Impact of Community Reinvestment Act on Minority and Female Employment Growth

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Abstract

In this paper, we examine how the Community Reinvestment Act (CRA) affected minority and female employment from 2012 to 2019. We also investigate whether the effects varied between metro and nonmetro areas. We combine demographic and income data from the American Community Survey (ACS) with employment data from the Census Longitudinal Employer-Household Dynamics Local Origin-Destination Employment Statistics (LODES). In order to determine the causal effects of the CRA on employment growth outcomes, a quasi-experimental study approach is used. According to the statistically significant findings, the CRA designation increased residence-based employment in CRA designated tracts, including job growth for female and minority groups. Additionally, we observe that these effects were higher in tracts located in non-metropolitan areas compared to metro areas.

Keywords: Community Reinvestment Act, U.S. Census Tract, Minority Employment Growth.

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1. Introduction

Credit access is critical for small businesses to address financial constraints (e.g., Rupasingha and Wang, 2017). The Community Reinvestment Act (CRA), enacted by Congress in 1977 and strengthened after the 1990s, is one of the policies designed to help local community members (including small farmers and small business owners) gain access to local banking institutions. The Act essentially guarantees the loans made by banks, to reduce their overall lending risks. In this paper we combine data from various sources to examine whether the CRA after 2012 independently impacted the census tract-level employment growth of different minority and racial groups. We use Regression Discontinuity Design (RDD) and Multivariate-distance matching to answer this question.

The Community Reinvestment Act (CRA) was enacted as a response to redlining, a practice in which banks and other financial institutions discriminated against low-income and minority communities by denying them access to credit (Federal Reserve Bank of St. Louis). The CRA requires banks to serve the credit needs of all communities in which they operate, including low- and moderate-income neighborhoods, and to make a concerted effort to provide credit to those who have been traditionally underserved. We are interested in whether the CRA helped to improve low-income and minority communities by examining the effects on employment.

One of the key benefits of the CRA has been spurring investment and economic development in low-income and minority communities. A study by the Federal Reserve Bank of Philadelphia found that CRA-regulated banks were more likely to lend in low-income and minority communities than non-CRA-regulated banks, and that these loans helped to create jobs and stimulate economic growth (Hill et al., 2015). Rupasingha and Wang (2017) studied the impacts of CRA on business growth outcome using county-level data and found that CRA loans have a statistically significant positive effect on small business growth at the county-level. Another benefit of the CRA has been to promote homeownership in underserved communities. Studies have shown that CRA-regulated banks are more likely to offer mortgages to low- and moderate-income borrowers and borrowers in minority neighborhoods, and that these loans have helped to increase homeownership rates in these communities (Bostic et al., 2005).

However, the CRA has also been criticized for being too burdensome and for not doing enough to address the root causes of poverty and inequality in low-income communities. Some argue that the CRA has led banks to make risky loans to underserved communities, which contributed to the subprime mortgage crisis of 2008 (e.g., Gramlich, 2007; Wallison, 2009; Wallison, 2011).

Despite these criticisms, the CRA remains an important tool for promoting economic development and homeownership in underserved communities. In recent years, there have been efforts to modernize the CRA to better address the changing needs of low-income communities, including a proposed rule by the Federal Reserve, the Office of the Comptroller of the Currency, and the Federal Deposit Insurance Corporation to update the CRA regulations (Federal Reserve Board). Overall, the CRA has had a significant impact on promoting economic development and homeownership in low-income and minority communities, but it is important to continue to evaluate and update its effectiveness to ensure that it continues to meet the needs of these communities. A novel contribution of our study is to examine impacts of the CRA on job growth among different ethnic or racial groups, as well as women.

2. Data

The data for our outcome variable – percentage changes in employment over time of different minority and racial groups – are from the LEHD Origin-Destination Employment Statistics (LODES) database.[1] Data files are organized by both Residence Area Characteristics (RAC) and Workplace Area Characteristics (WAC). The RAC reports employment based on the residence of workers, while the WAC is based on the working place of the workers. We use RAC in our analysis (plan to use WAC in a future study). The LODES data are available for most states for the years (2002-2020). However, for different minority and racial groups, the availability is restricted to years after 2009.

