The Long Run Effects of De Jure Discrimination in the Credit Market: How Redlining Increased Crime

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Abstract

Today in the United States the welfare costs of crime are disproportionately borne by individuals living in predominately African-American or Hispanic neighborhoods. This paper shows that redlining practices established in the wake of the Great Depression make present-day contributions to this inequity. In particular, I use an unannounced population cutoff that determined which cities were redline-mapped to show that redline-mapping increased present-day city-level crime. Channels though which redline-mapping influenced crime include increasing racial segregation, decreasing educational attainment and harming housing markets.

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Today in the United States the social costs of crime exceed 2 trillion dollars.[1] These welfare costs are not distributed evenly across racial and ethnic categories: nearly 60% of murder victims, for example, are either African-American or Hispanic.[2] These welfare costs are also unevenly distributed across neighborhoods. Predominantly African-American neighborhoods have 5 times as many violent crimes as predominantly Non-Hispanic White neighborhoods; predominantly Latino neighborhoods have about 2.5 times as many violent crimes as predominantly Non-Hispanic White neighborhoods[3] (Peterson and Krivo (2010)).

Because variation in crime is associated with a vast number of factors including income, racial segregation (Chetty et al. (2014)), school quality (Chetty et al. (2011)) and pollution (Stretesky and Lynch (2004)), researchers face a significant challenge in trying to identify the causes of these inequalities in the distribution of crime. In this paper, I use a regression discontinuity design to show that Federal housing policies established in the wake of the Great Depression increased present-day city-level crime. I use the same research design to show that redline-mapping influenced crime by increasing racial segregation, decreasing black educational attainment and harming housing markets.

To stabilize housing markets in the 1930's, a newly formed Federal agency, the Home Owner's Loan Corporation (HOLC), constructed maps of 239 US cities; these maps purported to grade neighborhoods in terms of lending risk, the riskiest neighborhoods being labeled in red and colloquially said to have been "redlined". Neighborhoods assigned low grades faced decades of reduced credit-access relative to neighborhoods assigned higher grades (Jackson (1987)). Thus, redlining policy provides a context in which a researcher can identify the long run effects of restricting credit-access to a neighborhood.

Beginning in 1936, HOLC surveyors and administrators classified neighborhoods on the basis of housing characteristics such as home value, home age, construction-type and rental values, as well as demographic characteristics such as the occupation of residents and, most controversially, the race and ethnicity of residents. In particular, HOLC surveyors were asked to detail whether or not it was expected that certain "inharmonious" or "subversive" groups were likely to move into the neighborhood. Because surveyors recorded demographics, expected demographics and explicitly expressed preferences about which races and ethnicities were more or less advantageous to neighborhood quality and less risky to lenders, many

[1] United States. Senate Committee on the Judiciary. Hearing on The Costs of Crime. September 19, 2006 (cited Barr and Smith (2017))

[2] Author calculations from NIBRS 2010 Crime Victimization data.

[3] A "predominantly African-American neighborhood" is defined as a census tract in which 70% or more of the residents are African-American. Similar definitions are used for "Latino" and "Non-Hispanic White".

researchers have claimed that redlining not only reflected existing racial discrimination but further institutionalized this racial animus in the public and private credit market, and have also suggested that redlining had a long-run effect on neighborhood formation (Jackson (1987)). Accordingly, the term "redlining" has come to denote the practice of credit-market discrimination on the basis of neighborhood characteristics such as racial demographics, rather than individual loan-applicant credit-worthiness.

This paper contributes to the growing literature on redlining as well as to the larger literatures on the determinants of crime and the effects of credit-access. Concerning redlining, in particular, this paper is the first to estimate the causal effect of redlining on crime. This paper is also the first to show that this effect on crime comes through increases in racial segregation, decreases in black educational attainment as well as harm to housing markets. These results build on Aaronson et al. (2017), which uses within-city variation to show that redlining increased racial segregation, decreased home ownership, home values and credit scores. Concerning the literature on the determinants of crime and the effects of credit-access more broadly, this paper is the first to show the long-run, persistent effects of credit-access on crime. While the nature of the variation does not allow me to demonstrate uniqueness of channel, the evidence in this paper suggests a straightforward labor market story: restricting credit-access by race increased racial segregation, which harmed local educational attainment, which, in turn, influenced job market outcomes and altered the likelihood of criminal perpetration and victimization by race.

1 Background

1.1 Institutional History of Redlining

Prior to the housing policies enacted in Franklin Roosevelt's "New Deal", homeownership was difficult for most middle class households. Home loans were neither amortized nor federally insured, and consequently most lenders offered home loans that were between 5 and 10 years in duration and required down payments of 30% or more (Jackson (1987) p.204). Moreover, the terms of these loans needed to be renegotiated every five years, leaving would-be homeowners subject to fluctuating interest rates. In the midst of the Great Depression, the home ownership market contracted even further as financially strapped families lost their homes and vacancies increased (Rothstein (2017)). In an effort to stabilize the housing market, the Roosevelt administration created the Home Owner's Loan Corporation (HOLC) in 1933. HOLC bought up billions of dollars of mortgages which were on the brink of foreclosure and renegotiated 15 to 25 year mortgages with uniform, amortized loan schedules; nearly 40% of eligible Americans sought HOLC assistance (Jackson (1987) p.196). In order to make such a large volume of loans, HOLC needed to gauge the riskiness of these new loan offers. Accordingly, HOLC hired local real estate agents to survey parts of a given city, dividing the city into neighborhoods and assigning to each of these neighborhoods a color-coded "security risk" grade. These HOLC-neighborhoods were not based on pre-existing Census designations such as Wards or Ennumeration Districts and were drawn at the discretion of the agency.

The resulting "Residential Security Maps" contained four ordinally ranked risk-grades: A(green), B(blue), C(yellow), D(red) (e.g. Figure A3). The highest ranked neighborhoods, graded "A" and colored in green, were described as "new, homogeneous", while the lowest ranked neighborhoods, graded "D" and colored red, were described as "hazardous" (Jackson (1987) p.198). HOLC surveyors assigned quality categories and accordingly classified neighborhoods on the basis of housing characteristics such as home value, home age, construction-type and rental values as well as demographic characteristics such as the occupation of residents and, most controversially, the race and ethnicity of residents. In particular, HOLC surveyors were asked to detail whether or not it was expected that certain "inharmonious" or "subversive" groups were likely to move into the neighborhood.[4]

In short, even though HOLC did influence neighborhood credit-access through its own loan-granting practices, its long-run influence is due to its influence on other institutions. In particular, HOLC and its Residential Security Maps influenced loan access in two ways: (1) by influencing private lenders[5] and (2) influencing FHA loan-insurance appraisals. Through these two channels HOLC maps influenced credit-access in hundreds of US cities for decades.

The use of these maps and loan practices have since been made illegal, first in the 1968

[4]See Figure A1 for an example of a surveyor document produced for a redlined neighborhood in Los Angeles, California.

[5]Jackson notes that "During the late 1930s, the Federal Home Loan Bank Board circulated questionnaires to banks asking about their mortgage practices. Those returned by the savings and loan associations and banks in Essex County (Newark), New Jersey indicated a clear relationship between public and private "red lining" practices. One specific question asked "What are the most desirable lending areas?" The answers were often "A and B" or "Blue" or "FHA only". Similarly, to the inquiry, "Are there ary areas in which loans will not be made?" the responses included "Red and most yellow", "C and D", "Newark", "Not in red" and "D areas". Obviously, private banking institutions were privy to and influenced by the governments' Residential Security Maps" (Jackson (1987) p.203). Hillier offers a dissenting view according to which private lenders were not very aware of the maps (Hillier (2003)). On Hillier's view, HOLC maps could influence outcomes in any substantial way only through influencing FHA loan insurance practices. Aaronson et al. (2017) offer an extended discussion of the debate in the literature concerning how widely the HOLC maps were used.

Fair Housing Act (FHA), but later in the 1974 Equal Credit Opportunity Act (ECOA) as well as later revisions to the FHA such as the Fair Housing Amendments Act of 1988, which strengthened penalties for discriminatory lending practices (See Figure 1). Nevertheless, there exists an active debate about whether or not such discriminatory practices still take place.[6] Whether or not there still exist *de facto* forms of discrimination, the *legal* use of HOLC maps from 1938 to 1968 created widespread *de jure* racially discriminatory practices in the credit market. This *de jure* discrimination restricted credit-access to neighborhoods which were given low grades for at least the duration of this 30 year period.

1.2 Existing Evidence on Redlining and Crime

While there is a large, interdisciplinary body of work exploring how housing policy in the 1930's may have shaped present-day neighborhood characteristics, the literature has not yet identified the effects of redlining on crime nor has it used used this massive Federal policy to address questions about the the determinants of crime and the effects of credit-access more broadly.

Jackson's seminal book, "*Crabgrass Frontier*" chronicles the activities of the HOLC and FHA in relation to several broader narratives he weaves together which include urbanization, suburbanization and the racially motivated history of United States housing policy. More recently Appel and Nickerson (2016) uses a spatial regression discontinuity design to show that homes just across the border of a lower HOLC security grade have less value in 1990. To establish the identification assumption that home values did not exhibit jumps prior to the policy, the paper uses home value data from 1940, which is soon after the maps were constructed.

Most recently, Aaronson et al. (2017) engages in a groundbreaking and ambitious project to chart the effects of redlining maps in over one hundred US cities across decades. Using a variety of empirical approaches including the construction of counterfactual boundaries that experienced the same pre-existing trends, they identify the causal effect of the HOLC maps on the racial composition and housing development of urban neighborhoods. In particular, this paper shows that being on the lower graded side of D-C (red-yellow) boundaries increased racial segregation from 1930 until about 1970 or 1980 before starting to decline thereafter, even though some gaps persist until 2010. They find that the effects on homeownership

[6]See Reibel (2000) and references. Aaronson et al. (2017) points out that even today there are substantial lawsuits which allege this sort of discrimination in major cities to the extend that the Consumer Financial Protection Bureau and the Department of Justice have open investigations concerning lending discrimination.

rates and house values dissipate over time along the D-C (red-yellow) boundary persistent along the C-B (yellow-blue) boundaries. This work is the first to explore and identify causal effects for a vast number of outcomes across over one hundred cities over three quarters of a century. Their work is also the first to highlight the importance of the C-B (yellow-blue) boundary and identify the long-run effects of "yellow-lining".

There still remain important gaps in the literature on redlining. I complement the existing literature by identifying the impact of redlining on crime. Furthermore, I add to the literature by using a population cutoff that determined whether a city would be redline-mapped to produce a an estimate of the causal impact of redline-mapping on crime, racial segregation and educational attainment. Given the findings in Aaronson et al. (2017), we would expect racial segregation to be one of the main mechanisms through which redlining influenced the formation of cities, which is indeed what I find.

Concerning the literature on the determinants of crime and the effects of credit-access more broadly, this paper is the first to show the long-run, persistent effects of credit-access on crime. Previous studies have identified effects of childhood exposure to credit-access on adulthood credit scores (Brown et al. (2016)), and the local effects of reduced local competition between banks on property crime (Garmaise and Moskowitz (2006)). Furthermore, there exists evidence that racial segregation is causally responsible for lower educational attainment for Blacks (Ananat (2007), Billings et al. (2013)) and that lower educational attainment is causally responsible for increased crime (Lochner and Moretti (2004)). This paper connects the literature on education and crime to the literature on credit-access by showing evidence of the following labor market story concerning redline-mapping: restricting credit-access by race increases racial segregation, which harms local educational attainment, which, in turn, influences job market outcomes and alters the likelihood of criminal perpetration and victimization.

2 Data

2.1 HOLC Administrative Data

I use archival HOLC data to determine whether HOLC constructed a redlining map for a given city.[7] I add this information to a rich dataset of city characteristics derived from the decennial Census 1890-2010 (Ruggles et al. (2018)). In the period before redline-mapping,

[7]These documents reside in National Archive Group 31.

I observe housing variables such as self-reported home-value and rental amounts as well as demographic information such as the race and ethnicity of residents.[8] Lastly, I use individual level National Incident Based Reporting System (NIBRS) crime victimization data from 2015, restrict to UCR classified Part 1 property and violent crimes and collapse by reporting agency, assigning each agency to the city which it polices. Summary statistics are reported in Table A1. I also use agency-month level FBI Uniform Crime Reports (UCR) (Kaplan (2018)), which I collapse to obtain city-year and city-decade level crime counts and rates. Summary statistics are reported in Table A2.

3 City-Level Effects of Redline-Mapping on Crime

In this section, I utilize an unannounced population cutoff which determined whether or not a city was redline-mapped to show that redline-mapping increased city-level crime. In Section 4, I use this same between-city variation to identify mechanisms for how redline-mapping increased crime which include increasing racial segregation, decreasing educational attainment, and harming housing markets.

3.1 Which Cities Were Mapped and Why?

HOLC residential security maps were made for 239 US cities including most modern, major metropolitan areas. Despite the broad coverage of the maps, hundreds of cities and smaller towns were never mapped. As Figure 2 shows, having a 1930 population above 40,000 nearly guaranteed that a city would be mapped, while having a population below 40,000 nearly guaranteed that a city would not be mapped. While smaller in population than the largest and most often studied metropolitan areas, cities within a reasonable bandwidth about the 1930 population cutoff of 40,000 are still home to significant numbers of US residents. In 1930 approximately one third of the US population lived in cities with 50,000 or less people. In California, cities whose 1930 population was near the cutoff include Stockton, Fresno and San Jose (which were redline-mapped) as well as Santa Barbara, Santa Monica and San Bernardino (which were not redline-mapped); in Texas, representative cities include Austin, Galveston and Waco (which were redline-mapped) as well as Lubbock, Laredo and Corpus Christi (which were not redline-mapped). Table A3 contains a list of representative cities, and Figure A2 shows the regional breakdowns of cities near the threshold. Midwestern and

[8] I do not observe migration or education attainment, since these were not introduced to the Census surveys until 1940.

Northeastern cities are slightly overrepresented, but there are cities from each region in the main bandwidths I consider.[9]

3.2 Estimation

I use a regression discontinuity design to identify the city-level impact of being redline-mapped on crime. I estimate regressions of the form:

$$Crime_c = \tau Above_c + \beta f(Pop30_c) + \gamma Above_c \times f(Pop30_c) + \epsilon_c. \tag{1}$$

where $Crime_c$ is the count of crimes in city c, $Pop30$ is the 1930 population of city c. This regression uses 1930 city population as the running variable variable and fits a local linear polynomial on either side of the mapping population cutoff of 40,000 people. I am primarily interested in τ, the coefficient on *Above*, an indicator variable which equals one when city's population is above the population mapping cutoff (40,000 people) and zero otherwise; τ, the coefficient on *Above*, measures the average jump that occurs at the population cutoff conditional on the local linear polynomials.

3.3 Crime Effects

Figure 3 shows evidence that HOLC mapping increased present-day city-level crime victimizations. In particular, Black crime victimizations appear to nearly double across the mapping threshold, while Hispanic crime victimizations increase by more than 70%, although this latter estimate is significant only at the 15 percent level. The estimates reported in Figure 3 (and listed in Table A5) imply that 176 Black and 65 Hispanic crime victimizations are attributable to redline-mapping. The same estimates in victimization rates per 1,000 people are given in Figure A6. Figure A7 shows that these results are robust to the choice of more than the optimal number of bins. Lastly, Figure A8 shows that these estimates are robust across a wide array of bandwidths

Results using UCR data are comparable. (See the Appendix "Comparing NIBRS and UCR Results" for details.) Aside from providing a useful comparison to measures in the NIBRS dataset, the main reason to utilize the UCR measures of crime is that the UCR dataset spans many decades and allows me to understand long-run dynamics. Using the same estimation strategy from Figure 3 and estimating Equation 1 using UCR decadal data,

[9]Conditional on 1930 city population, census region does not predict whether or not a city was redline-mapped.

Figure 4 shows the dynamics of the impact of redline-mapping on crime over the entire period after the Fair Housing Act.[10] The same estimates in arrest rates per 1,000 persons are given in Figure A10. The decadal estimates which are reported in Figures 4 and A10 show that the effects of redline-mapping peaked in the period around the passage of major anti-discriminatory laws (such as the Fair Housing Act), and, while having decreased in subsequent decades, nevertheless persist into the present-day. If legislation such as the Fair Housing Act did mitigate the effects on crime, it is not ex ante clear *exactly* when the estimates ought to peak since, once redline-mapping has influenced the development of a city, city-level crime volume is likely to persist even after the enactment of anti-discriminatory legislation. Nevertheless, it is clear from Figures 4 and A10 that the increases in crime attributable to redline-mapping decrease in the period after the Fair Housing Act and related legislation, when the use of redlining maps became illegal.

