Does the Community Reinvestment Act improve consumers' access to credit?*

Jacob Conway[1], Jack N. Glaser[2], and Matthew C. Plosser[3]

[1]Stanford University
[2]University of Chicago
[3]Federal Reserve Bank of New York

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Abstract

We study the impact of the Community Reinvestment Act (CRA) on access to consumer credit since 1999 using an individual-level panel and three distinct identification strategies: a regression discontinuity design centered on a CRA-eligibility cutoff; a comparison of neighboring census blocks; and an event study of changes in eligibility. All three rule out a significant effect of the CRA on consumer borrowing. We show this is in part explained by a shift in mortgages from non-banks, which are free from CRA obligations, to banks in need of CRA-eligible mortgages. Our findings underscore the pitfalls of a circumscribed regulatory regime. **JEL Codes:** G21, G28

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Email: jcconway@stanford.edu, glaserj@uchicago.edu, matthew.plosser@ny.frb.org.

1 Introduction

The Community Reinvestment Act (CRA) was enacted in 1977 to ensure that banks invested in the communities in which they raised deposits. The predominant form of bank investment is credit provision. Access to credit is critical for economic welfare as it allows households to smooth consumption over time and to fund investment, but credit provision is often restricted due to economic and institutional factors, including informational problems, high entry costs, and a history of discriminatory practices.[1] The CRA seeks to reduce inequities in credit access by requiring depository institutions to serve the needs of all communities in which they operate by targeting lending to low- and moderate-income (LMI) borrowers and census tracts.

Despite the public and private resources spent on regulation and compliance, there is mixed empirical evidence of the CRA's efficacy.[2] There are two major challenges in evaluating the causal effect of the CRA on consumer access to credit: the first is observing a comprehensive measure of household borrowing and the second is constructing a counterfactual for borrowing that would occur in the absence of CRA incentives. In addition to the empirical challenges, the market for consumer credit has evolved dramatically since 1977 and there is a dearth of evidence on the efficacy of the CRA in recent decades. This is particularly critical as reform efforts are underway to modernize CRA regulations. In this paper, we overcome the empirical challenges by using a rich consumer credit panel and an array of identification methods to assess the ability of the CRA to improve consumer access to credit. Our findings advance the discourse on the efficacy of the CRA and provide timely evidence of the CRA's impact on household borrowing and credit outcomes.

Our analysis covers the years 1999-2017 using a representative sample of US borrowers provided by the FRBNY-Equifax Consumer Credit Panel (CCP). We employ three distinct but complementary empirical strategies to construct relevant counterfactuals: a cross-sectional regression discontinuity design (RDD) using a sharp, census-tract-level income cutoff for CRA eligibility; a spatial analysis comparing individuals in neighboring census blocks; and an event study of eligibility changes in individual-level panel data. Using this rich data and our three identification methods, we find that the CRA does not have a statistically significant impact on consumer borrowing or credit-related outcomes. Our estimates

[1]For analysis of the benefits of consumer credit access, see for example Green (1987), Morduch (1995), and Zinman (2010). For analysis of the constraints to credit access, see for example Stiglitz and Weiss (1981) and Dymski (1995).

[2]Some research has found positive impacts of the CRA on lending (e.g., Butcher and Muñoz 2017; Ringo 2022; Lee and Bostic 2020; Ding and Nakamura 2021) and related outcomes (e.g., Avery et al. 2003; Agarwal et al. 2012), whereas other studies have argued that the CRA has been largely ineffective in (e.g., Bhutta 2011; Hylton 2006; White 2008).

are precise enough to rule out economically large impacts. For instance, our RDD estimates an effect of the CRA on individual debt with a 95% confidence interval ranging from -\$725 to \$850 (roughly $\pm 2\%$ of the average debt balance).

Our analysis of household borrowing relies on the design of CRA regulation to generate a variety of natural experiments that rely on distinct identification assumptions. Supervisors evaluate banks' compliance with the CRA by assessing their lending in low-to-moderate income (LMI) census tracts where the CRA defines LMI as having a median family income (MFI) less than 80 percent of that of the surrounding area. We compare borrowing in LMI tracts to borrowers elsewhere using three distinct methods with their own identification assumptions and corresponding counterfactuals. The first method, our preferred, exploits the discontinuous designation of census tracts at the 80 percent MFI threshold. Using a regression discontinuity design (RDD), we compare individual debt balances for households that reside in census tracts just above and below the LMI threshold. The RDD method assumes that households in tracts just above the cutoff are otherwise similar to those just below conditional on MSA-time fixed effects and linear controls for MFI.

Our second approach is also cross-sectional and relies on comparing census blocks that lie just inside LMI census tracts to neighboring census blocks outside LMI census tracts. For this analysis, the identifying assumption is that geographic neighbors are otherwise similar conditional on control variables. By focusing on neighbors, we can account for unobservable factors that vary by geography and over time. While we can more explicitly account for spatial variation, the geographic analysis relies on a smaller sample of individuals relative to the first approach.

The third and final approach evaluates the evolution of borrowing based on changes in LMI status over time. Status changes can occur for two reasons: the remapping of geographies and the reclassification of a census tract as eligible based on changes to its relative income. While the former is plausibly exogenous from determinants of borrowing, the latter reflects trends in income that could also impact borrowing. To account for evident pre-trends in this analysis, we employ a covariate correction (following Freyaldenhoven et al. 2019) based on the trends of neighbors. The identifying assumption is that eligibility changes are independent of loan demand conditional on the covariate correction. We also consider a subsample that is only based on the remapping of MSAs, which allows us to forgo the covariate correction. In addition to providing yet another identification approach, the event-study allows us to account for unobserved borrower heterogeneity using individual fixed effects.

Across the three methods we are unable to reject the hypothesis that the impact of the CRA on individual borrowing is zero at the 10% significance level. The lack of impact extends to the extensive margin and credit outcomes such as risk scores, bankruptcy, and delinquency. While the precision varies by specification, the range of possible outcomes around zero is relatively small. The 95% confidence intervals for the RDD suggest an impact up to 2% of the average debt balance; for the border regressions the upper bound is 2.4%. The event study has the widest range of possible outcomes with a positive impact as large as 7% at the 95% confidence intervals' upper bound. Taken together, the methods rule out a meaningful economic impact of the CRA on household borrowing in the 2000s.

In addition to the three methods, we implement several robustness tests to confirm our result. First, we consider alternative income bandwidths around the RDD and alternative event study specifications. In each instance, we fail to find a statistically significant impact of the CRA on household debt. Second, we investigate whether the impact of the CRA may be heterogeneous. We consider both the racial make-up of census tracts and the risk score of individuals. In both instances, we do not find meaningful heterogeneity, further reinforcing our findings.

We offer a potential explanation for the lack of impact on household borrowing by examining substitution between lenders subject to the CRA and lenders that are not subject to the CRA.[3] For this analysis we compare the share of mortgages originated (or purchased) by banks, which are subject to the CRA, versus non-banks, which are not, in census tracts around the eligibility threshold. Mortgages reflect the largest consumer credit balance (more than 80%) and therefore the most important debt for understanding consumer borrowing. We find that banks' share of lending is higher in just eligible tracts particularly for purchased loans. Because banks receive credit for originating or purchasing loans in LMI tracts, they can effectively increase their CRA lending without changing overall credit supply in the tract. Our results confirm the importance of the 80% eligibility threshold for lender incentives, but suggest that substitution from nonbanks and loan purchases allow banks to meet their CRA obligations without impacting the overall level of household credit. This substitution demonstrates how unregulated entities and transfers attenuate the impact of a narrow regulatory regime.

The literature has generally found weak evidence of a positive impact of CRA eligibility on credit access. The two most closely related papers also make cross-sectional comparisons across eligible census tracts; however, they do not have individual level data which can limit inference. Avery et al. (2003), which uses census cross-sections at the same 80% threshold, finds some evidence that the CRA led to higher homeownership rates, higher growth in owner-occupied units, and lower vacancy rates; however, conclusions vary across

[3] In the period after our sample period, some states have extended CRA requirements to nonbank lenders. For instance, New York and Illinois expanded the purview of the CRA in 2021.

specifications which leads the authors to note that their results are "mixed and difficult to interpret." In addition, the secondary metrics in this work cannot rule out that the findings are unrelated to consumer borrowing and instead a function of other CRA programs. For instance, the CRA also monitors areas outside the scope of our paper, such as small business lending and community investment projects.

Butcher and Muñoz (2017) is another study that uses an RDD approach similar to one of our analyses at the census tract level. The authors find that the CRA led to an increase in the number of total loans and in particular in auto loans in just eligible census tracts. However, after we control for population dynamics, the tract-level specification estimates a near-zero and insignificant estimate of the CRA's effect on consumer lending.[4] Our work not only supplements the RDD with other methods and looks at the most recent time period, but also conducts analysis at the individual-level which effectively controls for confounding composition changes in the population.

Two papers consider mortgage origination in response to the CRA. Berry and Lee (2007) uses data from 1995 to 2002 and finds no effect on new loan originations when comparing physically adjacent tracts with MFI just above and below the eligibility threshold. Bhutta (2011) uses a similar RDD methodology but does not require physical adjacency for tracts, and allows for heterogeneous effects across time periods and loan markets, finding a significant positive effect in large metro areas in the late 1990s and early 2000s but no effect in other time periods or in other areas. In contrast to these papers, we emphasize the level of borrowing rather than the flow (e.g. originations). Higher originations can be associated with more frequent refinancing or purchase activity but without impacting the stock of borrowing available to households.

Several contemporary papers also explore possible substitution effects of the CRA. Ding and Nakamura (2021) examines the Philadelphia area and finds a negative origination effect of a loss in CRA eligibility; specifically, the authors find that an eligibility loss causes CRA-covered institutions to decrease originations and FHA loan originations to increase by a smaller amount. Brevoort (2022) uses a recent subsample of the same Home Mortgage Disclosure Act data we use to show that banks increase loan purchases in CRA-eligible areas, substituting away from Government Sponsored Entity (GSE) purchases while leaving originations the same. Both of these papers lend support for our conclusion that the CRA induces some degree of substitution in origination and purchases. We are able to go a step further and show using various methods that the shift in originations and purchases

[4]In Appendix A, we roughly replicate the key findings in Butcher and Muñoz (2017), but show that this estimated effect is driven primarily by pre-existing population differences between CRA-eligible and ineligible census tracts.

is temporary and is ultimately neutral for the level of household borrowing, which is what matters for households' credit access.

The granularity and broad coverage of our data allow us to provide the most comprehensive analysis to date regarding the effects of the CRA on individual balances. In contrast, past work has generally focused only on specific areas or prior time periods, or has looked at originations (which can be complicated by refinancing activities or migration) rather than balances. Other analyses also struggled to construct valid control groups to effectively estimate the effects of the CRA, leading to mixed and imprecise results that are sensitive to empirical specifications. Our three-pronged empirical strategy allows for a more unambiguous understanding of the lack of effect of the CRA on consumer balances at a critical time when the design of the CRA is being modernized. Using data from the Home Mortgage Disclosure Act, we provide additional evidence of a substitution effect between CRA-covered banks and financial entities not covered by the CRA which in part explains the overall lack of impact on balances.

Our results do not necessarily contradict prior findings of effects from the CRA. In particular, we do not examine outcome variables such as homeownership or vacancy rates. We also do not consider credit pricing, although we would expect pricing differences to translate into balances. Further, we cannot comment on possible effects of the CRA in areas far from the eligibility cutoff or prior to our coverage dates (prior to 1999). This may be of particular importance, since there has long been an understanding that the CRA may have "encouraged banks to be aware of lending opportunities in all segments of their local communities as well as to learn how to undertake such lending in a safe and sound manner," (Kroszner 2008) suggesting that information gains may have occurred that no longer require legal reinforcement. Lastly, the CRA assesses business lending and community development, which are outside our area of focus.

The remainder of the paper is structured as follows. Section 2 explores the background of the CRA and details of its implementation. Section 3 describes our data sources. Section 4 lays out the specification and results of our three-pronged empirical strategy on our primary outcome of interest: individual balances. Section 5 discusses results on related credit outcomes, such as bankruptcies and credit scores, and several heterogeneity analyses. Section 6 presents evidence of substitution. Section 7 concludes the paper.

2 The Community Reinvestment Act

2.1 Background

The Community Reinvestment Act was one of several laws passed during the 1970s with the goal of improving credit access for disadvantaged communities. Rather than focusing on racial discrimination explicitly (as did the Equal Credit Opportunity Act, Fair Housing Act, and Home Mortgage Disclosure Act), the CRA requires depository institutions to serve the needs of all communities in which they operate, specifically targeting institutions that might take deposits from these communities but then refuse to lend to them. Loans and other activities are CRA-eligible if they are made in low-to-moderate income (LMI) census tracts. For the purposes of the CRA, LMI is precisely defined as census tracts in which the median family income of the tract is less than 80 percent of that of the surrounding geographic area, typically an MSA.[5] We will use the term MFI to refer to this median family income ratio.

Depository institutions, which include commercial banks and thrifts, are subject to the requirements of the CRA. Other financial institutions such as independent mortgage banks, credit unions, and payday lenders are not covered by the CRA. The affiliates of depository institutions are not themselves subject to the CRA, but depository institutions can include the activities of their affiliates in their own CRA assessments at their discretion (Avery and Brevoort 2015). Both originated and purchased loans count as part of a bank's CRA assessment. Depository institutions receive a CRA-compliance grade on a four-point scale as part of their regular supervisory examinations by the Board of Governors of the Federal Reserve System (FRB), the Federal Deposit Insurance Corporation (FDIC), the Office of the Comptroller of the Currency (OCC), and the Office of Thrift Supervision (OTS, now defunct). Past compliance with the CRA is considered as part of new branch and merger applications.

The CRA's scoring system ranges from "Outstanding" and "Satisfactory," which are considered passing grades, to "Needs to Improve" and "Substantial Noncompliance," which are failing grades on the basis of which a branch or merger application might be rejected. We report the distribution of CRA grades in Appendix Table B1 and plot their distribution over time in Appendix Figure C1. We note that the vast majority of grades are passing scores (97%), with far more "Satisfactory" than "Outstanding" scores (82% vs 15%).

Bank CRA grades are determined jointly by a lending test, an investment test, and a service test. These grades place emphasis on this first lending test, and historically the CRA has focused on mortgage loans and on the geographic dispersion of loans. In 1997, the CRA

[5]When a census tract falls outside of an MSA/MD, the denominator used in calculating MFI % is the median income of nonmetropolitan areas of the corresponding state.

was expanded to also consider lending to low to moderate income borrowers (again defined as MFI less than 80% of MSA median), even if these borrowers were not in low to moderate income census tracts.[6]

The intricacies of the law's implementation provide much of the structure for our analysis. The 80% MFI cutoff is key to the identification strategy of our RDD. Furthermore, since this cutoff is only necessary and sufficient for eligibility in metropolitan (non-rural) tracts, we limit our analysis to those areas. This is not a substantial reduction of our sample, as metropolitan tracts contain 86% of loans, 90% of loan balances, and 84% of borrowers over our sample period.

2.2 Contemporary Political Relevance

On May 5, 2022, the three agencies responsible for administering the CRA (the Fed, the OCC, and the FDIC) jointly released a "Notice of Proposed Rulemaking" (NPR) detailing potential changes to the rules for CRA implementation (Federal Reserve System, Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency 2022). The NPR was posted with the intention of soliciting public feedback. The most substantial changes in the proposed rule-making include a wider definition of banks assessment areas as well as more transparent metrics for the evaluations themselves.

While banks would continue to be assessed in areas where they receive deposits, under the new rules large banks would also be required to meet equitable lending criteria in areas where they have "certain concentrations of retail lending," regardless of whether they take deposits in those locations. Furthermore, assessment areas would also be updated to better consider the proliferation of online banking, with banks being assessed in areas where they engage in substantial online or mobile banking, regardless of physical branch locations.

The assessments themselves would also see changes, with a new, "metrics-based" approach for evaluation of retail lending and community development financing, which would come with the release of public benchmarks. Large banks would be required to meet these thresholds, while smaller banks would choose between being evaluated under the old framework or the new tests.

Importantly for the conclusions of this paper, the agencies also cite some concerns of loan churning, wherein "loans to targeted borrowers or census tracts were purchased and sold repeatedly by different banks, with the possibility of each bank receiving CRA credit

[6] Regulators have historically emphasized eligibility across geographies in their CRA examinations, rather than at the individual level. Brevoort (2022) similarly tests for an increase in mortgage originations at the individual income eligibility threshold, and finds no evidence of a CRA-induced increase in lending. We will show that bank shares of originated and purchased loans are different in these tracts, consistent with an impact of the CRA on bank behavior that does not extend to overall consumer borrowing.

equivalent to the banks that originated the loans." This activity would not provide any liquidity to the originator, and thus some stakeholders have argued should not grant CRA credit. Indeed, our analysis in Section 6 provides some evidence of this type of churn. Regulators are considering measures to address this behavior, such as only giving CRA credit for purchases made from the originator of the eligible loan, and solicited public feedback in the NPR for proposals for other methods to limit churn.

The NPR also includes a variety of other proposed changes to the collection of data, categorization of lenders, and logistical frameworks for implementation. The regulations would officially transition at the beginning of the first quarter at least 60-days after the publishing of the final rule, with staggered roll-out for provisions with more intense regulatory requirements.

3 Data

We conduct several natural experiments using a panel dataset of individual borrowing. The panel is merged with census-tract level data that determines whether an area is an eligible CRA assessment area and allows us to control for census-tract level observables.

3.1 Consumer Credit Panel

Our analysis is enabled by the New York Fed Consumer Credit Panel (CCP). Created by the Federal Reserve Bank of New York and the credit bureau Equifax, the CCP is a longitudinal database with detailed information on individuals' credit use and access as derived from anonymized consumer credit reports.

