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)
Distribution of Crime Costs

- Welfare effects of crime are large - 2 trillion dollars (Ludwig 2007)
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Cost disproportionately borne by people of color
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Why is crime concentrated by neighborhood, by race?
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- My focus: discontinuities in credit-access brought about by Federal Policies called “Redlining”
Background: Redlining and HOLC

“Redlining” is discrimination on the basis of neighborhood characteristics such as racial demographics, rather than individual loan-applicant credit-worthiness.

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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
Figure 1: LA’s HOLC Map (1939)
Defining Treatment Period: Legal Redlining

![Timeline of de jure Discrimination](image)

**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.
Disparities in credit access $\Rightarrow$ incentives for criminal perpetration (Garmais et al (2006), Cuffe (2013))
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Neighborhood characteristics ⇒ LR labor market (Chetty et al (2014)), crime outcomes (Peterson and Krivo (2010))
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Racially motivated credit disparities: racial segregation associated with higher white-black test score gap (Card and Rothstein (2007))
Research Questions

- **Distributional effect**: Did credit-access restrictions brought about by Redlining contribute to the concentration of crime by neighborhood, race?
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- **Distributional effect:** Did credit-access restrictions brought about by Redlining contribute to the concentration of crime by neighborhood, race?
- **Absolute effect:** Did these restrictions increase overall crime or merely shift it around?
- If there are effects, what channels are responsible for them?
I use 2 RD designs to provide first evidence that governmental credit-access policies in the late 1930s ("Redlining") affect present day crime.
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Redlining Literature

- We know Redlining . . .
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- Full cost/benefit analysis (don’t know crime effects)
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  - Estimates of racial animus impacts
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  - Further Channels: educ, housing
City Level Data

- City Mapping Assignment
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  - HOLC administrative documents recovered from Archives
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  - demography of victim
Figure 3: City Level: First Stage (Population Cutoff)
## City Level RD: Which Cities Were Redline-mapped?

### Sample of Cities in Bandwidth

<table>
<thead>
<tr>
<th>Not Mapped</th>
<th>Mapped</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tucson, AZ</td>
<td>Phoenix, AZ</td>
</tr>
<tr>
<td>Santa Barbara, CA</td>
<td>Stockton, CA</td>
</tr>
<tr>
<td>Bakersfield, CA</td>
<td>Fresno, CA</td>
</tr>
<tr>
<td>San Bernardino, CA</td>
<td>San Jose, CA</td>
</tr>
<tr>
<td>Ann Arbor, MI</td>
<td>Kalamazoo, MI</td>
</tr>
<tr>
<td>Ithaca, NY</td>
<td>Poughkeepsie, NY</td>
</tr>
<tr>
<td>Middletown, NY</td>
<td>Jamestown, NY</td>
</tr>
<tr>
<td>Lubbock, TX</td>
<td>Amarillo, TX</td>
</tr>
<tr>
<td>Brownsville, TX</td>
<td>Wichita Falls, TX</td>
</tr>
<tr>
<td>Abilene, TX</td>
<td>Port Arthur, TX</td>
</tr>
<tr>
<td>San Angelo, TX</td>
<td>Waco, TX</td>
</tr>
<tr>
<td>Corpus Christi, TX</td>
<td>Galveston, TX</td>
</tr>
<tr>
<td>Laredo, TX</td>
<td>Austin, TX</td>
</tr>
<tr>
<td>Bristol, VA</td>
<td>Lynchburg, VA</td>
</tr>
<tr>
<td>Green Bay, WI</td>
<td>Madison, WI</td>
</tr>
</tbody>
</table>

**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 ≤ 50,000 pop; Overall: 56% Urban, 44% rural.
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

- \( Crime_{c,2015} \equiv \log \text{count of crimes in city } c \text{ in 2015} \)
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- \( Crime_{c,2015} \equiv \log \text{count of crimes in city } c \text{ in 2015} \)
- \( Pop30_c \equiv 1930 \text{ population of city } c. \)
- \( Above_c \equiv 1(Pop30 \geq 40,000) \)
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)
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
City Level RD: Balancing

Figure 7: City Level Balancing
Figure 8: City Level Balancing, by Bandwidth
City Level RD: Impact of Redline-mapping on Racial Segregation

a) 1890-1930 (Pre-Period)  

b) 1940-2010 (Post-Mapping)  

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

Figure 9: City Level Segregation By Decade
City Level RD: Impact of Redline-mapping on Racial Segregation

Figure 10: City Level Segregation, by Bandwidth
Figure 11: City Level Educ
### City Level RD

**Impact of Redlining on Present Day Housing Market**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PCT Vacant</strong></td>
<td><strong>PCT Mortgaged</strong></td>
<td><strong>AVG Rent</strong></td>
<td></td>
</tr>
<tr>
<td><strong>RD Estimate</strong></td>
<td>0.0504***</td>
<td>-0.0696***</td>
<td>-121.21***</td>
</tr>
<tr>
<td></td>
<td>(0.0095)</td>
<td>(0.0091)</td>
<td>(26.61)</td>
</tr>
</tbody>
</table>

| 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: * ($p < 0.10$), ** ($p < 0.05$), ***($p < 0.01$)
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!
**Distributional effect:** Did credit-access restrictions brought about by Redlining contribute to the concentration of crime by neighborhood, race?