3.4 Pre-Period Balancing and Placebo Tests

Ex ante it seems unlikely that cities with slightly more than 40,000 people and those with slightly less than 40,000 would exhibit pre-existing jumps across this threshold for any covariate associated with crime, however, to be cautious, I use 1920-1930 Census data to show that observable city-level covariates are smooth across the threshold.

I focus my balancing tests on the percent of households that are Black, the percent that are Hispanic, as well as self-reported home values and rental values. I am most concerned about these covariates because any pre-period discontinuity in racial composition or socio-economic status would lead us to question whether that pre-existing racial or socio-economic difference were the common cause of both the choice of the population-cutoff and present-day crime volume.[11] Figure A11 shows RD diagrams for these four covariates. We can see that they do not exhibit significant jumps about the population cutoff. Figure A12 shows RD estimates for these covariates across a range of bandwidths. Across a wide range of bandwidths, none of these covariates exhibit evidence of a pre-existing jump.

To the best of my knowledge there does not exist crime data from 1930 or earlier which covers large numbers of cities.[12] Thus I cannot directly test for discontinuities in crime in

[10] See Figure 1 for the timing of major anti-discriminatory laws such as the Fair Housing Act.

[11] Figure A4 shows that the density of agencies reporting to NIBRS is smooth across the population threshold. Figure A5 shows that the results pass a standard manipulation ("McCreary") test. Thus the results I find are not driven by the agency-level decision to report to the NIBRS database.

[12] UCR historical data, which predates 1960, contains at most 400 agencies, all of which lie in very large metropolitan areas.

the pre-period.[13] Nevertheless, the covariate tests (Figures A11-A12) show that *if* there were some unobserved factor influencing present-day crime in cities just above the mapping threshold, this factor would have to be correlated with present-day crime and yet uncorrelated with the racial and socio-economic measures observed prior to mapping. Even if pre-period crime correlates with present-day crime, it is also likely to be correlated with pre-period racial and socioeconomic measures.

Lastly, I implement a series of placebo tests in which I estimate the "effect" of redline-mapping on present day crime using a range of population cutoffs. Figure A14 shows that both for Black and Hispanic crime victimization, we find positive estimates at the actual cutoff, but not at the simulated, placebo cutoffs.

4 Mechanisms: How Did Redlining Increase Crime?

4.1 Racial Segregation as a Mechanism

There exists evidence that present-day racial segregation is correlated with reduced intergenerational mobility (Chetty et al. (2014)), is associated with increases in the Black-White SAT test score gap (Card and Rothstein (2007)), and that racial segregation is causally responsible for lower income and educational attainment for Blacks as well as increased crime (Ananat (2007), Billings et al. (2013)).[14] Thus, one way redline-mapping may have increased crime is by increasing racial segregation. Indeed, Aaronson et al. (2017) uses within-city variation in HOLC mapping assignments to show that redlining increased racial segregation.

To empirically test the hypothesis that racial segregation is a channel through which

[13]Despite this data limitation, in Figure A13, I use the group quarters variable from the 1930 Census to test for city-level pre-period differences in the share residing in institutional group quarters. Because this variable measures not only individuals who are incarcerated, but also many non-incarcerated individuals (see note to Figure A13) it does not constitute an ideal variable to measure pre-period criminal activity. Nevertheless, if more individuals in cities just above the population threshold are incarcerated in the pre-period, and the institutional group quarters variable measures this difference across the threshold, this could be an indication of higher pre-existing crime rates in the cities just above the threshold if we believe that the percent incarcerated is an increasing function of criminal perpetration. However, the results in Figure A13 show that, if anything, mapped cities had a smaller share of incarcerated individuals and incarcerated black individuals compared to non-mapped cities. Both because there is considerable variation in these bins and the group quarters variable in 1930 measures certain non-incarcerated individuals together with the incarcerated, these estimates should be treated with caution.

[14]Shertzer et al. (2018) and Shertzer and Walsh (2016) highlight the importance of studying racial segregation in the pre-World War II period (1900-1930): while the relocation decisions of white households from 1900-1930 ("White Flight") explain a large share of racial segregation, policies concerning zoning and public transit infrastructure have also affected racial segregation in the prewar era.

redline-mapping increased crime, I consider racial segregation as an outcome variable in Equation 1. I measure racial segregation using the White-Black Dissimilarity Index (a standard measure of racial segregation in cities).[15] I pool decadal measures of racial segregation from 1890-2010 based on whether they were (a) in the period prior to any redline-mapping (1890-1930), (b) in the period after redline-mapping was first implemented (1940-2010) or (c) in the period after both redline-mapping and the Fair Housing Act (1970-2010).[16] Figure 5, subfigure (a), presents a placebo test which finds that there is not a significant difference in Black-White racial segregation across the population threshold prior to redline-mapping. Figure 5, subfigure (b), presents a regression discontinuity diagram that uses pooled city-decade level data from the entire period after redline-mapping was implemented (1940-2010); the reported estimate suggests that redline-mapping is responsible for an increase in racial segregation of 11.4 dissimilarity points (a 24% increase off the mean). Figure A15 shows that the estimates from Figure 5, subfigure (b), are robust to a wide array of bandwidths. Lastly, Figure A16 shows that these results are similar when done separately by decade. (See the Appendix section "Decadal Breakdowns of the Impact of Redlining" for an extended discussion.)

Figure 5, subfigure (c), presents a regression discontinuity diagram that uses pooled city-decade level data from the period after both redline-mapping was implemented and the Fair Housing Act was passed (1970-2010). During this period (1970-2010), even though there was no *de jure* discrimination, there may have been *de facto* discrimination as well as lagged effects of prior *de jure* discrimination. If the Fair Housing Act and the subsequent anti-discrimination laws, which ended *de jure* discrimination, mitigated the increases in racial segregation due to redline-mapping, we would expect the estimates from (c) to be attenuated versions of those from (b).[17] The estimates from 1970-2010 (reported in Figure 5, subfigure (c)) are both smaller in magnitude and less strongly significant than those from 1940-2010 (reported in Figure 5, subfigure (b)).[18] *If* we attribute this reduction in the estimate (namely, the redution from Figure 5, subfigure (b), to Figure 5, subfigure (c)) to the Fair Housing Act and other subsequent anti-discriminatory legislation, then we would conclude that the

[15] A Dissimilarity Index of n implies that n percent of one race would have to move within the city and between neighborhoods in order for the neighborhood composition to reflect the overall city demography.

[16] For more on the timing of redline-mapping, the Fair Housing Act and other anti-discriminatory legislation, see the timeline in Figure 1.

[17] It is important to note that this strategy does *not* identify the causal effect of the Fair Housing Act nor the full interactive effect of the Fair Housing Act and redline-mapping.

[18] In subfigure (c), I find an 18% effect as opposed to a 25% effect in subfigure (b). The estimate in subfigure (c) is significant only at the 15 percent level, as opposed to the estimate in subfigure (b) which is significant at the 10 percent level

Fair Housing Act may have mitigated as much as 34% of the increase in racial segregation brought about by redline-mapping.

I do *not* claim that increases in racial segregation are the *only* channel through which redline-mapping increased crime; however, comparing the magnitude of the effect of redline-mapping on segregation to the magnitude of the effect of redline-mapping on crime can give a useful back of the envelope estimate of the impact of racial segregation on crime. My estimates suggest that an 11.15 dissimilarity point increase in 1980 (see Figure A16, subfigure (b)) is associated with 11.42 additional Black arrests per one thousand people in 2000 (see Figure A10). This suggests that, for Black individuals born into a racially segregated city, a 10 percentage point increase in percent Black is associated with a 1.02 percentage point increase in likelihood of arrest by adulthood.[19] These estimates are very close to those found in Billings et al. (2013), and build on an existing body of evidence that shows that grouping together individuals who are at a high risk of committing crime increases the overall level of crime.[20]

4.2 Education as a Mechanism

Because there exists evidence that racial segregation is causally responsible for lower educational attainment for Blacks (Ananat (2007), Billings et al. (2013)) and that lower educational attainment is causally responsible for increased crime (Lochner and Moretti (2004)), and, as we just saw in Section 4.1, evidence that redline-mapping increased racial segregation, reductions in educational attainment are a channel through which redline-mapping may have increased crime.

To empirically test whether reductions in educational attainment are a channel through which redline-mapping increased crime, I consider various measures of educational attainment as outcome variables in Equation 1. Figure A17 shows evidence that prior to redline-mapping there were not significant differences in education levels across the population threshold.[21] Figure A18 tests whether redline-mapping and the increases in racial segregation

[19]Cohorts born in 1980 who commit crimes are likely to commit offenses that would be observed in 2000, thus my comparison is intended to be a back of the envelope estimate showing, for a black individual, the effect of being born into a city with more racial segregation on the likelihood of being arrested in adulthood.

[20]See citations in Billings et al. (2013). Billings et al. (2013) finds that a 10 percentage point increase in assigned school share minority led to an increase among minority males in the probability of ever being arrested and ever being incarcerated of about 1.3 percentage points. My back of the envelope calculation suggests that a 10 percentage point increase in city-level percent black is associated with a 1.02 percentage point increase in the likelihood of being arrested for a black individual.

[21]In Figure A17 education levels are measured by the share literate, the best available measure of education in the 1930 Census.

it caused influenced educational attainment at the city-level. The estimates in Figure A18 imply that redline-mapping caused Black individuals to be 4.4 percentage point less likely to finish high school (an 11% reduction off the mean) and 5.3 percentage points less likely to attend at least some college (a 25% reduction off the mean).

Taken together, the estimates reported in Figures A16-A18 suggest that redline-mapping decreased educational attainment for Black individuals (possibly in part by increasing Black-White racial segregation), which, in turn, increased crime. I do *not* claim that decreases in educational attainment (possibly occasioned by increases in racial segregation) are the *only* channel through which redline-mapping increased crime; however, comparing the magnitude of the effect of redline-mapping on educational attainment to the magnitude of the effect of redline-mapping on crime gives a useful back of the envelope estimate of the impact of educational attainment on crime. My estimates suggest that a 4.4 percentage point reduction in the likelihood of a Black individual completing high school in a city in 1980 (See Figure A18) is associated with 11.42 additional Black arrests per one thousand people in 2000 (see Figure A10), which suggests that for every additional black high school graduate, .26 fewer Black arrests will occur. When scaling for the share of arrests that result in incarceration, this estimate is larger than, but consistent with, Lochner and Moretti (2004), which finds that graduating high school reduces the likelihood of incarceration by 3.4 percentage points for Blacks.[22]

4.3 Housing as a Mechanism

Because there exists evidence that home vacancies are causally responsible for violent crime (Cui and Walsh (2015)) and that mortgage lending is responsible for decreased crime (Kubrin and Squires (2004)), harm to local housing markets that resulted in increased vacancies and decreased home ownership rates is a channel through which redline-mapping may have increased crime. Indeed, Aaronson et al. (2017) uses within-city variation in HOLC mapping assignments to show that redlining reduced home ownership.

To empirically test whether harm to present-day housing markets is a channel through which redline-mapping increased crime, I consider various measures of present-day housing

[22]Lochner and Moretti (2004) finds that completing high school reduces the probability of incarceration by about .76 percentage points for whites and 3.4 percentage points for Blacks. My estimate suggests that graduating high school reduces the likelihood of being arrested for Blacks by 26 percentage points, which implies a reduction of incarceration by Blacks of 12 percentage points. (I convert arrests to incarcerations using BJS (2019).) The fact that my estimates are roughly four times larger than Lochner and Moretti (2004) is likely due to the fact that redline-mapping worked through channels other than educational attainment.

market strength as outcome variables in Equation 1. Table A6 shows regression discontinuity estimates, which suggest that redline-mapping increased home vacancy by 5 percentage points (a 43% increase off the mean), decreased the percentage of homes underwritten by a mortgage by 7 percentage points (a 10% decrease off the mean) and decreased average monthly rental amounts by $121 (a 15% decrease off the mean).

One way in which redline-mapping could have influenced local housing markets is by changing the composition of housing stock. If minority would-be home buyers were prevented from accessing the credit market in redlined neighborhoods, there could arise an incentive for developers to favor large, multi-family housing units over single family homes in these redlined neighborhoods. Table A7 reports estimates obtained by using various housing stock measures in various decades as outcome variables in Equation 1. The estimates in Table A7 provide little evidence that redline-mapping changed the composition of housing stock at the city-level. Hence further research at the neighborhood-level is necessary to identify whatever effects there may be of redlining on housing stock, and, more generally, to further elaborate how redline-mapping did lasting harm to local housing markets.

5 Conclusion

In the United States today, the welfare costs of crime are disproportionately born by households living in predominately Black or Hispanic neighborhoods. This paper uses a regression discontinuity design to show that Federal housing policies established in the wake of the Great Depression have increased present-day city-level crime. I use the same research design to show that redline-mapping influenced crime by increasing racial segregation, decreasing black educational attainment and harming housing markets.

In particular, I find that redline-mapping a city is responsible for adding 176 Black and 65 Hispanic crime victimizations to a city in the present-day. I also find that redline mapping increased Black-White residential segregation since 1940 by 11.4 dissimilarity points (a 24% increase off the mean) and decreased Black educational attainment by 1980, making Black individuals 4.4 percentage point less likely to finish high school (an 11% reduction off the mean) and 5.3 percentage points less likely to attend at least some college (a 25% reduction off the mean). Lastly, I find that redline-mapping has harmed present-day housing markets, increasing home vacancies, the mortgage rate and rental values. While the nature of the variation does not allow me to demonstrate uniqueness of channel, the evidence in this paper suggests a straightforward labor market story: restricting credit-access by race increased racial segregation, which harmed local educational attainment, which, in turn, influenced job market outcomes and altered the likelihood of criminal perpetration and victimization by race.

The main results of this paper show how a Federal policy was able to radically alter the course of development of hundreds of cities by putting these cities on different paths in terms of housing, education and crime. In addition to showing how a policy can have lasting impact over three quarters of a century after its initial implementation, this paper also suggests lessons for present-day policy makers. First, the lasting harm done by redlining further underscores the importance of insuring that there exists a non-discriminatory credit market. Secondly, the mechanisms identified in this paper through which redlining increased crime suggest that racial segregation and educational attainment impact long-run city formation, so that a policy maker interested in reducing crime could target reductions in racial segregation and improvements in educational attainment.

