

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

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“There is no such thing really as was because the past is.”
(William Faulkner)

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- ▶ Why is crime concentrated by neighborhood, by race?
 - ▶ income, racial segregation, school quality, pollution?
- ▶ My focus: **discontinuities** in **credit-access** brought about by Federal Policies called “**Redlining**”

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- ▶ “Residential Security Maps”: A(green), B(blue), C(yellow), D(red).

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- ▶ “Residential Security Maps”: A(green), B(blue), C(yellow), D(red).
- ▶ HOLC influenced loan access in two ways: **(1) by influencing private lenders** and **(2) influencing the FHA**

Redlining Map: Los Angeles

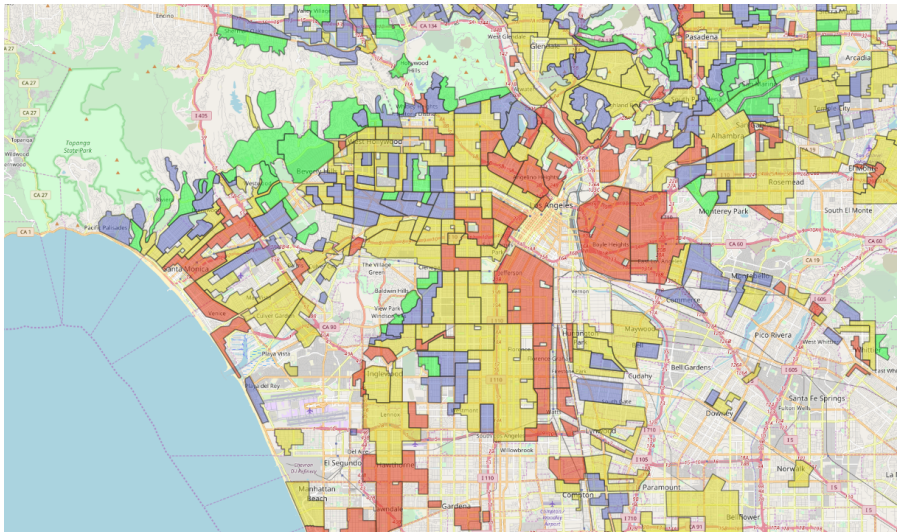


Figure 1: LA's HOLC Map (1939)

Defining Treatment Period: Legal Redlining

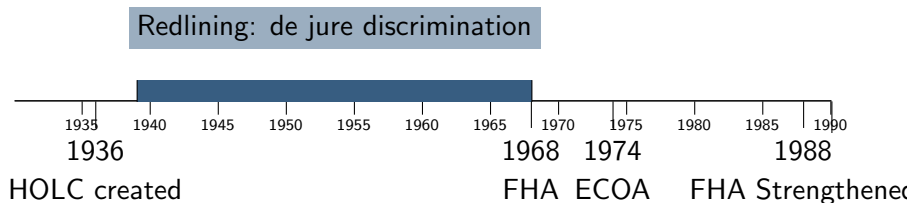


Figure 2: Timeline of de jure Discrimination

Note: Figure shows the period during which it was legal to discriminate in the loan market based on neighborhood demographics rather than applicant creditworthiness.

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

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- ▶ **Racially motivated** credit disparities: racial segregation associated with higher white-black test score gap (Card and Rothstein (2007))

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- ▶ **Absolute effect:** Did these restrictions increase overall crime or merely shift it around?
- ▶ If there are effects, what channels are responsible for them?

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- ▶ I also provide evidence that racial animus drove 1930 policies
- ▶ Overall: I find that racially motivated restrictions to credit-access harm people and neighborhoods three quarters of a century later

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 - ▶ Full cost/benefit analysis (don't know crime effects)
 - ▶ Estimates of racial animus impacts

City Level RD: Motivation and Strategy

Absolute effect: Did inequities in credit access within a city increase overall city-level crime?

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 - ▶ Long-run between-city crimes effects
 - ▶ Main Channel: Long-run racial segregation effects
 - ▶ Further Channels: educ, housing

City Level Data

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 - ▶ NIBRS crime-victimization data
 - ▶ demography of victim

City Level RD: First Stage (Population Cutoff)

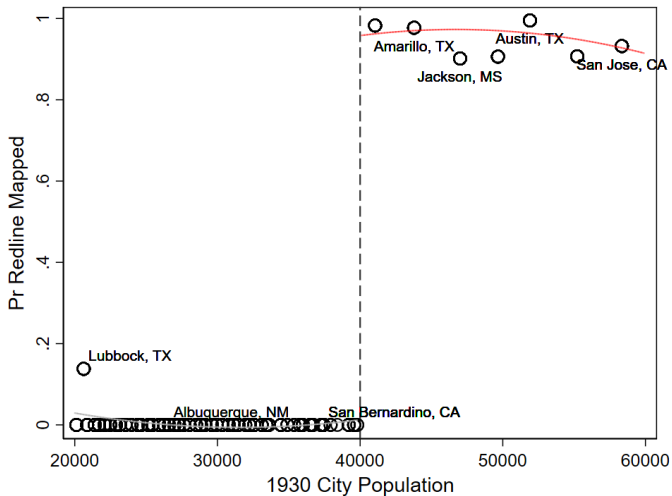


Figure 3: City Level: First Stage

City Level RD: Which Cities Were Redline-mapped?

Sample of Cities in Bandwidth

Not Mapped	Mapped
Tucson, AZ	Phoenix, AZ
Santa Barbara, CA	Stockton, CA
Bakersfield, CA	Fresno, CA
San Bernardino, CA	San Jose, CA
Ann Arbor, MI	Kalamazoo, MI
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: Source: 1930 Census and HOLC archival documents. Reported cities all have a 1930 population between 20,000 and 60,000, the mapping cutoff being 40,000. Context: In 1930: 1/3 of population lived in cities \leq 50,000

pop; Overall: 56% Urban, 44% rural [Zoom Into Threshold](#)