This dataset covers a representative five-percent sample of the U.S. and is available quarterly from 1999 to the present. The CCP includes an individual's credit score (Equifax Risk Score 3.0[7]), age, debt balances, number of accounts, delinquency status, balance limits, and utilization rates, all by category. Debt categories are quite granular and include student loans, first mortgages, junior mortgages, credit cards, etc. Many of the debt types, including mortgages and student loans, contain loan-level data for each individual. While individuals themselves are anonymized, the CCP provides detailed geographic information on individual

[7]The Equifax Risk Score is a proprietary credit score that estimates the likelihood that an individual will pay his or her debts without defaulting. A variety of factors that relate to loan performance contribute to credit scores, including previous payment history, outstanding debts, length of credit history, new accounts opened, and types of credit used (Federal Reserve Board 2007; Fair Isaac Corporation 2015); delinquency, large increases in one's debt, and events of public record (e.g., bankruptcy or foreclosure) often lead to low credit scores (Anderson 2007). The scores range from 280 to 850, with higher scores representing greater financial health and advantage.

borrowers each quarter including their home census block, as well as the larger census tract, zip code, state, etc. More information regarding the CCP is provided in an introduction to the dataset, Lee and Van der Klaauw (2010).

For our analysis we use the sample period from 1999 through 2017. For computational ease we only use half of the panel available in the CCP, a representative 2.5% sample of the U.S. We exclude student debt from our analysis because of its unique nature and lack of emphasis in the CRA; we focus on mortgage debt, auto loans, and credit cards. Table 1, Panel A summarizes the unconditional CCP sample as well as the sample conditional on our primary RDD bandwidth of 15% around the MFI cutoff. The full sample contains 367 million observations or about 4.8 million individuals per quarter with average total debt of $64k. The more restricted sample contains approximately 1.4 million borrowers with lower total debt, $43k, consistent with positive skewness in borrowing as income rises. In both samples mortgage debt is the predominant form of borrowing at roughly 80% of total debt.

3.2 Tract-Level Variables

We supplement the individual credit bureau data with census-tract-level demographics from the Federal Financial Institutions Examination Council (FFIEC). The demographics provided in this data are exactly the data used to determine CRA eligibility and include MFI among other characteristics. This data allows us to precisely identify census tract eligibility and provides the necessary running variables and other relevant controls for our RDD. Table 1, Panel B, summarizes statistics at the tract level for the overall sample and for observations within our baseline RDD bandwidth of the eligibility cutoff.

Whereas the CCP primarily uses geographic codes from the 2000 census, the FFIEC dataset uses 1990 census tracts prior to 2003, 2000 census tracts between 2003 and 2011 (inclusive), and 2010 census tracts after 2011. In order to resolve this geographic mismatch, we use publicly available Census relationship crosswalks between 1990, 2000, and 2010 census tabulation blocks.[8]

[8]To identify 1990/2010 census tracts, we map each individual from their 2000 block in the CCP to a the corresponding 1990/2010 census block based on crosswalks. We then use these census blocks to assign census tracts for 1990/2010. In rare cases where a 2000 census block splits into multiple 2010 census blocks, we check the individual's 2010 census block (which we have from the CCP after 2011). If it is one of the 2010 blocks their 2000 tract split into, we use it for the whole 2010 period; otherwise, we drop the individual. We also drop observations in the small percentage of cases in which our 2000 block is split between multiple 1990 tracts. We confirm the accuracy of our prediction procedure on data from 2014 onwards, where 2010 census geographies are available; predicted 2010 census tracts match observed census tracts in the vast majority of cases in which individuals have not moved from their 2000 census block.

3.2.1 Median Family Income

The FFIEC updates its source of MFI (a variable that determines CRA eligibility) and its definitions of geography on several occasions. These changes, whenever they occur, can cause some individuals to gain or lose CRA eligibility. When the FFIEC begins using income from a new source, tracts are assigned new MFI values, and may rise above or drop below the 80% threshold as a result. Similarly, when the geographical definitions of MSAs are changed, tracts may cross the 80% threshold, since the MFI of the MSA they are compared to may change.[9] See Figure 1 for a visualization of tract eligibility status in an example MSA.

In our event studies, it would be problematic to simply use the reported MFI as the primary running control in our analysis, since sharp changes in covariates simultaneous to the gain or loss of eligibility would confound identification of the CRA effect. So, for these specifications, we begin using new MFI values as soon as they are measured and linearly interpolate between those values. For example, we start using the 2000 census data in 2000q2, when it was measured, rather than in 2003q1, when the FFIEC begins using it. In quarters between 2000q2 and 2004q1, we use interpolated values between the 2000q2 update and the 2004q1 update (which was calculated at the same time the FFIEC began using it). Beginning in 2009, we use the 5-year ACS to estimate MFI for each year, linearly interpolating for quarters between these yearly updates. This approach gives a smooth estimate of MFI for all quarters for our event studies.

3.3 Mortgage Issuance

Our final set of analyses compares consumer loan originations by CRA-regulated institutions (e.g. banks) to non-CRA-regulated institutions. To do so, we require origination data that can be linked to CRA-eligible census tracts *and* to lending institutions inclusive of non-banks which are not subject to the CRA.

We use the Home Mortgage Disclosure Act (HMDA) data, which contains application-level information on nearly all U.S. mortgage applications, including the location of the property and the identity of the originating institution.[10] In addition, HMDA includes the loan amount and borrower characteristics such as income, race, and gender. The data also report whether the application resulted in an origination and if so, whether the loan was

[9]The switches in MFI source/geographic definition occur in the following quarters: 2003q1 (1990 Census → 2000 Census); 2004q1 (Change from 4-digit MSA/PMSAs to 5-digit MSA/MDs); 2012q1 (2000 Census → 2010 Census); 2014q1 (Change in MSA delineations); and 2017q1 (2010 Census → 2015 5-year ACS).

[10]HMDA reporting is mandatory for banks with assets above a low asset size cutoff (e.g., $40 million in 2011) that have a branch in a metropolitan statistical area and made at least one mortgage loan in a given year. See `https://www.ffiec.gov/hmda/reporter.htm`. Avery et al. (2007) contains a detailed description of HMDA data and its strengths and weaknesses for use in research.

sold/securitized in the same calendar year. We are able to identify the type of lending institution based on the classification of the high-holder for each reporting entity.

We restrict our analysis to originated and purchased loans less than $5 million during the period 2003 through 2017.[11] We exclude the largest loans to avoid skewing issuance toward rare but wealthy borrowers that are not the focus of our analysis. The sample period is chosen to align the census tract definitions with the tract-level variables. We use a concordance developed by Robert Avery to identify the type of lender and whether they are subject to the CRA.[12] The HMDA origination data is summarized in Table 1, Panel C. The HMDA sample contains 207 million originated or purchased loans with 52 million in census tracts within the 15% MFI bandwidth. In each sample, banks issue/purchase approximately two thirds of the underlying loans.

4 The CRA and Debt Balances

In this section, we present three complementary empirical strategies, leveraging each to evaluate our primary outcome of interest: whether household debt balances increase in CRA-eligible census tracts. Each of these three approaches relies upon a distinct set of identification assumptions and each concludes separately that the CRA does not have a statistically or economically significant effect on balances.

First, we compare individuals in CRA-eligible areas to those in similar but ineligible tracts using a cross-sectional regression-discontinuity design (RDD). We then compare CRA-eligible areas to their ineligible neighbors, exploiting a geographic rather than income-based discontinuity. Finally, we examine individuals whose neighborhoods gain CRA-eligibility using an event-study approach. The following subsections lay out the model specifications, discuss the unique identification assumptions for each strategy, and provide results on household balances. Later sections similarly show a lack of impact for other outcomes of interest and across demographic subgroups, and also provide possible drivers of our primary results.

4.1 Regression Discontinuity Design

Let i index individuals, c census tracts, and t calendar quarters. We model an outcome variable Y_{ict}, such as total debt balance. Let E_{ct} be an indicator for whether individual i lives in a CRA-eligible tract c in quarter t. MFI_{ct} is the tract's median family income as a percentage of the surrounding MSA, as defined in the FFIEC data. γ_{tm} are fixed effects for

[11] These excluded loans make up less than 1bp of the total sample.

[12] The file is available here: `https://sites.google.com/site/neilbhutta/data`. Both credit unions and mortgage companies (non-banks) are exempt from CRA obligations.

MSA m at time t. Finally, let ε_{ict} be an error term capturing idiosyncratic shocks unrelated to CRA-eligibility.

Our RDD specification is, then:

$$Y_{ict} = \beta_0 E_{ct} + \beta_1 MFI_{ct} + \beta_2 \left(E_{ct} \times MFI_{ct}\right) + \gamma_{tm} + \varepsilon_{ict} \tag{1}$$

The coefficient of interest, β_0, captures the discontinuous change in the dependent variable at the eligibility cutoff. Importantly, we limit our panel to individuals in tracts with an MFI within a fixed bandwidth on either side of the 80% cutoff for eligibility. Thus, this regression is identified by variation between individuals in tracts with similar income levels, but which differ in their CRA-eligibility. While the income is similar, it is slightly lower in eligible areas so we also have to assume that in the absence of the CRA there is a linear relation between income and consumer borrowing. In addition to individual level RDD analysis, we also consider similar specifications that are aggregated to the tract level. In both instances, standard errors are clustered at the census tract level to capture potential correlations within census tracts over time.

A typical concern with cutoffs is that over time agents make choices in response to the cutoff that results in sample selection around one-side of the discontinuity. Such behavior can undermine the identification assumption that individuals are otherwise similar on either side of the cutoff. While unlikely in this scenario, we confirm that there is not a discontinuity in sample density around the cutoff using a density manipulation test (McCrary 2008; Cattaneo et al. 2020); the test soundly rejects a density discontinuity.

Another common concern with cross-sectional comparisons is that they can mask an overall increase in lending in both eligible and ineligible areas. In the instance of the CRA, the concern might be that the CRA induces additional lending in all census tracts (not just in eligible tracts), and that this is missed by our comparison of eligible vs. ineligible tracts. For this to be the case, the presence of the CRA would need to induce some lenders to lend more in ineligible areas. In other words, lenders would forgo profitable lending opportunities in ineligible areas in the absence of the CRA. This premise seems unlikely given the size and scope of the U.S. mortgage market. There are a wide-array of bank and nonbank lenders and they have ready access to funding via GSE securitization programs. Regardless, the event study results are robust to this concern.

There is a well-understood bias-variance trade-off in the selection of optimal bandwidths in regression discontinuity designs (Imbens and Kalyanaraman, 2011). To establish an appropriate bandwidth for our analysis, we estimate the optimal bandwidth using individual-level data across the various types of debt (total, mortgage, auto, and card).[13] In each of these exercises, we weight observations using a triangular kernel based on distance from the cutoff to ensure the census tracts that are closest to the cutoff are emphasized. We find that the optimal bandwidth varies from 15.6% to 16.1% on either side of the 80% MFI cutoff across balances for different types of debt. For other outcome variables, the range varies from 11.8% to 17.2%. Optimal bandwidths for each of our outcome variables are displayed in Appendix Table B2. In the analysis that follows, we use a constant 15% bandwidth for all specifications to simplify exposition and comparisons, but our results are generally robust to any bandwidth in the optimally selected range–we present results using the outer bounds of the suggested range in Appendix B (see Appendix Tables B3-B12) and highlight any differences in the following text.

4.1.1 Results

Figure 2 illustrates the primary results of our RDD, a binscatter around the eligibility threshold. For each of the underlying specifications, the MFI bandwidth of observations around the 80% cutoff is optimally selected using the MSE-optimal bandwidth explained above. The precise numerical results of our primary RDD design are displayed in Table 2, Panel A, using a 15% bandwidth threshold. The key result is in column (1), which shows a near-zero point estimate for CRA-eligibility on total individual balances with a 95% confidence interval ranging from -$726 to $851 per borrower (small relative to an average debt balance $42,520).

We also decompose our results into major debt types; since mortgages compose the vast majority of consumer debt, effects on other debt types can be subsumed in the aggregate. The RDD shows no effect on either credit card or auto balance debts.[14]

In addition to the intensive margin of debt we consider the extensive margin of debt using a linear probability model. Practically speaking, we replace balances on the left-hand side of Eq. 1 with an indicator for having a non-zero debt. While the CRA may not lead to a change in dollar borrowing, it could increase the participation of households in credit markets. The results are summarized in Table 2, Panel B. The dependent variable is an indicator for having a positive balance in any category, column (1), a mortgage, (2), an auto loan, (3), and a credit card balance, (4). Across all three margins, we fail to find a statistically significant impact of the CRA. We find point estimates close to 0 (point estimate 0.09% for any debt

[13] We use the MSE-optimal bandwidth selection implemented in the `rdrobust` package (Calonico et al., 2017).

[14] Mortgage debt includes first liens, second liens, and home equity lines of credit (HELOC). Auto loans include loans from banks and finance companies. Credit card debt includes bank card, retail, and consumer finance loans. Total debt is defined as the sum of mortgage, auto, and credit card debt, and excludes student debt.

with 95% confidence interval [-0.15%, 0.34%]), with no notable variation across debt type. In sum, the RDD suggests that the CRA does not impact borrowing dollar amounts or the portion of consumers with debt.

We leverage a separate specification of our RDD to look at how the number of individuals included in the CCP dataset changes with CRA eligibility. Since only people with some activity recorded by Equifax will appear in the dataset, this is one measure of the portion of people in an area with some level of formal credit activity. When estimated at the tract-level, we find no significant effect of the relationship between CRA-eligibility and the number of individuals in the CCP dataset controlling for 1990 census population (see Appendix Table A2).

4.2 Neighbors Across CRA Eligibility Borders

The RDD approach above uses just-ineligible tracts within the same metro area and with similar income levels as control units for individuals in just-eligible tracts. A related neighbors-based approach uses geographically proximate individuals with different CRA eligibility as controls by comparing lending to individuals who live in adjacent census *blocks* but who live on opposite sides of a census tract CRA-eligibility border.[15] By focusing on neighboring census blocks, we ensure that our analysis compares individuals that are in relatively close proximity. We restrict to individuals living in a census block for which there is an adjacent census block that is on the opposite side of the 80% cutoff and, as a result, differs in CRA eligibility. In order to avoid comparing areas with disparate income, we also restrict to individuals living in a census block with a tract-level MFI within the 15% bandwidth for which there is an adjacent census block also within this tract-level MFI bandwidth but on the opposite side of the 80% cutoff.

We model the outcome of an individual i living in census tract c at time t as a function of her tract's CRA eligibility and MFI, and a border-quarter fixed effect, γ_{bt}.

$$Y_{ict} = \beta_0 E_{ct} + \beta_1 MFI_{ct} + \beta_2 \left(E_{ct} \times MFI_{ct}\right) + \gamma_{bt} + \varepsilon_{ict} \tag{2}$$

The border×quarter fixed effects ensure that the estimated impact of CRA eligibility, β_0, is identified by comparisons of neighbors along the same tract border and within the same quarter. Again, standard errors are clustered at the census tract level.

[15] Census blocks are subsets of tracts that are determined by physical boundaries, like roads, or nonvisible boundaries like city limits. In a city, a census block will typically be a city block bounded on all sides by streets. There are roughly 150 census blocks per census tract in the United States. Unlike tracts they do not have a typical population. There were more than 11 million census blocks in the 2010 U.S. census.

4.2.1 Results

Our cross-sectional analysis of neighbors across a CRA eligibility border estimates small and insignificant effects of the CRA on lending. In Table 3, Panel A, our neighbors analysis estimates a CRA effect of -\$425.40 on total individual balances, with a 95% confidence interval ranging from -\$1,449.70 to \$598.90. Relative to the RDD findings, the results are less precise. This reflects a much smaller sample, approximately 30% of that used in Table 2. Despite the lower precision, the upper bound of the 95% CI does not exceed 2.6% of the average debt balance. The results are consistent across debt types in columns (2), (3), and (4).

Table 3, Panel B, summarizes the extensive margin results. Again, we find no statistically significant impact on the likelihood of having debt. As with the balance results in Panel A, the standard errors are larger than those obtained using RDD. We find a CRA effect of roughly 0% (95% confidence interval [-0.35%, 0.35%]) on the number of accounts with a positive balance. The overall results affirm the earlier finding that the CRA has little to no effect on consumer debt.

4.3 Event Study

For our third approach, we consider an event study, or difference-in-differences (DiD), approach. In this approach we compare outcomes of individuals that gain eligibility over time relative to those that do not. This approach allows us to control for both individual and time fixed effects to account for yet another potential source of unobserved heterogeneity.

A key identifying assumption is that there are parallel trends across the treatment and control groups. In this setting, the results could be confounded by differing trends in census tracts that change eligibility relative to tracts that have no changes in eligibility over the event window. For instance, if income is trending in an area it may shift CRA eligiblity and impact the borrowing habits of individuals over time. Census tracts gain CRA-eligibility when their MFI decreases from $> 80\%$ to $\leq 80\%$, so tracts which cross the threshold are necessarily on a negative income trajectory relative to the surrounding area. Therefore, it is unlikely that a parallel trends assumption will hold, and, indeed, we show in Appendix Figure C2 that running a basic event study with two-way fixed effects (date and individual) reveals substantive pre-trends. Because of this, we focus our analysis on the following covariate-corrected event study.

We apply a method of covariate correction introduced in Freyaldenhoven et al. (2019), which is our preferred event-study specification as it addresses the disparate trends problem we lay out above. Here, we identify a covariate that is likely to trend similarly to an individual's balances, but which is unaffected by the policy in question. Then, using a two-stage least squares approach, we estimate and net out the portion of the variation in our outcome variable attributable to the covariate.

Our primary outcome variable in the event study is the log of debt balance (plus one to account for zeros). The log formulation is scale invariant which facilitates a covariate correction that is concerned with common pre-trends. If there are economic trends affecting the trajectory of debt balances in an area, we expect neighboring tracts to be moving in similar ways. Thus, for each individual, we use the average log balance of individuals in *adjacent* census tracts as the covariate in this analysis. We do not include neighbors in tracts that gain eligibility to ensure that they are not also exposed to possible effects from the policy.[16] Then, letting X_{it} be the average balance of individuals in ineligible census tracts adjacent to tract i at time t, we estimate the first-stage equation:

$$X_{it} = \sum_{j \notin \{-1,-2\}} \phi_j \mathbb{1}_{\{t+j=T_i\}} + \kappa Z_{it} + \rho MFI_{it} + \omega_t + \nu_i + \eta_{it} \tag{3}$$

where T_i is the first quarter individual i gains CRA eligibility,[17] MFI_{it} is the interpolated MFI for the census tract described in Section 3.2.1, and ω_t and ν_i are time and individual fixed effects, respectively.[18] Additionally, our excluded instrument Z_{it} is a lead term for eligibility, equal to 1 if $t >= \tau - 1$ when individual i gains eligibility on date τ.