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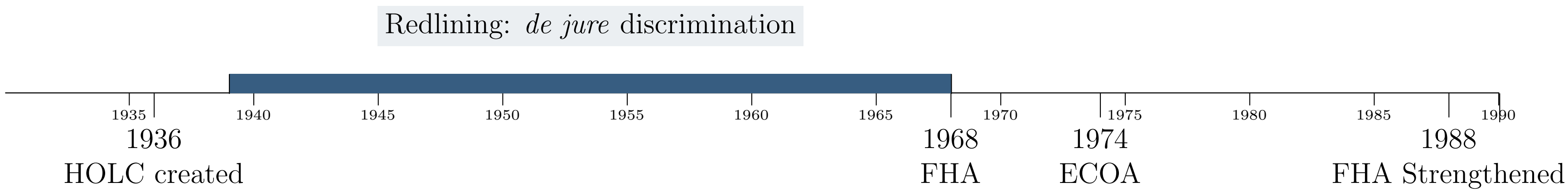
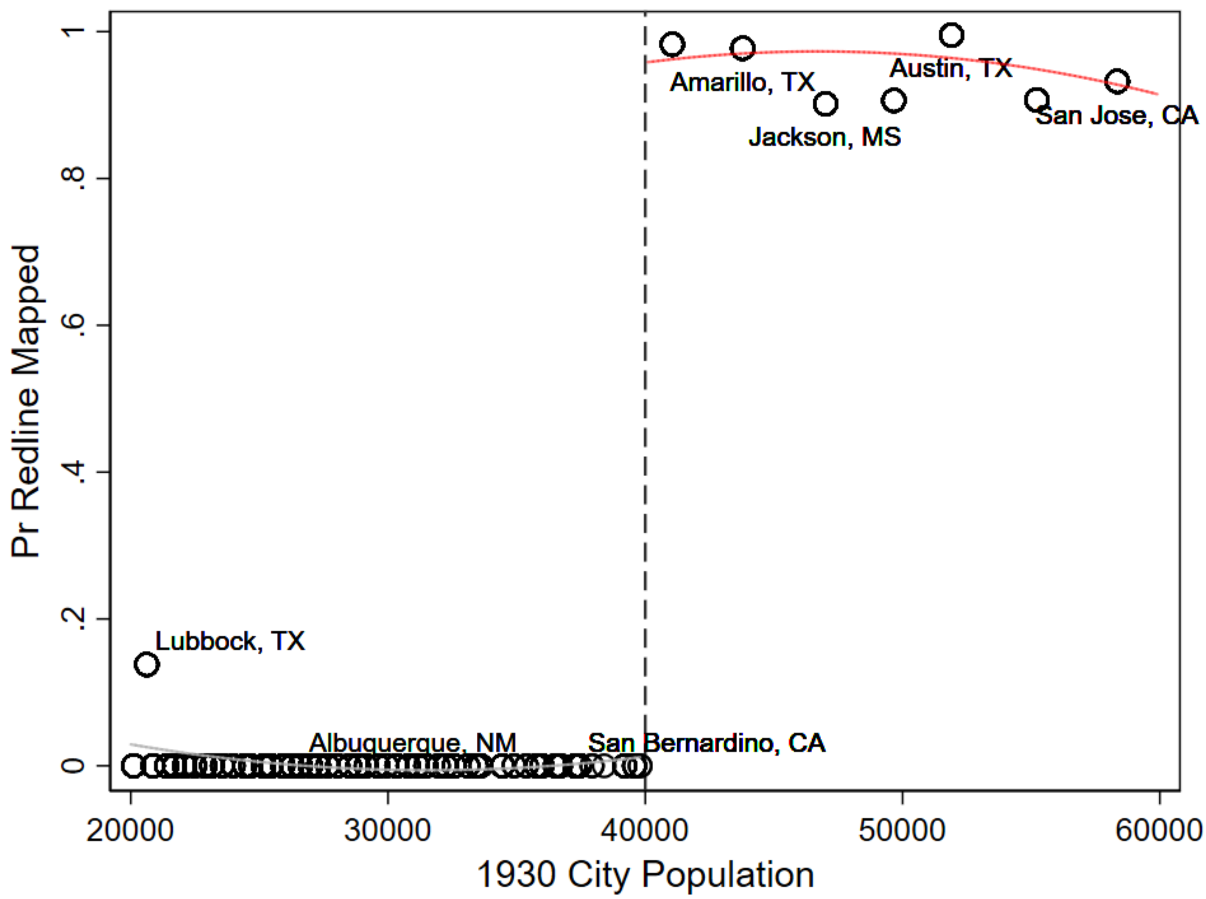
Figure 1: Timeline of *de jure* Discrimination Implemented by Redlining



Fair Housing Act (FHA) outlawed discrimination. Anti-discriminatory laws strengthened in 1974 (Equal Credit Opportunity Act) and in 1988.

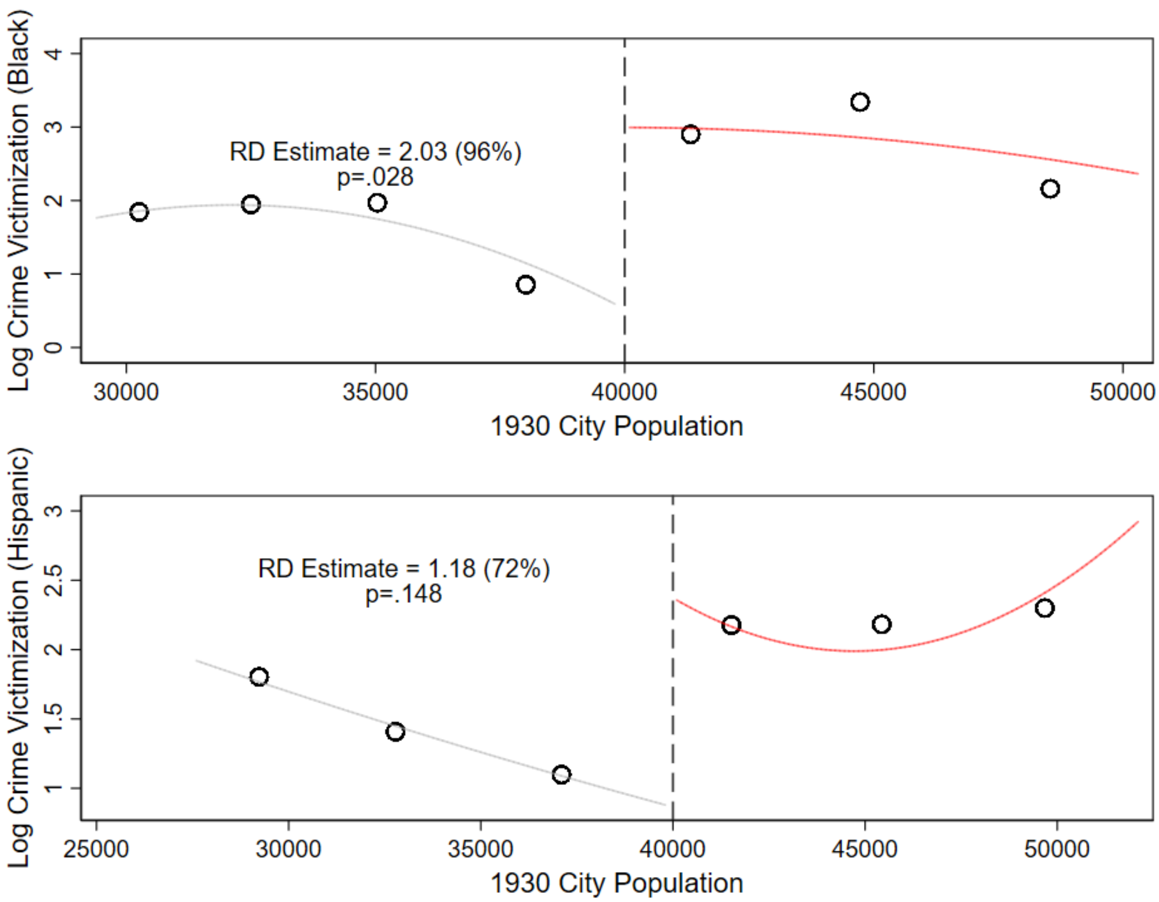
Note: The figure shows the period during which it was legal to discriminate ("*de jure* discrimination") in the loan market based on neighborhood demographics rather than loan-applicant creditworthiness.

Figure 2: 1930 Population and Redline-Mapping: Between-City First Stage



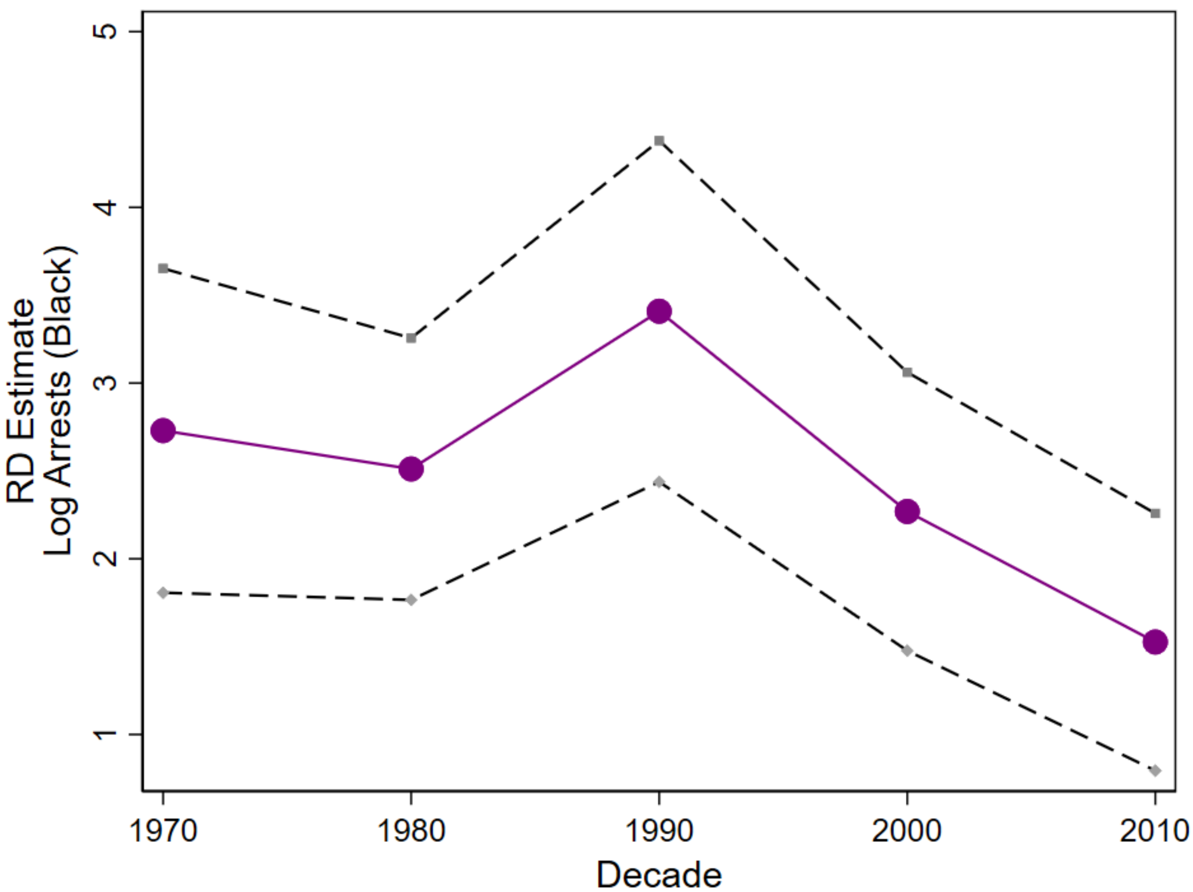
Note: The figure shows a regression discontinuity diagram where the outcome variable is the likelihood that HOLC constructed a Residential Security Map ("Pr Redline-Mapped") for a given city in the 1930's. Observations are at the city-level. The running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth size is chosen to be 20,000 people. Bin numbers are chosen optimally following Calonico (2017). Data sources are the 1930 Census and Home Owner Loan Corporation (HOLC) archival records.

Figure 3: Impact of Redline-Mapping on Crime: Between-City Estimates



Note: Each figure shows a regression discontinuity diagram where the outcome variable is the log of crime victimizations in a given city in 2015. Observations are at the agency-level. The running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth size and bin numbers are chosen optimally following Calonico (2017). There are 133 agencies included in NIBRS 2015 data who report crime outcomes for cities whose 1930 population places them within the optimal bandwidth; there are 84 reporting agencies on the left-hand side and 49 on the right-hand side. The estimates imply that 176 Black and 65 Hispanic crime victimizations per city in 2015 are attributable to redline-mapping. Data sources are individual-level NIBRS crime victimization data and Home Owner Loan Corporation (HOLC) archival records.

Figure 4: Impact of Redline-Mapping on Arrests: Between-City Estimates Over Decades



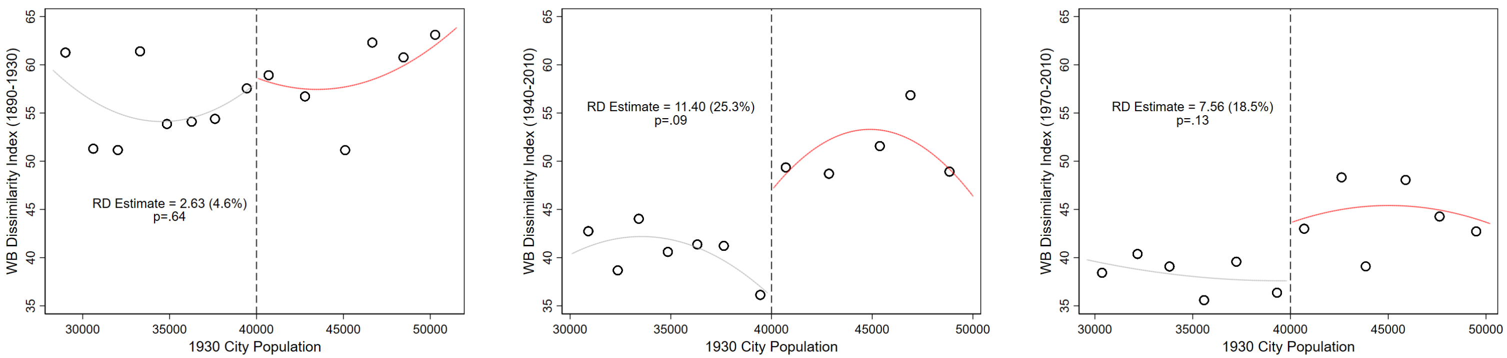
Note: The figure shows a profile of regression discontinuity estimates and 95% confidence intervals obtained by estimating Equation 1 on decadal UCR data. (Decadal UCR data is obtained by pooling monthly UCR data across decades.) In each estimate the outcome variable is the log of black arrests in a given city in a given decade. Data sources are UCR arrest data (1974-2016) and Home Owner Loan Corporation (HOLC) archival records.

Figure 5: Impact of Redline-Mapping on Racial Segregation: Pooled Between-City Estimates

a) 1890-1930
(Pre-Period)

b) 1940-2010
(Post-Mapping)

c) 1970-2010
(Post-Mapping & Post-FHA)



Note: Figure shows a regression discontinuity diagram where the outcome variable is White-Black Dissimilarity Index for a given city in a given year The running variable is always 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth size and bin numbers are chosen optimally following Calonico (2017). Subfigure (a) shows a placebo test for White-Black segregation in the period prior to redline-mapping, pooling data from 1890 to 1930. Subfigure (b) shows the impact of redline-mapping on White-Black segregation over the entire modern period, pooling data from 1940 to 2010. Subfigure (c) shows the impact of redline-mapping on White-Black segregation on the period after the Fair Housing Act (FHA) which first outlawed *de jure* discrimination in the credit market. Data sources are Cutler et al. (1999), Logan (2014), and Home Owner Loan Corporation (HOLC) Archival records.

Appendix: For Online Publication

Figure A1: Home Owner's Loan Corporations Survey Report

AREA DESCRIPTION

Security Map of LOS ANGELES COUNTY

1. POPULATION: a. Increasing Slowly Decreasing - Static -

b. Class and Occupation Artisans, oil well, service & white collar workers, Petty Naval officers, etc. Income $1200-2500

c. Foreign Families 20% Nationalities Mexicans, Japanese & Italians d. Negro 5 %

e. Shifting or Infiltration Slow increase of subversive racial elements.

2. BUILDINGS:

	PREDOMINATING 80%		OTHER TYPE %	
a. Type and Size	4 and 5 room		Large old dwellings 10%	
b. Construction	Frame (few stucco)		Apts.& Multi-family 10%	
c. Average Age	17 years			
d. Repair	Poor to fair			
e. Occupancy	98%			
f. Owner-occupied	25%			
g. 1935 Price Bracket	$1750-2500	% change	$	% change
h. 1937 Price Bracket	$2000-2750	%	$	%
i. 1939 Price Bracket	$2000-2750	%	$	%
j. Sales Demand	Fair			
k. Predicted Price Trend (next 6-12 months)	Static			
l. 1935 Rent Bracket	$15.00-27.50	% change	$	% change
m. 1937 Rent Bracket	$17.50-30.00	%	$	%
n. 1939 Rent Bracket	$17.50-30.00	%	$	%
o. Rental Demand	Good			
p. Predicted Rent Trend (next 6-12 months)	Static			

3. NEW CONSTRUCTION (past yr.) No. 50 Type & Price 5 rooms $3500-$3750 How Selling Moderately

4. OVERHANG OF HOME PROPERTIES: a. HOLC 3 b. Institutions Few

5. SALE OF HOME PROPERTIES (3 yr.) a. HOLC 38 b. Institutions Few

6. MORTGAGE FUNDS: Limited and Selective 7. TOTAL TAX RATE PER $1000 (193 1937-38) $ 53.40 County $37.80 - City $15.60

8. DESCRIPTION AND CHARACTERISTICS OF AREA:

Terrain: Level to rolling with noticeable slope from north to south. No construction hazards. Land improved 80%. Zoning is mixed, ranging from single to light industrial. However, area is overwhelmingly single family residential. Conveniences are all readily available. This area is very old and has slowly developed into a laboring man's district, with a highly heterogeneous population. A majority of the Mexican, Japanese and Negro residents of Long Beach are domiciled in this area. During the past five years residential building has been moderately active. Construction is generally of substandard quality and maintenance is spotted but usually of poor character. Improvements include many shacky dwellings and a number of low grade apartment houses and other multi-family structures. Land values are low, generally ranging from $8 to $10 per front foot. The Negro population is more or less concentrated along California Ave., but Mexicans and Japanese are scattered throughout. Proximity to the down town business section and industrial employment is a favorable factor. It is a good cheap rental district. The subversive influence of the Signal Hill oil field, which is adjacent on the north, is reflected throughout the area, which is accorded a "medial red" grade.