City Level RD: Estimation

Estimate regressions of the form:

$$Crime_{c,2015} = \tau Above_c + \beta f(Pop30_c) + \gamma Above_c \times f(Pop30_c) + \epsilon_c.$$

where

- ▶ $Crime_{c,2015} \equiv$ log count of crimes in city c in 2015

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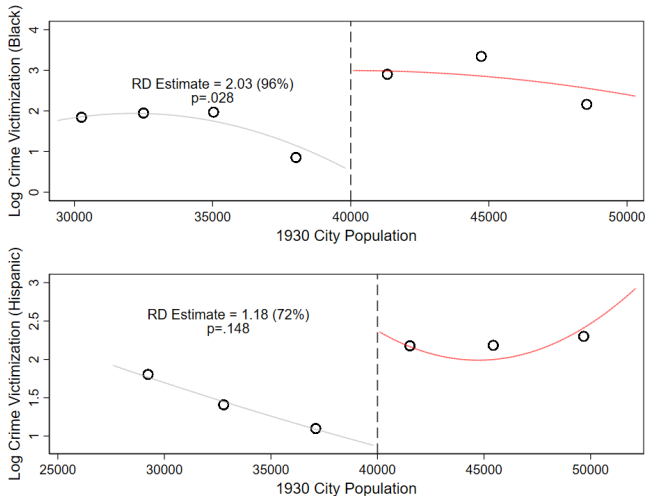
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- ▶ $Pop30_c \equiv$ 1930 population of city c .
- ▶ $Above_c \equiv \mathbb{1}(Pop30 \geq 40,000)$

City Level RD: Impact of Redline-Mapping on Crime



Note: Estimates imply 176 Black and 65 Hispanic crime victimizations per city attributable to mapping.

Figure 4: City Level RD: NIBRS (2015)

Bins

Rates

Migration

City Level RD: Impact of Redline-Mapping on Crime, by Bandwidth

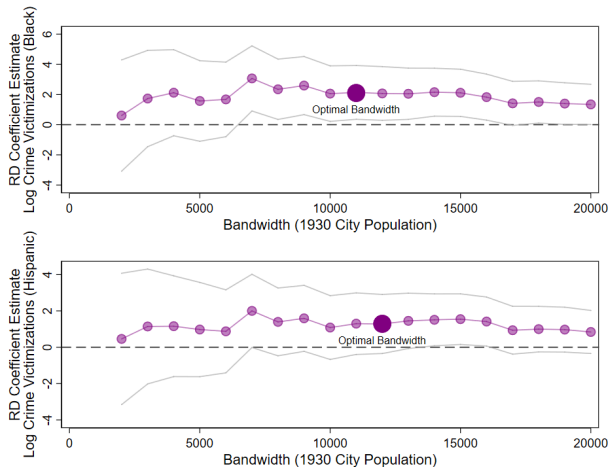


Figure 5: City Level RD: NIBRS (2015)

Reporting Density

City Level RD: Impact of Redline-Mapping on Arrests, Across Decades

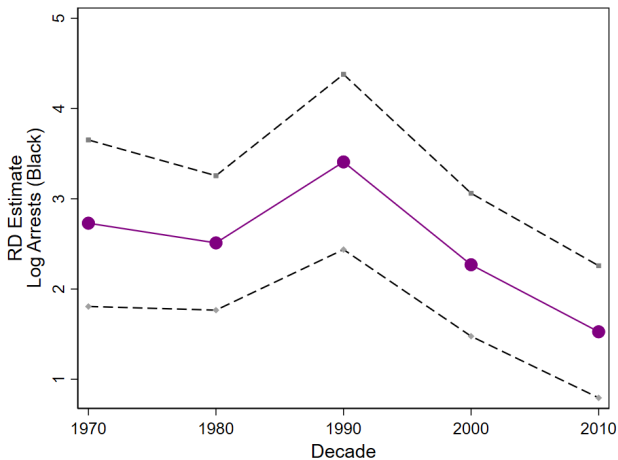


Figure 6: City Level RD: UCR

[Compare](#)