Our primary hypothesis is that CRA-loan eligibility has a positive causal effect on employment at the census tract level. A census tract is defined as eligible if its median family income (MFI) is below 80 percent of that in the surrounding Metropolitan Statistical Area (MSA) for MSA tracts or state for non-MSA tracts (Kim et al., 2021). Tract boundaries changed in 2012 when various tracts were divided and merged. Before 2012, MFI from the 2000 Census was used to determine

[1] https://lehd.ces.census.gov/data/

CRA eligibility; since 2012, MFI from the 2006-2010 5-year American Community Survey is used. Considering a consistent CRA eligibility definition and availability of the LODES data, our main sample is restricted to 2012-2019. However, in future work, we can also include the 2009-2011 sample in our analysis to account for the census tract boundary changes in 2012 and switches of CRA-eligible and non-eligible tracts.

The CRA data can be extracted from the CRA page of the Federal Financial Institutions Examination Council's (FFIEC) website.[2] This data reports CRA loans by different types (farm and business) and sizes (small, medium, and large) in terms of loan numbers and amounts. However, we do not use the CRA loans data in our regression models as we are only interested in whether or not a census tract is eligible for a CRA loan. We also use additional census tract-level control variables as regressors from various resources, including the American Community Survey (ACS).

3. Methods and Models

We first use a sharp RDD to assess the effect of CRA eligibility, defined above. For (rural) tracts outside MSAs, the state's non-MSA MFI is used as the denominator (Kim et al., 2021). We use the 80% cutoff to assign RDD treatment status. RDD has been gaining popularity for causal inference in many fields of Economics. A comprehensive review can be found in Cattaneo & Titiunik (2022), Imbens & Lemieux (2008), and Lee & Lemieux (2010). Relevant to our paper, a handful of papers have used the RDD methods to explore the CRA impact. For example, Kim et al. (2021) find that loan numbers and amounts increased if a census tract was designated as CRA-eligible. Other variables, including mortgage lending, small business lending, and small business employment at the firm level are also examined in previous CRA works (Ding et al., 2022; Kim, 2023; Kim et al., 2021).

We estimate a linear regression model for our sharp RDD in equation (1) for census tract *i*:

$$Emp_i = \alpha + \tau D_i + f(m_i) + \rho X_i + \epsilon_i \tag{3}$$

The dependent variable Emp_i is employment of different racial and minority groups, including Whites, Blacks, Hispanics, and Females. The total employment is also used as a dependent variable. We calculate the dependent variable as the percentage change between 2012-2019 for

[2] https://www.ffiec.gov/cra/craflatfiles.htm

each group of the employment variable. D_i is the treatment variable where D_i =1 if a census tract is CRA eligible. The m_i is the forcing variable which is calculated as the ratio of tract median family income (MFI) to MFI of MSA for tracts located in metro areas or statewide MFI for the tracts located in nonmetro areas We define f as a quadratic control function in the main analysis, allowing the quadratic coefficients to vary above and below the cutoff. X_i is the vector of census-tract level control variables all measured using 2006-2010 ACS data, including the share of different populations by racial group, share of population by age groups, share of population by educational attainment, unemployment, and population density. Table 1 shows the descriptive statistics of all the variables.

The RDD estimates Local Average Treatment Effects (LATE) around the cutoff point (Calonico et al., 2020). Besides the global regression using the full sample, we use different bandwidths to restrict the sample, including 5%, 10%, and 20% deviations from the cutoff points. One of the important assumptions of RDD validity is the absence of manipulations around the RDD cutoff points. Specifically, this means census tracts respondents do not underreport their MFI to choose to become CRA-eligible tracts; otherwise, the RDD results are biased.

As noted, the RDD method has often been used in the CRA impact literature (e.g., Ding et al., 2022; Kim, 2023; Kim et al., 2021). However, specific to our research question – the impact of CRA on employment of different minority and racial groups, the method may not be suitable. As discussed above, the RDD estimates LATE around the cutoff point. Large shares of the minority groups are likely to be far below the CRA 80 percent cutoff point (e.g., 50 percent), in which case the 5%, 10%, and 20% RDD bandwidths will exclude many of the targeted communities and this would downward bias our RDD estimates to show small or even no effects. To address this potential bias using RDD, we use an alternative model, multivariate (or Mahalanobis) distance matching (MDM), as an supplemental test.

