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Does the Community Reinvestment Act increase lending to small businesses in lower income neighborhoods?☆

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ABSTRACT

We estimate the impact of the Community Reinvestment Act (CRA) on small business lending in lower-income neighborhoods. Using 2004–2016 panel data on census tracts, we apply a combined regression discontinuity and fixed effect method. We find that the number of small business loans increases by about 3 to 7 percent and the total dollar amount of small business loans by about 6 to 10 percent in tracts becoming treated by the CRA. The results are robust along many dimensions and suggest that the CRA has a positive impact on access to finance for small businesses in lower income areas.

1. Introduction

Lack of access to finance is a potentially critical barrier to advancement of lower-income populations. Borrowers in lower-income neighborhoods may face tougher credit constraints, including "redlining", by which banks exclude these areas from lending activities (e.g., Immergluck, 2004; Kim et al., 2021). The principal policy response is the Community Reinvestment Act (CRA), intended to incentivize banks to lend and provide financial services, including to small businesses in "eligible" census tracts. Banks' incentives to comply with the CRA mainly hinge on ratings from supervisory examinations that could affect approvals of mergers and acquisitions, and on reputational concerns in their local communities. There is no enforcement or explicit punishment, and the extent to which bank lending is influenced by the CRA regulation is a priori unclear.

In this paper, we examine whether the CRA increases small business lending in eligible lower-income neighborhoods. Using 2004–2016 CRA data from the Federal Financial Institutions Examination Council (FFIEC), and exploiting exogenous variation created by the regulatory income threshold for CRA eligibility of tracts and changes in eligibility over time, we apply regression discontinuity design (RDD) and tract fixed-effect panel regression methods. We estimate with different bandwidths to compare results when all tracts are included to estimates with narrower bandwidths where tracts are more similar, except for CRA eligibility.

While several studies investigate the CRA impact on mortgage loans (e.g., Bhutta, 2011; Bhutta and Ringo, 2015; Avery and Brevoort, 2015; Lee and Bostic, 2020), there is relatively little research on small business lending. Bostic and Lee (2017) estimate the CRA impact on small business lending using RDD with pooled cross-section data from 1996 to 2014. The RDD allows them to compare similar tracts around the CRA threshold, but they do not exploit the temporal variation in tract eligibility to control for unobserved heterogeneity. More recently, Ding et al. (2020) use changes in eligibility to estimate the CRA impact. They rely on 818 newly eligible and 395 newly ineligible tracts from MSA boundary changes in 2014, using data for the period 2012–2015.[1]

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[1] Other related papers include Bates and Robb (2015), who use the Kauffman firm survey to examine lending in minority neighborhoods at the zip code level,

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Our approach builds on this research but differs from it along several dimensions. Besides applying RDD, we exploit the time variation arising from the major CRA eligibility change in 2012, in addition to MSA boundary changes in 2014, providing a much larger number of tracts switching eligibility over time. Previous research probably avoided using the 2012 switches because tract boundary changes in the same year create inconsistencies in before–after comparisons. Our solution is to use the Census Bureau Tract Relationship File, which contains detailed information on the coverage of tracts from before to after 2012. We use this crosswalk to construct measures of tract consistency, for example for pairs of tracts with overlapping land area covering at least 90 percent of the population before and after the 2012 change. To examine the impact of tracts becoming eligible, we focus on those that were ineligible before 2012, and our basic analysis, based on the 90 percent criterion, contains a total of 4,754 switching tracts resulting from recalculation of local incomes in 2012 (4,455 switchers) and changes in MSA boundaries in 2014 (299 changes). This procedure not only provides much more identifying variation, but it also provides a longer estimation period and enables us to control for unobserved heterogeneity with tract fixed effects. We estimate using eight years of pre-treatment and five years of post-treatment data, and we conduct an event study of the lending dynamics around tract eligibility changes. We examine robustness of the results to alternative definitions of tract consistency and to changes in regression specification.