City Level RD: Balancing

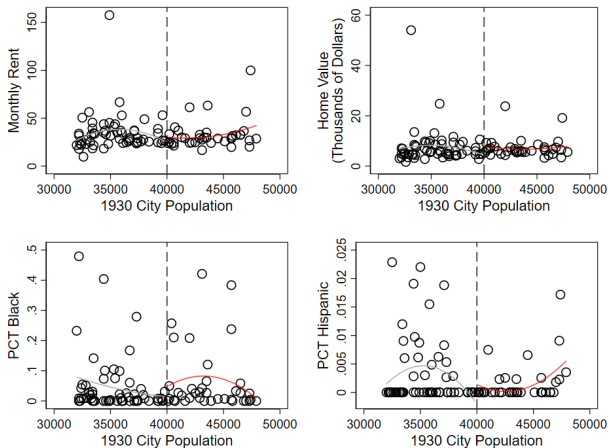


Figure 7: City Level Balancing GQ

City Level RD: Balancing, by Bandwidth

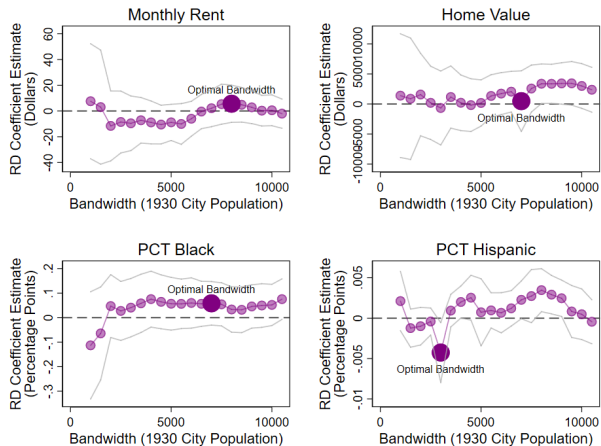


Figure 8: City Level Balancing, by Bandwidth

City Level RD: Impact of Redline-mapping on Racial Segregation

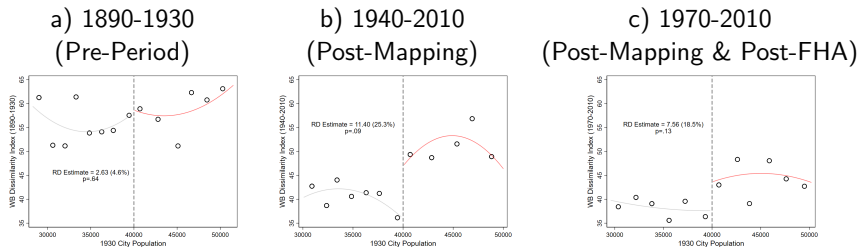


Figure 9: City Level Segregation

By Decade

City Level RD: Impact of Redline-mapping on Racial Segregation

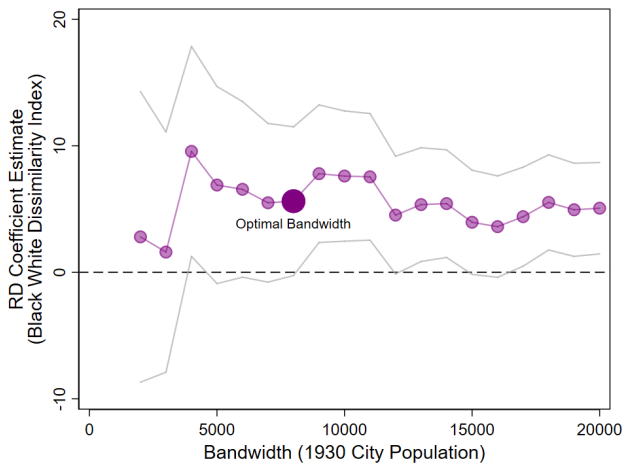


Figure 10: City Level Segregation, by Bandwidth

City Level RD

Impact of Redlining on Long Run Educational Outcomes

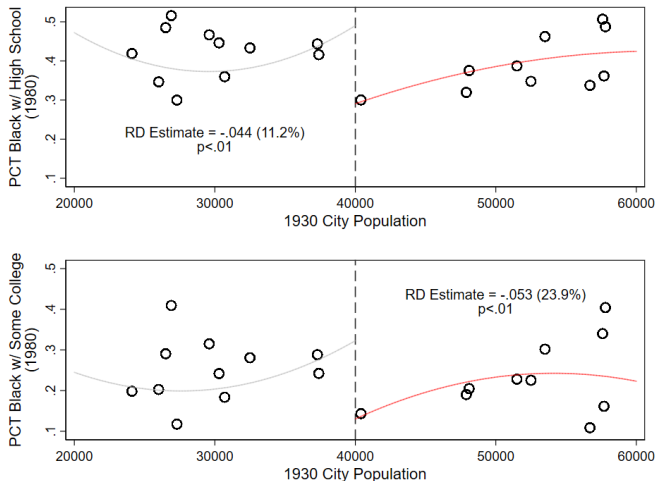


Figure 11: City Level Educ

City Level RD

Impact of Redlining on Present Day Housing Market

	(1)	(2)	(3)
	PCT Vacant	PCT Mortgaged	AVG Rent
RD Estimate	0.0504*** (0.0095)	-0.0696*** (0.0091)	-121.21*** (26.61)
Observations	3203	3202	3184
Mean	.125	.691	792.3

Note: Source: 2010 Census, HOLC archival documents. Reported mean is for non-mapped cities within population bandwidth. Significance levels indicated by: * ($p < 0.10$), ** ($p < 0.05$), ***($p < 0.01$)

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Absolute Effect: Did credit access inequities within a city increase overall crime?

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- ▶ Overall: **Major Federal Policy** that put cities on **different paths!**

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- ▶ Compare within-city estimates to between-city estimates above

Spatial RD Motivation

Redlining Map: Los Angeles

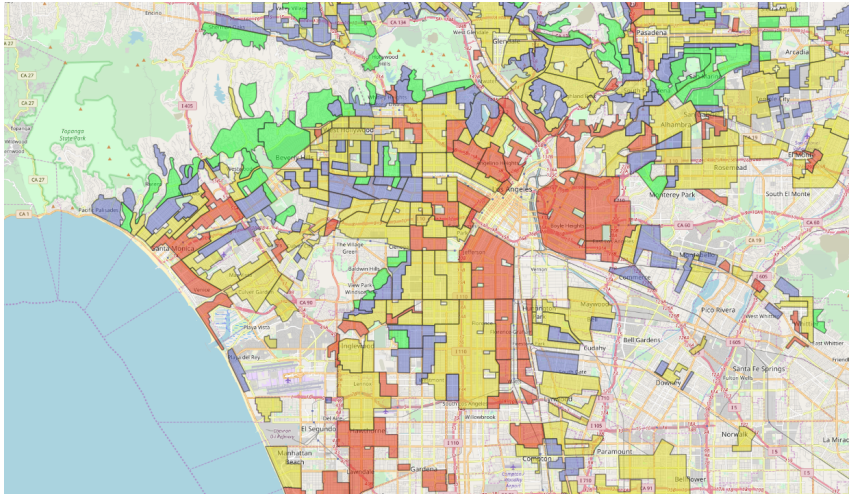


Figure 12: LA's HOLC Map (1939)

Spatial RD Motivation: Crime Unevenly Distributed

The most dangerous 10 pct bear 80 pct of crime burden!

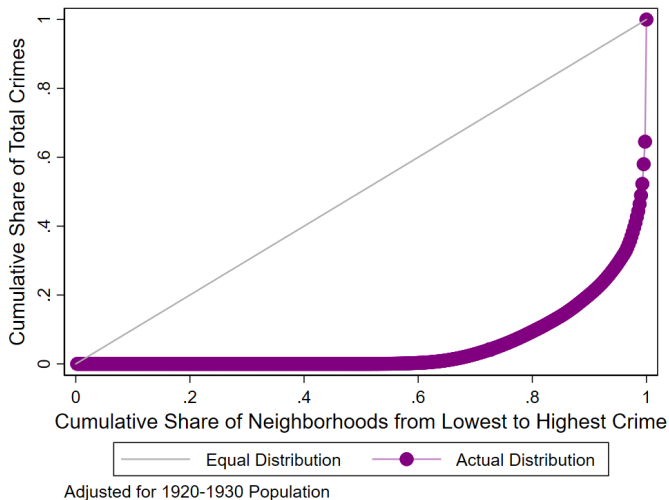


Figure 13: Gini: Crime in LA

Motivation: Crime Connected to Assignments?