9. LOCATION Long Beach SECURITY GRADE 4th AREA NO. D-63 DATE 5-4-39

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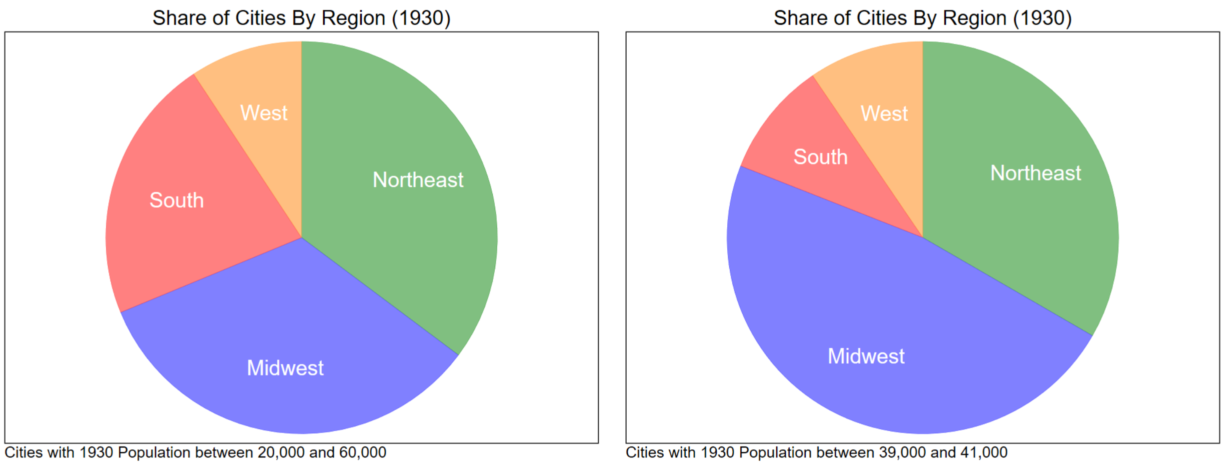
Note: Figure shows a survey report produced for a neighborhood in Los Angeles by the Home Owner's Loan Corporation (HOLC) in May of 1939. This neighborhood is in the South of Los Angeles, in the Long Beach area; it was graded "4th" or "Red" and hence is said to be have been "redlined"; the "red" grade indicates that this neighborhood is considered to be among the riskiest neighborhoods for lenders. Surveyor expectations about neighborhood-level racial demography can in found in item 1.e, "Shifting or Infiltration", which is boxed above.

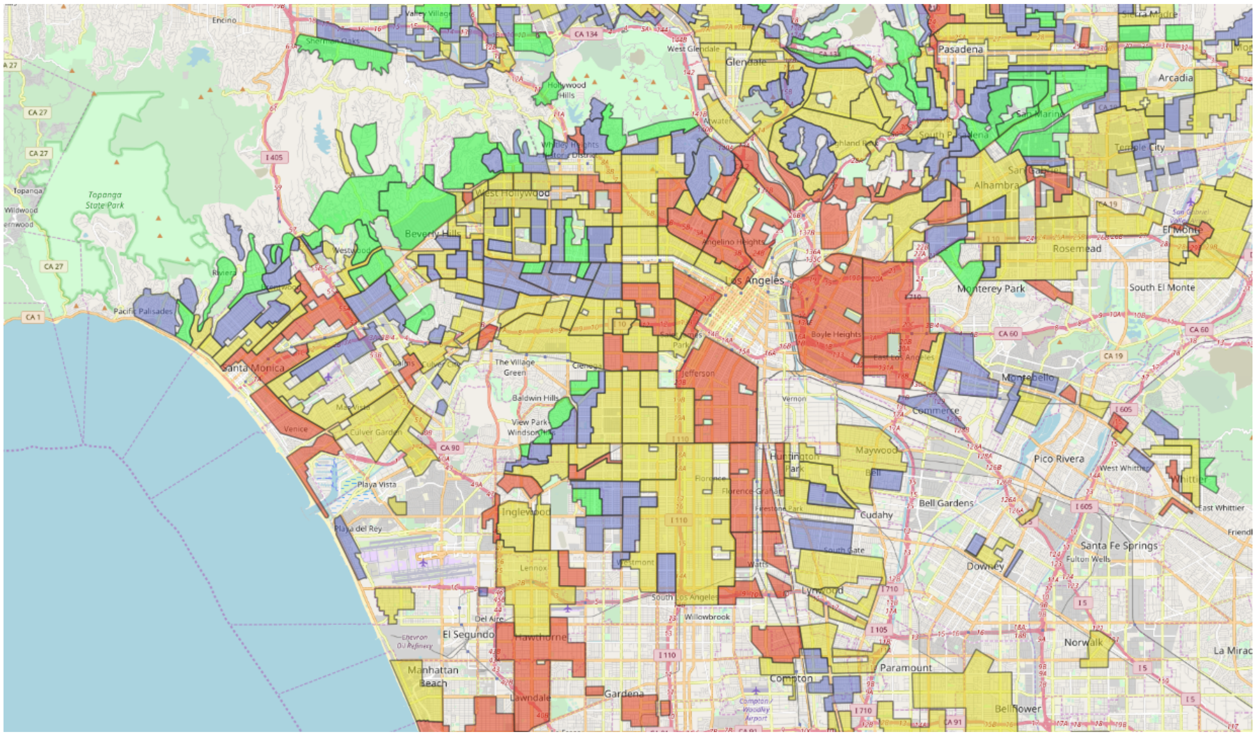
Figure A2: Regional Breakdown of Cities with Redline-Mapping Bandwidth: Between-City Regional Breakdowns



(a) 1930 City Pop $\in [20,000, 60,000]$ (b) 1930 City Pop $\in [39,000, 41,000]$

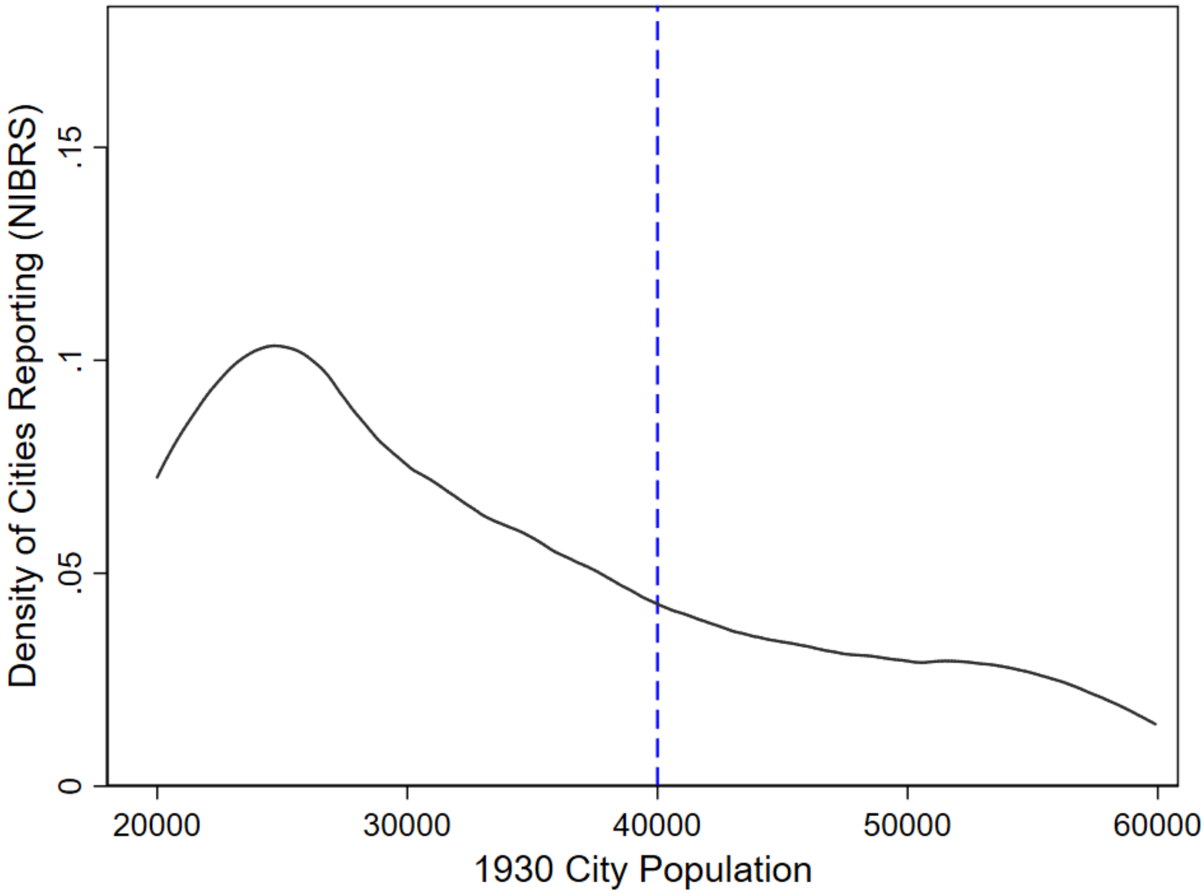
Note: The figure shows the regional share of cities that lie in two small bandwidths around the redling-mapping population threshold: in the left panel the regional shares for cities with 1930 population between 20,000 and 60,000 are shown, while in the right panel the regional shares for cities with 1930 population between 39,000 and 41,000 are shown. (The redline-mapping threshold was 40,000 people.) Data sources are the 1930 Census and Home Owner Loan Corporation (HOLC) archival records.

Figure A3: Residential Security Map of Los Angeles



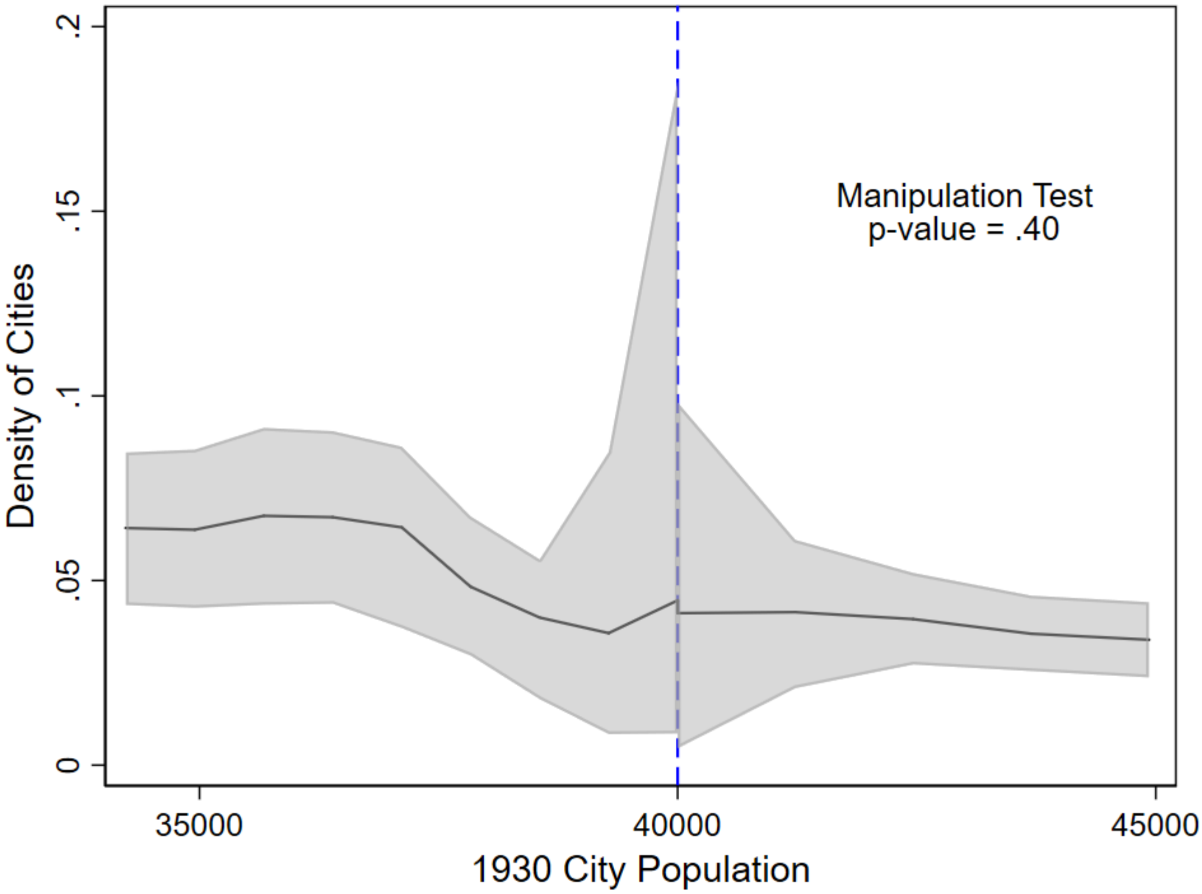
Note: Figure shows a georeferenced version of the Residential Security Maps constructed for Los Angeles by the Home Owners Loan Corporation (HOLC) in 1939. Neighborhoods were assigned ranked security risk categories which correspond to colors on the maps. Areas colored green were considered the best and to bear the least risk; blue were considered next best, followed by yellow and finally red. Areas colored red were considered the most risky and least deserving of credit-access and, accordingly are said to have been "redlined".

Figure A4: Density of Agencies Reporting to NIBRS: Between-City Crime Data



Note: The figure shows the density of agencies reporting to the National Incident Based Reporting System (NIBRS) in 2015 across the 1930 city population in which the agency operates. Data sources are individual level NIBRS data from 2015 and Home Owner Loan Corporation (HOLC) archival records.

