutta's estimate.[28] In addition, there are substantial differences in the measures and the time periods of the two studies. Our measure should be thought of as a measure of the stock of mortgages in a given census tract in a given quarter, while Bhutta's measure is a measure of mortgage originations, or a flow. 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. Taking those factors into account, it may not be surprising that we do not find a statistically significant effect at the CRA threshold for this period.

Column 5 of Table 2 presents evidence for the log of the sum of auto loans in a census tract in a quarter. The coefficient on LMI indicates that there are about 6 percent more auto loans 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 zero.

The results thus far indicate that the CRA expands credit in LMI neighborhoods. However, the question remains: by doing so, does the CRA put more consumers at risk

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[27] 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 Equifax data in all quarters, and since we are taking the log of the sum of mortgages, and the log of zero is undefined, the sample size is different for mortgage outcomes and for the number of people in a census tract.

[28] So all tracts with median family incomes from 79 percent to 79.5 percent are averaged together, etc.

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 (i.e., not more than 30 days past due). Thus, the sum of delinquencies in a neighborhood can be higher both if there are more people with a single delinquency and/or a single person with a large number of delinquencies. 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 are higher at the CRA threshold. The estimated coefficient on LMI in column 6 indicates that delinquencies are about 5.7 percent higher at the CRA eligibility threshold, but this estimate is imprecise and is not statistically different from zero. It is worth noting, however, that even if it were statistically different from zero, the point estimate for delinquencies is 5.7 percent, while the point estimate for all trades is 9 percent, suggesting that the delinquency risk per trade or account is actually better at the CRA threshold.

Finally, column 7 of Table 2 presents estimates for the impact of CRA eligibility on the average risk score in a census tract in a quarter. A higher risk score indicates that the individual is considered more likely to pay back a loan. *A priori* it is unclear how the CRA, were it 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 there may be no effect on individuals' credit scores. 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.

Unfortunately, the estimate in column 7 of Table 2 is inconclusive: the point estimate is a positive 1.74, but it is not statistically different from zero. The 95 percent confidence around the point estimate ranges from –1.74 to 5.22; since the mean of the average risk score in a census tract/year is 671.5, the range of estimates imply only a small role for the CRA, if any, in affecting risk scores.

In sum, the results from Table 2 suggest that CRA eligibility did expand LMI neighborhoods' access to credit markets in the 2004–2012 period. Census tracts that just barely qualify for CRA eligibility by virtue of having RMFI just below 80 percent of the metropolitan area median family incomes have 9 percent more total trades, 7 percent more people in the Equifax data, and are 0.5 percentage points less likely to have missing risk score information (about a 5 percent reduction), compared to 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 recession.

Housing outcomes before and after the financial crisis

Table 3 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 interventions in the credit markets related to housing have come in for particular criticism as exacerbating (or creating) the financial crisis, it is particularly worthwhile to examine whether there is a difference in the estimated impact that living in a CRA-eligible neighborhood has on housing outcomes before and after the financial crisis. Table 3 presents two sets of results for each housing outcome. The first set of results is from estimating equations, as in column 4 of Table 1 and Table 2. The second set comes from estimating equation (5), discussed above but reproduced here for reference.

(5)

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

We will focus on the estimates of β_1 and β_4: β_1 tells us whether there is a discontinuous jump at the CRA threshold prior to the crisis, and β_4 tells us whether the jump at the LMI threshold is *different* after the beginning of the crisis. If the estimate of β_4 is not statistically different from zero, 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 β_1 and β_4. Any year after 2006 (2007 and later) is a postcrisis year. As in the earlier 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 last two years, and the sum of foreclosures as a fraction of the sum of mortgages, called "fraction foreclosures." 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 there was a foreclosure in the last seven years. There is also a measure in the Equifax data of foreclosures initiated in the last two years, so these can be thought of as a stock of recently initiated foreclosures. Finally, the fraction foreclosure measure is the stock of foreclosures initiated in the last seven 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 post-crisis years, so if housing outcomes got relatively worse on average in that period in neighborhoods that are CRA eligible, our measures should pick that up.

It is important also to keep in mind that the CCP/Equifax data track individuals, and if the individuals move, then their census tract changes. If CRA eligibility increases foreclosures, and individuals move when they are foreclosed on, and they move to census tracts that are not at the CRA eligibility threshold, then this will bias the coefficient on LMI toward zero. We will address this after presenting the results below.