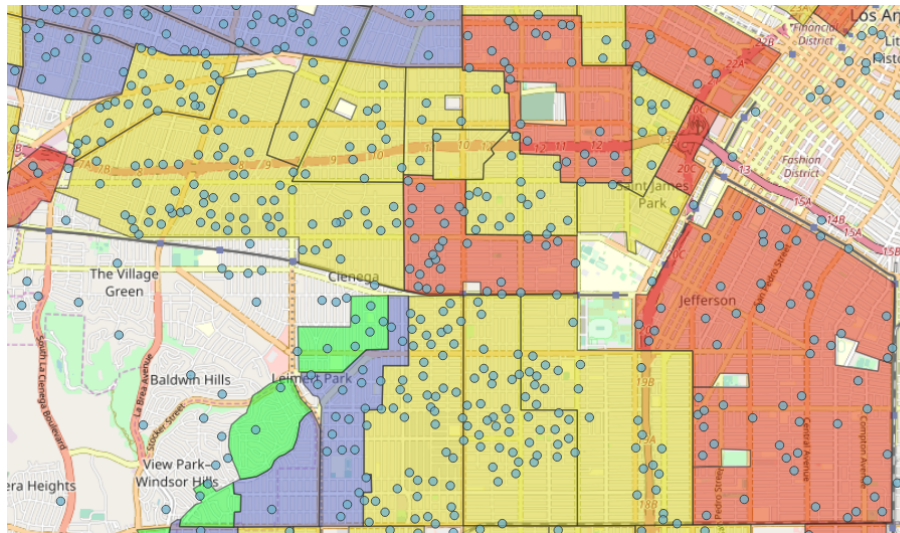


Figure 14: Hypothetical Murders in LA (Evenly Spaced by Population)

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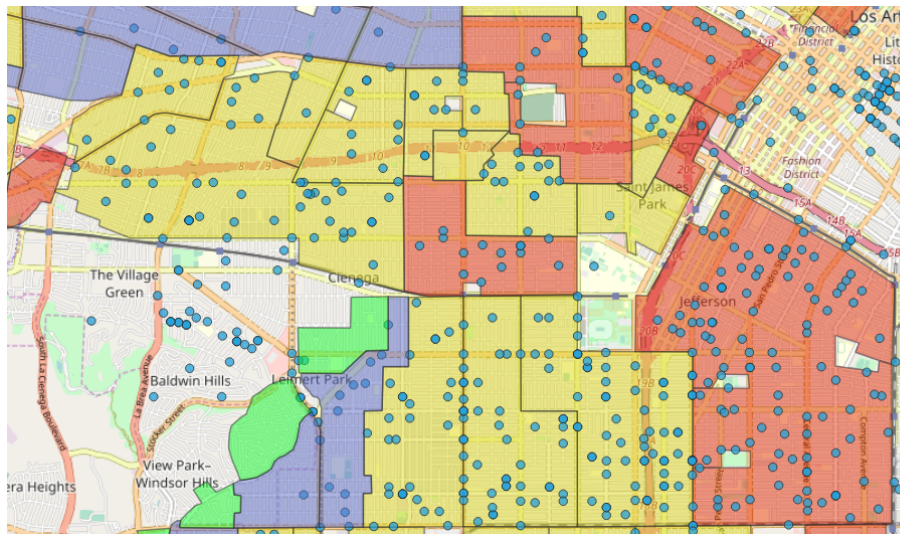


Figure 15: Murders in LA (2010 Actual)

Motivation: Descriptive Estimates

Table 1: Maybe Demography is Not Destiny

	(1)
2010 Violent Crime Count	
1939 Mexican Population	382.3** (193.4)
Observations	416
Mean	530.3
Pseudo R^2	.094

Note: Source: 1939 HOLC Data and 2010 Crime Data. Average marginal effects from Poisson regressions reported. Controlling for population using 1920-1930 Census data. Significance levels indicated by: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$)

Motivation: Descriptive Estimates

Table 2: Maybe Demography is Not Destiny

	(1)	(2)
2010 Violent Crime Count		
1939 Mexican Population	382.3** (193.4)	-35.1 (261.7)
Blue		111.6*** (36.9)
Yellow		698.1*** (219.6)
Red		963.5** (412.3)
Observations	416	416
Mean	530.3	530.3
Pseudo R^2	.094	.168

Note: Source: 1939 HOLC Data and 2010 Crime Data. Average marginal effects from Poisson regressions reported. Controlling for population using 1920-1930 Census data. Significance levels indicated by: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$)

Motivation: Racial Animus

Were HOLC neighborhood assignments racially motivated?

- ▶ Well-documented history of racially charged language in HOLC, FHA documents (“subversive”, “inharmonious”, etc.)

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Were HOLC neighborhood assignments racially motivated?

- ▶ Well-documented history of racially charged language in HOLC, FHA documents (“subversive”, “inharmonious”, etc.)
- ▶ Was this language associated with observable behavior of HOLC?

Racial Animus: Sample HOLC Survey Report

Long Beach, LA (Red)

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	<u>4 and 5 room</u>		<u>Large old dwellings</u>	<u>10%</u>
b. Construction	<u>Frame (few stucco)</u>		<u>Apts. & Multi-family</u>	<u>10%</u>
c. Average Age	<u>17 years</u>			
d. Repair	<u>Poor to fair</u>			
e. Occupancy	<u>98%</u>			
f. Owner-occupied	<u>25%</u>			
g. 1935 Price Bracket	<u>\$1750-2500</u>	<u>% change</u>	<u>\$</u>	<u>% change</u>

Racial Animus: Stated Racial Preferences

WARNING: DISCRIMINATORY LANGUAGE!

"Shifting or Infiltration": Sample Text Responses

A threat of subversive racial infiltration from nearby areas.

Area is hopelessly gone and cannot go much further

Being a beach resort, there is always danger of infiltration of lower racial elements.

Continued infiltration of Mexicans and Negroes

Deed restrictions protect against racial hazards.

Definite threat of further infiltration of subversive racial elements

Few Mexicans moving in along Filmore Place - Currier and along Holt. Ave. west of Filmore

Infiltration of Japanese and Negroes is a threat

Infiltration of goats, rabbits, and dark skinned babies indicated.

Infiltration of inharmonious Jewish element predicted. Thought remote.

Mexicans living on border agricultural lands a threat.

Mexicans said to be diminishing

Negroes are moving out but slowly

No further increase of subversive racial groups is anticipated

Possible future infiltration because of lack of restrictions

Said to be slight infiltration of well-to-do immigrant Jews into apartment houses

Serbs and Italians of better class

Said to be considerable infiltration of Jewish families

Note: Source: 1939 HOLC Data.