2. Data

Our main data source is the Federal Financial Institutions Examination Council (FFIEC), which provides the 2004–2016 CRA Aggregate Flat File, containing information on small business loans at the census tract level. In this paper, we focus on small business loans defined as originations of \$1 million or less to businesses with gross annual revenues of \$1 million or less. We study both the number and amount of small business loan originations as outcome variables.[2]

We link the CRA Flat File to FFIEC Census and Demographic Data to obtain tract-level median family income (MFI) and its ratio to the MFI in a reference area (the surrounding Metropolitan Statistical Area (MSA) for MSA tracts or state for non-MSA tracts). A tract is "eligible" for CRA when this ratio is below 80 percent.

Tract boundaries were almost constant from 2004 to 2011, but they changed in 2012. Based on the 2010 Census, tracts were merged and divided, resulting in significant numbers of many-to-many relationships of tracts from before to after 2012. To address this issue, we use the Census Bureau Tract Relationship File, a crosswalk from the 2000 to 2010 Census tracts. In our basic analysis, we match tracts with overlapping land area including at least 90 percent of the population in both 2000 and 2010, accounting for 85 percent of all tracts.[3] A major advantage of this procedure is that it enables us to estimate the impact of CRA on a large sample of switchers with tract fixed-effects.

We exclude tracts not meeting this criterion, and we further restrict our sample to tracts that were ineligible before 2012. This results in a control group similar to the treatment group that become newly eligible for CRA in 2012 or after. After these restrictions, we have 523,696 tract-year observations on 40,332 tracts, of which switchers number 4,754, in total.

Both for descriptive statistics and regression analysis, we show results for four subsets of the data, based on the bandwidth for the pre-2012 ineligible sample: 100 percent (all tracts with MFI ratio ≥ 0.8), 20 percent ($0.8 \leq MFI < 1.0$), 10 percent ($0.8 \leq MFI < 0.9$), and 5 percent ($0.8 \leq MFI < 0.85$). For each of these bandwidths, Table 1 provides descriptive statistics on tract-level variables. In the 100 percent bandwidth sample, the average number of tract-level small business loans is 44 and the average dollar volume is 1.375 million. There is large variation across tracts in both variables; the standard deviations are at least as large as the means in all samples.

As the bandwidth decreases, the average MFI ratio falls and the average number and amount of loans decrease, consistent with a positive correlation between MFI and lending. Of course, the sample size also decreases, implying the usual tradeoff between bias reduction and precision. The 5 percent bandwidth has only about 8 percent of the full sample and about one-third the number of switching tracts.

3. Methods

We apply a regression discontinuity design (RDD) in a panel regression framework to estimate the impact of the CRA on lending to small businesses. The RDD exploits the geographic variation created by the tract-level MFI ratio threshold at 80 percent. The threshold creates a sharp discontinuity, and tracts cannot manipulate MFI.

Another source of variation is the changes in CRA eligibility resulting from MFI recalculation, which occurred in 2012 based on 2006–2010 5-year estimates from the American Community Survey (ACS). The MFI ratio was partly updated in 2014 as MSA boundaries changed, altering some tract-level CRA eligibility. One concern is that these changes may reflect economic trends such as gentrification that bias the estimated effect downwards. To address this issue, we control for the MFI ratio as running variable and use different bandwidths including narrow ones close to the MFI threshold. We estimate the following specification.

$$LOAN_{it} = \alpha_i + \theta_t + \beta \cdot CRA_{it} + \delta \cdot D_i \rho_{it} + f(MFI_{it}) + \epsilon_{it} \tag{1}$$

where $LOAN_{it}$ is the log number or amount of small business loans for a tract i in year t, α_i are tract fixed effects, θ_t are year fixed effects, CRA_{it} is an indicator for CRA eligibility, D_i is a dummy for tracts that become eligible, ρ_{it} is a linear event-time trend, and $f(MFI_{it})$ is a function of the MFI ratio. In alternative specifications, we specify $f(MFI_{it})$ in different ways using functional forms of the running variable that are standard in RDD: MFI alone, interacted with CRA, and in quadratic form. Standard errors are clustered at tract level.