This estimation gives us our estimated values of the adjacent tract average log balances, $\widehat{X_{it}}$, which captures the declining local economic trends of tracts that gain eligibility. Then, we can run our second stage, effectively netting out the explained effects of this general trajectory from our estimation of the post-gain indicator coefficients. The equation for this stage is:

$$Y_{it} = \sum_{j \notin \{-1,-2\}} \beta_j \mathbb{1}_{\{t+j=T_i\}} + \xi \widehat{X_{it}} + \gamma MFI_{it} + \alpha_t + \delta_i + \varepsilon_{it} \tag{4}$$

where Y_{it} is an individual i's log balance at time t, and our coefficients of interest are β_j where $j \geq 0$, since these will capture the change in outcomes after our event. It is important to note that this use of neighbors' balances as a control adds an assumption for theoretical

[16]Since some individuals enter and exit the CCP data every quarter, we balance the panel by including all individuals whose first observation was within the 15% bandwidth MFI bandwidth around the 80% eligibility cutoff. As with the RDD, we choose these individuals for their similarities along other characteristics, but, unlike the RDD, our identification does not rely upon any assumptions of continuity of covariates around the threshold. Results are not sensitive to other sensible ways of balancing the panel.

[17]Individuals whose addresses change eligible tracts are not considered to have gained eligibility.

[18]We also note that we group all indicators prior to $j = -4$ and after $j = 8$ into binned indicators (one for $j < -4$ and one for $j > 8$) capturing all quarters before and after our window of interest, which is one year prior to our eligibility change, and two years after.

validity: that the effects of CRA eligibility do not spill over into adjacent geographical areas.

To supplement our correction for pre-trends, we also include a matching specification where we match each individual who gains eligibility to a CRA-ineligible individual who does not go on to gain eligibility. More specifically, at the date of each eligibility change, we record the difference between the previous two measurements of MFI. We then split the entire population into percentiles of this change in MFI and use coarsened exact matching to pair "treatment-group" individuals to "control-group" individuals, randomly assigning matches within percentiles. In this instance, the treatment group consists of those individuals who gain eligibility at the date in question.[19] The control group consists of individuals who (a) never gain CRA-eligibility and (b) are not CRA-eligible at the time of the switch. We then run the same event study as above, replacing the individual fixed effects with pairwise fixed effects.

We consider a second method to remove income trends as a potential confounder. We restrict our "naive" event-study analysis to eligibility gains that occur due to plausibly exogenous geography re-definitions, rather than due to income changes. Specifically, there were changes in the larger MSA geography delineations used to define the denominator of a census tract's MFI ratio. These changes occurred in 2004Q1 (the change from 4-digit MSA/PMSAs to 5-digit MSA/MDs) and in 2014Q1, a change in MSA delineations. There were no other updates to the income data used in these quarters.

4.3.1 Event Study Results

Our primary covariate-corrected event study estimates near-zero effects of the CRA in Figure 3, with point estimates between -9.2% and -1.4% across quarters in the years following a CRA-eligibility gain. The results have an insignificant pre-trend and a less prominent post treatment trend compared to the naive event study (Appendix Figure C2) and the matching specification detailed above (Appendix Figure C3). Our alternative analysis restricting to eligibility gains caused by geography redefinitions (Appendix Figure C4) also has an insignificant pre-trend and estimates near-zero CRA impacts. All four specifications reject a significant positive effect of the CRA on debt balances.

Notably, the 2SLS covariate-correction procedure in our primary specification uses the estimated value of neighboring balances as a control which reduces the precision of the estimates compared to the naive and matched approaches. Specifically the primary specification has 95% confidence intervals as low as -17.6% and upper bounds as high as 3.2% in the years following eligibility gain. Our alternative matching specification similarly rejects positive CRA impacts on balances with greater precision (95% confidence intervals range from as

[19]For individuals who gain eligibility multiple times, only the first gain is included.

low -3.3% to as high as 1.3%) but shows some significant differences between treated and control-group trends in the pre-treatment period.

Our analysis restricting to eligibility gains due to geography redefinitions estimates near-zero CRA impacts, trading off less precision (95% confidence intervals range from -7.1% to 7.7%) in order to avoid selection on income trends. While the event study estimates are somewhat imprecise or less well-identified, the fact that results are consistent with our other approaches further reinforces the findings that balances are not materially impacted by the CRA.

5 The CRA and Other Outcomes

We consider several alternative outcome variables using the three distinct empirical specifications outlined in Section 4. In particular, we explore a variety of negative credit outcomes, such as bankruptcy, attempting to detect possible unintended consequences of expanding consumer credit. We also use the RDD to investigate the possibility that the CRA has a heterogeneous impact across different segments of the population.

5.1 Credit Scores and Negative Credit Outcomes

There are a variety of other credit outcomes of interest provided in the CPP. We specifically consider possible effects of the CRA on credit scores (using the Equifax Risk Score 3.0 included in the CCP), as well as the negative credit outcomes of bankruptcy, foreclosure, and delinquency.

In theory, the CRA could have either positive or negative effects on risk score. Increased access to credit could help people build credit, or it could increase their probability of experiencing negative credit outcomes such as default, which would hurt their credit. However, our previous results suggest that the CRA is unlikely to substantially affect either of these avenues, since we see no evidence of it increasing access to credit. Indeed, our RDD results (Table 4) show a negative and insignificant point estimate using our primary bandwidth, and similar results across specifications. Similarly, our border regressions (Table 5) shows a near-zero and insignificant impact on risk score. Finally, our event-study results (Figure 4) corroborate this trend, showing modest and only marginally statistically significant declines (consistent with slightly negative pre-trends) in credit score after eligibility gain.

Our RDD likewise shows near-zero point estimates across the three negative credit outcomes we study: bankruptcy, foreclosure, and delinquency. These results can also be found in Table 4. Our other empirical strategies (neighbors and event studies) similarly estimate small and insignificant effects of CRA-induced lending on negative credit outcomes (see Table 5 and Figure 4).

5.2 Heterogeneous Impacts

While the CRA does not seem to have an effect on household borrowing, the large administrative and enforcement costs of the law might still be justified if key sub-populations benefit in ways that are drowned out when effects are analyzed in the aggregate. Therefore, we apply our preferred empirical strategy to separately analyze the effects of the CRA on areas with varying minority populations and to test for heterogeneous effects across the credit score distribution.

First, we look at subsamples organized by the tract-level share of minority populations. Specifically, we split individuals into quintiles based upon their tract's proportion of non-white individuals in the 1990 census. Then, we run our individual-level RDD on each of these subsamples. Results for both balances and the extensive margin (Figure 5) cohere with our full-sample results: point estimates are near-zero and almost all insignificant at the 95% level (even without adjusting for multiple-hypothesis testing), suggesting that the CRA does not have an impact on individual borrowing for any of the populations of interest.[20]

We also separately analyze subsamples splitting individuals into quintiles by their Equifax Risk Score. Results for balances and the extensive margin (Figure 5) also show near-zero point estimates that are entirely statistically insignificant for each of these subsamples. This suggests that the CRA does not differentially affect individuals with higher vs. lower risk scores.

6 Substitution from Uncovered to Covered Lenders

In our final empirical exercise, we use loan-level HMDA data to explore a possible explanation for the null effects on household balances. Specifically, we compare lending by banks, which are covered by the CRA, to non-bank financial institutions, which are not subject to the CRA. If the CRA induces additional lending in eligible census tracts, we would expect to see higher market share by banks in CRA-eligible areas relative to non-CRA institutions and relative to CRA-ineligible areas. This shift in supply could occur even if there is no net effect on consumer debt due to substitution between the covered and uncovered lenders. For this analysis, we explore both tract- and loan-level composition.

[20]See Appendix Figures C5-C8 for heterogeneity by debt type.

Mortgage originations are a natural laboratory to understand the incentives induced by the CRA. Mortgages reflect the largest form of consumer debt, more than 80% (excluding student debt); hence they are critical to understanding the evolution of consumer borrowing. In addition, the mortgage market has several properties that facilitate a comparison across lenders. A significant share of mortgage lending is done by non-bank issuers that are not subject to the CRA. Also, mortgage loans are similar across lenders, especially conforming GSE loans that are more likely to be securitized.

6.1 RDD: Mortgage Originations

Before exploring the substitution across lenders, we first verify that mortgage originations do not exhibit increased issuance around the eligibility cutoffs. To do so, we use a model similar to Equation (1), where the dependent variable is a measure of mortgage origination activity in census tract c in quarter t:

$$Y_{ct} = \beta_0 E_{ct} + \beta_1 MFI_{ct} + \beta_2 \left(E_{ct} \times MFI_{ct}\right) + \beta_3 Pop_t + \gamma_{tm} + \varepsilon_{ct}. \tag{5}$$

We consider four measures of mortgage activity, Y_{ct}: the dollar amount of originations and purchases (in thousands), the log of the dollar amount, the corresponding number of mortgages, and the log of the number of mortgages. For the log specifications we weight by the lagged amount of activity in the census tract. As before we include Date-MSA fixed effects, γ_{tm}, and controls for the 2000 census population. The parameter of interest, β_0, captures the jump in the mortgage originations at the eligibility cutoff. We use the same 15% bandwidth and triangular weightings to emphasize tracts close to the eligibility cutoff. Standard errors are clustered by census tract.

The results of this analysis are summarized in Table 6. Across all four measures of mortgage lending, the impact of the CRA is statistically indistinguishable from zero. Neither the amount of lending, columns (1) and (2), or the number of loans, columns (3) and (4), increase at the eligibility cutoff. The results are consistent with our earlier findings that show the level of consumer balances are unaffected by the CRA.

6.2 RDD: Bank Market Share

We further modify the RDD used for mortgage originations, Eq. 6, to evaluate the impact of the CRA on the share of originations and purchases made by CRA-covered lenders (e.g. banks). Banks receive CRA "credit" for purchased loans in the same way they do for loans that they originate.

$$Y_{ct} = \beta_0 E_{ct} + \beta_1 MFI_{ct} + \beta_2 \left(E_{ct} \times MFI_{ct}\right) + \gamma_{tm} + \varepsilon_{ct} \tag{6}$$

The modifications in this specification account for the change in the dependent variables. First, we exclude the population control because our analysis is in shares; second, we weight some specifications by the amount of lending in the tract to limit the impact of less relevant tracts. We consider market share based on loan amounts and the number of loans. In all of these cases, the coefficient β_0 reflects the change in bank tract-level market share at the eligibility cutoff.

We replicate this analysis at the loan-level using a linear probability model. Here, the dependent variable is a binary variable that indicates whether the lender is a bank subject to the CRA. The loan-level approach allows us to include granular controls related to the mortgage in some specifications.

$$Y_{ict} = \beta_0 E_{ct} + \beta_2 MFI_{ct} + \beta_3 \left(E_{ct} \times MFI_{ct}\right) + \beta_3 X_{it} + \gamma_{tm} + \varepsilon_{ict} \tag{7}$$

The loan level controls, X_{it}, include log of applicant income, log of loan amount, and indicator variables for applicant race and gender, whether the property is owner-occupied, loan purpose, loan type (conventional, FHA, VA, FSA), jumbo status, an indicator for missing applicant income, and whether there is a co-applicant. We consider specifications weighted by loan amount, which corresponds to a dollar-based market share, and other specifications that are unweighted, which corresponds to a count based market share. The resulting linear probability model estimates the likelihood that a loan is issued by a bank lender around the census tract eligibility cutoff.

Because these analyses compare relative origination activity by different types of institutions, rather than the level of consumer balances, they do not comment on an overall change in credit supply. Rather, a positive coefficient on the eligibility indicator, E_{ct}, would imply substitution between types of lenders that are covered by the CRA versus lenders that are uncovered by the CRA. Moreover, the results in Table 6 imply that market share shifts are purely substitution between types of lenders, as there is not a significant difference in origination activity in CRA eligible census tracts.

We consider two distinct alternatives to the loan-level model to better understand the source of market share shifts. First we focus only on originated loan share and exclude loans that are purchases. Then, we consider loans that are sold within the calendar year and what share of sold loans are sold to banks. For the latter, we include calendar month controls to account for the significant seasonality related to the share of loans sold within a calendar year (loans originated later in the year are less likely to be sold before the year ends). The two analyses help reveal the manner in which market share is shifting in CRA eligible areas.

6.2.1 Results

At the tract level, our analysis suggests that CRA eligibility modestly increases the share of bank mortgage lending in a census tract. Panel A of Table 7 shows that bank share is about half a percentage point higher in eligible areas. The results are similar whether the specification is weighted or if we consider dollar amounts, columns (1) and (2), or loan counts, (3) and (4). The weighted results are all significant at the 5% level and the unweighted results are significant at the 10% level.

The linear probability model shown in Panel B gives similar, albeit slightly lower estimates. Both the dollar weighted specifications in columns (1) and (2) as well as the loan count specifications in (3) and (4) imply a shift in share of around one-third of a percent towards banks. Hence, while overall lending may not increase as a result of the CRA designation, it does appear to encourage lenders subject to CRA rules to lend or purchase more, consistent with substitution across lenders rather than an overall increase in supply.

We decompose this substitution effect into originations vs. purchases in Table 8. Panel A shows a smaller and statistically insignificant impact of the CRA on the bank share of originations (∼20bps). Including loan controls in columns (2) and (4) roughly halves this effect. In contrast, Panel B shows a larger and statistically significant impact on the bank share of *purchases*; mortgages are about 0.4% more likely to be purchased by banks (relative to non-bank institutions or GSEs) in CRA-eligible areas. The results are slightly stronger when loan controls are included.

More than 70% of purchased loans by banks in CRA eligible areas are re-sold within the calendar year, two-thirds of those sales are to GSEs — this suggests that banks are able to meet CRA requirements without changing the ultimate owner of the loan or significantly changing the liquidity of those loans. Also, bank purchases in eligible areas are more likely to be sold to other banks and affiliated institutions than purchases in ineligible areas, consistent with concerns that some CRA eligible loans are 'churned' to satisfy CRA expectations. Regardless of destination or eligibility status, the extent to which purchased loans are re-sold suggests that the liquidity benefits to the loan originators are modest.[21] In sum, banks are more likely to purchase loans in eligible areas and once purchased they tend to further transfer these loans regardless of eligibility status.

[21] Details on the re-sale of purchased loans are summarized in Appendix Table B13 where we summarize the re-sale behavior of banks in eligible and ineligible areas. While there may be more salient differences across eligibility status after conditioning on loan characteristics, our goal here is to simply demonstrate that re-sales are common regardless of where they are originated.

Combined with our aggregate estimates yielding null point estimates, these results suggest that increased bank lending and purchasing in eligible areas is accompanied by a proportionate decrease in non-bank activity, which explain the lack of net changes on the consumer side. This result also shows the potential pitfalls of giving banks credit for purchasing loans they do not originate, as banks seem to comply with the CRA in part by purchasing loans and then reselling these loans, without increasing the total level of lending to populations targeted by the CRA.[22]

7 Conclusion

To quantify the impact of the CRA on consumer credit outcomes during the 1999-2017 period studied, we use data from consumer credit reports and mortgage originations combined with three complementary empirical strategies: an RDD around a census-tract income-eligibility cutoff; a comparison of individuals in neighboring census blocks that differ in CRA eligibility; and an event study around changes in CRA eligibility. The approaches combine cross-sectional comparisons of eligible CRA areas to ineligible areas with time-series comparisons of within census tract borrowing as eligibility varies. As a consequence, the results are robust to identifying assumptions and difficult to reconcile with alternative interpretations.

Each approach estimates statistically insignificant impacts of the CRA on the level of household borrowing, ruling out economically significant impacts larger than $\pm 2\%$ of the average lending balance. We similarly find no evidence of economically or statistically significant impacts of the CRA on lending in different debt categories, on the extensive margin, in neighborhoods with higher rates of ethnic minorities, or across the individual risk score distribution. We also estimate small and insignificant impacts of the CRA on individual credit scores and negative credit outcomes. In short, the CRA seems to have little if any effect from the perspective of borrowers.

We explore one contributing factor for the lack of impact on consumer borrowing. By examining mortgage originations, we show that the CRA does induce mortgage substitution from unregulated non-bank lenders to regulated depository institutions. Banks receive credit for purchased loans in their CRA examinations (rather than just from originated loans), and banks make up a higher share of mortgage purchases (relative to purchases by non-banks) in just-eligible vs. just-ineligible census tracts. Banks then sell the majority of purchased mortgages to GSEs within the calendar year and thus may use credit from short-lived mortgage purchases to comply with CRA lending requirements without increasing the

[22] See Brevoort (2022) for analysis which similarly finds evidence of CRA compliance through the purchase of loans originated by other lenders.

supply of credit to CRA-eligible borrowers.

With respect to policy, our results can be interpreted in two ways. On the one hand, the lack of impact on borrowing is consistent with mortgage demand being satisfied. In this case, there may no longer be a clear public need for a program focused on household access to finance. On the other hand, our research may provide empirical support for recent calls to expand the CRA to the nonbank sector and for regulators' concern with loan "churning" or repeated purchases by banks of CRA-eligible loans as a form of CRA compliance.[23] Limiting credit for repeatedly purchased and then resold CRA-eligible loans might mitigate this form of ineffective compliance and could help the CRA to better achieve its goal of ensuring that depository institutions serve the needs of all communities in which they operate.

[23] "Fed's Powell embraces idea of CRA for nonbanks", *American Banker*, May 21, 2021; Federal Reserve System, Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency 2022, page 172.