Racial Animus: Revealed Racial Preferences

	Ordered Logit
Pr(Redlined)	
Increasing Black	0.127** (0.064)
Increasing Hispanic	0.039 (0.034)
Increasing Jewish	0.018 (0.048)
Increasing Japanese	0.103* (0.061)
Increasing Subversive	0.082** (0.035)
No Inc Subversive	-0.025 (0.026)
Restrictive Covenant	-0.027 (0.040)
Test of Joint Significance	$\chi^2 = 339.4$ $p < .001$
Observations	416
Mean	.24
Pseudo R^2	.630

Note: Average marginal effects from ordered logit. Results conditional on 1939 neighborhood income, median home price, average new build price, expectations about future trends in the foreign born population, wealth levels, and overall population dynamics. Controlling for population using 1920-1930 Census data.

Spatial RD: Identification Strategy

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 - ▶ Show jump in crimes around Redlines

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- ▶ Running Variable

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- ▶ Running Variable
 - ▶ Distance to Redline From Non-Red Color

Why Spatial RD?

“The HOLC’s work served to solidify practices that had previously only existed informally. As long as bankers and brokers calculated creditworthiness according to their own perceptions, there was considerable flexibility and a likelihood that one person’s bad risk might be another’s acceptable investment. The HOLC **wiped out that fuzziness** by getting Charlotte’s leading real estate agents to compare notes, and then publishing the results. The handsomely printed map with its **sharp-edged boundaries** made the practice of deciding credit risk on the basis of neighborhood seem objective and put the weight of the U.S. government behind it.” (Hanchett P. 231)

Why Spatial RD?

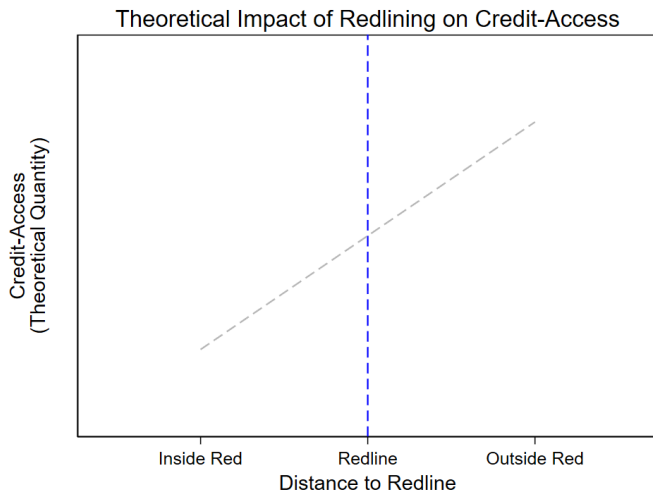


Figure 17: Institutional Motivation for Spatial RD

Why Spatial RD?

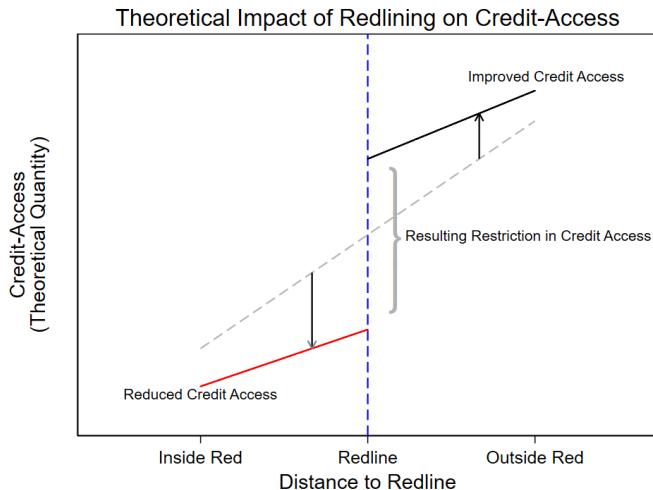


Figure 18: Institutional Motivation for Spatial RD

Spatial RD: Estimation

Estimate regressions of the form:

$$\text{Crime}_{nd} = \tau \text{Redlined}_d + \beta f(\text{DtoRedline}_n) + \gamma \text{Redlined}_d \times f(\text{DtoRedline}_n) + \epsilon_{nd}.$$

where

- $\text{Crime}_{nd} \equiv$ count of crimes d miles away from redlined neighborhood n

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- ▶ $\text{Redlined}_d \equiv \mathbb{1}(\text{redlined})$

Neighborhood Level Data

- ▶ HOLC color assignments, racial preferences

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 - ▶ novel geocoded dataset produced from HOLC administrative documents

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Spatial RD: Impact of Redlining on Crime