We apply these methods using different bandwidths above the 80 percent threshold. Tracts becoming eligible are likely to have lower MFI than those remaining ineligible, and a narrower bandwidth should reduce this difference. Fig. 1, provides the pre-treatment difference in the mean number and amount of loans between treated and non-treated tracts for each bandwidth. As the bandwidth narrows, the difference shrinks towards zero and becomes statistically insignificant. The standard error increases, illustrating the tradeoff between bias reduction and precision.

The key identifying assumption is that without CRA tract eligibility changes, the outcome variables in tracts becoming eligible in 2012 or after would have evolved similarly as in tracts remaining ineligible. To examine the validity of the common trend assumption, we use an event study approach, permitting the CRA effect to vary by year of event time.

and the recent working paper of Chakraborty et al. (2021), who in a study mostly of county-level outcomes also include a tract-level regression of loan growth on change in CRA status, which only identifies immediate effects in the same year as the policy change. Dore and Mach (2018) provide more background on the CRA policy and data.

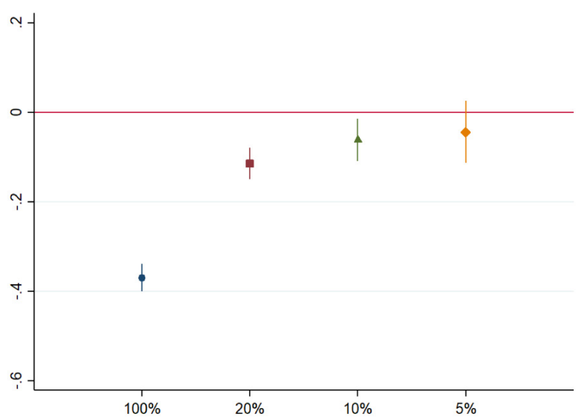
2 The CRA data also include loan purchases and small loans (\$1 million or less) to all businesses, regardless of size, but we focus on originations to small firms.

3 This calculation is based on ineligible tracts in 2011. Because of the possibility that tracts with changing boundaries differ systematically, we also carry out robustness checks using alternative criteria of 99 percent (accounting for 82 percent of tracts) and 80 percent (86 percent of tracts), with similar results, shown in the Appendix.

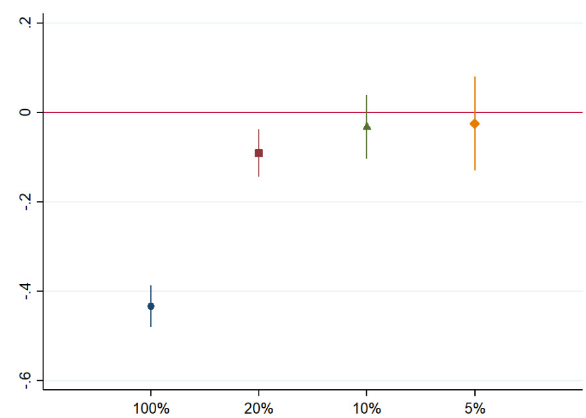
Table 1
Descriptive statistics for regression samples.

	Bandwidth 100%	Bandwidth 20%	Bandwidth 10%	Bandwidth 5%
Number of loans to small business	44	34	32	32
	(44)	(35)	(35)	(38)
Amount of loans to small business (in $1000s)	1375	1051	1020	1028
	(1749)	(1416)	(1425)	(1517)
Population	4242	4096	4064	4060
	(1692)	(1614)	(1603)	(1630)
MFI ratio	1.15	0.90	0.85	0.83
	(0.36)	(0.11)	(0.10)	(0.10)
Number of tract-year observations	523,696	202,090	92,784	42,977
Number of tracts	40,332	15,557	7,145	3,311
Number of switching tracts	4,754	4,128	2,743	1,530

Note: The table reports means (standard deviations) for each variable across all years for four different regression samples, based on bandwidth above the CRA MFI cutoff. The sample is restricted to tracts ineligible for CRA before 2012 and to those with common land area accounting for at least 90% of the population from before to after 2012, when tract boundaries changed. Switching tracts are those becoming eligible either in 2012 or 2014. The data are from the FFIEC CRA Aggregate Flat and Demographic Files from 2004 to 2016, linked using the Census Bureau Tract Relationship File from 2000 to 2010.