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Tables

Table 1: Summary Statistics

	Full Sample				15% Bandwidth			
	Mean	Median	Std. Dev	Obs.	Mean	Median	Std. Dev	Obs.
Panel A: CCP Account Level								
CRA Eligible	0.25	0.00	0.43	365,970,724	0.42	0.00	0.49	107,555,627
Positive Debt Balance	0.72	1.00	0.45	367,132,532	0.69	1.00	0.46	107,819,988
Debt Balances								
Mortgage	54,558.09	0.00	141,966.46	367,132,532	34,539.97	0.00	96,952.28	107,819,988
Auto	4,299.01	0.00	10,996.51	367,132,532	3,947.03	0.00	10,182.92	107,819,988
Card	4,186.95	565.00	12,625.03	367,132,532	3,569.71	384.00	10,158.51	107,819,988
Total	64,220.46	4,874.00	149,128.18	367,132,532	43,054.01	2,815.00	103,129.62	107,819,988
Riskscore	692.57	714.00	106.30	329,295,991	673.46	684.00	108.00	94,926,464
Delinquent Indicator	0.01	0.00	0.10	367,132,532	0.01	0.00	0.11	107,819,988
Bankrupt Indicator	0.04	0.00	0.33	367,132,532	0.04	0.00	0.35	107,819,988
Foreclosure Indicator	0.09	0.00	0.29	367,132,532	0.10	0.00	0.30	107,819,988
	Full Sample				15% Bandwidth			
	Mean	Median	Std. Dev	Obs.	Mean	Median	Std. Dev	Obs.
Panel B: Tract Level								
Median Family Income	100.86	96.12	43.55	4,066,739	81.14	81.74	8.54	1,235,063
CRA Eligible	0.31	0.00	0.46	4,035,622	0.44	0.00	0.50	1,231,233
Population (Equifax)	90.28	82.00	54.64	4,066,739	87.30	80.00	48.24	1,235,063
Population (1990 Census)	4,028.89	3,804.00	1,932.70	2,832,795	4,067.00	3,848.00	1,816.41	882,714
Total Debt Balances								
Mortgage	4,925,334.91	2,974,730.00	6,310,223.66	4,066,739	3,015,311.43	2,107,602.00	3,330,478.50	1,235,063
Auto	388,101.64	297,774.00	376,723.77	4,066,739	344,572.30	279,442.00	290,125.28	1,235,063
Card	377,985.11	301,843.00	337,954.68	4,066,739	311,632.47	264,181.00	235,731.29	1,235,063
Total	5,797,623.31	3,755,729.00	6,895,222.66	4,066,739	3,758,579.37	2,798,953.00	3,736,160.13	1,235,063
Share with Debt Balances								
Mortgage	0.29	0.29	0.14	4,066,739	0.25	0.25	0.10	1,235,063
Auto	0.26	0.26	0.10	4,066,739	0.26	0.26	0.09	1,235,063
Card	0.62	0.64	0.13	4,066,739	0.60	0.61	0.10	1,235,063
Total	0.70	0.72	0.12	4,066,739	0.68	0.69	0.09	1,235,063
	Full Sample				15% Bandwidth			
	Mean	Median	Std. Dev	Obs.	Mean	Median	Std. Dev	Obs.
Panel C: HMDA Loan Level								
Issued by Bank	0.67	1.00	0.47	207,222,883	0.66	1.00	0.47	52,002,120
Purchased	0.27	0.00	0.44	207,248,696	0.27	0.00	0.45	52,005,769
Loan Amount (Thousands)	195.89	157.00	172.21	207,248,696	151.80	125.00	120.07	52,005,769
Applicant Income (Thousands)	101.74	76.00	106.86	172,689,340	79.56	62.00	79.30	42,802,493
Co-Applicant Indicator	0.61	1.00	0.49	207,248,696	0.56	1.00	0.50	52,005,769
Owner Occupied indicator	0.90	1.00	0.30	207,248,696	0.88	1.00	0.32	52,005,769
Home Purchase Indicator	0.43	0.00	0.50	207,248,696	0.45	0.00	0.50	52,005,769
Refinancing Indicator	0.57	1.00	0.50	207,248,696	0.55	1.00	0.50	52,005,769
Jumbo Loan Indicator	0.06	0.00	0.23	207,248,696	0.03	0.00	0.16	52,005,769
Loan Type								
Conventional	0.82	1.00	0.39	207,248,696	0.78	1.00	0.41	52,005,769
FHA Insured	0.13	0.00	0.33	207,248,696	0.16	0.00	0.37	52,005,769
VA Guaranteed	0.04	0.00	0.20	207,248,696	0.04	0.00	0.20	52,005,769
Race and Ethnicity Indicators								
White	0.57	1.00	0.49	207,248,696	0.57	1.00	0.50	52,005,769
Black	0.05	0.00	0.21	207,248,696	0.06	0.00	0.24	52,005,769
Asian	0.04	0.00	0.19	207,248,696	0.03	0.00	0.17	52,005,769
Hispanic or Latino	0.07	0.00	0.25	207,248,696	0.09	0.00	0.28	52,005,769
Unknown	0.32	0.00	0.47	207,248,696	0.32	0.00	0.47	52,005,769
Gender Indicator								
Male	0.58	1.00	0.49	207,248,696	0.55	1.00	0.50	52,005,769
Female	0.23	0.00	0.42	207,248,696	0.26	0.00	0.44	52,005,769
Unknown	0.18	0.00	0.39	207,248,696	0.19	0.00	0.39	52,005,769

Notes: 15% bandwidth sample includes observations within 15% of the CRA income cutoff. This includes census tracts with a median family income between 65%-95% of that of the metropolitan statistical area. (C) includes only originated or purchased loans. Credit unions, subsidiaries of credit unions, credit union service companies owned by 3 or more credit unions, liquidated credit unions, and independent mortgage banks (including those affiliated with depository institutions) are defined as non-bank institutions.

Table 2: Individual Level RDD Results

	(1) Total Balance	(2) Mortg Balance	(3) Auto Balance	(4) Card Balance
Panel A: Intensive Margin				
CRA Eligible	62.57	84.08	-20.46	11.87
	(402.1)	(374.8)	(24.62)	(19.39)
MFI% - 80	795.9***	711.8***	34.74***	35.17***
	(36.27)	(33.63)	(2.276)	(1.777)
CRA Eligible × MFI% - 80	-41.01	-50.89	3.365	3.554
	(48.91)	(45.38)	(3.321)	(2.675)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	107,474,131	107,474,131	107,474,131	107,474,131
Tracts	34,733	34,733	34,733	34,733
R-Squared	0.037	0.039	0.014	0.004
Mean Y	42519.847	34045.551	3931.224	3556.171

	(1) % with Balance	(2) % with Mortg Balance	(3) % with Auto Balance	(4) % with Card Balance
Panel B: Extensive Margin				
CRA Eligible	0.0985	0.0403	-0.0494	0.117
	(0.125)	(0.153)	(0.117)	(0.123)
MFI% - 80	0.300***	0.368***	0.168***	0.302***
	(0.0112)	(0.0144)	(0.0108)	(0.0110)
CRA Eligible × MFI% - 80	0.0667***	0.0233	0.0260	0.0517***
	(0.0170)	(0.0206)	(0.0159)	(0.0169)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	107,474,131	107,474,131	107,474,131	107,474,131
Tracts	34,733	34,733	34,733	34,733
R-Squared	0.010	0.016	0.014	0.013
Mean Y	68.910	25.450	26.296	60.400

Notes: Unit of observation is individual-quarter. Only observations within 15% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff. Standard errors in parentheses are clustered at the census-tract level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Border Regressions

	(1) Total Balance	(2) Mortg Balance	(3) Auto Balance	(4) Card Balance
Panel A: Intensive Margin				
CRA Eligible	-425.4	-386.8	-51.13*	-3.632
	(522.6)	(486.4)	(30.24)	(29.63)
MFI % - 80	685.3***	618.7***	24.40***	31.79***
	(46.14)	(43.19)	(2.610)	(2.498)
CRA Eligible × MFI % - 80	-85.19	-84.54	-2.733	-0.700
	(63.53)	(59.66)	(3.410)	(3.586)
Date × Border FEs	Yes	Yes	Yes	Yes
Observations	42,304,209	42,304,209	42,304,209	42,304,209
Borders	13,950	13,950	13,950	13,950
R-Squared	0.057	0.058	0.032	0.022
Mean Y	42955.405	34787.960	3715.749	3600.963
	(1) % with Balance	(2) % with Mortg Balance	(3) % with Auto Balance	(4) % with Card Balance
Panel B: Extensive Margin				
CRA Eligible	-0.000782	-0.162	-0.262*	0.0265
	(0.178)	(0.206)	(0.151)	(0.175)
MFI % - 80	0.236***	0.309***	0.109***	0.246***
	(0.0147)	(0.0182)	(0.0128)	(0.0142)
CRA Eligible × MFI % - 80	0.0435**	0.00245	0.00151	0.0239
	(0.0211)	(0.0244)	(0.0169)	(0.0209)
Date × Border FEs	Yes	Yes	Yes	Yes
Observations	42,304,209	42,304,209	42,304,209	42,304,209
Borders	13,950	13,950	13,950	13,950
R-Squared	0.028	0.043	0.036	0.031
Mean Y	68.513	23.653	25.186	60.606

Notes: Unit of observation is individual-quarter. Observations at the individual-quarter level. Only observations within 15% of the CRA income cutoff and on the border of a tract with different CRA eligibility. Standard errors in parentheses are clustered by border pairs. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: RDD Results on Credit Outcomes

	(1) Risk Score	(2) % w/ Bankruptcy	(3) % w/ Foreclosure	(4) % w/ Delinquency
CRA Eligible	0.105	-0.0507	0.0344	-0.00355
	(0.523)	(0.0513)	(0.0391)	(0.00950)
MFI% - 80	1.070***	-0.00377	-0.0288***	-0.00770***
	(0.0478)	(0.00483)	(0.00305)	(0.000852)
CRA Eligible × MFI% - 80	0.150**	0.0212***	0.00418	0.00204
	(0.0721)	(0.00718)	(0.00544)	(0.00129)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	94,618,160	107,474,131	27,617,811	107,474,131
Tracts	34,731	34,733	34,656	34,733
R-Squared	0.043	0.003	0.016	0.001
Mean Y	672.629	4.078	2.082	1.283

Notes: Unit of observation is individual-quarter. Only observations within 15% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff. Standard errors in parentheses are clustered at the census-tract level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Border Regressions on Credit Outcomes

	(1) Risk Score	(2) % w/ Bankruptcy	(3) % w/ Foreclosure	(4) % w/ Delinquency
CRA Eligible	0.849	-0.120	-0.0191	-0.0113
	(0.532)	(0.0753)	(0.0607)	(0.0120)
MFI % - 80	0.915***	-0.0137**	-0.0349***	-0.00659***
	(0.0475)	(0.00618)	(0.00467)	(0.00103)
CRA Eligible × MFI % - 80	0.122*	0.0215**	0.0179**	0.00334**
	(0.0682)	(0.00918)	(0.00739)	(0.00148)
Date × Border FEs	Yes	Yes	Yes	Yes
Observations	37,243,251	42,304,209	9,973,058	42,304,209
Borders	13,869	13,950	12,661	13,950
R-Squared	0.084	0.014	0.057	0.012
Mean Y	670.828	4.037	2.240	1.310

Notes: Unit of observation is individual-quarter. Only observations within 15% of the CRA income cutoff and on the border of a tract with different CRA eligibility. Standard errors in parentheses are clustered by border pairs. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: RDD: Tract-Level Mortgage Lending

	(1) Amount	(2) Log(Amount)	(3) Count	(4) Log(Count)
CRA Eligible	-189.4	-0.0444	-0.915	-0.0359
	(116.7)	(0.0398)	(0.541)	(0.0258)
MFI % - 80	127.0***	0.0218***	0.674***	0.0164***
	(11.50)	(0.00334)	(0.0533)	(0.00215)
CRA Eligible × MFI % - 80	-39.53**	-0.00492	-0.209***	-0.00431
	(13.14)	(0.00410)	(0.0623)	(0.00280)
2000 Census Pop	1.141***	0.000133***	0.00800***	0.000152***
	(0.0461)	(0.00000855)	(0.000258)	(0.00000613)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	1,097,083	1,087,407	1,097,083	1,087,407
Tracts	30,696	30,678	30,696	30,678
R-Squared	0.438	0.658	0.463	0.676
Mean Y	5,140.11	9.20	34.44	4.01
Loan Weights	No	Yes	No	Yes

Notes: The unit of observation is census tract-quarter. LHS is total loans (amount or count) approved or purchased, either as levels in columns (1) and (3) or transformed by $log(x+1)$ in columns (2) and (4). Loan amounts are in thousands of dollars. Limited to tracts within 15% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff. Weights are multiplied by total loan amount (or count) approved or purchased in a tract in specifications with loan weights. Standard errors in parentheses are clustered at the census-tract level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: RDD: Bank Mortgage Market Share

	(1) Bank Amount Share	(2) Bank Amount Share	(3) Bank Count Share	(4) Bank Count Share
Panel A: Tract Level				
CRA Eligible	0.482***	0.405**	0.514***	0.320**
	(0.122)	(0.188)	(0.123)	(0.133)
MFI% - 80	0.0383***	0.0591***	0.0174	0.0340***
	(0.0118)	(0.0180)	(0.0118)	(0.0125)
CRA Eligible × MFI% - 80	-0.0105	-0.0223	0.00277	-0.00552
	(0.0161)	(0.0253)	(0.0163)	(0.0175)
2000 Census Pop	-0.000293***	-0.000216***	-0.000271***	-0.000164***
	(0.0000251)	(0.0000281)	(0.0000257)	(0.0000232)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	1,084,949	1,084,949	1,084,949	1,084,949
Tracts	30,660	30,660	30,660	30,660
R-Squared	0.433	0.603	0.468	0.611
Mean Y	68.024	66.137	68.622	67.303
Loan Weights	No	Yes	No	Yes

	(1) Bank Indicator	(2) Bank Indicator	(3) Bank Indicator	(4) Bank Indicator
Panel B: Loan Level				
CRA Eligible	0.364**	0.282**	0.321***	0.270***
	(0.162)	(0.114)	(0.112)	(0.0995)
MFI% - 80	0.0434***	0.0154	0.0250**	0.0161*
	(0.0153)	(0.0106)	(0.0103)	(0.00909)
CRA Eligible × MFI% - 80	-0.0212	-0.0186	-0.00937	-0.00865
	(0.0225)	(0.0157)	(0.0152)	(0.0136)
Date × MSA FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	51,952,697	51,952,697	51,952,698	51,952,698
Tracts	33,841	33,841	33,841	33,841
R-Squared	0.073	0.089	0.067	0.078
Mean Y	64.988	64.988	66.263	66.263
Loan Weights	Yes	Yes	No	No

Notes: Panel A contains a sample of census tract-quarters. The dependent variable is the share of originated or purchased loans made by banks. Columns (1) and (2) are based on dollar amounts, columns (3) and (4) are based on loan counts. Panel B contains loan-level mortgage originations or purchases. The dependent variable is 100 if the loan was originated/purchased by a bank. In both panels, only observations in census tracts within 15% of the CRA income cutoff are included. Observations weighted with a triangular kernel based on distance from cutoff. Weights multiplied by loan amount or loan count in specifications with loan weights. Non-bank institutions are defined as credit unions, subsidiaries of credit unions, credit union service companies owned by 3 or more credit unions, liquidated credit unions, and independent mortgage banks (including those affiliated with depository institutions). Loan controls are log of income, missing income, loan-to-income ratio, and indicators for co-applicant, non-conforming loan status (jumbo loans), owner occupancy, loan purpose (home purchase, refinancing), loan type (conventional, FHA, VA), race, ethnicity, and sex. Standard errors in parentheses are clustered at the census-tract level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

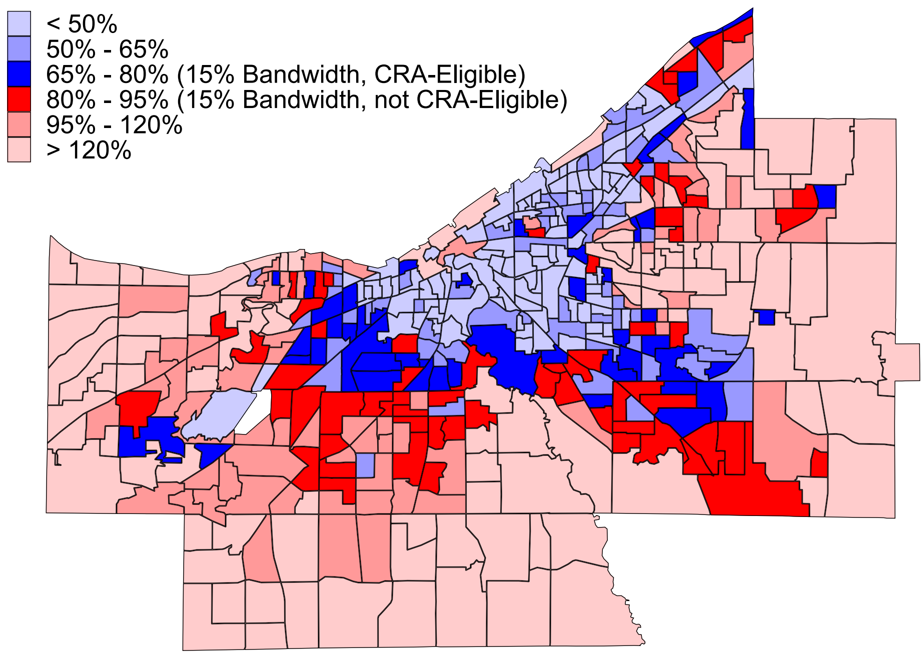
Table 8: RDD: Bank Share of Mortgage Originations and Purchases of Sold Loans

	(1) Bank Indicator	(2) Bank Indicator	(3) Bank Indicator	(4) Bank Indicator
Panel A: Originations				
CRA Eligible	0.217	0.108	0.261	0.154
	(0.235)	(0.167)	(0.166)	(0.142)
MFI% - 80	0.0614***	0.0243	0.0331**	0.0224*
	(0.0220)	(0.0151)	(0.0152)	(0.0128)
CRA Eligible × MFI% - 80	-0.0148	-0.0121	0.00552	0.00447
	(0.0323)	(0.0223)	(0.0220)	(0.0190)
Date × MSA FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	37,818,808	37,818,808	37,818,809	37,818,809
Tracts	33,838	33,838	33,838	33,838
R-Squared	0.084	0.116	0.085	0.112
Mean Y	58.543	58.543	60.852	60.852
Loan Weights	Yes	Yes	No	No
	(1) Bank Indicator	(2) Bank Indicator	(3) Bank Indicator	(4) Bank Indicator
Panel B: Purchases of Sold Loans				
CRA Eligible	0.391***	0.438***	0.356***	0.404***
	(0.0498)	(0.0483)	(0.0388)	(0.0383)
MFI% - 80	0.00734	0.00685	0.00245	0.00373
	(0.00454)	(0.00427)	(0.00362)	(0.00352)
CRA Eligible × MFI% - 80	-0.0124*	-0.0161***	-0.00835	-0.0114**
	(0.00652)	(0.00621)	(0.00529)	(0.00516)
Date × MSA FE	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	37,059,206	37,059,206	37,059,207	37,059,207
Tracts	33,802	33,802	33,802	33,802
R-Squared	0.022	0.032	0.024	0.033
Mean Y	8.794	8.794	8.305	8.305
Weighted by Loan Amount	Yes	Yes	No	No