Figure A5: Manipulation Test



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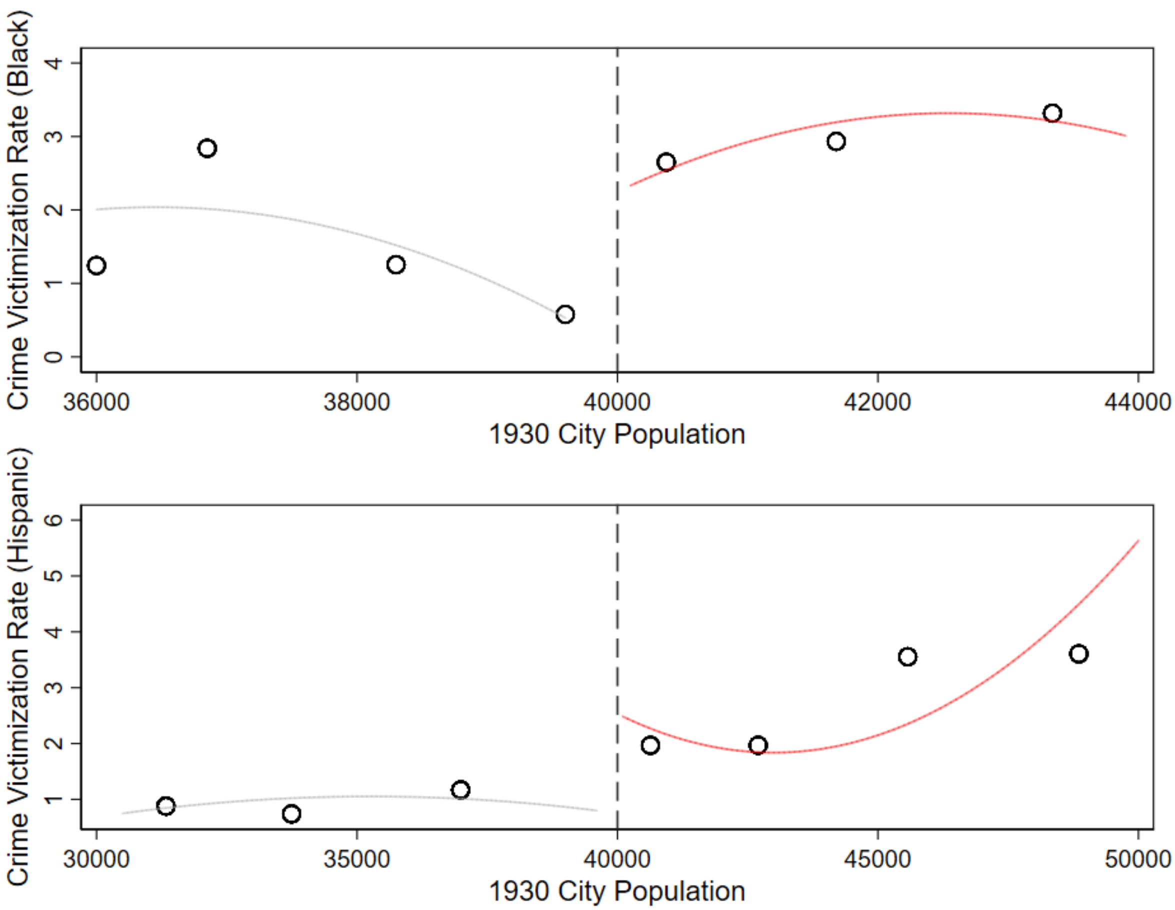
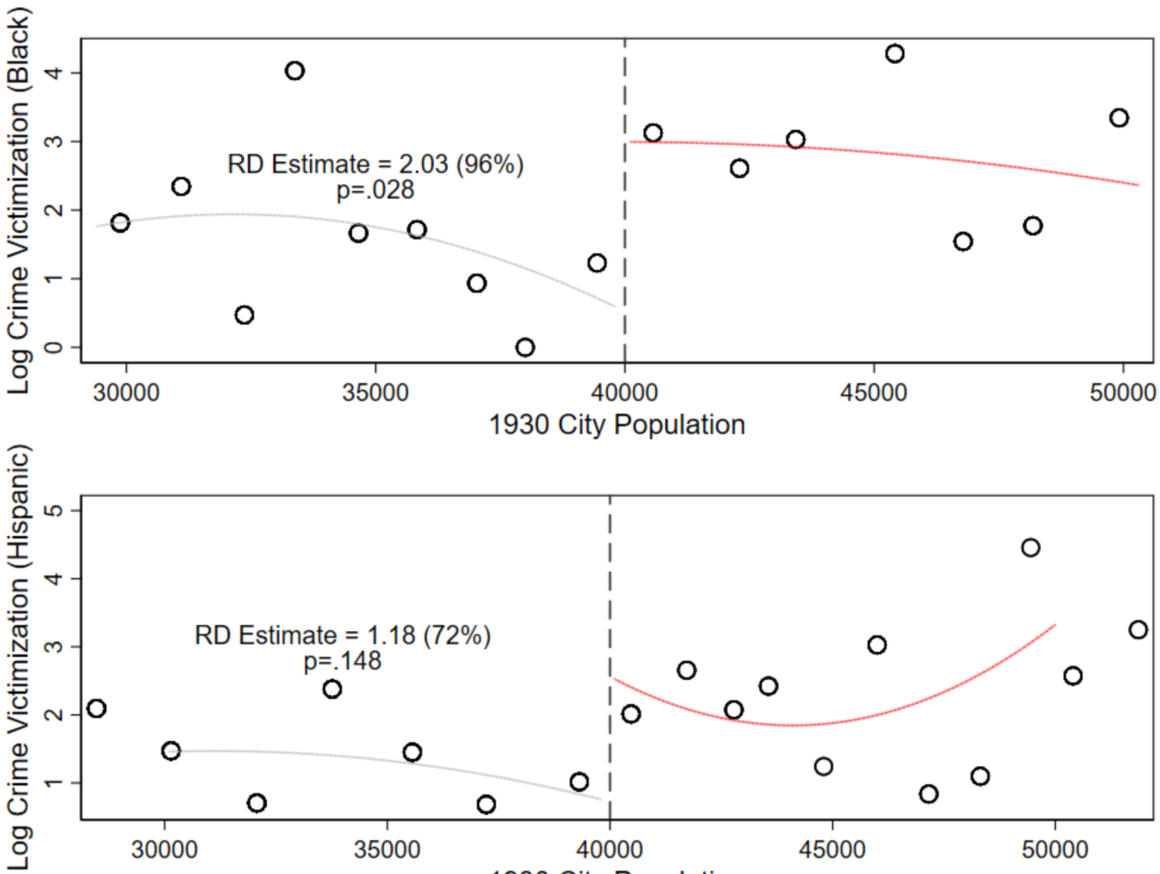
Note: The figure shows the results of a manipulation test (sometimes called a "McCreary test") following the methods of Cattaneo et al. (2018)

Figure A6: Impact of Redline-Mapping on Crime: Between-City Estimates



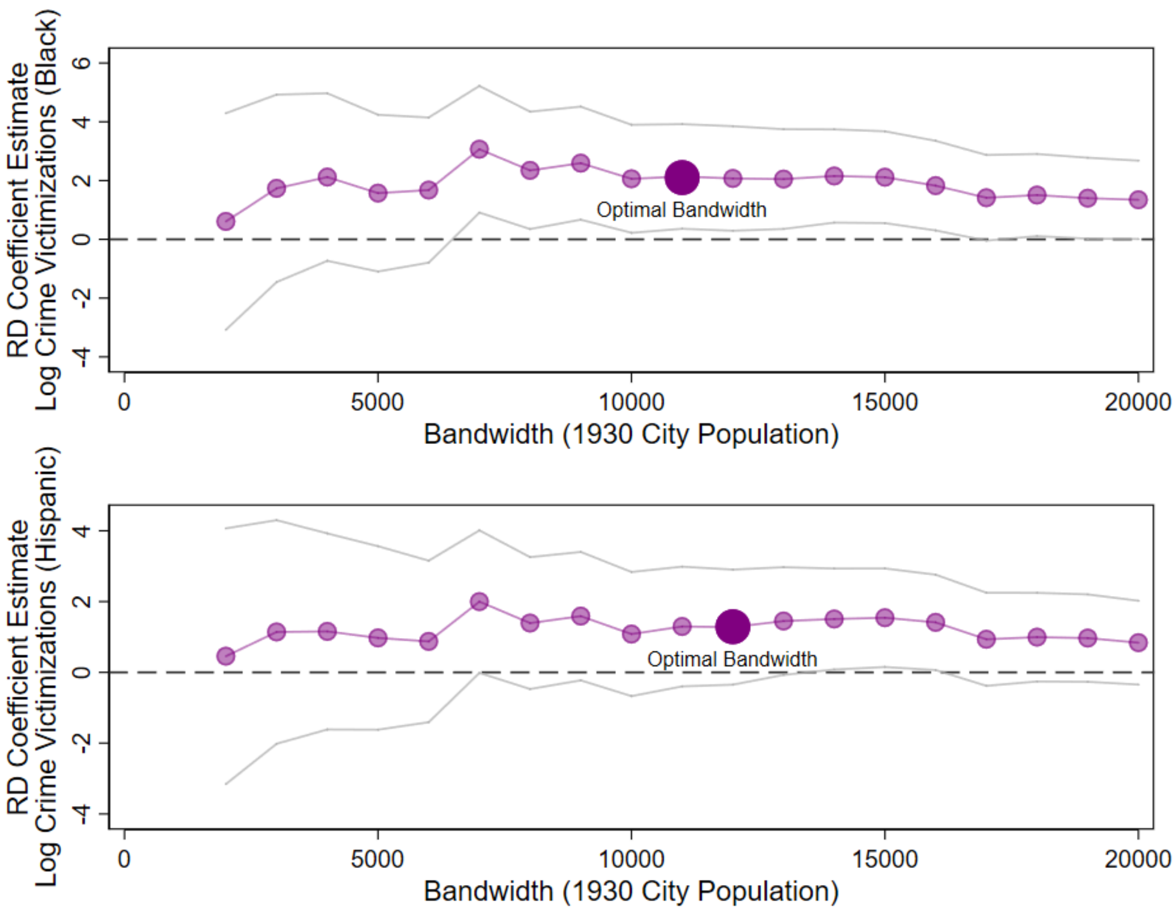
Note: Each figure shows a regression discontinuity diagram where the outcome variable is rate of crime victimization per 1,000 people in a given city in 2015. Observations are at the agency-level. The running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth size is chosen optimally following Calonico (2017). There are 133 agencies included in NIBRS 2015 data who report crime outcomes for cities whose 1930 population places them within the optimal bandwidth; there are 84 reporting agencies on the left-hand side and 49 on the right-hand side. Data sources are individual-level NIBRS crime victimization data and Home Owner Loan Corporation (HOLC) archival records.

Figure A7: Impact of Redline-Mapping on Crime: Between-City Estimates (Non-Optimal Bin Number)



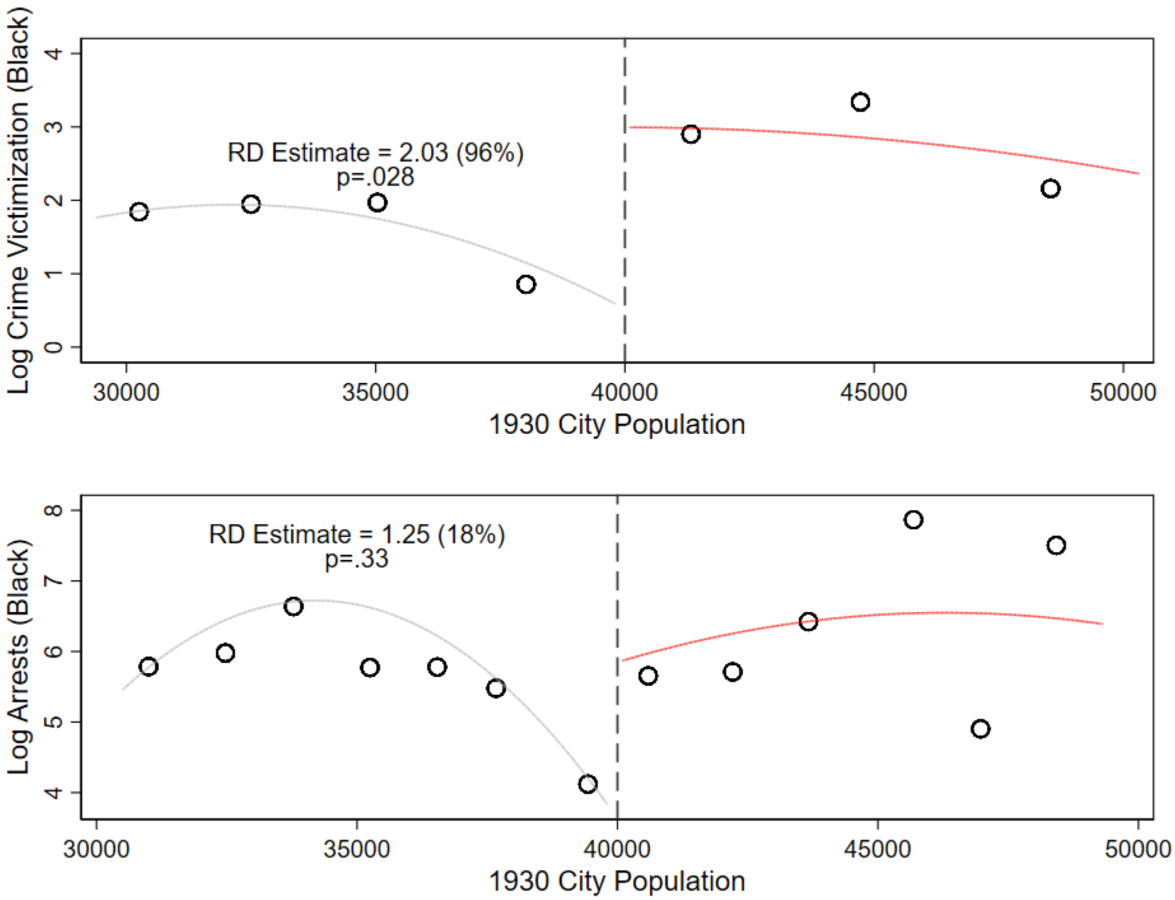
Note: Each figure shows a regression discontinuity diagram where the outcome variable is the log of crime victimizations in a given city in 2015. The running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth size and bin numbers are chosen optimally following Calonico (2017). There are 133 agencies included in NIBRS 2015 data who report crime outcomes for cities whose 1930 population places them within the optimal bandwidth; there are 84 reporting agencies on the left-hand side and 49 on the right-hand side. The estimates imply that 176 Black and 65 Hispanic crime victimizations per city in 2015 are attributable to redline-mapping. Data sources are individual-level NIBRS crime victimization data and Home Owner Loan Corporation (HOLC) archival records. These figures differ from those in Figure 3 in only one way: in Figure 3 techniques from Calonico (2017) are used to select the number of bins on each side of the cutoff optimally, whereas in these figures the bin size is manually selected to show more of the variation in the outcome variable across the running variable.

Figure A8: Impact of Redline-Mapping on Crime: Between-City Estimates, by Bandwidth



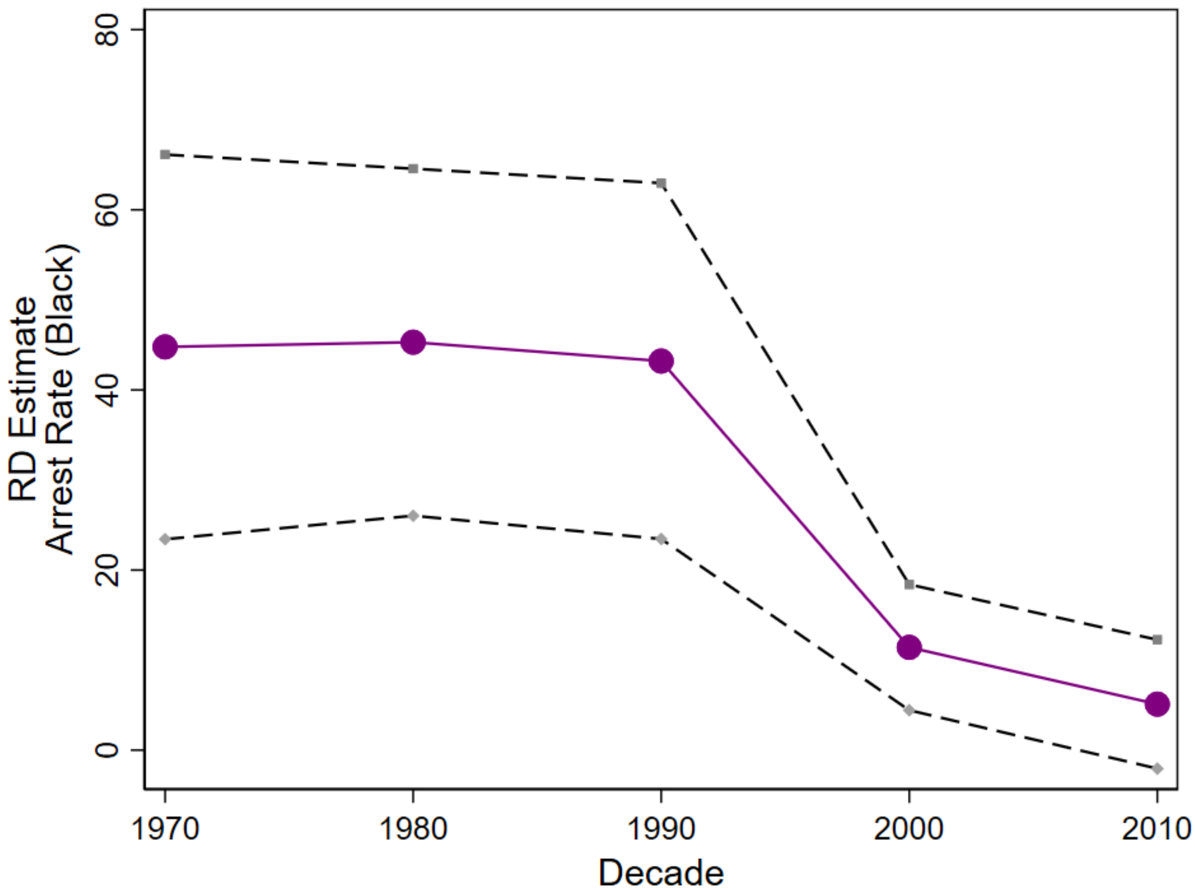
Note: Each figure shows a profile of regression discontinuity coefficent estimates and 95% confidence intervals across a range of bandwidth selections. The outcome variable is the log of crime victimizations in a given city in 2015. The top panel show results for the log of Black crime victimizations, while the bottom panel shows results for the log of Hispanic crime victimizations. The running variable is always 1930 city population. Circles represent estimates, with the large circle representing the estimate for the optimal bandwidth. Data sources are individual-level NIBRS crime victimization data and Home Owner Loan Corporation (HOLC) archival records.