- Empirical strategy: using discretionary placement of Redline boundaries within Los Angeles
Spatial RD: Motivation

**Distributional effect:** Did credit-access restrictions brought about by Redlining contribute to the concentration of crime by neighborhood, race?

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  - Neighborhood polygons do not correspond to pre-existing Wards, Enumeration Districts
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  - Drawn at discretion of HOLC
- 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)
Motivation: Crime Connected to Assignments?

Figure 15: Murders in LA (2010 Actual)
## Motivation: Descriptive Estimates

### Table 1: Maybe Demography is Not Destiny

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<tr>
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<td></td>
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<tr>
<td>1939 Mexican Population</td>
<td>382.3**</td>
</tr>
<tr>
<td></td>
<td>(193.4)</td>
</tr>
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| 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: * ($p < 0.10$), ** ($p < 0.05$), ***($p < 0.01$)
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<td>-35.1</td>
</tr>
<tr>
<td></td>
<td>(193.4)</td>
<td>(261.7)</td>
</tr>
<tr>
<td>Blue</td>
<td></td>
<td>111.6***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(36.9)</td>
</tr>
<tr>
<td>Yellow</td>
<td></td>
<td>698.1***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(219.6)</td>
</tr>
<tr>
<td>Red</td>
<td></td>
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</tr>
<tr>
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Motivation: Racial Animus

Were HOLC neighborhood assignments racially motivated?

- Well-documented history of racially charged language in HOLC, FHA documents ("subversive", "inharmonious", etc.)
Motivation: Racial Animus

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?
AREA DESCRIPTION

Security Map of LOS ANGELES COUNTY

1. POPULATION:  
   a. Increasing  
   b. Slowly  
   c. Decreasing  
   d. Static  
   e. Shifting or Infiltration  
      Slow increase of subversive racial elements.

2. BUILDINGS:  
   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  
      $  
      $
“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

<table>
<thead>
<tr>
<th></th>
<th>Ordered Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pr(Redlined)</strong></td>
<td></td>
</tr>
<tr>
<td>Increasing Black</td>
<td>0.127** (0.064)</td>
</tr>
<tr>
<td>Increasing Hispanic</td>
<td>0.039 (0.034)</td>
</tr>
<tr>
<td>Increasing Jewish</td>
<td>0.018 (0.048)</td>
</tr>
<tr>
<td>Increasing Japanese</td>
<td>0.103* (0.061)</td>
</tr>
<tr>
<td>Increasing Subversive</td>
<td>0.082** (0.035)</td>
</tr>
<tr>
<td>No Inc Subversive</td>
<td>-0.025 (0.026)</td>
</tr>
<tr>
<td>Restrictive Covenant</td>
<td>-0.027 (0.040)</td>
</tr>
<tr>
<td><strong>χ² = 339.4</strong></td>
<td>p &lt; .001</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>416</td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td>0.24</td>
</tr>
<tr>
<td><strong>Pseudo R²</strong></td>
<td>0.630</td>
</tr>
</tbody>
</table>

**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

- Spatial RD about distance to Redline
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  - Show covars from 1920-1930 Census are smooth around Redlines
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Spatial RD: Identification Strategy

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  - Show covars from 1920-1930 Census are smooth around Redlines
  - Show jump in crimes around Redlines
- Running Variable
  - Distance to Redline From Non-Red Color
“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
Figure 18: Institutional Motivation for Spatial RD
Estimate regressions of the form:

\[ Crime_{nd} = \tau \text{Redlined}_d + \beta f(DtoRedline_n) + \gamma \text{Redlined}_d \times f(DtoRedline_n) + \epsilon_{nd}. \]

where

- \( Crime_{nd} \equiv \) count of crimes \( d \) miles away from redlined neighborhood \( n \)
Estimate regressions of the form:

\[
\text{Crime}_{nd} = \tau \text{Redlined}_d + \beta f(DtoRedline_n) + \gamma \text{Redlined}_d \times f(DtoRedline_n) + \epsilon_{nd}.
\]

where

- \(\text{Crime}_{nd} \equiv \) count of crimes \(d\) miles away from redlined neighborhood \(n\)
- \(DtoRedline_n \equiv \) distance to nearest redline
Spatial RD: Estimation

Estimate regressions of the form:

\[
Crime_{nd} = \tau \text{Redlined}_d + \beta f(DtoRedline_n) + \gamma \text{Redlined}_d \times f(DtoRedline_n) + \epsilon_{nd}.
\]

where

- \( Crime_{nd} \equiv \text{count of crimes } d \text{ miles away from redlined neighborhood } n \)
- \( DtoRedline_n \equiv \text{distance to nearest redline} \)
- \( \text{Redlined}_d \equiv 1(\text{redlined}) \)
Neighborhood Level Data

- HOLC color assignments, racial preferences
Neighborhood Level Data

- HOLC color assignments, racial preferences
  - novel geocoded dataset produced from HOLC administrative documents