MDM is a statistical technique used to compare two groups of individuals or entities based on multiple variables. It involves measuring the distance between each member of one group and every member of the other group in terms of their values on the multiple variables of interest. The goal is to identify pairs of individuals or entities from the two groups that are similar in terms of their values on the different variables, which can then be used to make comparisons between the groups. This technique has been used in various fields, including economics, public policy, and health research, to study the effects of policies or interventions on different groups of individuals or entities (Stuart, 2010; Rubin, 2001; Iacus, 2012; Austin, 2008). In our study, we use a comprehensive set of pre-treatment covariates to do the matching, including pre-treatment employment levels for various groups, the share of different racial and minority groups, share of different age groups, share of different education groups, population density, and the rurality status of a tract. We include pre-treatment levels of employment outcomes to account for unobservable characteristics and time-invariant differences as proposed by Heckman, Ichimura, and Todd (1998) and others (Abadie, Diamond, and Hainmueller, 2010; Neaumark and Young, 2019). Including several years of pre-treatment levels of employment effectively controls for pre-treatment employment changes between time periods (Neaumark and Young, 2019).

4. Results

Figure 2 shows the geographical distribution of CRA eligibilityfor total employment and racial, ethnic, and gender sub-groups analyzed in the paper. Panels A-E show the RDD figures, where the X-axis is the income ratio and the vertical line is at the RDD cutoff 80%, the Y-axis is the dependent variable used in each Panel of Table 2. Clearly, we do not see any significant jumps at the cutoff.

Table 1 reports descriptive statistics by CRA eligibility, while Figure 1 maps the eligible tracts nationally. About 34% of all the tracts are CRA-eligible. Overall, CRA-eligible tracts are more distressed in that unemployment rates are higher; also, the share of college-degree workers is lower.

Table 2 presents our main RDD regressions. The dependent variable is the percentage change of different employment variables – including total jobs overall, total jobs for Whites, total jobs for Blacks, total jobs for Hispanics, and total jobs for the females. The results reported in the first column – the global regression using the full sample - show statistically significant positive effects of the CRA-eligible variable for total, White, Black, and female jobs, but not for Hispanic jobs. However, for RDD regressions using 10 percent bandwidth selections, we do not find statistically significant effects on any of the groups studied. These results were also tested with bandwidth selections of 5% and 20%, however there was no discernible difference in the outcomes. This may indicate that the RDD is not an appropriate method for our research question as many targeted communities are well below the 80 percent cutoff point. For example, the share of the black group at the 90 percentile or above has an income ratio (as defined in the Data section) of 61%. In comparison, the share of the black group at the bottom 90 percentile has an income ratio of over 100%.

Next, we implemented a matching exercise by selecting a comparison group of tracts based on number of pre-treatment covariates from among non-CRA using kernel matching based on Mahalanobis distance in which the weights are based on the inverse of the covariates' variance–covariance matrix. All tracts from the control group are taken into account by the kernel matching, and the longer the Mahalanobis distance, the less weight that tract should have in relation to the treated tract.

We matched control tracts to each treated tract by matching on pre-treatment residence-based employment 2009 and 2011separately for each sample investigated and other covariates from 2010 listed in Table 1. We also exact-matched census tracts based on Rural-Urban Commuting Area (RUCA) codes for 2010 developed by USDA – Economic Research Service. Bias adjusted balancing statistics from kernel matching for the total employment change are reported in in Table 1A in the appendix and they and the same for subsamples showed that the matching procedure ensures balance across these covariates between matched census tracts. The mean difference within the matched pairs is closer to zero compared to the mean difference between treated and comparison tracts before the matching, including the pre-treatment changes in the employment outcomes. The variance between the treated and untreated groups must also be closer to each other for there to be a good balance after matching. The variance ratio in the matched sample is closer to 1 for the majority of the variables, as shown in Table 1B, demonstrating good matching.Table 3 Panel A shows our main matching results for the full sample and they show statistically significant positive effects of CRA on total jobs, black jobs, and female jobs. In the matched estimates, the statistically significant mean difference in employment growth rate show clear evidence that CRA designation increased residence-based employment in treated tracts for all samples studied in the analysis. The employment growth impacts for residence-based employment for females is positive but just missed being statistically significant. Next, we explore how the program affected the rural-urban metro and nonmetro tracts separately by dividing census tracts into those that are located in metro areas

(RUCA codes 1-3) and nonmetro areas (RUCA codes 4-10). These results are reported in Table 3 Panels B and C, respectively. Overall, we find stronger and more consistent effects of CRA in non-metro areas. Results shown in Panel B demonstrate that the CRA has a favorable and significant impact on employment growth in nonmetropolitan tracts across all racial, ethnic, and gender groupings. Only the black and Hispanic groups in metro tracts are seen to benefit positively from the program (Panel C of Table 3).