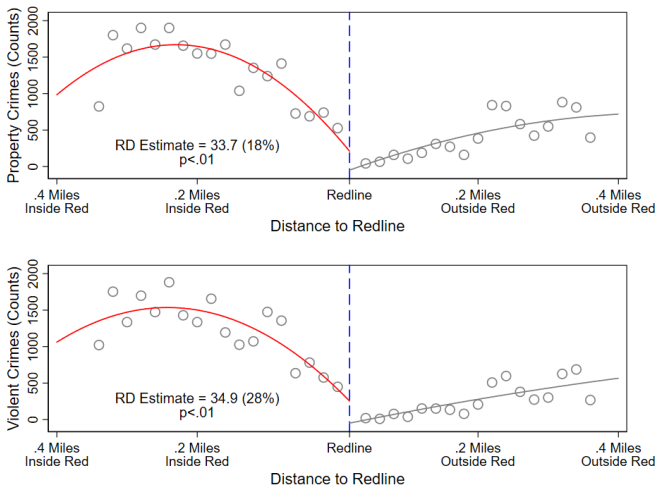


Figure 19: Spatial RD Red/Yellow

Spatial RD: Impact of Redlining on Crime, by Bandwidth

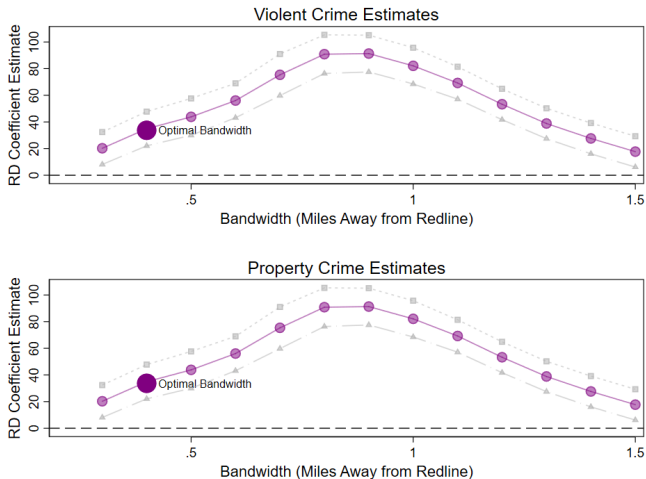


Figure 20: RD: Bandwidth Sensitivity

Spatial RD: Balancing

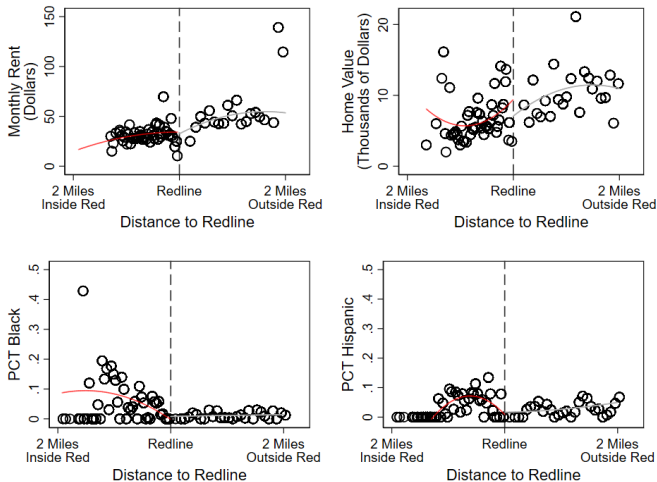


Figure 21: Pre-Period Covariates

Spatial RD: Balancing, by Bandwidth

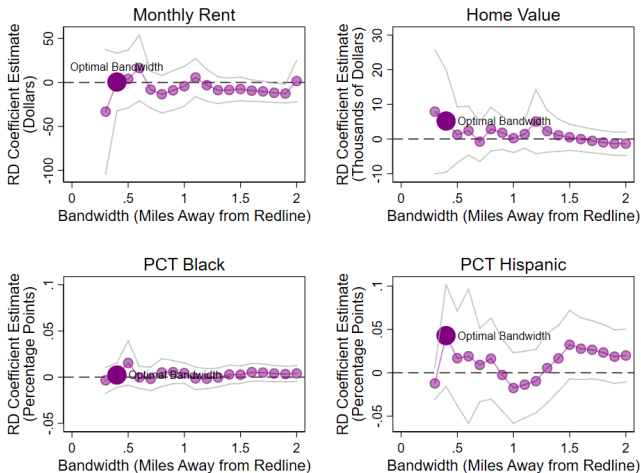


Figure 22: Pre-Period Covariates

Spatial RD: Review

Distributional Effect: Did credit-access restrictions brought about by Redlining contribute to the concentration of crime by neighborhood?

- ▶ Spatial RD: on average, Redlining added 70 crimes to redlined neighborhoods (20% increase)

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 - ▶ Excluding “Pasadena Freeway” (I 110), Los Angeles River
 - ▶ Present day law enforcement station boundaries
 - ▶ Inclusion of boundary FE's (redline-FE's)

Conclusion

Results

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 - ▶ City Level RD: on average, Redline-mapping added 175 Black and 65 Hispanic crime victimizations to redlined cities (70% increase)

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- ▶ **Distributional Effect:** Did credit-access restrictions brought about by Redlining contribute to the concentration of crime by neighborhood?
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- ▶ **Absolute Effect:** Did these restrictions increase overall crime or merely shift it around?
 - ▶ City Level RD: on average, Redline-mapping added 175 Black and 65 Hispanic crime victimizations to redlined cities (70% increase)
 - ▶ Back of Envelope: 1/3 of crime increases in redlined neighborhoods are “new” crimes (not shuffled within city)

Conclusion

Results

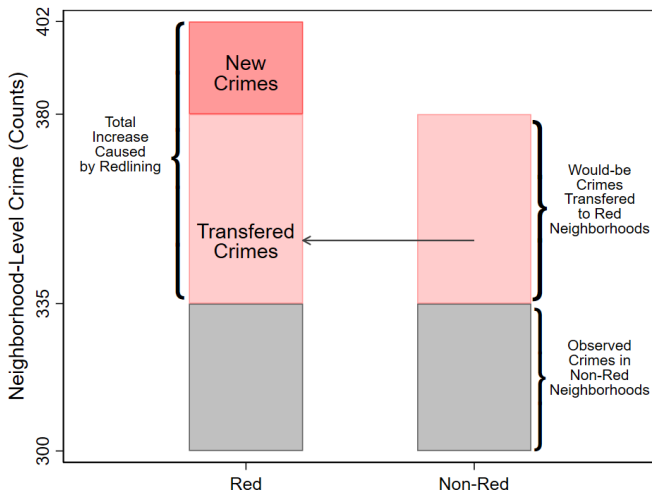


Figure 23: Comparing Size of Between-City and Within-City Estimates

Conclusion

Any Winners?

Compare Spatial RD to City-level RD

- ▶ Result: Redlining *decreased* crime in non-red neighborhoods

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 \Rightarrow non-red neighborhoods benefited from the mapping process:

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 - ▶ (1) Redlining transferred would-be crime from non-red neighborhoods to redlined

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Any Winners?

Compare Spatial RD to City-level RD

- ▶ Result: Redlining *decreased* crime in non-red neighborhoods
- ▶ Intuition: crime in neighborhoods in non-mapped city \geq crime in non-red neighborhood in mapped city
 \Rightarrow non-red neighborhoods benefited from the mapping process:
 - ▶ (1) Redlining transferred would-be crime from non-red neighborhoods to redlined
 - ▶ (2) rational for person living in a would-be highly ranked neighborhood, whose preferences do not involve neighborhoods other than her own, to prefer mapping

City Level RD: Which Cities Were Redline-mapped?