Notes: Observations at the loan level. Only observations in census tracts within 15% of the CRA income cutoff are included. Observations are weighted with a triangular kernel based on distance from cutoff. Columns (1) and (2) are weighted by loan amount. Panel A includes the sample of new originations (excluding purchased loans). The dependent variable is 100 if a loan is originated by a bank. Panel B includes the sample of loans sold within the same calendar year of the initial origination or purchase listed in HMDA. The dependent variable is 100 if a sold loan is purchased by a bank. Panel B includes calendar month fixed effects to account for sold loan seasonality. Non-bank institutions are defined as credit unions, subsidiaries of credit unions, credit union service companies owned by 3 or more credit unions, liquidated credit unions, and independent mortgage banks (including those affiliated with depository institutions). Standard errors in parentheses are clustered at the census-tract level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

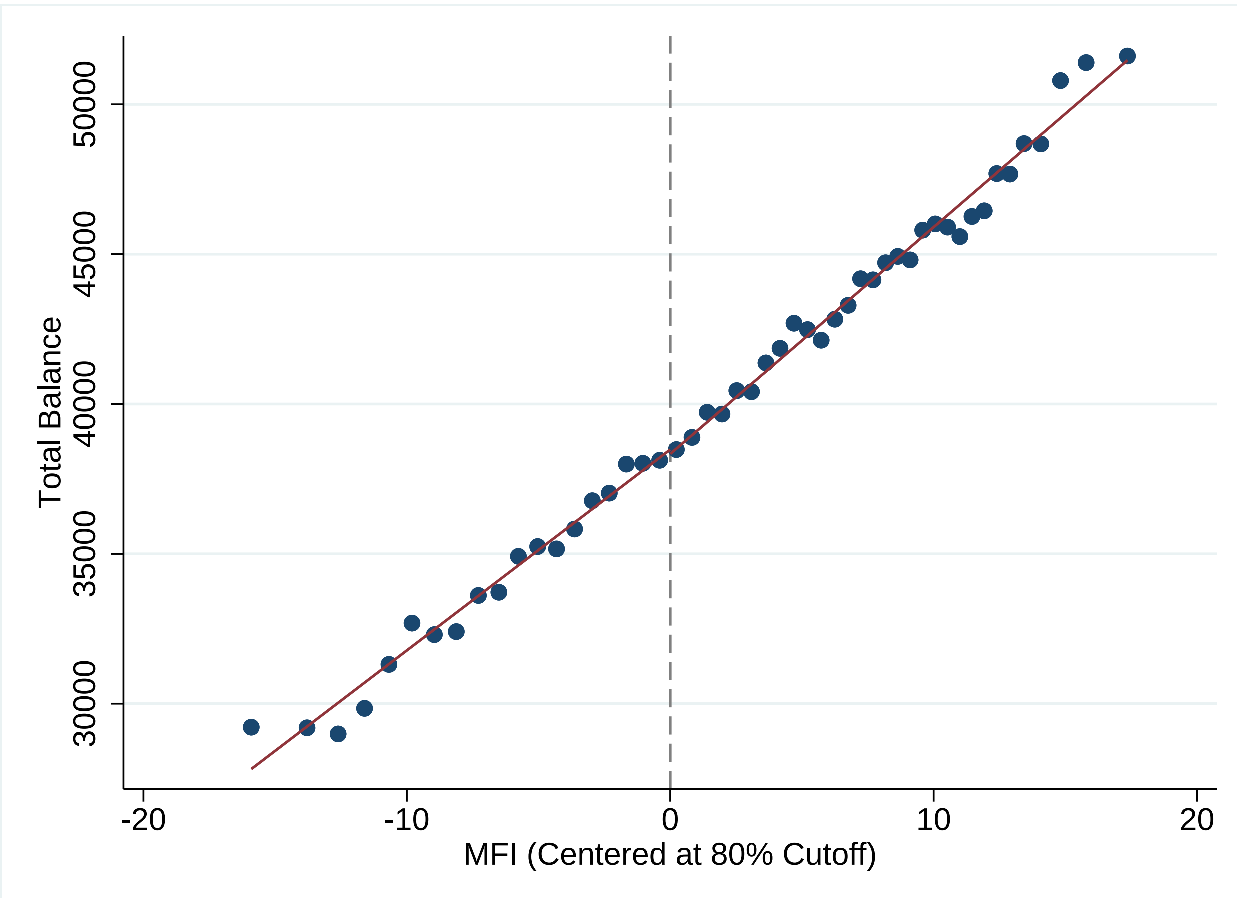
Figures

Figure 1: Tract Income and CRA Eligibility in Cuyahoga County



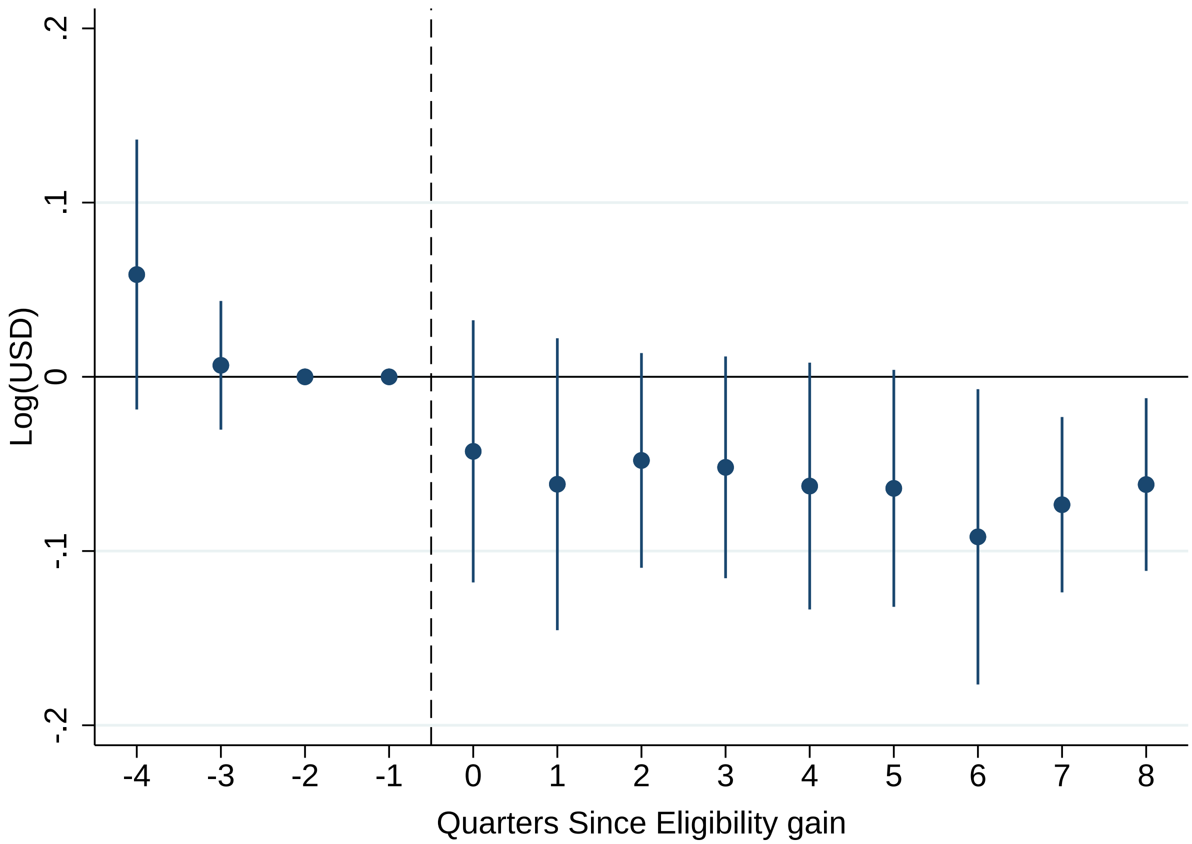
Notes: Tract Median Family Income (MFI) is represented as a percentage of the Cleveland-Elyria Metropolitan Statistical Area MFI. Data is a cross-section from 2016. Blue tracts are below the 80% eligibility cutoff and are subject to CRA oversight, and red tracts are above the 80% cutoff and not subject to CRA oversight. White tracts indicate missing income data from FFIEC.

Figure 2: RDD Binscatter



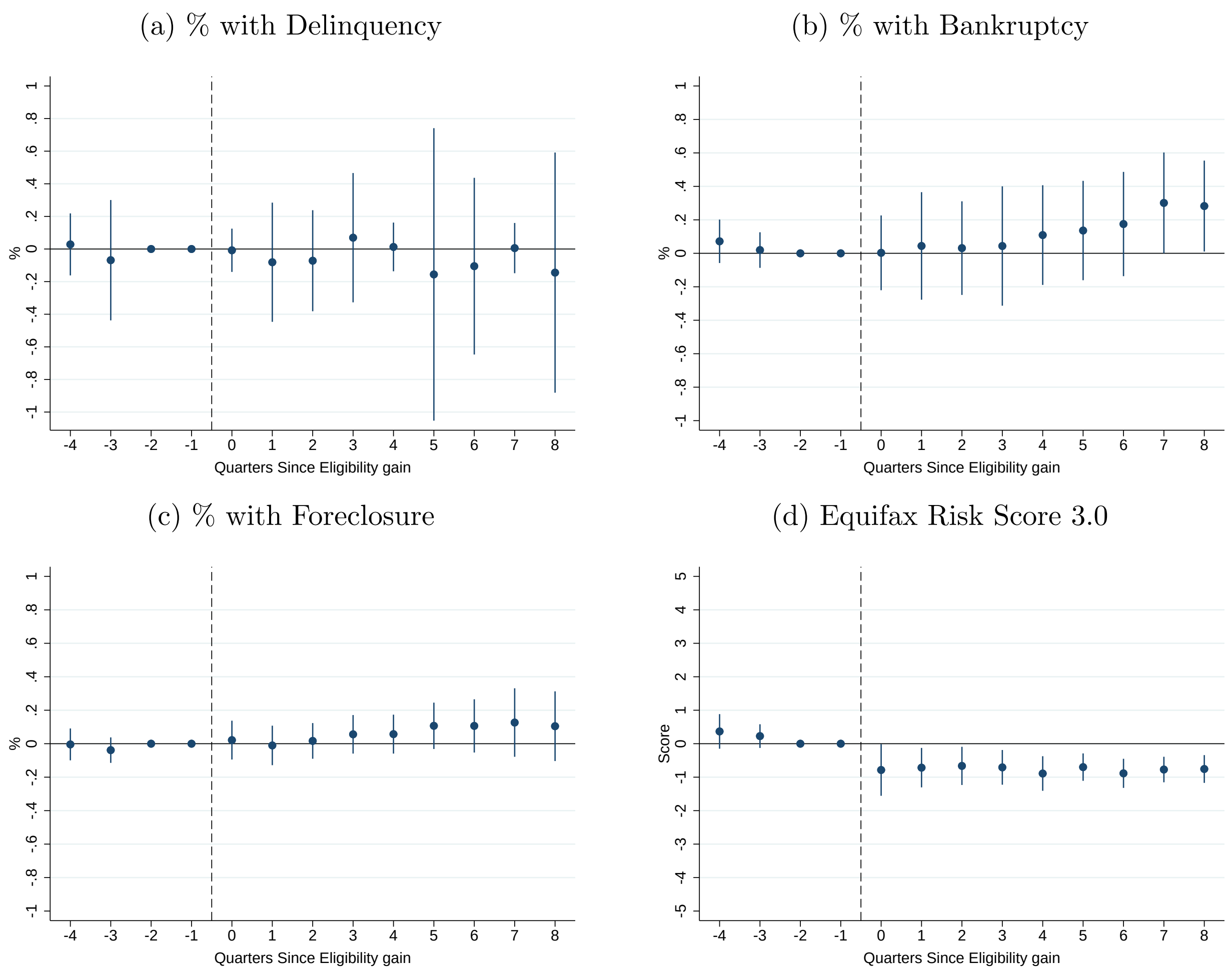
Notes: Limited to tracts within 15% bandwidth around the CRA income cutoff. Unit of observation is individual-quarter. Date×MSA fixed effects included.

Figure 3: Event Study Results



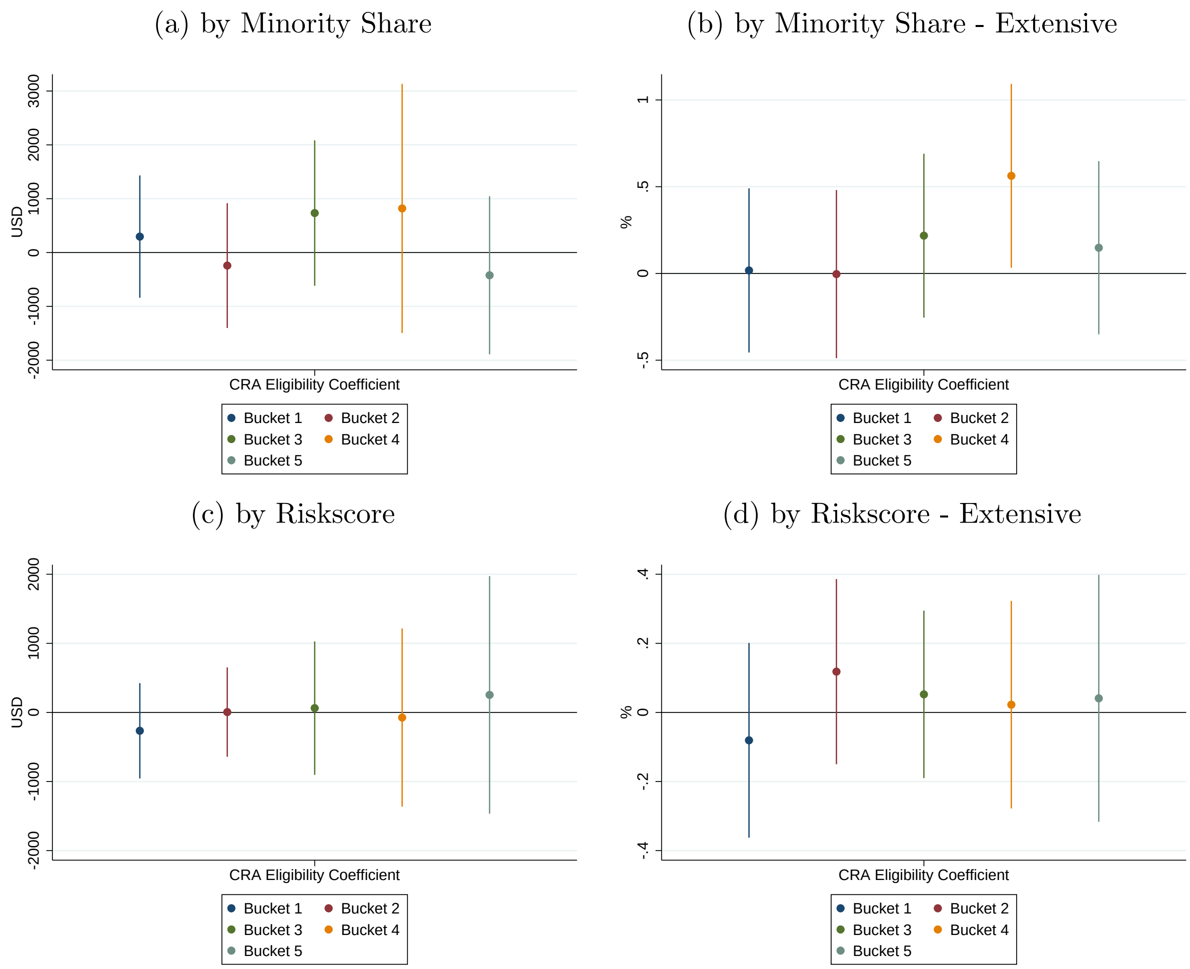
Notes: Point estimates and 95% confidence intervals are shown for each coefficient. Coefficients for $t < -4$ and $t > 8$ are included in regression, but excluded from figure. Standard errors clustered at the census-tract level. Unit of observation is individual-quarter. Individual and Date fixed effects included in regressions. Sample limited to tracts with first observation in 15% MFI bandwidth of the CRA eligibility cutoff. Observations weighted by lag of total balance. Corrects for average of logged neighbor balances using 2SLS method from Freyaldenhoven et al. (2019).

Figure 4: Event Study - Secondary Credit Outcomes



Notes: Point estimates and 95% confidence intervals are shown for each coefficient. Coefficients for $t < -4$ and $t > 8$ are included in regression, but excluded from figure. Standard errors clustered at the census-tract level. Unit of observation is individual-quarter. Individual and Date fixed effects included in regressions. Sample limited to tracts with first observation in 15% MFI bandwidth of the CRA eligibility cutoff. Corrects for % of neighbors with delinquency, bankruptcy or foreclosure or average Equifax Risk Score 3.0 using 2SLS method from Freyaldenhoven et al. (2019).

Figure 5: Heterogeneous RDD Results - Total Balances



Notes: Point estimates and 95% confidence intervals are shown for each coefficient. Standard errors clustered at the census-tract level. Unit of observation is individual-quarter. Observations split into quintile buckets based on tract minority share or Equifax Riskscore in each quarter, where Bucket 1 represents the 1st quintile (0%-20%) and Bucket 5 represents the 5th quintile (80%-100%). Empirical specification matches the individual RDD results in Table 2: Observations are limited to individuals in tracts within 15% of CRA income cutoff; Observations weighted with triangular kernel based on distance from cutoff; Standard errors clustered at the census-tract level.