5. Conclusion and Future work

This paper examines the impacts of the CRA on employment by minority and female populations. It also examines whether the program impacts on these categories differed based whether tracts were located in nonmetro or metro areas. The statistically significant results using matching show that there is evidence that the program increased residence-based employment in treated tracts and these increases are mainly due to the overall impacts of the program in rural areas.

In future work, we will combine the RDD and matching methods as a new model. Specifically, we will explore running the RDD using a matched sample. This would yield a LATE on comparable treatment and control groups. Our current results are based on the residence of workers; we will also update our regression results using workers' place of work. We will also conduct additional robustness checks for matching results, including testing against an alternative time-period, randomly assigning treatment indicators for tracts, and using alternative matching methods and synthetic control method combined with difference in difference analysis.

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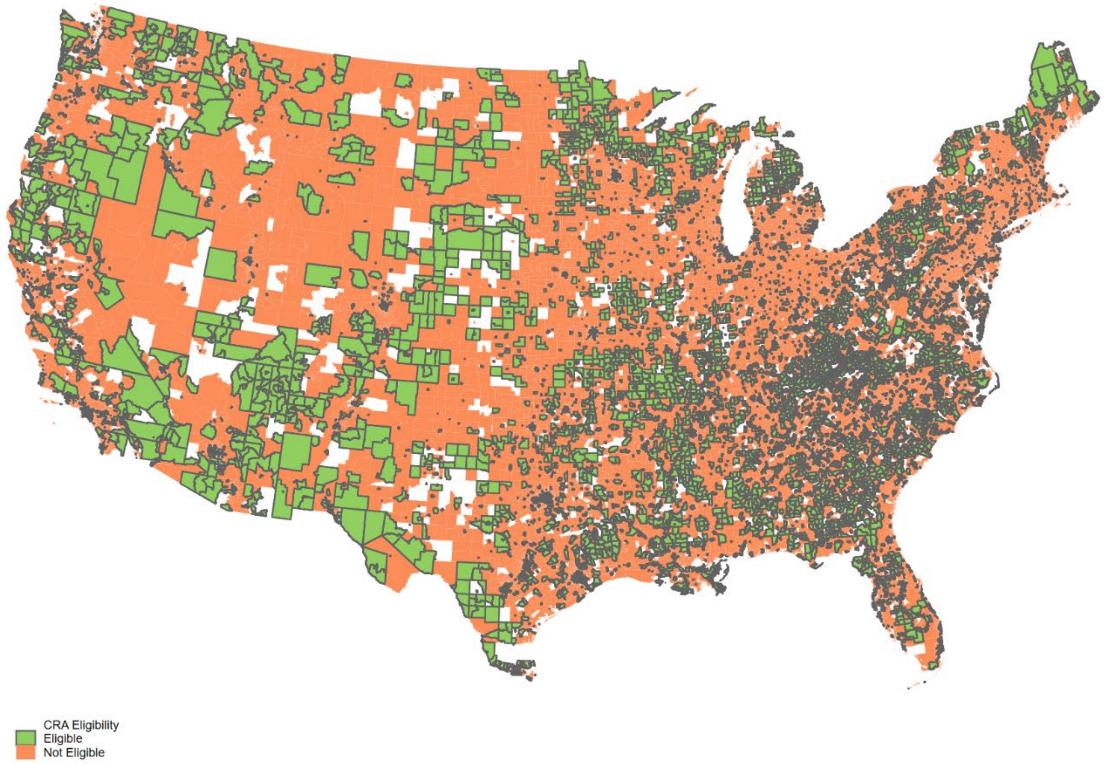
Figures and Tables