- Pre-period covariates
  - geocoded 1920, 1930 Census data

- Crime Outcomes
  - city of Los Angeles geocoded crime data (2010-2016)
  - address level
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Spatial RD: Impact of Redlining on Crime

**Figure 19: Spatial RD**

- **Property Crimes (Counts)**
  - Red/Yellow
  - RD Estimate = 33.7 (18%)
  - p < .01

- **Violent Crimes (Counts)**
  - Red/Yellow
  - RD Estimate = 34.9 (28%)
  - p < .01
Figure 20: RD: Bandwidth Sensitivity
Figure 21: Pre-Period Covariates
Spatial RD: Balancing, by Bandwidth

Figure 22: Pre-Period Covariates
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)
**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)
- Pre-period covar smoothness
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)

- Pre-period covar smoothness
  - Smooth for covars most concerned about (House Value, Rent Amount, PCT Black, PCT Hispanic)
**Distributional Effect:** Did credit-access restrictions brought about by Redlining contribute to the concentration of crime by neighborhood?

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- Robust to:
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  - Bandwidths where $h \in [.3, 2]$ miles
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- Robust to:
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  - Excluding “Pasadena Freeway” (I 110), Los Angeles River
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- Robust to:
  - Bandwidths where $h \in [.3, 2]$ miles
  - Excluding “Pasadena Freeway” (I 110), Los Angeles River
  - Present day law enforcement station boundaries
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- Robust to:
  - Bandwidths where \( h \in [.3, 2] \) miles
  - Excluding “Pasadena Freeway” (I 110), Los Angeles River
  - Present day law enforcement station boundaries
  - Inclusion of boundary FE’s (redline-FE’s)
Conclusion

Results

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

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Conclusion

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Conclusion

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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)
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
Conclusion

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 ≥ crime in non-red neighborhood in mapped city
  ⇒ non-red neighborhoods benefited from the mapping process:
Conclusion

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- Result: Redlining decreased crime in non-red neighborhoods
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    - (1) Redlining transferred would-be crime from non-red neighborhoods to redlined
Conclusion

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 ≥ crime in non-red neighborhood in mapped city
⇒ 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?

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

**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.
## City Level RD: Which Cities Were Redline-mapped?

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

**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.
City Level RD: Which Cities Were Redline-mapped?

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

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

Figure 24: City Level: Share Mapped
City Level RD: Impact of Redline-Mapping on Crime

Figure 25: City Level RD: NIBRS (2015), Non-Optimal Bin Number
City Level RD: Impact of Redline-Mapping on Crime (Rates)

Figure 26: City Level RD (Rates)

**Figure 27: City Level RD: NIBRS vs UCR**

- **Log Crime Victimization (Black)**
  - RD Estimate = 2.03 (96%)
  - $p = .028$

- **Log Arrests (Black)**
  - RD Estimate = 1.25 (18%)
  - $p = .33$
City Level RD: Impact of Redline-Mapping on Racial Composition

Figure 28: City Level RD
Figure 29: City Level RD: Cities Reporting to NIBRS (2015)
City Level RD: Balancing

(a) Pre-Period Incarceration
(b) Pre-Period Incarceration: Black

Figure 30: Placebo Tests with Institutional Group Quarters
City Level RD: Impact of Redline-mapping on Racial Segregation

Figure 31: City Level RD: Segregation

- a) 1930 (Pre-Period)
- b) 1980 (Post)
- c) 1990 (Post)
Spatial RD: Impact of Redlining on Crime
Restricted to Red and Yellow Neighborhoods

Figure 32: Spatial RD
### Racial Animus: Revealed Racial Preferences

<table>
<thead>
<tr>
<th></th>
<th>Pr(Redlined)</th>
<th>Pr(Yellow)</th>
<th>Pr(Blue)</th>
<th>Pr(Green)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increasing Black</td>
<td>0.127**</td>
<td>0.063</td>
<td>-0.109*</td>
<td>-0.081*</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.040)</td>
<td>(0.059)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Increasing Hispanic</td>
<td>0.039</td>
<td>0.019</td>
<td>-0.033</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.018)</td>
<td>(0.029)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Increasing Jewish</td>
<td>0.018</td>
<td>0.009</td>
<td>-0.016</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.024)</td>
<td>(0.041)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Increasing Japanese</td>
<td>0.103*</td>
<td>0.051*</td>
<td>-0.088*</td>
<td>-0.065*</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.031)</td>
<td>(0.052)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Increasing Subversive</td>
<td>0.082**</td>
<td>0.041**</td>
<td>-0.071**</td>
<td>-0.052**</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.020)</td>
<td>(0.030)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>No Inc Subversive</td>
<td>-0.025</td>
<td>-0.012</td>
<td>0.022</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.013)</td>
<td>(0.022)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Restrictive Covenant</td>
<td>-0.027</td>
<td>-0.013</td>
<td>0.023</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.020)</td>
<td>(0.034)</td>
<td>(0.025)</td>
</tr>
</tbody>
</table>

- **Observations**: 416
- **Mean**: 0.24, 0.42, 0.23, 0.11
- **Pseudo $R^2$**: 0.169, 0.169, 0.169, 0.169