A Appendix: Replication of Butcher and Muñoz (2017)

Butcher and Muñoz (2017) apply a similar RDD approach to the one used in this paper, but find that the CRA increases the availability of credit. While their results on total balances cohere with those presented in this work (i.e., they find no increase in balances comparing just-eligible areas compared to just ineligible ones), they find a positive effect in the total number of "trades," or active accounts in the CCP data. We find this result is due to preexisting population trends in eligible census tracts.

We replicated their findings using an RDD carried out at the census-tract level, limited to the 5% threshold around the 80% MFI cutoff. To repeat their methodology as closely as possible, we also limited our sample to the years 2004-2012 and to MSAs with over 2 million people, and we included a control for the median age in each census tract. In Appendix Table A1, we show the direct replication of the results of interest, showing an increase in total accounts in the just-eligible areas. But, after adding a control for each tract's population in the 1990 census in Appendix Table A2, the significance of the results goes away, indicating that the increase in total accounts is primarily attributable to larger populations in eligible areas.

To further illustrate this point, we present a placebo test in Appendix Table A3, with 1990 census population on the left-hand side rather than total accounts. The significant, positive coefficient on the CRA eligiblity variable further suggests the primary results from Butcher and Muñoz (2017) are driven by selection.

Appendix Table A1: Tract-Level RDD - No Population Control

	(1) Log(Total Accounts)	(2) Log(Mortg Accounts)	(3) Log(Auto Accounts)	(4) Log(Card Accounts)
CRA Eligible	0.0630**	0.0357	0.0482*	0.0645**
	(2.24)	(1.18)	(1.74)	(2.30)
CRA MFI - 80	0.0405***	0.0417***	0.0349***	0.0403***
	(5.84)	(5.65)	(5.10)	(5.84)
CRA Eligible × CRA MFI - 80	-0.0227**	-0.0218**	-0.0139	-0.0230**
	(-2.33)	(-2.10)	(-1.43)	(-2.36)
Date FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Age Control	Yes	Yes	Yes	Yes
Bandwidth	5%	5%	5%	5%
Observations	199,531	198,332	198,809	199,490
Tracts	10,057	10,041	10,053	10,057
R-Squared	0.229	0.304	0.293	0.240

Notes: t statistics in parentheses. Standard errors clustered at the census-tract level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Table A2: Tract-Level RDD - 1990 Census Population Control

	(1) Log(Total Accounts)	(2) Log(Mortg Accounts)	(3) Log(Auto Accounts)	(4) Log(Card Accounts)
CRA Eligible	0.0290	-0.00742	0.0197	0.0325
	(1.21)	(-0.27)	(0.81)	(1.36)
CRA MFI - 80	0.0271***	0.0250***	0.0217***	0.0273***
	(4.48)	(3.70)	(3.58)	(4.53)
CRA Eligible × CRA MFI - 80	-0.0186**	-0.0159	-0.00747	-0.0190**
	(-2.29)	(-1.64)	(-0.87)	(-2.33)
Log(1990 Census Pop)	0.891***	0.850***	0.889***	0.890***
	(30.98)	(26.75)	(29.38)	(31.45)
Date FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Age Control	Yes	Yes	Yes	Yes
Bandwidth	5%	5%	5%	5%
Observations	139,615	138,792	139,079	139,592
Tracts	6,184	6,175	6,181	6,184
R-Squared	0.635	0.580	0.609	0.638

Notes: t statistics in parentheses. Standard errors clustered at the census-tract level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Table A3: Tract-Level RDD - Placebo Test

	(1) Log(1990 Census Pop)	(2) Log(1990 Census Pop)	(3) Log(1990 Census Pop)
CRA Eligible	0.115**	0.0828***	0.0367
	(2.38)	(2.92)	(1.63)
CRA MFI - 80	0.0493	0.0159**	0.0115***
	(1.60)	(2.26)	(3.41)
CRA Eligible × CRA MFI - 80	-0.0157	0.00827	-0.00616
	(-0.40)	(0.84)	(-1.29)
Date FE	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes
Age Control	Yes	Yes	Yes
Bandwidth	2%	5%	8%
Observations	54,213	139,647	224,983
Tracts	2,641	6,184	9,187
R-Squared	0.228	0.149	0.131

Notes: t statistics in parentheses. Standard errors clustered at the census-tract level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: New York Fed Consumer Credit Panel / Equifax

B Appendix: Additional Tables

Appendix Table B1: Distribution of CRA Ratings

	#	%
Outstanding	11,389	15
Satisfactory	63,197	82
Needs to Improve	2,662	3
Substantial Noncompliance	264	0

Notes: Summarized in this table are the share of CRA grades received across depository institutions and years, by rating. We note that "Outstanding" and "Satisfactory" both represent passing grades, while "Needs to Improve" and "Substantial Noncompliance" are both considered failing grades.

Source: FFIEC Interagency CRA Rating File

Appendix Table B2: Optimal Bandwidths

	Observations	Mean	Optimal Bandwidth
Equifax: Individual Balances			
Total Balance	440,529,168	59,733.21	16.13%
Mortgage Balance	440,529,168	50,032.25	15.95%
Auto Balance	440,529,168	4,283.71	15.61%
Card Balance	440,529,168	4,076.72	15.61%
Equifax: Extensive Margin			
Total Balance	440,529,168	0.71	15.24%
Mortg Balance	440,529,168	0.28	15.67%
Auto Balance	440,529,168	0.26	17.03%
Card Balance	440,529,168	0.63	14.74%
Equifax: Credit Outcomes			
Risk Score	394,645,519	691.67	13.08%
% with Bankruptcy	440,529,168	3.46	17.19%
% with Foreclosure	440,529,168	9.12	14.24%
% with Delinquency	440,529,168	1.08	11.77%
HMDA: Loan Level			
Bank Indicator	321,437,130	0.63	14.18%
HMDA: Tract Level			
Amount Approved (Thousands)	3,455,217	9,167.55	13.74%
Weighted (Population)			16.49%
Bank Amount Share (%)	3,396,060	68.34	11.51%
Weighted (Total Tract Amount)			14.40%
Bank Count Share (%)	3,396,060	68.48	11.56%
Weighted (Total Tract Count)			13.43%

Notes: Bandwidths chosen using MSE-optimal bandwidth selection procedure implemented in the `rdrobust` package (Calonico et al., 2017). Standard error clustered at the census-tract level.

Source: New York Fed Consumer Credit Panel / Equifax, Home Mortgage Disclosure Act

Appendix Table B3: RDD Results - 10% Bandwidth

	(1) Total Balance	(2) Mortg Balance	(3) Auto Balance	(4) Card Balance
Panel A: Intensive Margin				
CRA Eligible	72.55	42.62	-4.574	29.08
	(446.1)	(414.2)	(29.21)	(22.86)
MFI% - 80	795.9***	698.3***	41.52***	40.12***
	(60.02)	(55.71)	(3.970)	(3.153)
CRA Eligible × MFI% - 80	-39.47	-37.46	-6.082	-1.138
	(85.61)	(79.80)	(5.781)	(4.706)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	72,129,935	72,129,935	72,129,935	72,129,935
Tracts	27,115	27,115	27,115	27,115
R-Squared	0.036	0.039	0.014	0.004
Mean Y	42206.481	33760.188	3919.545	3544.419
	(1) % with Balance	(2) % with Mortg Balance	(3) % with Auto Balance	(4) % with Card Balance
Panel B: Extensive Margin				
CRA Eligible	0.228	0.102	0.0625	0.212
	(0.149)	(0.183)	(0.140)	(0.147)
MFI% - 80	0.339***	0.384***	0.212***	0.333***
	(0.0203)	(0.0255)	(0.0192)	(0.0200)
CRA Eligible × MFI% - 80	0.0269	0.00644	-0.0313	0.0178
	(0.0299)	(0.0367)	(0.0280)	(0.0298)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	72,129,935	72,129,935	72,129,935	72,129,935
Tracts	27,115	27,115	27,115	27,115
R-Squared	0.009	0.016	0.014	0.012
Mean Y	68.837	25.298	26.235	60.324

Notes: Standard errors in parentheses. Unit of observation is individual-quarter. Standard errors clustered at the census-tract level. Only observations within 10% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Table B4: RDD Results - 20% Bandwidth

	(1) Total Balance	(2) Mortg Balance	(3) Auto Balance	(4) Card Balance
Panel A: Intensive Margin				
CRA Eligible	-49.62	0.766	-34.03	1.274
	(359.5)	(336.2)	(21.66)	(17.09)
MFI% - 80	792.3***	714.2***	31.64***	32.80***
	(25.34)	(23.59)	(1.538)	(1.192)
CRA Eligible × MFI% - 80	-59.61*	-75.25**	6.661***	6.080***
	(33.83)	(31.48)	(2.272)	(1.798)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	141687132	141687132	141687132	141687132
Tracts	41,392	41,392	41,392	41,392
R-Squared	0.037	0.040	0.014	0.004
Mean Y	42961.248	34455.028	3942.530	3570.173
	(1) % with Balance	(2) % with Mortg Balance	(3) % with Auto Balance	(4) % with Card Balance
Panel B: Extensive Margin				
CRA Eligible	0.0177	-0.0362	-0.126	0.0563
	(0.109)	(0.134)	(0.103)	(0.108)
MFI% - 80	0.279***	0.357***	0.149***	0.284***
	(0.00744)	(0.00958)	(0.00722)	(0.00726)
CRA Eligible × MFI% - 80	0.0905***	0.0267*	0.0496***	0.0726***
	(0.0116)	(0.0139)	(0.0109)	(0.0115)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	141687132	141687132	141687132	141687132
Tracts	41,392	41,392	41,392	41,392
R-Squared	0.011	0.018	0.014	0.014
Mean Y	69.010	25.646	26.346	60.510

Notes: Standard errors in parentheses. Unit of observation is individual-quarter. Standard errors clustered at the census-tract level. Only observations within 20% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Table B5: RDD Results on Credit Outcomes - 10% Bandwidth

	(1) Risk Score	(2) % w/ Bankruptcy	(3) % w/ Foreclosure	(4) % w/ Delinquency
CRA Eligible	-0.0678	-0.0149	-0.0472	-0.00165
	(0.634)	(0.0622)	(0.0700)	(0.0115)
MFI% - 80	0.981***	0.00866	-0.114***	-0.00529***
	(0.0899)	(0.00860)	(0.00958)	(0.00157)
CRA Eligible × MFI% - 80	0.280**	0.00728	0.00940	-0.00245
	(0.130)	(0.0128)	(0.0144)	(0.00233)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	63,453,094	72,129,935	72,129,935	72,129,935
Tracts	27,113	27,115	27,115	27,115
R-Squared	0.042	0.003	0.008	0.002
Mean Y	672.197	4.089	10.348	1.287

Notes: Standard errors in parentheses. Unit of observation is individual-quarter. Standard errors clustered at the census-tract level. Observations at the individual-quarter level. Only observations within 10% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Table B6: RDD Results on Credit Outcomes - 20% Bandwidth

	(1) Risk Score	(2) % w/ Bankruptcy	(3) % w/ Foreclosure	(4) % w/ Delinquency
CRA Eligible	0.0966	-0.0652	0.0180	-0.00170
	(0.459)	(0.0447)	(0.0506)	(0.00830)
MFI% - 80	1.062***	-0.00782**	-0.0930***	-0.00809***
	(0.0313)	(0.00312)	(0.00335)	(0.000558)
CRA Eligible × MFI% - 80	0.165***	0.0262***	-0.0149***	0.00337***
	(0.0486)	(0.00480)	(0.00548)	(0.000861)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	124890710	141687132	141687132	141687132
Tracts	41,389	41,392	41,392	41,392
R-Squared	0.046	0.003	0.008	0.001
Mean Y	673.260	4.060	10.255	1.276

Notes: Standard errors in parentheses. Unit of observation is individual-quarter. Standard errors clustered at the census-tract level. Observations at the individual-quarter level. Only observations within 20% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Table B7: HMDA: Tract Level Lending - 10% Bandwidth

	(1) Amount	(2) Log(Amount)	(3) Count	(4) Log(Count)
CRA Eligible	-130.6	-0.0496	-0.397	-0.0317
	(126.6)	(0.0383)	(0.568)	(0.0237)
MFI % - 80	135.4***	0.0234***	0.795***	0.0201***
	(17.96)	(0.00372)	(0.0867)	(0.00258)
CRA Eligible × MFI % - 80	-58.09**	-0.0116*	-0.419***	-0.0124***
	(20.69)	(0.00528)	(0.0976)	(0.00337)
2000 Census Pop	1.134***	0.000128***	0.00794***	0.000148***
	(0.0566)	(0.0000101)	(0.000316)	(0.00000712)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	723,506	717,384	723,506	717,384
Tracts	23,314	23,302	23,314	23,302
R-Squared	0.427	0.671	0.456	0.685
Mean Y	5,079.50	9.19	34.11	4.00
Loan Weights	No	Yes	No	Yes

Notes: Standard errors in parentheses. Unit of observation is census tract-quarter. Standard errors clustered at the census-tract level. LHS is total loan amount (or count) approved or purchased in a census tract in each quarter. Observations weighted Limited to tracts within 10% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff. Weights are multiplied by total loan amount (or count) approved or purchased in a tract in specifications with loan weights.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Home Mortgage Disclosure Act

Appendix Table B8: HMDA: Tract Level Lending - 20% Bandwidth

	(1) Amount	(2) Log(Amount)	(3) Count	(4) Log(Count)
CRA Eligible	-212.6*	-0.0421	-1.205*	-0.0370
	(103.7)	(0.0364)	(0.491)	(0.0241)
MFI % - 80	129.4***	0.0215***	0.651***	0.0157***
	(8.116)	(0.00237)	(0.0383)	(0.00158)
CRA Eligible × MFI % - 80	-38.73***	-0.00251	-0.157***	-0.00159
	(9.224)	(0.00289)	(0.0442)	(0.00200)
2000 Census Pop	1.147***	0.000137***	0.00806***	0.000155***
	(0.0387)	(0.00000739)	(0.000216)	(0.00000534)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	1,455,302	1,441,925	1,455,302	1,441,925
Tracts	36,982	36,965	36,982	36,965
R-Squared	0.448	0.648	0.471	0.671
Mean Y	5,211.92	9.21	34.76	4.02
Loan Weights	No	Yes	No	Yes

Notes: Standard errors in parentheses. Unit of observation is census tract-quarter. Standard errors clustered at the census-tract level. LHS is total loan amount (or count) approved or purchased in a census tract in each quarter. Observations weighted Limited to tracts within 20% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff. Weights are multiplied by total loan amount (or count) approved or purchased in a tract in specifications with loan weights.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Home Mortgage Disclosure Act

Appendix Table B9: HMDA: Bank Share - 10% Bandwidth

	(1) Bank Amount Share	(2) Bank Amount Share	(3) Bank Count Share	(4) Bank Count Share
Panel A: Tract Level				
CRA Eligible	0.439***	0.351	0.469***	0.283*
	(0.148)	(0.232)	(0.151)	(0.163)
MFI% - 80	0.0372*	0.0473	0.0159	0.0339
	(0.0218)	(0.0335)	(0.0220)	(0.0232)
CRA Eligible × MFI% - 80	-0.0144	-0.00659	0.000381	-0.00679
	(0.0294)	(0.0473)	(0.0298)	(0.0321)
2000 Census Pop	-0.000306***	-0.000235***	-0.000282***	-0.000181***
	(0.0000301)	(0.0000336)	(0.0000307)	(0.0000281)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	715,802	715,802	715,802	715,802
Tracts	23,291	23,291	23,291	23,291
R-Squared	0.440	0.604	0.474	0.612
Mean Y	68.061	66.154	68.664	67.321
Loan Weights	No	Yes	No	Yes
	(1) Bank Indicator	(2) Bank Indicator	(3) Bank Indicator	(4) Bank Indicator
Panel B: Loan Level				
CRA Eligible	0.325	0.295**	0.303**	0.276**
	(0.199)	(0.148)	(0.135)	(0.132)
MFI% - 80	0.0278	0.0189	0.0215	0.0182
	(0.0287)	(0.0209)	(0.0191)	(0.0185)
CRA Eligible × MFI% - 80	0.00256	-0.0120	-0.000799	0.00334
	(0.0418)	(0.0314)	(0.0275)	(0.0273)
Date × MSA FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	34,426,465	28,305,100	34,426,466	28,305,101
Tracts	26,634	26,631	26,634	26,631
R-Squared	0.073	0.093	0.067	0.086
Mean Y	64.892	64.527	66.174	65.875
Loan Weights	Yes	Yes	No	No

Notes: Standard errors in parentheses. Unit of observation is (A) census tract-quarter and (B) loan level. Standard errors clustered at the census-tract level. Only observations within 10% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff. Weights multiplied by loan amount or loan count in specifications with loan weights.

Credit unions, subsidiaries of credit unions, credit union service companies owned by 3 or more credit unions, liquidated credit unions, and independent mortgage banks (including those affiliated with depository institutions) are defined as non-bank institutions. Loan controls are log of income, missing income, loan-to-income ratio, and indicators for co-applicant, non-conforming loan status (jumbo loans), owner occupancy, loan purpose (home purchase, refinancing), loan type (conventional, FHA, VA), race, ethnicity, and sex.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Home Mortgage Disclosure Act

Appendix Table B10: HMDA: Bank Share - 20% Bandwidth

	(1) Bank Amount Share	(2) Bank Amount Share	(3) Bank Count Share	(4) Bank Count Share
Panel A: Tract Level				
CRA Eligible	0.491***	0.388**	0.529***	0.316***
	(0.106)	(0.160)	(0.108)	(0.116)
MFI% - 80	0.0376***	0.0519***	0.0170**	0.0290***
	(0.00775)	(0.0112)	(0.00777)	(0.00806)
CRA Eligible × MFI% - 80	-0.0111	-0.0112	0.00129	0.00257
	(0.0106)	(0.0163)	(0.0107)	(0.0116)
2000 Census Pop	-0.000288***	-0.000218***	-0.000266***	-0.000162***
	(0.0000223)	(0.0000249)	(0.0000228)	(0.0000204)
Date × MSA FE	Yes	Yes	Yes	Yes
Observations	1,438,638	1,438,638	1,438,638	1,438,638
Tracts	36,949	36,949	36,949	36,949
R-Squared	0.430	0.604	0.465	0.612
Mean Y	68.008	66.170	68.599	67.330
Loan Weights	No	Yes	No	Yes
	(1) Bank Indicator	(2) Bank Indicator	(3) Bank Indicator	(4) Bank Indicator
Panel B: Loan Level				
CRA Eligible	0.366***	0.300***	0.332***	0.309***
	(0.138)	(0.107)	(0.0986)	(0.0972)
MFI% - 80	0.0395***	0.0153**	0.0221***	0.0159**
	(0.00961)	(0.00747)	(0.00682)	(0.00670)
CRA Eligible × MFI% - 80	-0.0127	-0.00795	-0.00223	0.00490
	(0.0145)	(0.0113)	(0.0101)	(0.0101)
Date × MSA FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	69,410,907	57,189,186	69,410,909	57,189,187
Tracts	39,790	39,782	39,790	39,782
R-Squared	0.073	0.092	0.067	0.085
Mean Y	65.116	64.780	66.374	66.098
Loan Weights	Yes	Yes	No	No

Notes: Standard errors in parentheses. Unit of observation is (A) census tract-quarter and (B) loan level. Standard errors clustered at the census-tract level. Only observations within 20% of the CRA income cutoff. Observations weighted with triangular kernel based on distance from cutoff. Weights multiplied by loan amount or loan count in specifications with loan weights.