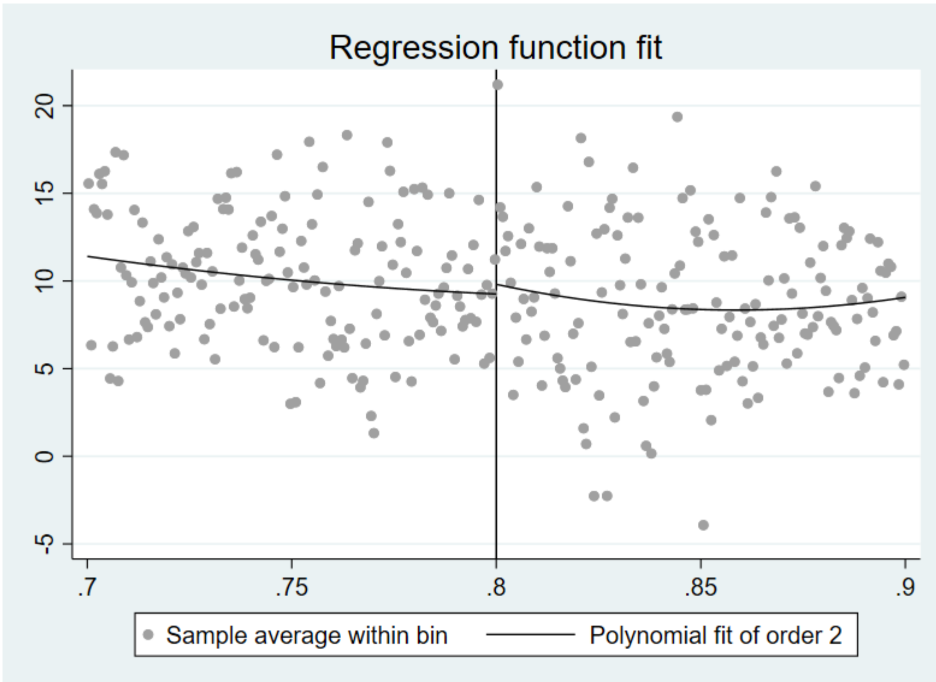
Figure 1 Geographical distribution of CRA-eligibility



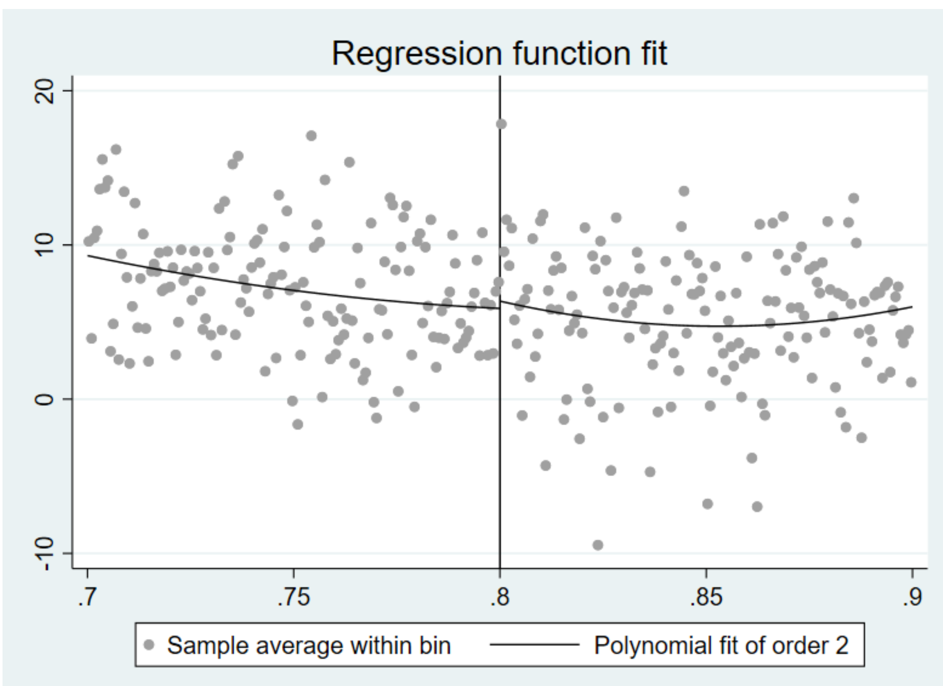
Source: ACS 2006-2010 with authors' calculation.