Not Mapped	Mapped
Green Bay, WI	Oshkosh, WI
Superior, WI	Battle Creek, MI
La Crosse, WI	Muskegon, MI
Sheboygan, WI	Council Bluffs, IA
Norristown Borough, PA	Dubuque, IA
Hazleton, PA	Portsmouth, OH
East Cleveland, OH	Lima, OH
Steubenville, OH	Lorain, OH
Zanesville, OH	Warren, OH
Butte, MT	Ogden, UT
Danville, IL	Joliet, IL
Auburn, NY	Poughkeepsie, NY
Bloomfield, NJ	Kearny, NJ
Montclair, NJ	Perth Amboy, NJ
Arlington, MA	Salem, MA
Revere, MA	Chicopee, MA
Taunton, MA	Fitchburg, MA
Cranston, RI	
Raleigh, NC	Lynchburg, VA
High Point, NC	Columbus, GA
Alameda, CA	Amarillo, TX
San Bernardino, CA	Wichita Falls, TX

Note: Source: 1930 Census and HOLC archival documents. Reported cities all have a 1930 population between 35,000 and 45,000, the mapping cutoff being 40,000.

[Return To First Stage](#)

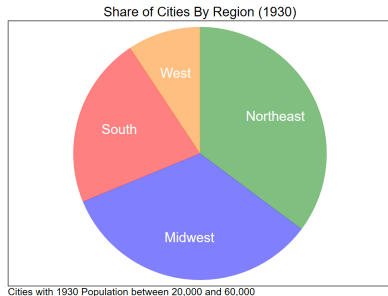
City Level RD: Which Cities Were Redline-mapped?

Not Mapped	Mapped
Anderson, IN	Lynchburg, VA
East Cleveland, OH	Warren, OH
Quincy, IL	Muskegon, MI
Sheboygan, WI	Oshkosh, WI
La Crosse, WI	Council Bluffs, IA
Butte, MT	Ogden, UT
Bloomfield, NJ	Kearny, NJ
Montclair, NJ	Poughkeepsie, NY
Meriden, CT	Dubuque, IA
Waltham, MA	Fitchburg, MA
	Saint Petersburg, FL

Note: Source: 1930 Census and HOLC archival documents. Reported cities all have a 1930 population between 38,000 and 42,000, the mapping cutoff being 40,000.

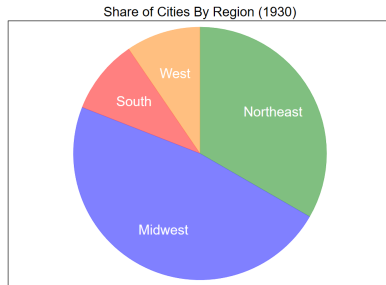
[Return To First Stage](#)

City Level RD: Which Cities Were Redline-mapped?



Cities with 1930 Population between 20,000 and 60,000

1930 City Pop $\in [20,000, 60,000]$



Cities with 1930 Population between 39,000 and 41,000

1930 City Pop $\in [39,000, 41,000]$

Figure 24: City Level: Share Mapped

[Return To First Stage](#)

City Level RD: Impact of Redline-Mapping on Crime

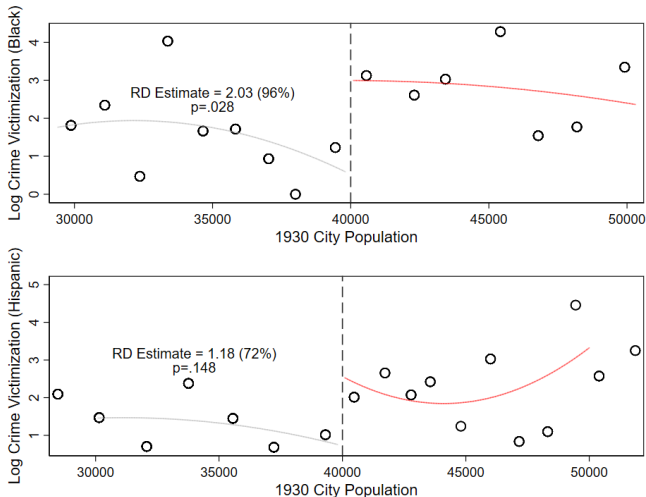


Figure 25: City Level RD: NIBRS (2015), Non-Optimal Bin Number [Back](#)

City Level RD: Impact of Redline-Mapping on Crime (Rates)

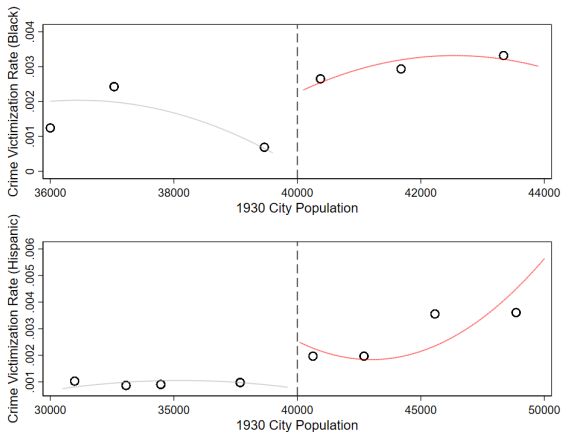


Figure 26: City Level RD (Rates)

[Back to City Level](#)

City Level RD: Impact of Redline-Mapping on Crimes and Arrests (2015)

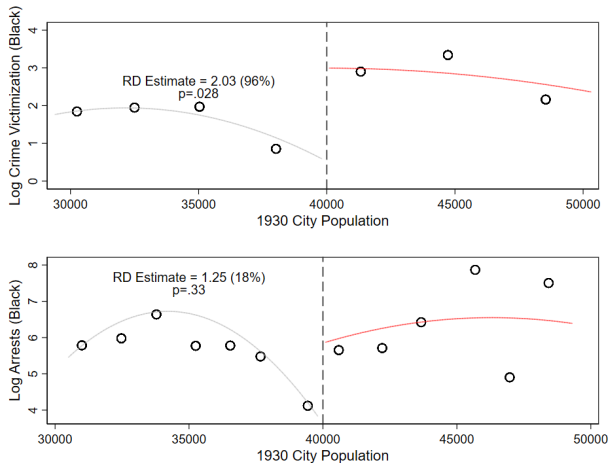


Figure 27: City Level RD: NIBRS vs UCR [Back](#)