Credit unions, subsidiaries of credit unions, credit union service companies owned by 3 or more credit unions, liquidated credit unions, and independent mortgage banks (including those affiliated with depository institutions) are defined as non-bank institutions. Loan controls are log of income, missing income, loan-to-income ratio, and indicators for co-applicant, non-conforming loan status (jumbo loans), owner occupancy, loan purpose (home purchase, refinancing), loan type (conventional, FHA, VA), race, ethnicity, and sex.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Home Mortgage Disclosure Act

Appendix Table B11: HMDA: Originations vs. Purchases - 10% Bandwidth

	(1) Bank Share (%)	(2) Bank Share (%)	(3) Bank Share (%)	(4) Bank Share (%)
Panel A: Originations				
CRA Eligible	0.173	0.106	0.249	0.136
	(0.285)	(0.196)	(0.194)	(0.166)
MFI% - 80	0.0357	0.0216	0.0255	0.0216
	(0.0409)	(0.0273)	(0.0275)	(0.0233)
CRA Eligible × MFI% - 80	0.0382	0.000756	0.0336	0.0164
	(0.0592)	(0.0407)	(0.0389)	(0.0339)
Date × MSA FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	25,026,485	23,243,833	25,026,486	23,243,834
Tracts	26,631	26,630	26,631	26,630
R-Squared	0.085	0.113	0.086	0.110
Mean Y	58.392	58.283	60.724	60.650
Loan Weights	Yes	Yes	No	No

	(1) Bank Share (%)	(2) Bank Share (%)	(3) Bank Share (%)	(4) Bank Share (%)
Panel B: Purchases				
CRA Eligible	0.352***	0.392***	0.307***	0.347***
	(0.0597)	(0.0648)	(0.0461)	(0.0517)
MFI% - 80	-0.00112	-0.00367	-0.00647	-0.00623
	(0.00779)	(0.00833)	(0.00626)	(0.00701)
CRA Eligible × MFI% - 80	-0.0105	-0.0130	-0.00684	-0.00766
	(0.0115)	(0.0122)	(0.00926)	(0.0103)
Date × MSA FE	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	24,539,615	20,242,229	24,539,616	20,242,230
Tracts	26,606	26,599	26,606	26,599
R-Squared	0.022	0.038	0.024	0.039
Mean Y	8.807	9.503	8.317	8.881
Weighted by Loan Amount	Yes	Yes	No	No

Notes: Standard errors in parentheses. Observations at the loan level. Standard errors clustered at the census-tract level. Only observations within 10% of the CRA income cutoff. Observations at the loan-level. Non-bank institutions are defined as credit unions, subsidiaries of credit unions, credit union service companies owned by 3 or more credit unions, liquidated credit unions, and independent mortgage banks (including those affiliated with depository institutions).
Panel A concerns only originated loans. Panel B considers the purchaser type of loans sold on the secondary market within the same calendar year of the initial origination or purchase listed in HMDA.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Home Mortgage Disclosure Act

Appendix Table B12: HMDA: Originations vs. Purchases - 20% Bandwidth

	(1) Bank Share (%)	(2) Bank Share (%)	(3) Bank Share (%)	(4) Bank Share (%)
Panel A: Originations				
CRA Eligible	0.220	0.101	0.270*	0.164
	(0.203)	(0.147)	(0.148)	(0.127)
MFI% - 80	0.0571***	0.0166*	0.0300***	0.0181**
	(0.0140)	(0.0101)	(0.0102)	(0.00868)
CRA Eligible × MFI% - 80	-0.00963	-0.000197	0.00834	0.0130
	(0.0209)	(0.0150)	(0.0147)	(0.0129)
Date × MSA FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	50,588,385	47,018,570	50,588,387	47,018,571
Tracts	39,783	39,781	39,783	39,781
R-Squared	0.085	0.113	0.085	0.109
Mean Y	58.741	58.639	61.016	60.943
Loan Weights	Yes	Yes	No	No

	(1) Bank Share (%)	(2) Bank Share (%)	(3) Bank Share (%)	(4) Bank Share (%)
Panel B: Purchases				
CRA Eligible	0.402***	0.464***	0.368***	0.428***
	(0.0430)	(0.0475)	(0.0339)	(0.0383)
MFI% - 80	0.00823***	0.00881***	0.00306	0.00663**
	(0.00294)	(0.00319)	(0.00237)	(0.00267)
CRA Eligible × MFI% - 80	-0.0106**	-0.0150***	-0.00608*	-0.0120***
	(0.00436)	(0.00479)	(0.00353)	(0.00399)
Date × MSA FE	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Observations	49,567,521	40,940,071	49,567,523	40,940,072
Tracts	39,746	39,730	39,746	39,730
R-Squared	0.022	0.038	0.024	0.038
Mean Y	8.795	9.494	8.301	8.868
Weighted by Loan Amount	Yes	Yes	No	No

Notes: Standard errors in parentheses. Observations at the loan level. Standard errors clustered at the census-tract level. Only observations within 20% of the CRA income cutoff. Observations at the loan-level. Non-bank institutions are defined as credit unions, subsidiaries of credit unions, credit union service companies owned by 3 or more credit unions, liquidated credit unions, and independent mortgage banks (including those affiliated with depository institutions).
Panel A concerns only originated loans. Panel B considers the purchaser type of loans sold on the secondary market within the same calendar year of the initial origination or purchase listed in HMDA.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Home Mortgage Disclosure Act

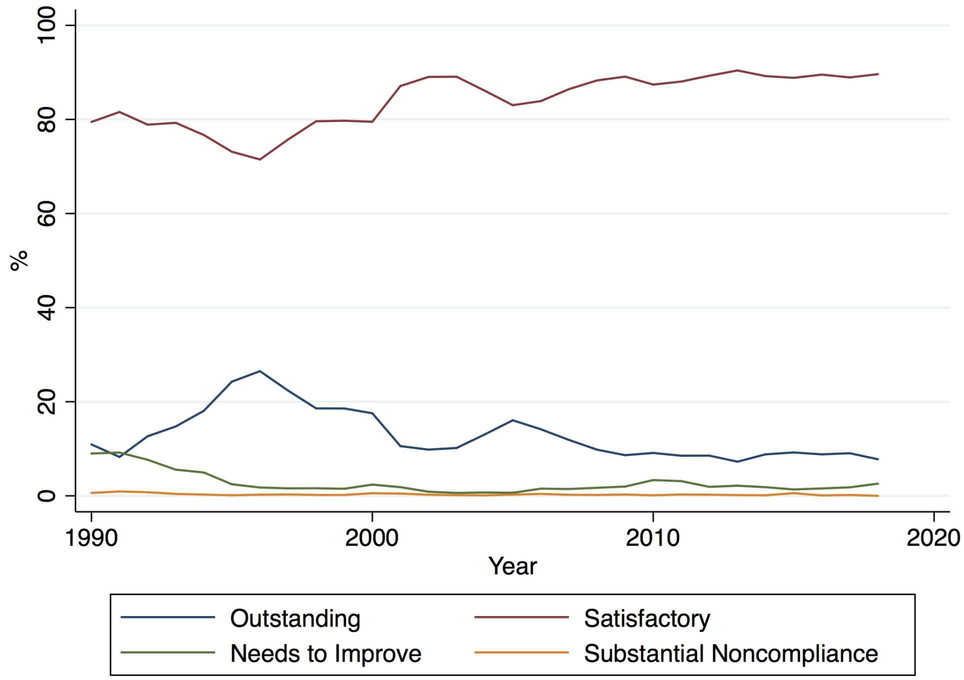
Appendix Table B13: Resale of Mortgages Purchased by Banks

	CRA Eligible	CRA Ineligible	15% BW, CRA Eligible	15% BW, CRA Ineligible
% sold by year end	72.94	78.37	73.82	76.98
% of sales to:				
GSEs	65.38	70.81	66.01	68.63
Banks	4.10	2.83	4.00	2.94
Affiliates	18.68	17.20	18.41	18.11
Non-banks	3.65	2.66	3.54	2.99

Notes: Sample includes all mortgages purchased by banks after 2004 in the first 9 months of the calendar year. The fourth quarter is excluded to avoid the year end effects on these metrics.

C Appendix: Additional Figures

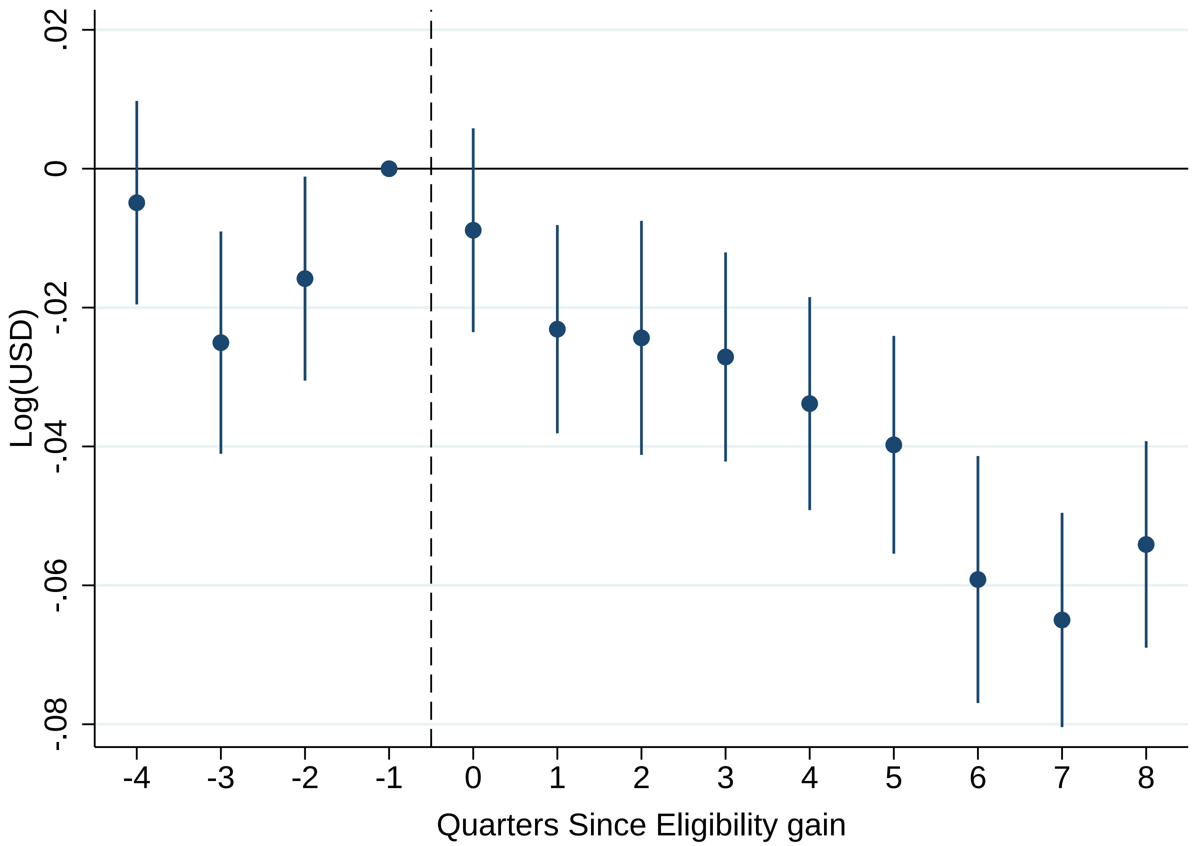
Appendix Figure C1: CRA Ratings by Year



Notes: Plotted are the share of Community Reinvestment Act examinations resulting in a given grade, by year. "Outstanding" and "Satisfactory" both represent passing grades, while "Needs to Improve" and "Substantial Noncompliance" are both considered failing grades.

Source: FFIEC Interagency CRA Rating File

Appendix Figure C2: Naive Event Study



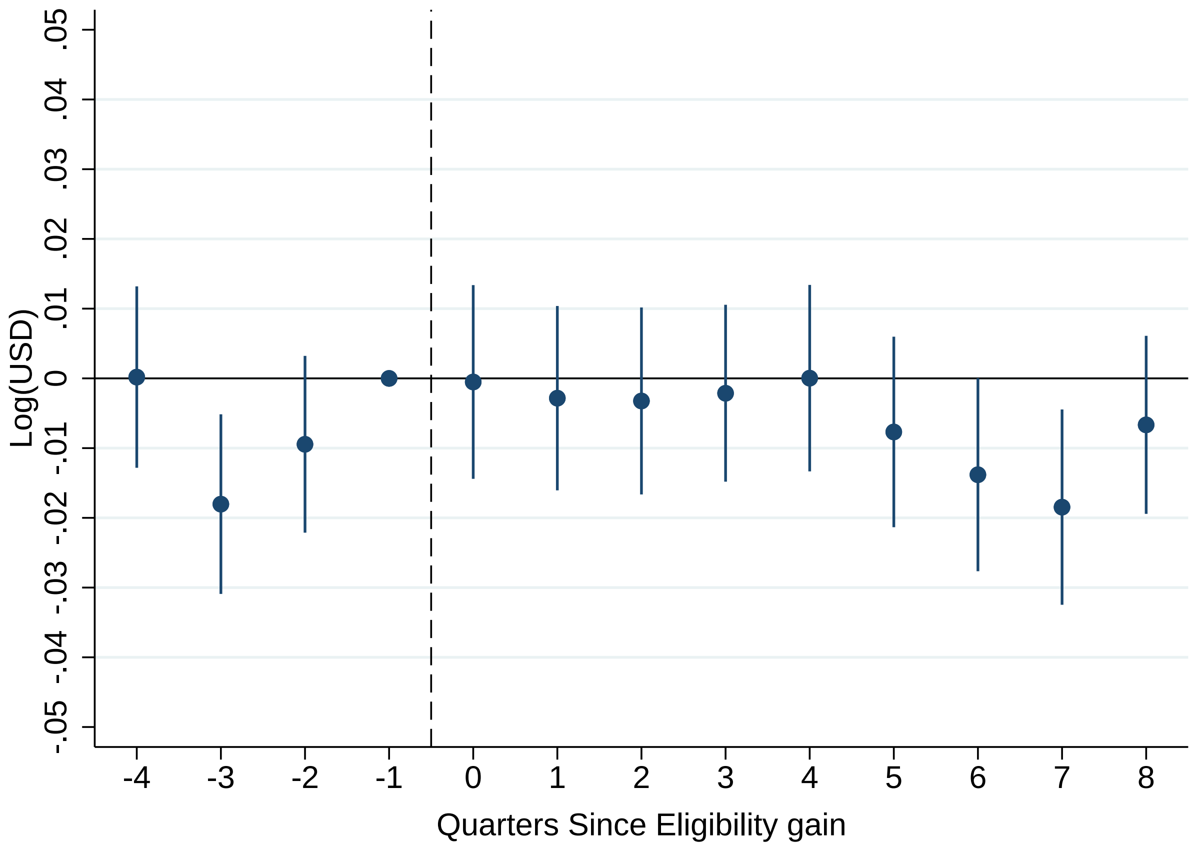
Notes: Point estimates and 95% confidence intervals are shown for each event-study coefficient from the following regression specification:

$$Y_{it} = \sum_{j \neq -1} \beta_j \mathbb{1}_{\{t+j=T_i\}} + \gamma MFI_{ct} + \alpha_t + \delta_i + \varepsilon_{it} \tag{8}$$

Coefficients for $t < -4$ and $t > 8$ are included in regression, but excluded from figure. Standard errors clustered at the census-tract level. Unit of observation is individual-quarter. Lagged and contemporaneous Interpolated MFI Controls and Individual and Date fixed effects included in regressions. Sample limited to tracts with first observation in 15% MFI bandwidth of the CRA eligibility cutoff. Observations weighted by lagged total balance.