Figure 2 RDD Figures for Panels A-F of Table 2

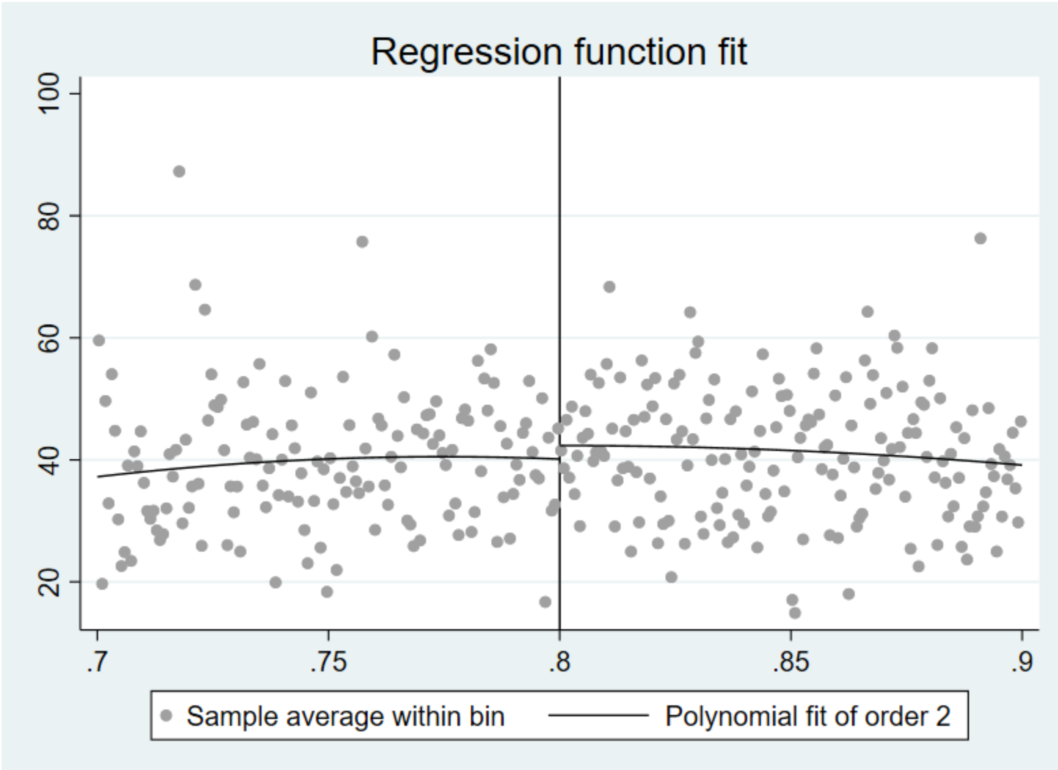
Panel A: Total employment change



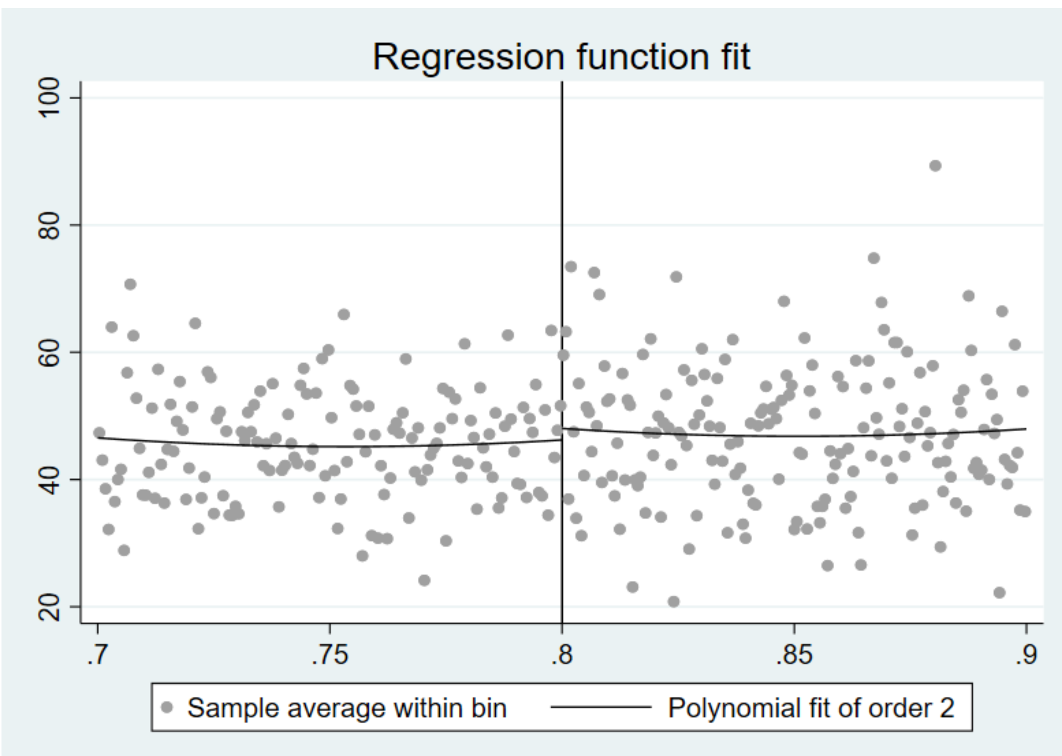
Panel B: White employment change



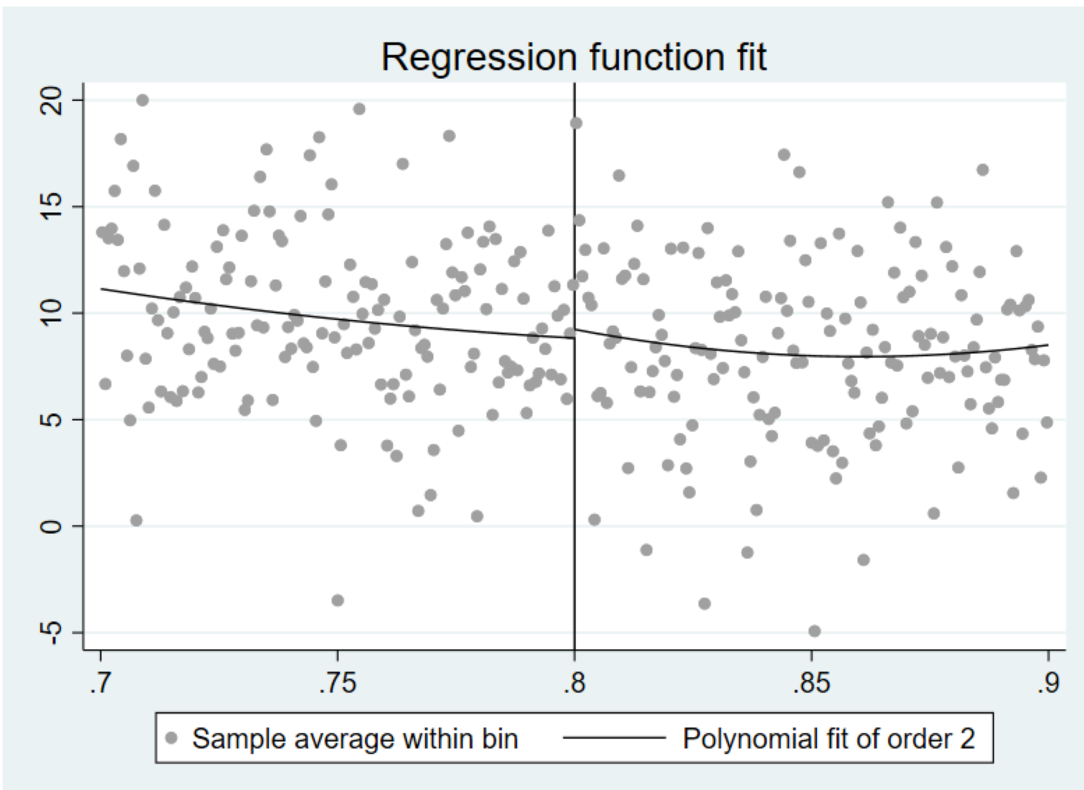
Panel C: Black employment change



Panel D: Hispanic employment change



Panel E: Female employment change



Sources: ACS and LODES with authors' calculation. The X-axis in all charts indicates the income ratio and the vertical line is at the RDD cutoff 80%, and the Y-axis is the dependent variable (employment change for each group between 2012 and 2019).

Table 1: Descriptive Statistics

	cra_eligible		
	0	1	Test
N	48,128 (65.9%)	24,929 (34.1%)	
pct_12_19_JobsTotal	10.483 (31.558)	14.862 (29.377)	<0.001
pct_12_19_JobsRaceWhite	6.723 (35.060)	13.418 (34.342)	<0.001
pct_12_19_JobsRaceBlack	42.699 (67.889)	34.899 (64.199)	<0.001
pct_12_19_JobsEthnicityHispanic	49.015 (58.334)	45.306 (61.433)	<0.001
pct_12_19_JobsSexFemale	10.387 (32.867)	14.838 (29.508)	<0.001
Share of Black population	0.077 (0.140)	0.250 (0.302)	<0.001
Share of Hispanic population	0.104 (0.149)	0.228 (0.271)	<0.001
share of population under 5 yearsl old	0.059 (0.026)	0.074 (0.034)	<0.001
share of population over 64 years old	0.140 (0.077)	0.122 (0.074)	<0.001
Share less than HS degree (pop 25 over) - excluded no no school	0.100 (0.074)	0.231 (0.118)	<0.001
share of high schoold graduate abd GED only	0.272 (0.114)	0.335 (0.094)	<0.001
share of some college only	0.290 (0.079)	0.261 (0.082)	<0.001
share of college or more	0.331 (0.185)	0.154 (0.110)	<0.001
unemployment rate (use pop and 16 over)	0.043 (0.024)	0.071 (0.039)	<0.001
population density	3,593.279 (8,521.765)	8,371.085 (15,720.977)	<0.001