Figure A9: Impact of Redline-Mapping on Crimes and Arrests: Between-City Estimates



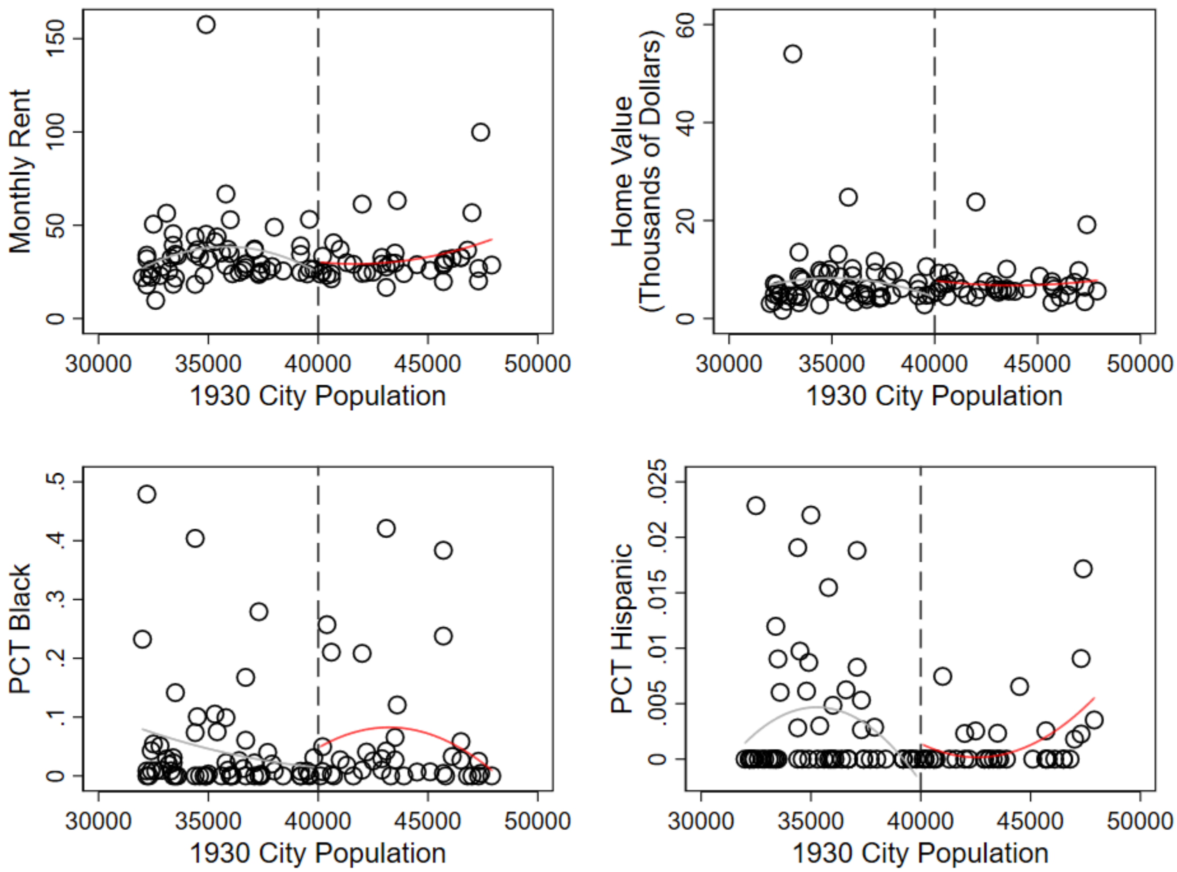
Note: Each figure shows a regression discontinuity diagram. In the top panel, the outcome variable is the log of crime victimization in a given city in 2015, while in the bottom panel the outcome variable is the log of arrests in a given city in 2015. In both panels, observations are at the agency-level and the running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth size and bin numbers are chosen optimally following Calonico (2017). In the top panel, there are 133 agencies included in NIBRS 2015 victimization data who report crime outcomes for cities whose 1930 population places them within the optimal bandwidth; there are 84 reporting agencies on the left-hand side and 49 on the right-hand side. The estimates in the top panel imply that 176 Black crime victimizations per city in 2015 are attributable to redline-mapping. In the bottom panel, there are 131 agencies included in UCR 2015 arrest data who report crime outcomes for cities whose 1930 population places them within the optimal bandwidth; there are 82 reporting agencies on the left-hand side and 49 on the right-hand side. The estimates in the bottom panel imply that 61 Black arrests per city in 2015 are attributable to redline-mapping. Data sources are UCR arrest data and NIBRS victimization data, as well as and Home Owner Loan Corporation (HOLC) archival records.

Figure A10: Impact of Redline-Mapping on Arrests: Between-City Estimates Over Decades



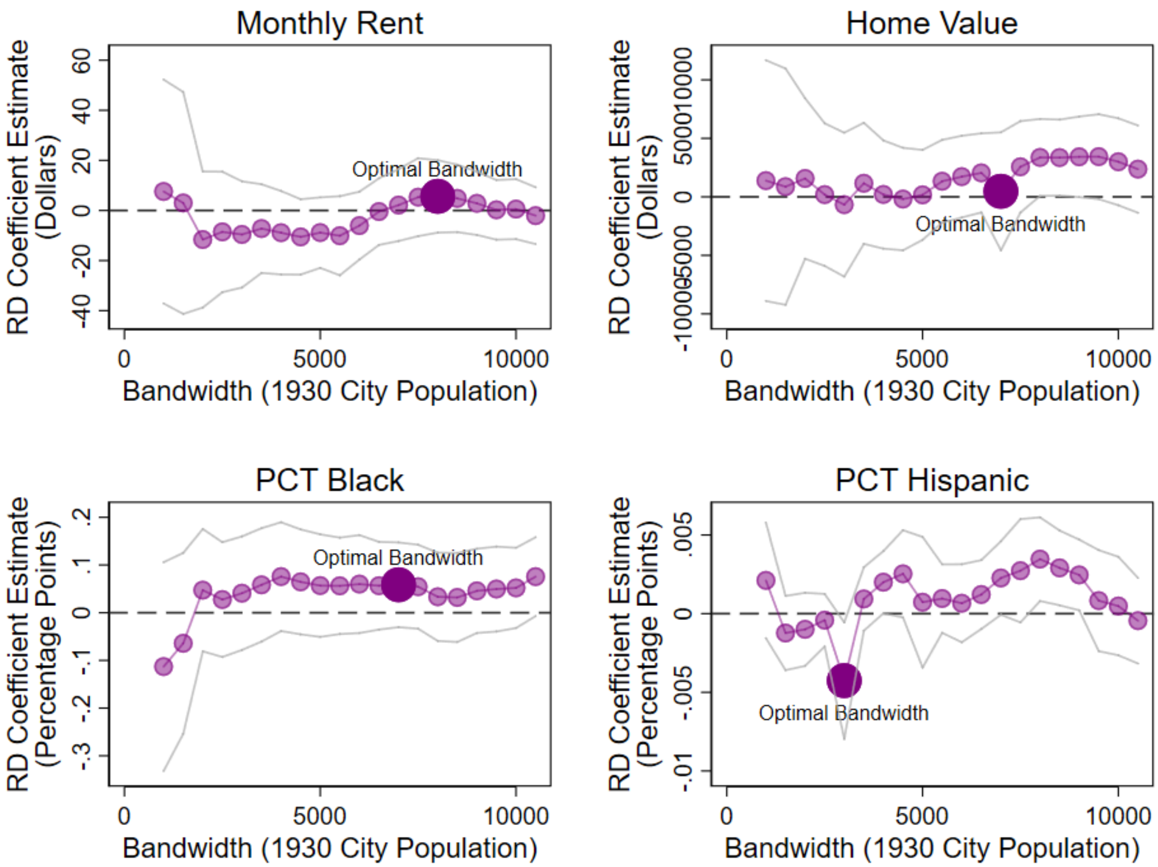
Note: The figure shows a profile of regression discontinuity estimates and 95% confidence intervals obtained by estimating Equation 1 on decadal UCR data. (Decadal UCR data is obtained by pooling monthly UCR data across decades.) In each estimate the the outcome variable is black arrest rate per 1,000 people in a given city in a given decade. Data sources are UCR arrest data (1974-2016) and Home Owner Loan Corporation (HOLC) archival records.

Figure A11: Balancing Tests: Between-City 1920-1930 Covariates



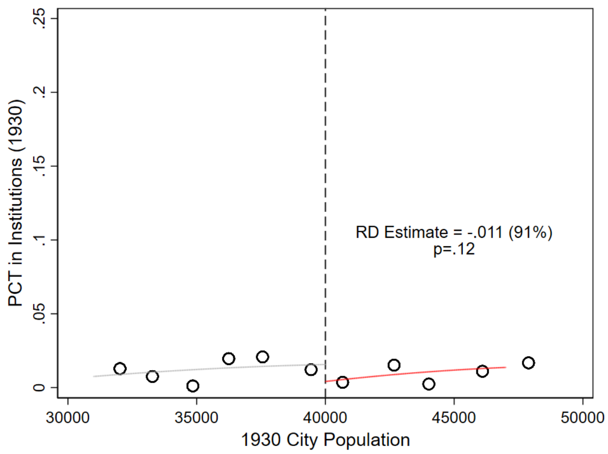
Note: Each figure shows a regression discontinuity diagram where the dependent variable is given city-level pre-period covariate measured in 1920-1930. The top panels show results for self-reported monthly rent and home value, respectively, while the bottom panels show results for the percent of a city's population that is Black and the percent that is Hispanic, respectively. Circles represent bin means, while lines represent fitted quadratic curves. Bin number is fixed at 80 cities to ease comparison. The running variable is always 1930 city population. Bandwidth size is fixed at 7,000 people to ease comparison. Data sources are 1920-1930 Census and Home Owner Loan Corporation (HOLC) archival records.

Figure A12: Balancing Tests: Between-City 1920-1930 Covariates, Bandwidth Sensitivity

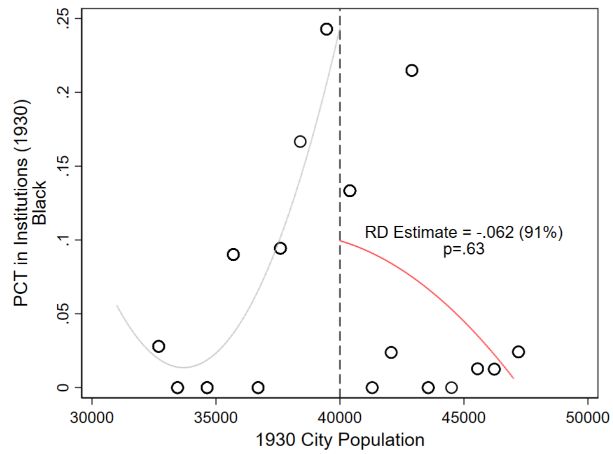


Note: Each figure shows a profile of regression discontinuity coefficient estimates across a range of bandwidth selections. The top panels show results for self-reported monthly rent and home value, respectively, while the bottom panels show results for the percent of an area that is Black and the percent that is Hispanic, respectively. Circles represent estimates, with the large circle representing the estimate for the optimal bandwidth. The running variable is always 1930 city population. Data sources are 1920-1930 Census and Home Owner Loan Corporation (HOLC) archival records.

Figure A13: Impact of Redline-Mapping on Incarcerated Population: Placebo Tests with Institutional Group Quarters



(a) Pre-Period Incarceration

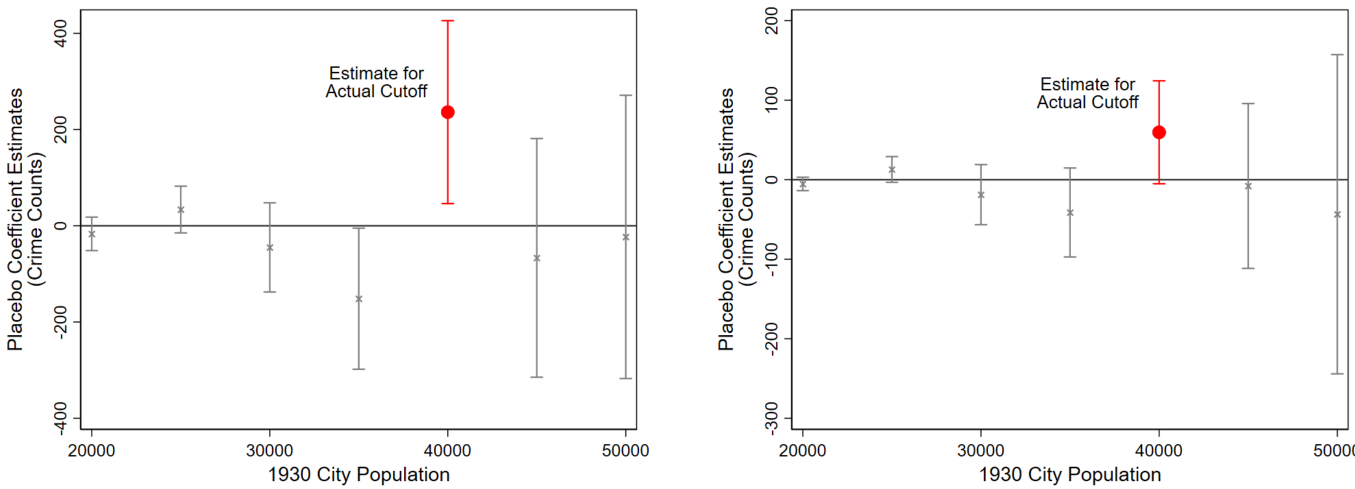


(b) Pre-Period Incarceration: Black

Note: Each figure shows a regression discontinuity diagram. In the top panel, the outcome variable is the share of individuals who report living in an institutional group quarter in a given city in 1930, while in the bottom panel the outcome variable is the share of black individuals who report living in an institutional group quarter in a given city in 1930. Institutional group quarters include correctional facilities, nursing homes and mental hospitals. Starting in 1980, institutional group quarters excludes persons living in non-institutional group quarters such as college dormitories, miliary barracks, group homes, mission and shelters. However, in the 1930 Census, institutionalized group quarters includes "non-inmates" who would have been classified as living in non-institutional group quarters after 1980 (See the IPUMS documentation for the variable "GQ".) In both panels, The running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth and bin numbers are chosen optimally following Calonico (2017). Data sources are the 1930 Census, as well as and Home Owner Loan Corporation (HOLC) archival records.

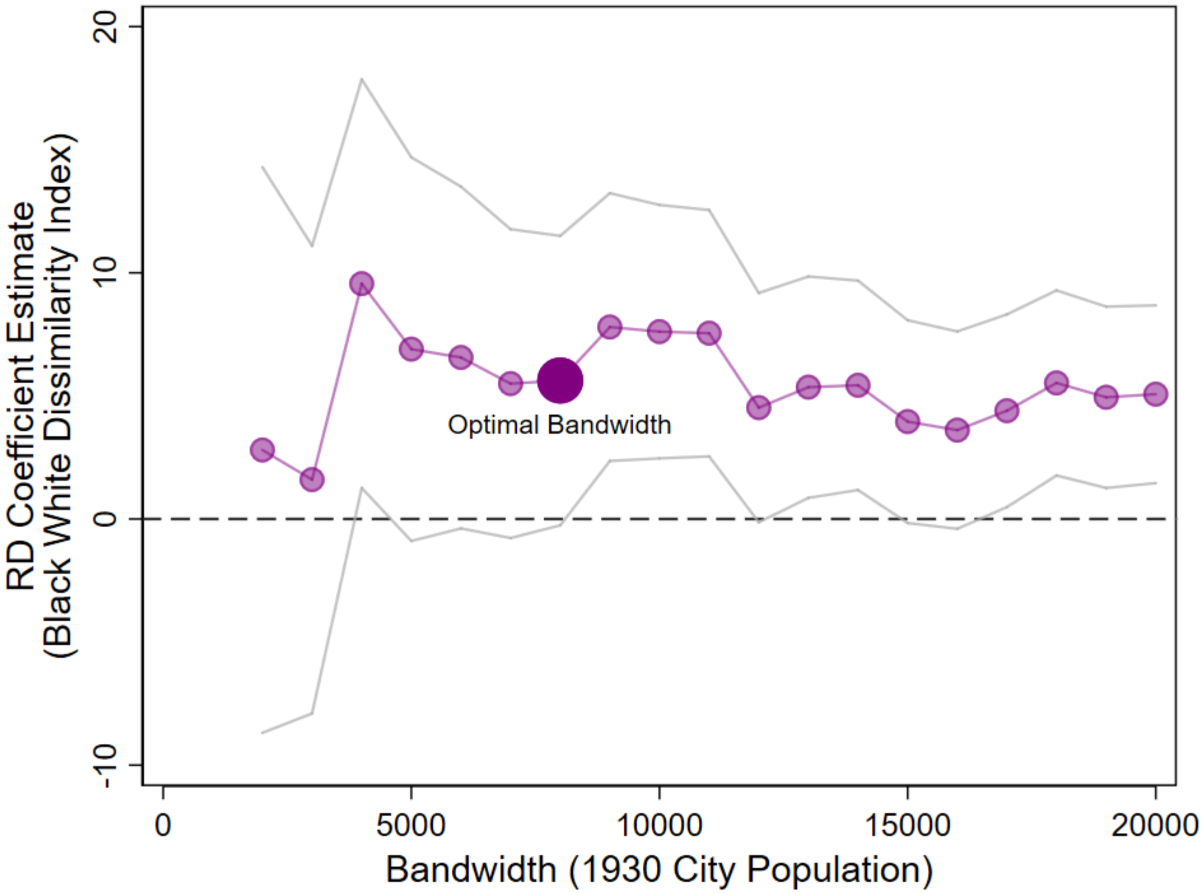
Figure A14: Impact of Redline-Mapping on Crime: Placbo Tests

a) Black b) Hispanic



Note: Each figure shows a series of placebo tests which report estimates of equation 1 at simulated or “placebo” cutoff values. The left panel presents these results for 2015 Black crime victimization, while the left panel presents these results for 2015 Hispanic crime victimization. Estimates at the actual cutoff (40,000) imply that redline-mapping added 176 Black crime victimizations and 65 Hispanic crime victimizations.