Source: New York Fed Consumer Credit Panel / Equifax

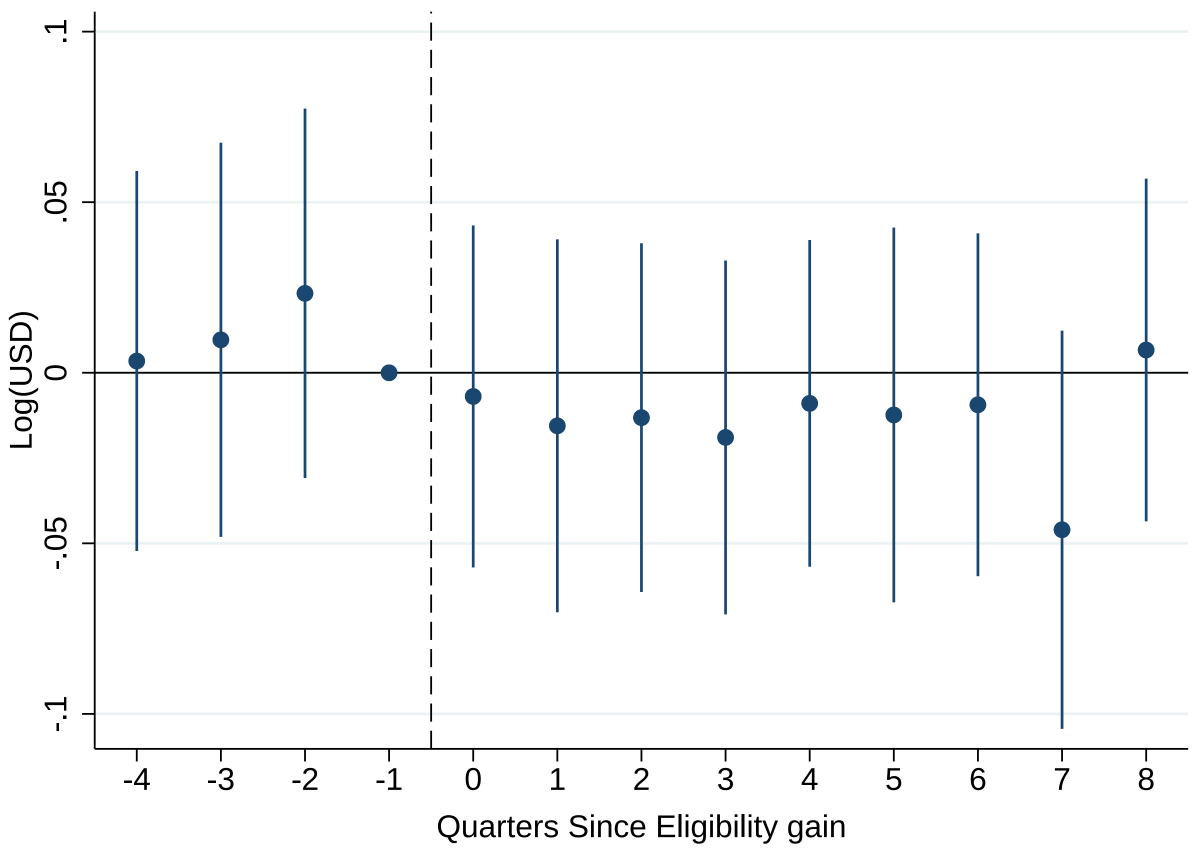
Appendix Figure C3: Matched Event Study



Notes: Point estimates and 95% confidence intervals are shown for each coefficient. Coefficients for $t < -4$ and $t > 8$ are included in regression, but excluded from figure. Standard errors clustered at the census-tract level. Unit of observation is individual-quarter. Sample limited to tracts with first observation in 15% MFI bandwidth of the CRA eligibility cutoff. Each member of treatment matched to a member of control based on similar MFI change using coarsened exact matching. Observations weighted by lagged raw total balance. Interpolated MFI Control and Matched-Pair and Date FEs included.

Source: New York Fed Consumer Credit Panel / Equifax

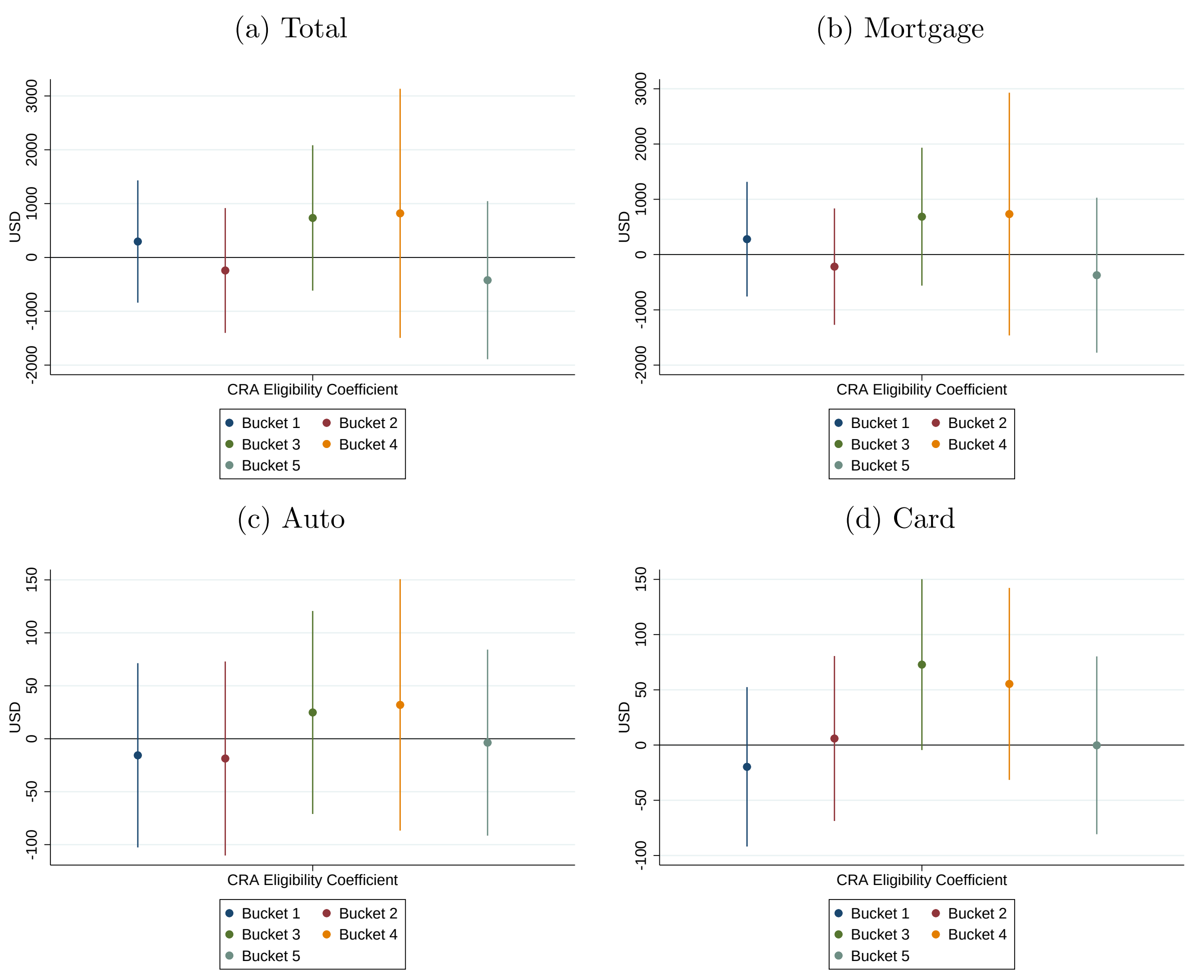
Appendix Figure C4: Event Study – Restricting to Geography Redefinitions



Notes: Point estimates and 95% confidence intervals are shown for each coefficient, following Equation 8. Coefficients for $t < -4$ and $t > 8$ are included in regression, but excluded from figure. Standard errors clustered at the census-tract level. Unit of observation is individual-quarter. Eligibility changes are defined only as changes that occurred in 2004q1 and 2014q1, which reflect updated MSA delineations instead of updates to census-tract income. Lagged and contemporaneous Interpolated MFI Controls and Individual and Date fixed effects included in regressions. Sample limited to tracts with first observation in 15% MFI bandwidth of the CRA eligibility cutoff. Observations weighted by lagged total balance.

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Figure C5: RDD Results by Tract Minority Share - Balances



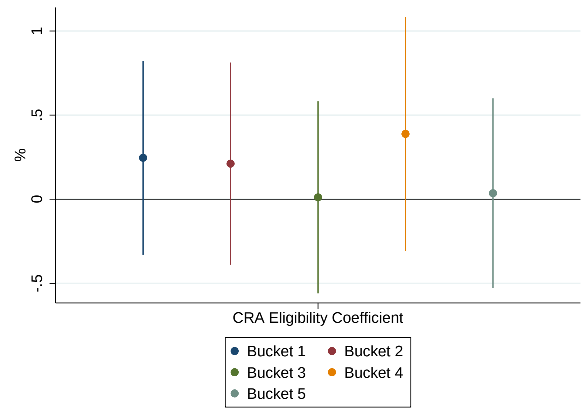
Notes: Point estimates and 95% confidence intervals are shown for each coefficient. Observations split into quintile buckets based on tract minority share in each quarter, where Bucket 1 represents the 1st quintile (0%-20%) and Bucket 5 represents the 5th quintile (80%-100%). Empirical specification matches the individual RDD results in Table 2: Observations are limited to individuals in tracts within 15% of CRA income cutoff; Observations weighted with triangular kernel based on distance from cutoff; Standard errors clustered at the census-tract level.

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Figure C6: RDD Results by Tract Minority Share - Extensive

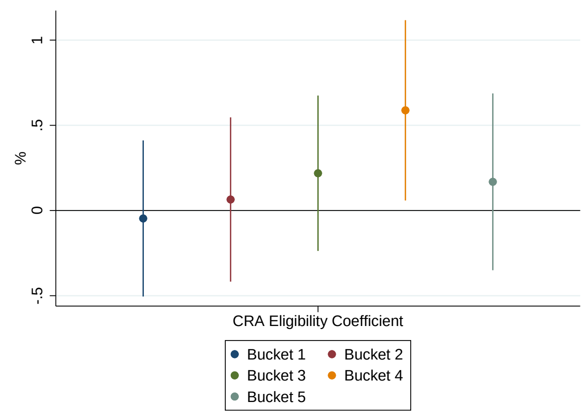
(a) Total

(b) Mortgage



(c) Auto

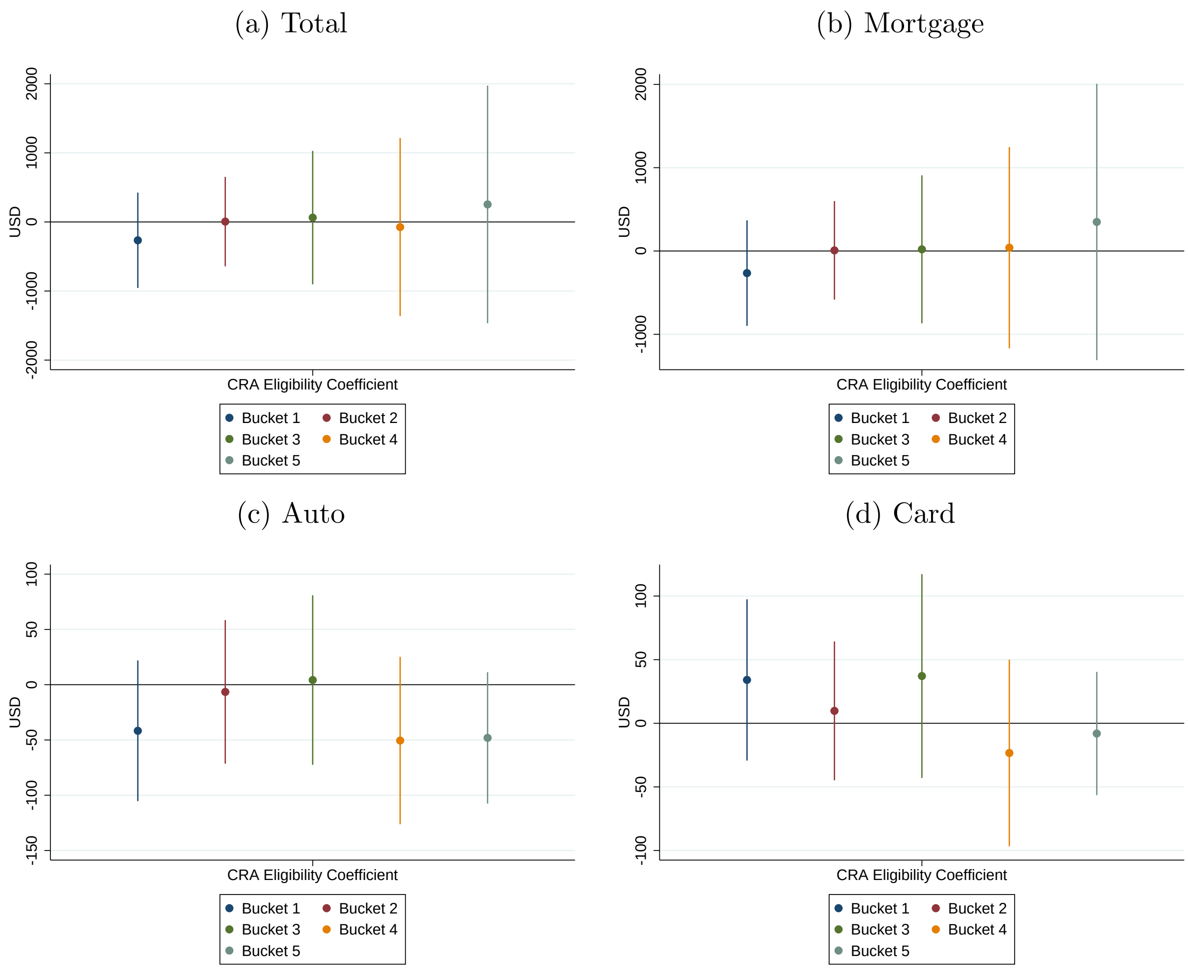
(d) Card



Notes: Point estimates and 95% confidence intervals are shown for each coefficient. Observations split into quintile buckets based on tract minority share in each quarter, where Bucket 1 represents the 1st quintile (0%-20%) and Bucket 5 represents the 5th quintile (80%-100%). Empirical specification matches the individual RDD results in Table 2: Observations are limited to individuals in tracts within 15% of CRA income cutoff; Observations weighted with triangular kernel based on distance from cutoff; Standard errors clustered at the census-tract level.

Source: New York Fed Consumer Credit Panel / Equifax

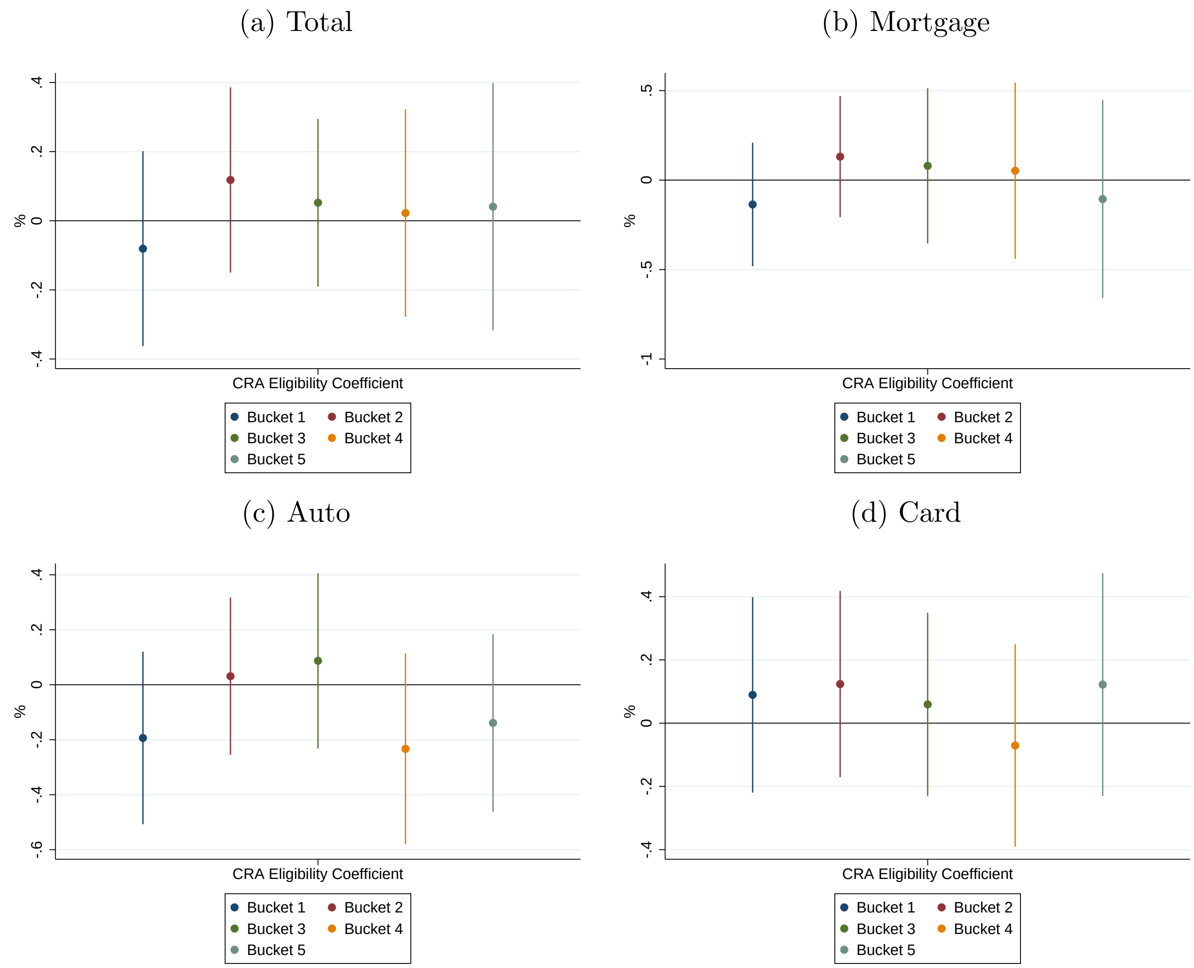
Appendix Figure C7: RDD Results by Equifax Riskscore - Balances



Notes: Point estimates and 95% confidence intervals are shown for each coefficient. Observations split into quintile buckets based on Equifax riskscore share in each quarter, where Bucket 1 represents the 1st quintile (0%-20%) and Bucket 5 represents the 5th quintile (80%-100%). Empirical specification matches the individual RDD results in Table 2: Observations are limited to individuals in tracts within 15% of CRA income cutoff; Observations weighted with triangular kernel based on distance from cutoff; Standard errors clustered at the census-tract level.

Source: New York Fed Consumer Credit Panel / Equifax

Appendix Figure C8: RDD Results by Equifax Riskscore - Extensive



Notes: Observations split into quintile buckets based on Equifax riskscore share in each quarter, where Bucket 1 represents the 1st quintile (0%-20%) and Bucket 5 represents the 5th quintile (80%-100%). Empirical specification matches the individual RDD results in Table 2: Observations are limited to individuals in tracts within 15% of CRA income cutoff; Observations weighted with triangular kernel based on distance from cutoff; Standard errors clustered at the census-tract level.

Source: New York Fed Consumer Credit Panel / Equifax