Table 2 Effects of CRA on Employment using RDD

	(1)	(2)
Panel A: Total Employment		
cra_eligible	1.3343***	-1.0657
	(0.3611)	(1.0421)
Panel B: White Employment		
cra_eligible	0.7980**	-1.0431
	(0.3998)	(1.1152)
Panel C: Black Employment		
cra_eligible	3.1558***	-2.8487
	(1.0109)	(3.5770)
Panel D: Hispanic Employment		
cra_eligible	1.2899	-4.5914
	(0.9100)	(3.0486)
Panel E: Female Employment		
cra_eligible	1.2114***	-0.8691
	(0.3656)	(1.0433)
Sample	all	10% bandwidth
Observations	68,069	13,878
County FE	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Table 3 Effects of CRA on Employment using Matching

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Total	White	Black	Hispanic	Female
Panel A: All Sample					
cra_eligible	1.89	2.26	7.40	7.05	1.72
	(1.07)*	(1.59)	(1.65)***	(2.17)***	(1.09)
Panel B: Non-metro Sample					
cra_eligible	4.60	4.90	5.28	3.72	4.99
	(1.14)***	(1.35)***	(2.52)**	(2.16)*	(1.12)***
Panel C: Metro Sample					
cra_eligible	1.24	1.76	5.48	6.54	0.76
	(1.35)	(1.89)	(1.93)***	(2.83)**	(1.39)

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table 1A. Mean balance table for matched and unmatched tracts

	Raw			Matched(ATT)		
Means	Treated	Untreated	StdDif	Treated	Untreated	StdDif
l_JobsTotal2009	7.084295	7.339826	-.3423877	7.105293	7.105293	-1.19e-15
l_JobsTotal2010	7.092399	7.3822	-.4165935	7.110605	7.110605	0
l_JobsTotal2011	7.145255	7.498103	-.6959413	7.159401	7.159401	0
JobsTotal2012	1451.017	2028.397	-.6862634	1461.555	1442.007	.0232348
sh_black	.2495257	.0715753	.7646507	.2474831	.2474831	-2.39e-16
sh_hisp	.2283888	.0974013	.608653	.227477	.227477	0
sh_under5	.0743865	.0595948	.4993753	.0739303	.0739303	0
sh_over64	.1217483	.1403731	-.2481888	.1222151	.1222151	-1.85e-16
sh_less_highsch	.2311409	.0931862	1.43861	.2290884	.2290884	-2.89e-16
high_sch_grad	.3345569	.2679283	.646432	.3351582	.3351582	0
some_coll	.260654	.2905619	-.3782473	.2616941	.2616941	0
coll_more	.1541112	.3412686	-1.240977	.1552056	.1552056	0
urate	.0707073	.0422656	.9078091	.0699468	.0699468	-4.43e-16
popden	8372.286	3506.51	.3849875	8033.053	8033.053	-7.20e-17

Table 1B. Variance ratio table for matched and unmatched tracts

	Raw			Matched(ATT)		
Variances	Treated	Untreated	Ratio	Treated	Untreated	Ratio
l_JobsTotal2009	.5241442	.5898399	.8886211	.4874925	.4491031	1.08548
l_JobsTotal2010	.4473258	.5205198	.859383	.4163744	.4042945	1.029879
l_JobsTotal2011	.2768257	.2372876	1.166625	.2563972	.2288179	1.120529
JobsTotal2012	494374.9	921327.4	.5365899	484726	414106.5	1.170535
sh_black	.0910241	.0172942	5.263264	.089705	.0994674	.9018526
sh_hisp	.0736658	.0189639	3.884521	.0726869	.0874037	.8316231
sh_under5	.0011326	.0006221	1.820536	.0010535	.0008805	1.196561
sh_over64	.0055407	.0057221	.9683091	.0054957	.0030076	1.827251
sh_less_highsch	.0139288	.0044627	3.121192	.0134361	.0158751	.8463599
high_sch_grad	.0087462	.0125012	.6996335	.0085571	.0071788	1.191997
some_coll	.0066627	.0058413	1.140608	.0064538	.0051019	1.264973
coll_more	.01213	.0333601	.3636072	.0121351	.0080346	1.510366
urate	.001481	.0004822	3.071585	.0013314	.0013401	.9935213
popden	2.47e+08	7.23e+07	3.418871	2.06e+08	2.41e+08	.8564865