(a) Number of Small Business Loans



(b) Amount of Small Business Loans

Fig. 1. Number and amount of small business loans, treated vs. control.
Note: For the two outcome variables of the logged number and amount of small business loans, the graphs show the pre-treatment differences in means between treatment and control tracts. Error bars show the associated 99 percent confidence intervals. Samples are the same as in Table 1 during the pre-treatment period.

4. Results

Table 2 presents estimates of the average effect of CRA eligibility. Each cell contains the coefficient (standard error) on CRA for a different dependent variable and specification (by column) and bandwidth (by row). All the coefficient estimates are positive. As the bandwidth narrows, standard errors increase, as expected, while coefficients fall for amount but rise and then fall for number of loans. Controlling for the running variable, MFI ratio, raises the estimated coefficient, but further additions to the $f(MFI_{it})$ function tend to reduce the coefficient and raise the standard error.

Based on our analysis of pre-treatment differences in the outcomes variables in Fig. 1, the most credible specifications are those based on the 10 and 5 percent bandwidths with running variable controls. These imply a 3–7 percent increase in the number and an 6–10 percent in the volume of loans. The 5 percent bandwidth coefficients are based on smaller samples and thus are less precisely estimated (as well as identified from a subsample of the 10 percent bandwidth). Overall, the results imply that CRA has a positive, and usually significant impact on both the number and amount of small business loans. Estimates with the 10 percent bandwidth are always significant and robust to different functional forms of the MFI ratio.

To check the validity of the common trend assumption and examine possible lags in the CRA effect, we permit the coefficient to vary by year of event time. Fig. 2 shows the results for the two dependent variables with a 10 percent bandwidth and the simple CRA running variable. τ represents the first year of treatment and $\tau - 1$ is the reference year. For both dependent variables, the pre-treatment coefficients are all statistically insignificant. Only when tracts become CRA eligible does the difference become positive and significant, and it increases over event time for the number of loans. The event time coefficients are less precisely estimated for the amount of small loans but they decline in the pre-treatment period and then jump in the first treatment year. Overall, this analysis is consistent with the common trend assumption and also suggests that lender response to CRA is lagged in the number of loans to newly eligible tracts.

We conduct several robustness checks. First, we examine estimates using 99 percent and 80 percent tract consistency thresholds. Second, we estimate all the results using population weights, because variation in tract population may affect banks' lending activities. Third, our results include not only tracts in MSAs, but also non-MSA areas, but some other CRA studies restrict their samples to MSAs under the assumption that the CRA is more effective in urban areas (Bhutta, 2011; Ding et al., 2020), so we check this in our data. Fourth, we carry out a similar analysis with two other loan variables available in the FFIEC data: the number

Table 2
The impact of CRA on small business loans.

Bandwidth	Log(Number of Small Business Loans)				Log(Amount of Small Business Loans)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
100%	0.028***	0.037***	0.013	0.012	0.101***	0.117***	0.089***	0.107***
	(0.007)	(0.007)	(0.009)	(0.010)	(0.015)	(0.015)	(0.017)	(0.019)
20%	0.034***	0.072***	0.043***	0.038***	0.065***	0.106***	0.077***	0.095***
	(0.008)	(0.009)	(0.010)	(0.011)	(0.017)	(0.019)	(0.020)	(0.023)
10%	0.027***	0.066***	0.039***	0.030**	0.063***	0.099***	0.077***	0.084***
	(0.010)	(0.012)	(0.013)	(0.015)	(0.022)	(0.026)	(0.027)	(0.029)
5%	0.017	0.065***	0.036*	0.028	0.031	0.085**	0.060	0.083*
	(0.015)	(0.019)	(0.019)	(0.023)	(0.032)	(0.038)	(0.039)	(0.044)
MFI	No	Yes	Yes	Yes	No	Yes	Yes	Yes
CRA × MFI	No	No	Yes	Yes	No	No	Yes	Yes
MFI squared	No	No	No	Yes	No	No	No	Yes
CRA × MFI squared	No	No	No	Yes	No	No	No	Yes