Columns 1 and 2 of Table 3 show the results for the log of the sum of mortgages. There is a statistically insignificant 2.75 percent jump in mortgages at the CRA threshold in column 1 (results in column 1 are a repetition of Table 2, column 4). In column 2 we see that the interaction between LMI and the postcrisis period is negative, indicating that the jump in mortgages at the CRA threshold is lower in the later time period, but this term is not statistically different from zero. There is no statistically meaningful change in the discontinuity at the CRA eligibility threshold after the financial crisis. The estimates for both periods are positive, but neither is statistically different from zero. Thus, there is no evidence of a change in mortgage outcomes in the 2004–2012 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 that overall, CRA eligibility is associated with a 0.2 percent increase in the stock of foreclosures, but this is not statistically different from zero. Column 4 suggests that in the pre-crisis period, CRA eligibility was associated with a 3.4 percent increase in foreclosures, not statistically different from zero, but this became a –1.1 percent decline in foreclosures after the financial crisis (calculated by summing the coefficients on LMI and LMI*Postcrisis). Again, none of these estimates is statistically different from zero. Results using the log of the sum of foreclosures in the past two years follow a similar pattern. Finally, the estimated impact of CRA eligibility on fraction foreclosure (column 7) is a small, imprecisely estimated, positive number (a coefficient of 0.0011 where 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 pre- and postcrisis period (column 8), we see that there is an estimated change in the size of the jump at the CRA threshold. The coefficient on LMI is negative, but not statistically different from zero for the precrisis period. The interaction term between LMI and the postcrisis period is positive and statistically different from zero, indicating that there is a statistically meaningful change in the size of the jump, and that change was toward there being a higher fraction of foreclosures in CRA-eligible neighborhoods in the postcrisis period. However, the estimated size of the jump in the post crisis period is small, 0.005, and is not statistically different from zero.[29] Thus, there is no evidence here that being in a CRA-eligible neighborhood affected the housing market either beneficially or adversely in the 2004–2012 period. There is certainly no evidence, given the measures in the Equifax data and the definitions used here, of an increase in foreclosures due to CRA eligibility.

Is our nonresult for mortgages and foreclosures due to the fact that if an individual moves after a foreclosure, he or she is no longer living in a neighborhood at the threshold of CRA eligibility? While that is possible, it seems unlikely to have generated the pattern of our results. First, a foreclosure will show up on an individuals' credit record before any change of address is required. Neither the longer-term measure of ever having had a foreclosure on one's record nor the measure of foreclosures within the past two years shows an effect of CRA eligibility on foreclosures, and the estimates are very similar in size. If there were a lot of movement of individuals associated with CRA-generated foreclosures, then one might expect these measures that use a different timing to show quite different effects of CRA eligibility on foreclosures.

[29] 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 pre- and postcrisis era. To ensure that this is not somehow affecting the coefficient on LMI, we also ran the regressions separately for the pre- and postcrisis periods. When do this, the coefficients (p-values) for LMI pre-2007 and post-2007 are –0.0055 (0.141) and 0.0047 (0.177), respectively, which are very similar to the estimates in column 8.

Second, when an individual moves away from a neighborhood at the CRA threshold, that person is no longer there to increase the total number of trades, the number of individuals in the neighborhood, or to reduce the fraction of individuals in the neighborhood with missing risk score data. Thus, if there is a problem with foreclosures generating movement that biases the results toward zero, the effect of the CRA on overall credit market activity is likely much higher than estimated in Table 2.

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 earlier research found statistically significant effects of CRA eligibility on mortgage originations in these larger areas, but not in others. Bhutta argues that there may be more CRA enforcement activities 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 analysis above for all areas, not just those in large metropolitan areas. The results, which are presented in Table 4, follow closely the outcomes presented in Table 2. 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.

There are now two studies, to our knowledge, that 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.

Discussion and conclusions

The research presented here uses credit data from the New York Federal Reserve Bank's Consumer Credit Panel (a subset of data maintained by Equifax) to examine the effect of the Community Reinvestment Act on consumer credit outcomes. These data allow us to expand on earlier research by focusing on a broad set of consumer credit outcomes for which there is little prior evidence of the CRA's impacts. We follow previous research using regression discontinuity methodology to examine whether a neighborhood's eligibility for the Community Reinvestment Act affects credit outcomes. Eligibility for CRA is determined by whether a neighborhood's/census tract's median family income is less than 80 percent of its metropolitan statistical area's median family income. This methodology relies on the assumption that neighborhoods with median family incomes at 79 percent of the metropolitan area median family income are very similar to neighborhoods at 80 percent, except that the former are eligible for the CRA and the latter are not. The regression discontinuity methodology reveals whether there is a discontinuous change in consumer credit outcomes at the CRA eligibility threshold. If there is, that is evidence that CRA affects credit outcomes.

