The Lasting Impact of Historical Residential Security Maps on Experienced Segregation

Daniel Aaronson Federal Reserve Bank of Chicago

Daniel Hartley Federal Reserve Bank of Chicago Joel Kaiyuan Han Loyola University

Bhashkar Mazumder Federal Reserve Bank of Chicago



ABFER conference May 20, 2024

The views expressed are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Chicago, the Board of Governors of the Federal Reserve System.

### Motivation

- Growing concern about the fragmentation and polarization of American society along income and other lines (e.g. Fischer and Mattson, 2009, Smith et al., 2014, Doob, 2019)
- Traditional economics research focuses on residential segregation (e.g. Boustan, 2011, Cutler and Glaeser, 1997, Jargowsky, 2016)
- Newer work on various forms of *non-residential* segregation such as face-to-face interactions over the day (Moro et al., 2021), we refer to this as "experienced segregation" (Athey et al, 2020)
- But how did "experienced segregation" arise? We focus on one potential source, which is historical housing policy from 1930s. Residential Security Maps, or "redlining", maps drawn by HOLC

## HOLC Maps and Security Grades

HOLC maps (1935-1937) created neighborhoods and assigned 4 color coded grades A, B, C and D for over 200 cities





A=green (least) B=blue C=yellow D=red (most) U=unclassified

#### Our Previous Work

- Use several empirical approaches including "low propensity" borders –those least likely to be drawn based on observables
- Stylized Example, to close a polygon



• Neighborhoods on the lower graded side of a boundary experienced higher segregation, lower home ownership, reduced house values and lower rents from 1940 to onwards (Aaronson et al, *AEJ Policy*, 2021)

#### Results from Paper 1(AEJ, 2021)

![](_page_4_Figure_1.jpeg)

![](_page_4_Figure_2.jpeg)

![](_page_4_Figure_3.jpeg)

![](_page_4_Figure_4.jpeg)

### Our Previous Work (cont.)

• Children growing up on lower graded side when maps were drawn had reduced education and income as adults (Aaronson et al, *JEL*, 2022)

![](_page_5_Figure_2.jpeg)

![](_page_5_Figure_3.jpeg)

![](_page_5_Figure_4.jpeg)

Effects of a D or C Grade on Wage and Salary Inc

#### Our Previous Work (cont.)

• Find significant place-based effects using modern "Opportunity Atlas" outcomes for 1980s cohorts (Aaronson et al, *RSUE*, 2021)

![](_page_6_Figure_2.jpeg)

# Did the Maps Also Affect Experienced Segregation?

### Data and Methods

- Safegraph: Monthly Neighborhood Patterns database (2018-19)
- Tracks visits to destination Census block groups from origin block group based on cell phone pings
- Linked to HOLC maps for 149 cities from "Mapping Inequality" project. Covers 60 percent of "redlined" cities
- Focus on C-B boundaries ("yellow-lined") that are at least ¼ mile long. No racial differences or pre-trends when maps were drawn
- Spatially link block group visits to boundaries. Restrict sample to reduce ambiguous matches. See paper for details.

#### Outcomes

- **Outgoing** Historical HOLC grade: Are visits more likely to Block Groups that were low graded (C or D)
- Outgoing SES measures from ACS (2013-17):
  - fraction non-White residents
  - fraction Black residents
  - fraction college graduates
  - log median household income
- **Incoming** Visits –look at the same measures for origin block groups.

#### Table 2: C-B Boundary Effects on Outgoing Visit Patterns, Historical Credit Risk Grades

Fraction of Outgoing Visits to:	C,	,D	D	)	(	2	А	,В
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lower Graded (C) Side	0.093***	0.106***	0.023***	0.024**	0.057***	0.068***	-0.070***	-0.078***
	(0.014)	(0.023)	(0.005)	(0.008)	(0.012)	(0.019)	(0.012)	(0.020)
Observations	452	220	452	220	452	220	452	220
Standard Deviation of Dependent Variable								
• Overall	0.225	0.225	0.109	0.109	0.136	0.136	0.087	0.087
Within-Boundary	0.053	0.053	0.042	0.042	0.046	0.046	0.035	0.035
Ratio of Point Estimate to Std Dev								
Overall Std Dev	0.412	0.470	0.210	0.224	0.420	0.503	-0.801	-0.891
Within-Boundary Std Dev	1.743	1.993	0.549	0.587	1.250	1.496	-2.004	-2.229
Sample: Low Propensity Boundaries		Y		Y		Y		Y

Statistical significance: p < 0.1, p < 0.05, p < 0.01, p < 0.001, p < 0.001.