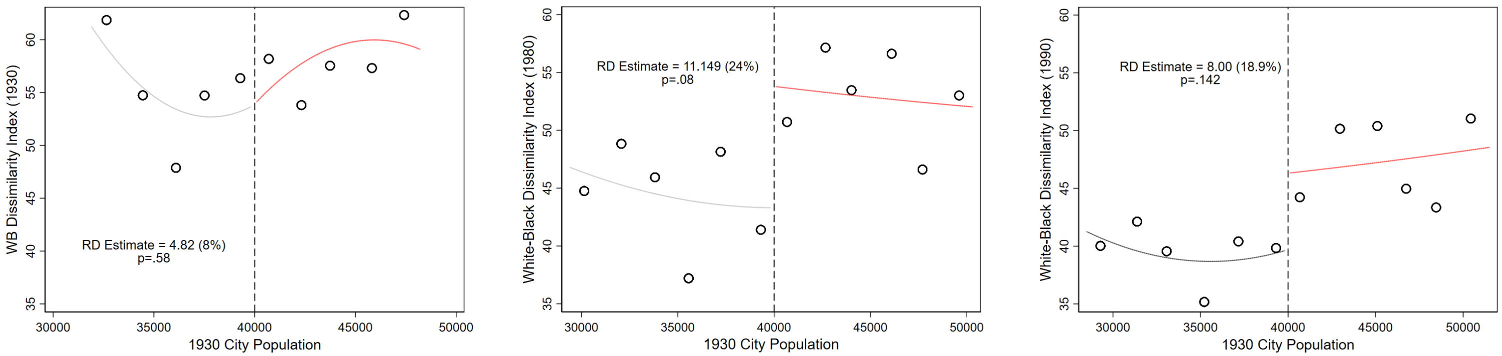
Figure A15: Impact of Redline-Mapping on Segregation: Bandwidth Sensitivity



Note: The figure shows a profile of regression discontinuity estimates and 95% confidence intervals obtained by estimating Equation 1 on decadal segregation measures. These estimates constitute a bandwidth sensitivity test for panel (b) of Figure 5. Data sources are Cutler et al. (1999), Logan (2014), and Home Owner Loan Corporation (HOLC) Archival records.

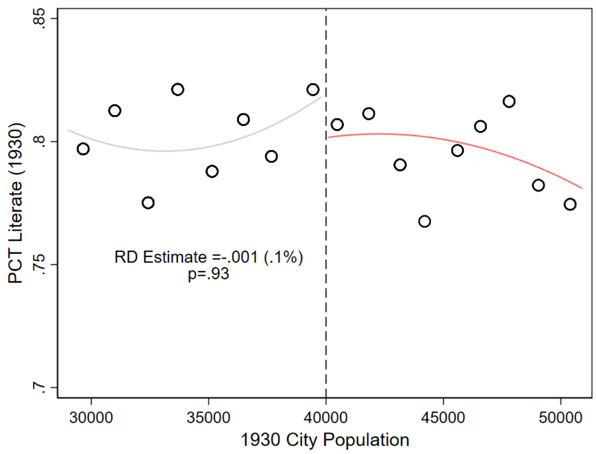
Figure A16: Impact of Redline-Mapping on Racial Segregation: Between-City Estimates over Decades

a) 1930 (Pre-Period) | b) 1980 (Post-Mapping) | c) 1990 (Post-Mapping)

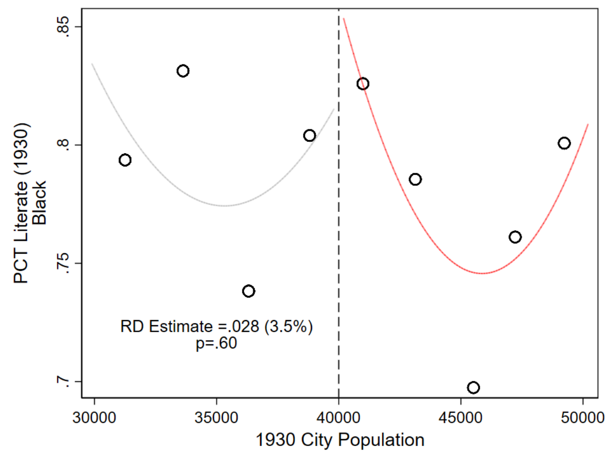


Note: Figure shows a regression discontinuity diagram where the outcome variable is White-Black Dissimilarity Index for a given city in a given year The running variable is always 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth size and bin numbers are chosen optimally following Calonico (2017). Subfigure (a) shows a placebo test for White-Black segregation in the pre-period. Subfigures (b)-(c) show the impacts of redline-mapping on White-Black segregation in 1980 and 1990, respectively. Data sources are Cutler et al. (1999), Logan (2014), and Home Owner Loan Corporation (HOLC) Archival records.

Figure A17: Impact of Redline-Mapping on Educational Attainment: Placebo Tests with Literacy



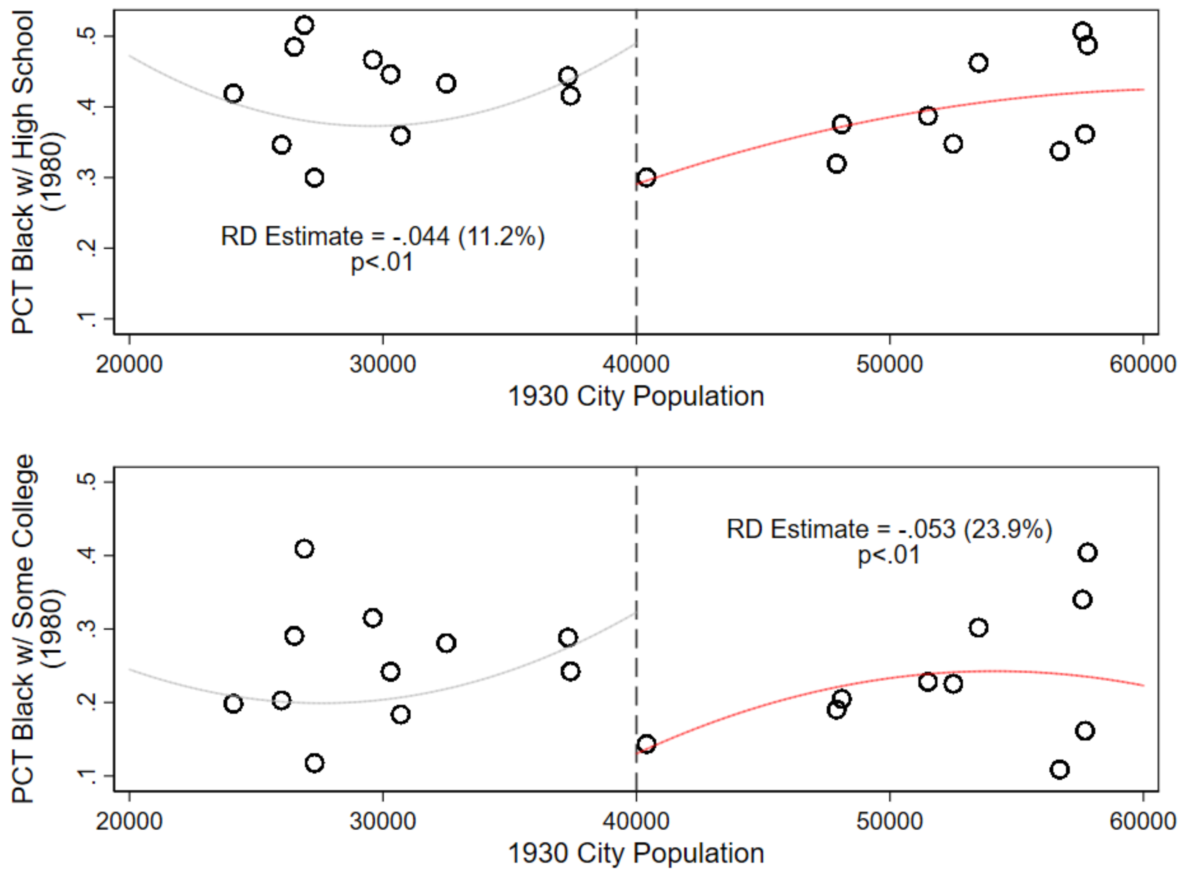
(a) Pre-Period Education



(b) Pre-Period Education: Black

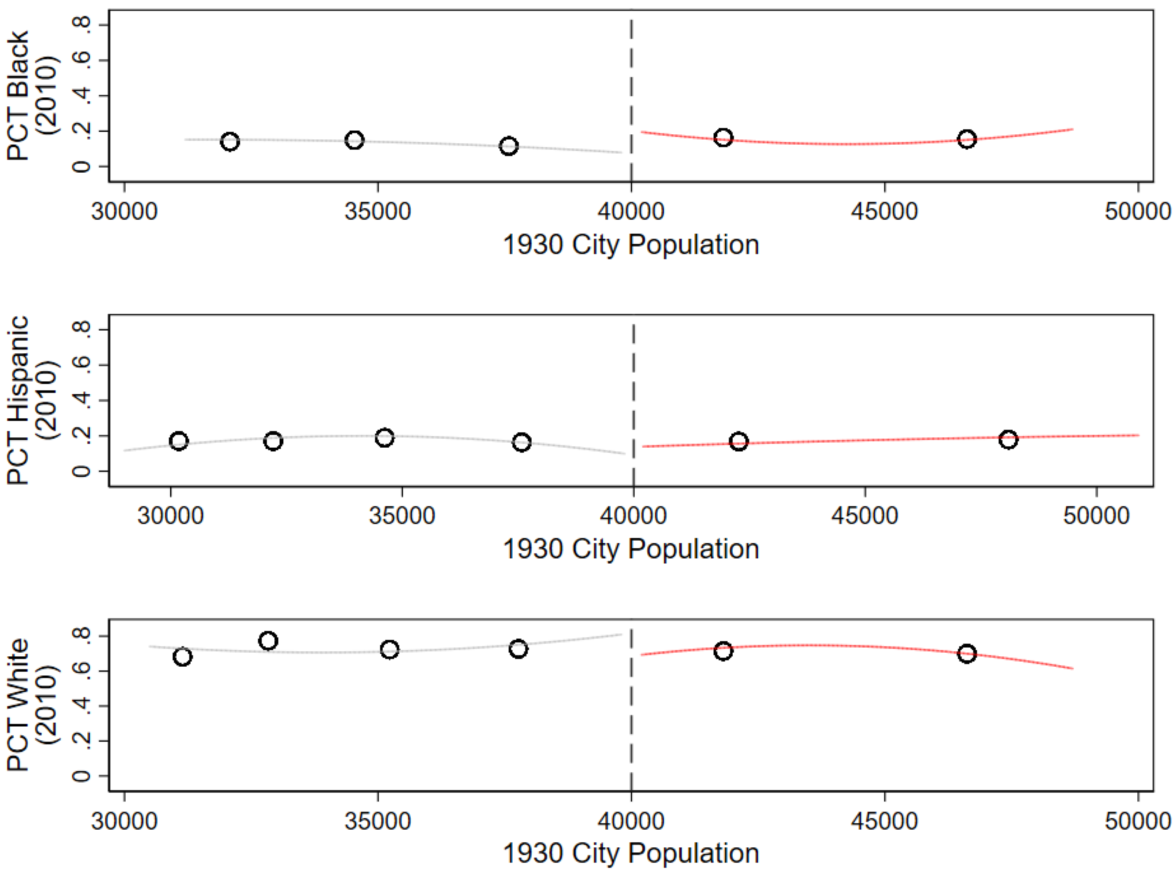
Note: Each figure shows a regression discontinuity diagram. In the top panel, the outcome variable is the share of individuals who report being literate in a given city in 1930, while in the bottom panel the outcome variable is the share of black individuals who report being literate in a given city in 1930. In both panels, The running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bandwidth and bin numbers are chosen optimally following Calonico (2017). Data sources are the 1930 Census, as well as and Home Owner Loan Corporation (HOLC) archival records.

Figure A18: Impact of Redline-Mapping on Educational Attainment: High School, Some College



Note: Each figure shows a regression discontinuity diagram. In the left panel, the outcome variable is the share of black individuals who report having graduated high school in a given city in 1980, while in the right panel the outcome variable is the share of black individuals who report having attended at least some college in a given city in 1980. In both panels, The running variable is 1930 city population. Circles represent bin means, while lines represent fitted quadratic curves. Bin numbers are chosen optimally following Calonico (2017), but bandwidth was set at 20,000 population to ease visual comparison (the optimal bandwidths being slightly over 22,000 and 28,000 population respectively). Data sources are the 1980 Census, as well as and Home Owner Loan Corporation (HOLC) archival records.

Figure A19: Impact of Redline-Mapping on Demography: Between-City Estimates of Compositional Migration



Note: The figure shows a set of regression discontinuity diagrams depicting the possible impact of redline-mapping on present-day racial demography. Coefficient estimates are reported in Table A9. Data sources are the 2010 Census and Home Owner Loan Corporation (HOLC) archival records.

Table A1: Summary Statistics

Panel A: City Level	Mapped	Non-Mapped	Total
Crime Victimizations			
All (White)	765.61	477.11	569.15
	(1385.38)	(1060.01)	(1179.46)
Violent (White)	101.03	57.19	71.17
	(179.96)	(129.90)	(148.89)
Property (White)	664.58	419.93	497.98
	(1223.03)	(936.79)	(1041.33)
All (Black)	262.74	95.59	148.92
	(729.44)	(323.91)	(496.21)
Violent (Black)	70.61	22.20	37.65
	(194.54)	(75.94)	(128.21)
Property (Black)	192.13	73.39	111.27
	(543.87)	(249.91)	(373.33)
All (Hispanic)	90.97	47.74	61.54
	(309.95)	(175.13)	(227.46)
Violent (Hispanic)	18.48	9.12	12.11
	(52.81)	(29.42)	(38.63)
Property (Hispanic)	72.50	38.62	49.43
	(260.30)	(149.61)	(192.26)
Observations	119	254	373
1930 Demography			
City Population	48,640.00	28,954.92	33,343.31
	(6,933.42)	(7,893.42)	(11,238.84)
PCT White	0.91	0.94	0.93
	(0.12)	(0.11)	(0.11)
PCT Black	0.09	0.06	0.07
	(0.12)	(0.11)	(0.11)
PCT Naturalized Citizens	0.07	0.08	0.08
	(0.06)	(0.06)	(0.06)
PCT Married (Spouse Present)	0.42	0.42	0.42
	(0.04)	(0.05)	(0.05)
PCT HH Having a Radio	0.45	0.48	0.47
	(0.16)	(0.18)	(0.18)
PCT in School	0.22	0.22	0.22
	(0.03)	(0.04)	(0.04)
PCT Literate	0.80	0.79	0.80
	(0.04)	(0.05)	(0.05)
PCT in Labor Force	0.42	0.41	0.41
	(0.04)	(0.05)	(0.05)
PCT Wage Workers	0.39	0.37	0.37
	(0.04)	(0.05)	(0.05)
Average Home Value ($)	6,976.20	6,636.16	6,711.97
	(2,955.04)	(4,276.88)	(4,018.21)
Average Rental Amount ($)	31.19	31.04	31.07
	(11.51)	(13.67)	(13.20)
Observations	70	244	314

Note: Means reported with standard errors in parentheses. Sample is restricted to observations for cities with a 1930 population between 20,000 and 60,000 people. Distributions are reported separately for cities which were redline-mapped and for those not mapped. Panel C Crime Victimization: Source is NIBRS 2015 Crime Victimization Data. Observations are at the agency-level. Panel C 1930 Demography: Source is address-level 1920-1930 Census Data. Observations are at the city-level.