City Level RD: Impact of Redline-Mapping on Racial Composition

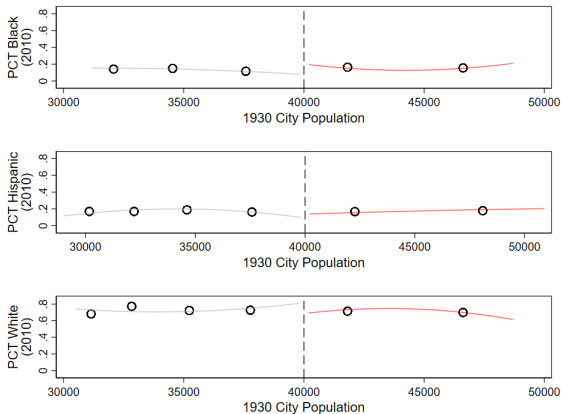


Figure 28: City Level RD [Back to City Level](#)

City Level RD: Cities Reporting Crime Data

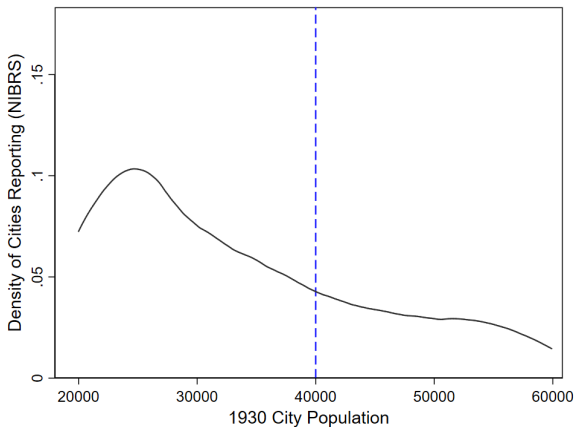
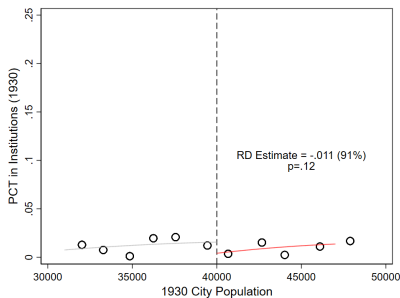


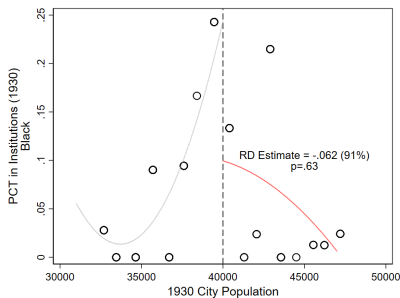
Figure 29: City Level RD: Cities Reporting to NIBRS (2015)

[Back to City Bandwidth](#)

City Level RD: Balancing



(a) Pre-Period Incarceration



(b) Pre-Period Incarceration: Black

Figure 30: Placebo Tests with Institutional Group Quarters [Back](#)

City Level RD: Impact of Redline-mapping on Racial Segregation

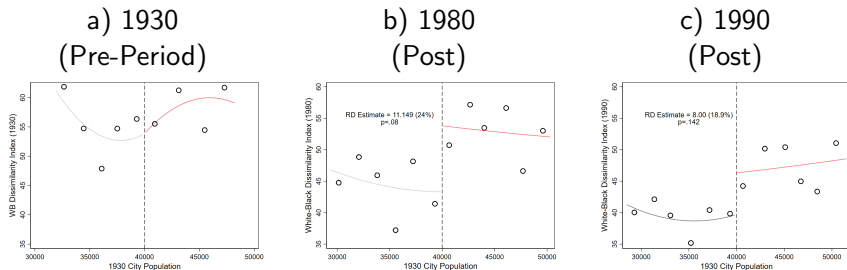


Figure 31: City Level RD: Segregation [Back](#)

Spatial RD: Impact of Redlining on Crime

Restricted to Red and Yellow Neighborhoods

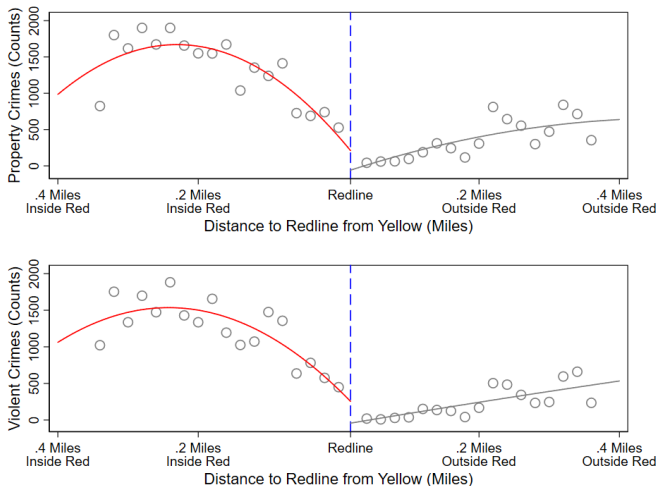


Figure 32: Spatial RD [Back to Spatial RD](#)

Racial Animus: Revealed Racial Preferences

	Ordered Logit			
	Pr(Redlined)	Pr(Yellow)	Pr(Blue)	Pr(Green)
Increasing Black	0.127** (0.064)	0.063 (0.040)	-0.109* (0.059)	-0.081* (0.045)
Increasing Hispanic	0.039 (0.034)	0.019 (0.018)	-0.033 (0.029)	-0.025 (0.022)
Increasing Jewish	0.018 (0.048)	0.009 (0.024)	-0.016 (0.041)	-0.012 (0.030)
Increasing Japanese	0.103* (0.061)	0.051* (0.031)	-0.088* (0.052)	-0.065* (0.039)
Increasing Subversive	0.082** (0.035)	0.041** (0.020)	-0.071** (0.030)	-0.052** (0.023)
No Inc Subversive	-0.025 (0.026)	-0.012 (0.013)	0.022 (0.022)	0.016 (0.017)
Restrictive Covenant	-0.027 (0.040)	-0.013 (0.020)	0.023 (0.034)	0.017 (0.025)
Observations	416	416	416	416
Mean	.24	.42	.23	.11
Pseudo R^2	.169	.169	.169	.169