We find evidence that the CRA expanded consumers' credit market footprint: there is a 9 percent increase in all trades, or accounts, at the CRA threshold. There is also a 7 percent increase in the number of people who have a record in the Equifax data at the CRA threshold, as well as a 0.5 percentage point (around 5 percent of the mean) decrease in the incidence of individuals missing a risk score – a likely indication of a thin record of activity in the Equifax data – at the CRA threshold. These results strongly suggest that the CRA is having an effect on a dimension of 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 just having a presence in the credit report data is an outcome with potential implications for individuals' well-being. We find no evidence that adverse outcomes, such as loan delinquencies, 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 *a priori*. For example, since 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 indicates that the estimated impacts are sensitive to the sample's geographic area and time period. Following Bhutta (2011), we focus on a sample from metropolitan areas with populations of at least 2 million in population, but although our point estimates are positive, they are not statistically different from zero. On the other hand, the time frame we examine is one in which many mortgages were being extended by many types of lending institutions, and thus CRA eligibility may not have been much of a determining factor in whether or not members of the target population were able to obtain a mortgage during this period.

In terms of adverse housing-related outcomes, we use three different methods of measuring foreclosures and find no evidence of a discontinuous change in foreclosures at the CRA threshold. We also find no evidence of a significant jump in foreclosures at the CRA threshold, whether we focus on the time period before or during and after the financial crisis. Our finding of a jump in consumer credit market activity at the CRA threshold suggests a role for CRA beyond the housing market.

Finally, it is important to keep in mind that the regression discontinuity methodology does have drawbacks. In particular, it really only tells us what happens right at the threshold where we cross over from CRA eligibility to ineligibility. If the CRA gives regulated lending institutions an incentive to loan 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 low- and moderate-income consumers (loans that receive CRA credit), many of whom can be found in neighborhoods with median family incomes at 80 percent, 81 percent, etc. of the metropolitan median. This would tend to erode any differences between neighborhoods right below and above the thresholds. In short, the fact that there is a jump at the CRA eligibility threshold in our broad measures of consumer credit market activity is evidence of an effect of the CRA, but the magnitudes should be interpreted with caution.

Table 1. Estimated regression coefficients for log(sum of all trades in census tract): Large metropolitan areas

	(1)	(2)	(3)	(4)	(5)	(6)
Low- to Moderate-Income Tract (LMI)	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
Relative Median Family Income(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

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 area with populations of 2 million or more.

LMI is a dummy variable equal to 1 if the median family income in the census tract is less than 80 percent of the MSA median family income, indicating the census tract is CRA eligible, and 0 otherwise

RMFI is median family income in the census tract divided by median family income in the MSA, 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. There are 2,509 clusters.

Table 2. 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
Low- to Moderate-Income Tract (LMI)	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
Relative Median Family Income (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

Notes: The dependent variable is the indicated consumer credit outcome in a census tract in a given quarter.
LMI is a dummy variable equal to 1 if the median family income in the census tract is less than 80 percent of the MSA median family income, indicating the census tract is CRA eligible, and 0 otherwise. RMFI is median family income in the census tract divided by median family income in the MSA, 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. There are 2,509 clusters.

Table 3. 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 last 2 yrs)	(6) log(Sum of Foreclosures in last 2 yrs)	(7) Fraction Foreclosures	(8) Fraction Foreclosure
Low- to Moderate-Income Tract (LMI)	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*Post2007		–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
Relative Median Family Income (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

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, etc.), The first set of results is from estimating equations as in column 4 of Table 1 and Table 2, and the second set comes from estimating equation (5).
LMI is a dummy variable equal to 1 if the median family income in the census tract is less than 80 percent of the MSA median family income, indicating the census tract is CRA eligible, and 0 otherwise. RMFI is median family income in the census tract divided by median family income in the MSA, 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.

Table 4. 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)	(5) Fraction Foreclosures	(7) Average Risk Score
Low- to Moderate-Income Tract (LMI)	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
Relative Median Family Income (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

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 in the census tract is less than 80 percent of the MSA median family income, indicating the census tract is CRA eligible, and 0 otherwise. RMFI is median family income in the census tract divided by median family income in the metropolitan area, 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. There are 7,088 clusters.

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