Table A2: Summary Statistics

Panel B: City Level, Continued	Mapped	Non-Mapped	Total
Criminal Arrests			
All (White)	438.25	300.83	347.68
	(911.49)	(547.62)	(695.45)
Violent (White)	114.87	70.57	85.67
	(271.90)	(163.89)	(207.89)
Property (White)	323.38	230.26	262.00
	(683.40)	(415.58)	(523.61)
All (Black)	271.60	116.70	169.50
	(511.23)	(231.70)	(359.80)
Violent (Black)	95.70	36.40	56.62
	(200.39)	(71.26)	(133.28)
Property (Black)	175.90	80.30	112.89
	(337.32)	(167.95)	(243.40)
Observations	150	290	440

Note: Means reported with standard errors in parentheses. Sample is restricted to observations for cities with a 1930 population between 20,000 and 60,000 people. Distributions are reported separately for cities which were Redline-Mapped and for those not mapped. Panel B Criminal Arrests: Source is UCR 2015 Arrest Data. Observations are at the agency-level.

Table A3: Selected List of Redline-Mapped and Not Mapped Cities

Not Mapped	**Mapped**
Tucson, AZ	Phoenix, AZ
Santa Barbara, CA	Stockton, CA
Bakersfield, CA	Fresno, CA
San Bernardino, CA	San Jose, CA
Colorado Springs, CO	Pueblo, CO
Orlando, FL	St. Petersburg, FL
Champaign, IL	Joliet, IL
Bloomington, IL	Aurora, IL
Ashland, KY	Lexington, KY
Melrose, MA	Pittsfield, MA
Gloucester, MA	Holyoke, MA
Ann Arbor, MI	Kalamazoo, MI
St. Cloud, MN	Rochester, MN
Vicksburg, MS	Jackson, MS
Ithaca, NY	Poughkeepsie, NY
Middletown, NY	Jamestown, NY
Lubbock, TX	Amarillo, TX
Brownsville, TX	Wichita Falls, TX
Abilene, TX	Port Arthur, TX
San Angelo, TX	Waco, TX
Corpus Christi, TX	Galveston, TX
Laredo, TX	Austin, TX
Bristol, VA	Lynchburg, VA
Green Bay, WI	Madison, WI

Note: Reported cities all have a 1930 population between 20,000 and 60,000, the redline-mapping cutoff being 40,000. Data sources are 1930 Census and HOLC archival records.

Table A4: Impact of Redline-Mapping on Educational Attainment: Between City Estimates

	(1) PCT Black with High School	(2) PCT Black with College
RD Estimate	-0.044***	-0.053***
	(0.009)	(0.008)
Observations	573,683	573,683
Mean	.390	.221

Note: Table shows regression discontinuity estimates of the impact of redline-mapping on educational attainment with standard errors reported in parentheses. Observations are at the individual level. The outcome variable is the percent of black individuals having graduated high school and having attended at least some college, in columns (1) and (2) respectively. The running variable is 1930 city population. Bandwidth size is chosen optimally following Calonico (2017). Source: 1980 Census and HOLC archival documents. The reported mean is for non-mapped cities within the optimal population bandwidth. Significance levels indicated by: * ($p < 0.10$), ** ($p < 0.05$), ***($p < 0.01$)

Table A5: Impact of Redline-Mapping on Crime: Between-City Estimates, By Crime-Type, Race

	(1) Black	(2) Hispanic
Panel A: All Crimes		
RD Estimate	176.36**	64.60
	(72.56)	(105.69)
Observations	966	966
Mean (Bandwidth)	161.11	83.95
Mean (Non-Mapped)	60.07	23.93
Panel B: Property Crimes		
RD Estimate	117.48**	27.59
	(54.03)	(98.28)
Observations	966	966
Mean (Bandwidth)	122.26	64.31
Mean (Non-Mapped)	47.17	19.77
Panel C: Violent Crimes		
RD Estimate	18.56	18.88
	(22.47)	(13.63)
Observations	966	966
Mean (Bandwidth)	34.24	13.91
Mean (Non-Mapped)	12.9	4.16
Bandwidth (1930 Population)	7,655	11,002

Note: Table shows regression discontinuity estimates of the impact of redline-mapping on crime with standard errors reported in parentheses. Observations are at the agency-level. The outcome variable is the count of crime victimizations in a given city in 2015. Reported means are city-level counts of crime victimizations in 2015. The running variable is always 1930 city population. Bandwidth size is chosen optimally following Calonico (2017). Data sources are NIBRS Crime Victimization Data (2015) and HOLC archival documents.

Table A6: Impact of Redline-Mapping on Present-Day Housing Market: Between City Estimates

	(1) PCT Vacant	(2) PCT Mortgaged	(3) AVG Rent
RD Estimate	0.050***	-0.070***	-121.21***
	(0.009)	(0.009)	(26.61)
Observations	3203	3202	3184
Mean	.125	.691	$792.35

Note: Table shows regression discontinuity estimates of the impact of redline-mapping on measures of housing market strength with standard errors reported in parentheses. Observations are at the city-level. The outcome variable is the percent of vacant homes, the percent of homes under mortgage and average reported monthly rent in 2010 dollars in columns (1), (2) and (3) respectively. The running variable is always 1930 city population. Bandwidth size is chosen optimally in each column following Calonico (2017). Slight differences in the number of observations arise from there being different optimal bandwidths for each outcome variable. The reported mean is for non-mapped cities within the optimal population bandwidth. Source: 2010 Census and HOLC archival documents. Significance levels indicated by: * ($p < 0.10$), ** ($p < 0.05$), ***($p < 0.01$)

Table A7: Impact of Redline-Mapping on Housing Stock: Between City Estimates

	(1) PCT Detached Single Family Homes	(2) PCT Attached Single Family Homes	(3) PCT 2-4 Family Housing Units	(4) PCT 5+ Family Housing Units	(5) PCT Mobile Home Units	(6) PCT Other Housing Stock
Panel A1: 1960 Housing Stock						
RD Estimate	0.1203	0.0146	-0.0507	-0.0633	-0.0140	-0.0000
	(0.0734)	(0.0272)	(0.0474)	(0.0404)	(0.0136)	(0.0003)
Mean	.4704	.0615	.1612	.0816	.02053	.0004
Panel A2: 1960 Housing Stock With Black Residents						
RD Estimate	0.2519	0.0621	-0.0974	-0.1668**	-0.0042	-0.0009
	(0.1954)	(0.0930)	(0.0778)	(0.0808)	(0.0139)	(0.0011)
Mean	.3568	.0864	.1571	.1039	.0245	.0006
Panel B1: 1980 Housing Stock						
RD Estimate	0.0367	-0.0089	0.0122	-0.0304	-0.0068	-0.0000
	(0.0398)	(0.0202)	(0.0165)	(0.0243)	(0.0098)	(0.0000)
Mean	.6493	.0457	.0993	.1619	.0140	.00005
Panel B2: 1980 Housing Stock With Black Residents						
RD Estimate	-0.0487	-0.0050	0.0315	0.0246	0.0011	.
	(0.0687)	(0.0335)	(0.0291)	(0.0765)	(0.0045)	.
Mean	.5487	.0610	.1246	.2256	.0034	.
Panel C1: 2000 Housing Stock						
RD Estimate	0.0423	-0.0149	-0.0227	-0.0040	-0.0016	-0.0031
	(0.0647)	(0.0261)	(0.0217)	(0.0467)	(0.0112)	(0.0033)
Mean	.6044	.0668	.1046	.1954	.01988	.0092
Panel C2: 2000 Housing Stock With Black Residents						
RD Estimate	-0.0335	-0.0333	0.0005	0.0479	0.0019	0.0001
	(0.0993)	(0.0380)	(0.0610)	(0.0818)	(0.0112)	(0.0071)
Mean	.4761	.0633	.1432	.3168	.00537	.0102
Observations	143	143	143	143	126	126

Note: The table shows regression discontinuity estimates of the impact of redline-mapping on city-level housing stock and city-level black housing occupancy. The outcome variables are aggregated tabulations of the Census variable UNITSSTR. In panels A1, B1 and C1 the outcome variables measure available housing stock at the city year level; in panels A2, B2 and C2 the outcome variables measure housing stock with black residents at the city year level. The running variable is always 1930 city population. Bandwidth size is chosen optimally following Calonico (2017). The reported mean is for cities within the optimal population bandwidth. There is a small amount of variation in the number of cities reporting non-missing UNITSSTR values across decades; reported observations are for the 2000 sample. In 1980, the estimate for "other" housing stock with black residents is missing because there is not enough support in the outcome variable over the bandwidth to perform the estimation. The sources are the Decennial Census and HOLC archival documents. Significance levels indicated by: * ($p < 0.10$), ** ($p < 0.05$), ***($p < 0.01$)

Table A8: Impact of Redline-Mapping On Short Run Migration (1940): Between-City Estimates

	(1) Same House	(2) Same Community	(3) Same City	(4) Moved Within County	(5) Moved Wthn St	(6) Btw St (Contig)
City Was HOLC Mapped	0.0670***	0.0617***	0.0617***	-0.00815*	0.00314	0.00114
	(0.00981)	(0.0123)	(0.0123)	(0.00408)	(0.00214)	(0.00270)
Observations	266	266	266	266	266	266
Mean	.2227	.6407	.6407	.4524	.0199	.0394

Note: Table reports estimates of the impact of redline-mapping on various measures of short-run migration. Observations are at the city-level. The estimates are obtained by regressing a given short-run migration measure against an indicator variable for whether a city were mapped. The sample is restricted to cities with a 1930 population between 20,000 and 60,000. Each measure is obtained from respondent's answer on the 1940 Census to questions about residency on April 1, 1935. In column (1) the outcome variable is an indicator for whether or not the respondent reports living in the same house at the time of survey as in 1935. Columns (2)-(4) use similar measures at the community, city and county level. Column (5) uses a measure of moving within the state of residence, and column (6) uses a measures of moving between contiguous states as the outcome variable. The reported mean is for non-mapped cities within this population bandwidth. Source: 1940 Census and HOLC archival documents Significance levels indicated by: * ($p < 0.10$), ** ($p < 0.05$), ***($p < 0.01$)

Table A9: Impact of Redline-Mapping on Demography: Between-City Estimates of Compositional Migration

	(1) PCT Black	(2) PCT Hispanic	(3) PCT White
RD Estimate	0.06	-0.03	-0.01
	(0.07)	(0.08)	(0.07)
Observations	559	559	559
Mean (Bandwidth)	.14	.17	.72

Note: Table shows regression discontinuity estimates of the possible impact of redline-mapping on present-day racial demography. Corresponding regression discontinuity diagrams are displayed in Figure A19. Observations are at the city-level. Data sources are the 2010 Census and Home Owner Loan Corporation (HOLC) archival records.

Appendix: Redlining and Migration

Redline-mapping could cause both within-city migration across neighborhoods and between-city migration across cities or even regions. Thus, understanding both types of migration is important for interpreting the reduced form impact of redlining both at the within-city and between-city-level.

The estimates reported in Table A8 provide evidence that redline-mapping did not cause either significant within or between city migration in the short run.[23] If we saw evidence of differential within-city migration from the estimates in Table A8, this might suggest that the within-city effects of redlining on crime could be due largely to residents of a city sorting themselves between neighborhoods in response to the mapping. However, the estimates in columns (1)-(3) of Table A8 suggest that redline-mapping may have *decreased* within-city moves by about 6 percentage points (a 10% decrease off the mean) in the short run; columns (4)-(6) suggest redline-mapping did not affect between-cities moving rates in the short run.

It is still possible that redline-mapping is responsible for shaping long-run between-city migration patterns. For example, it could be that some of the well known "Great Migration" patterns of black residents moving away from Southeastern states were influenced by redline-mapping practices. Figure A19 and Table A9 shows regression discontinuity estimates of the possible impact of redline-mapping on present-day city-level racial composition; they utilize the same city-level identification strategy I describe in Section 3.2. The estimates provide suggestive evidence that redline-mapping may have increased share black and decreased share white at the city-level; these estimates are consistent with an account in which some, but not all,[24] of the reduced form effect of redline-mapping on crime is due to between-city migration and accompanying shifts in the racial composition of cities.

I am in the process of using restricted Census data which links individuals in various Census surveys to their place of birth to more definitively answer the question of whether between-city migration was affected by redline-mapping.

[23]The short run in this case is the period of time between April 1, 1935 and the date of the 1940 Census survey. Because this is the first year the Census began to ask this migration question it is not possible to run a similar specification using the 1930 Census. Redline-mapping began in 1935 and continued through 1940. In Los Angeles, for example, city mapping occurred mainly in March of 1939 while the 1940 decennial Census surveys were given out so as to be reflective of conditions April 1, 1940. While there is variation in when cities were mapped, it is reasonable to think that the migration responses of a survey in April of 1940 could pick up migration patterns in the immediate aftermath of redline-mapping.

[24]Back of the envelope calculations show that the point estimates in Table A9 can at most explain a third of the city-level crime effects

Appendix: Comparing NIBRS and UCR Results

Figure A9 shows that the city-level estimates of the impact of redline-mapping on crime using NIBRS are comparable to the estimates obtained using UCR data, which measure arrests by city by race. The estimates reported in Figure A9 (obtained by estimating Equation 1 on UCR data) imply that 61 additional Black arrests per city in 2015 are attributable to redline-mapping. Thus, if we assume that the additional Black arrests are for crime perpetrated against Black victims, these estimates would suggest an arrest rate of roughly 35%, which is not far from the national average for UCR Type 1 crimes.[25]

Furthermore, preliminary tests on the distribution of crime as measured by NIBRS and UCR reveal that these datasets give consistent measures of criminality by race. To test consistency, for example, I construct a variable that measures the difference between Black (UCR Type 1) crime victimizations reported to NIBRS and Black (UCR Type 1) criminal arrests reported to the UCR. This variable, which measures consistency between the two datasets, is very nearly mean zero, and, more importantly, does not jump at the 40,000 population threshold. This suggests that whatever noise there is in these data at the city-level is an instance of classical measurement error, or at least not systematically connected to redline-mapping.

[25] FBI (2010)

Appendix: Decadal Breadkdowns of the Impact of Redlining on Racial Segregation

To complement the results displayed in Figure 5, I also consider specifications which estimate city-decade level measures by decade. Figure A16 shows a panel of city-level regression discontinuity diagrams where the outcome is White-Black racial segregation in a given year as measured by the White-Black Dissimilarity Index (a standard measure of racial segregation in cities). Figure A16, subfigure (a), shows a placebo test for White-Black segregation in the period just before redline-mapping was implemented: I find no significant difference in White-Black racial segregation across the population threshold in 1930.

Figure A16, subfigures (b)-(c), show estimates of the impact of redline-mapping on White-Black segregation in 1980 and 1990, respectively. (By 1980, cities which were redline-mapped had been subject to *de jure* discrimination in the credit market for approximately 30 years.) I estimate that in 1980 redline-mapping was responsible for an increase of 11 dissimilarity points, approximately a 24% increase off the mean. This estimate is significant at the ten percent level (See Figure A16, subfigure (b)). I separately estimate that in 1990 redline-mapping was responsible for an increase of 8 dissimilarity points, approximately a 19% increase off the mean. This estimate is significant at the fifteen percent level (See Figure A16, subfigure (c)).

The estimate for 1980, for example, suggests that, as a result of being redline-mapped, in redline-mapped cities 11% *more* White households would have to move neighborhoods in order for each neighborhood to have the same racial composition as the city as a whole. Taken together, subfigures (a)-(c) of Figure A16 suggest that redline-mapping caused increases in racial segregation by slowing the rate at which racial segregation was otherwise declining at the national level. In other words, redline-mapping seems to have allowed racial segregation to persist longer than it would have in the absence of mapping.