Note: Estimates of Eq. (1) in the text. All specifications include tract fixed effects, year fixed effects, and a linear group time trend for treated tracts. Numbers of observations are given in Table 1, which contains other notes.
***Standard errors are clustered at the tract-level. $p < 0.01$.
**Standard errors are clustered at the tract-level. $p < 0.05$.
*Standard errors are clustered at the tract-level. $p < 0.1$.

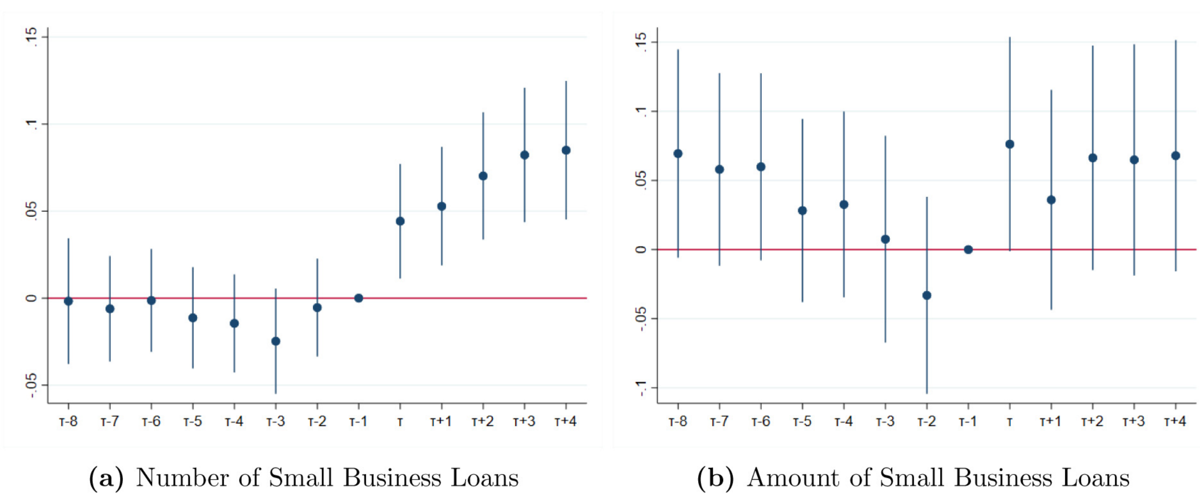


Fig. 2. Event study: Small business loans on CRA.
Note: Each figure shows the estimated difference between treated and control tracts in each time period relative to that in one year before the change in CRA eligibility. 99 percent confidence intervals are reported in error bars. The estimations are using 10 percent bandwidth sample.

and amount of loans less than $100,000 in the tract. Results, shown in the Appendix, are similar along all these dimensions.[4]

Caveats to these results include the limitations of tract-level data, which we analyze in the absence of firm-level loan data. Our results pertain to tracts with relatively consistent boundaries. Finally, the association of CRA with decreases in relative MFI, associated with economic decline, may impart a downward bias to the estimates.

5. Conclusion

The reporting requirements and rating procedures of the CRA would not seem to provide strong incentives for bank behavior. Our examination of the impact on small business lending extends Bostic and Lee (2017) and Ding et al. (2020), using a tract crosswalk to exploit larger changes in eligibility. The results provide further evidence of positive effects. The estimates are not large, but they are suggestive that strengthening CRA incentives could further raise small business lending in lower-income neighborhoods.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2021.110146.

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[4] In other robustness checks, we also estimated the impact using a later set of CRA changes in 2017 and using a broader definition of loans, including all business loans under $1 million, regardless of firm size, again with qualitatively similar results.

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