Notes: An observation is a census block group located at C-B boundaries that follows the sample restrictions and the definition of the low propensity score sample described in the text. Block groups are added to the sample with repetition if they are part of multiple boundaries. The dependent variable is the fraction of visits by residents of boundary block groups to destinations in neighborhoods with historical credit risk grades given in the column header. All specifications control for boundary fixed effects. The overall standard deviation is estimated using all block groups in cities with Residential Security Maps. The within-boundary standard deviation is estimated from boundary block groups using the residual variance from a secondary regression of the dependent variable on boundary fixed effects. Standard errors are clustered by boundary.

# Table 3: C-B Boundary Effects on Outgoing Visit Patterns, Frequency-Weighted Means of Present-Day Destination Neighborhood Characteristics

Destination Neighborhood:	Income		College		Non-White		Black	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lower Graded (C) Side	-0.053*** (0.009)	-0.047*** (0.012)	-0.015*** (0.003)	-0.012** (0.004)	0.016* (0.008)	0.005 (0.012)	0.013 <sup>+</sup> (0.007)	0.006 (0.011)
Observations	452	220	452	220	452	220	452	220
Standard Deviation of Dependent Variable								
• Overall	0.309	0.309	0.131	0.131	0.190	0.190	0.165	0.165
Within-Boundary	0.065	0.065	0.030	0.030	0.040	0.040	0.042	0.042
Ratio of Point Estimate to Std Dev								
• Overall Std Dev	-0.171	-0.152	-0.116	-0.094	0.085	0.025	0.078	0.036
<ul> <li>Within-Boundary Std Dev</li> </ul>	-0.810	-0.721	-0.513	-0.416	0.399	0.118	0.306	0.140
Sample: Low Propensity Boundaries		Y		Y		Y		Y

#### Table 7: C-B Boundary Effects on Incoming Visits

Home Neighborhood of Incoming Visits:					
	(1)	(2)	(3)	(4)	(5)
	Pr(C or D Grade)	Income	College	Non-White	Visits/Capita
Lower Graded (C) Side	0.139***	-0.047**	-0.018**	0.012	0.070
	(0.025)	(0.017)	(0.006)	(0.014)	(0.054)
Observations	220	220	220	220	220
Within-boundary Standard Deviation	0.089	0.115	0.041	0.062	1.614
Point Estimate / Std Dev	1.556	-0.409	-0.440	0.193	0.043

Statistical significance: p < 0.1, p < 0.05, p < 0.01, p < 0.01, p < 0.001.

Notes: This table reports results analogous to those in Tables 2 and 3 but for incoming visits. The dependent variable is: the fraction of incoming visits that originate in home neighborhoods with a historical grade of C or D (column 1), the popularity-weighted mean of home neighborhood log median income, fraction non-White, or fraction college graduates (columns 2 to 4), or the number of incoming visits per neighborhood resident (column 5). See the notes to Tables 2 and 3 for further details.

### Mechanisms

- Use counterfactual mediation analysis (Heckman et al. 2013; Heckman and Pinto, 2015)
  - Use the following observables: Non-White share, college graduation rate, homeownership rate, log median rent, log home value, and log median income
  - Model unobserved factors under some assumptions
  - These variables explains relatively little
- Suggests other explanations for differential interactions, e.g. amenities, reputation
- Symmetry b/w outgoing and incoming might be supportive of this explanation

### Robustness

- Not just due to proximity, robust to excluding nearby visits
- Excludes visits to work, school, and find that results are driven by non-work visits
- Exclude infrequent visits, Safegraph adds noise for differential privacy concerns

## City-level Differences

- Maps were only drawn for cities with a population of 40,000
- Previous studies have exploited this cutoff (Aaronson et al, 2021, Anders, 2023, Hynsjö and Perdoni, 2024)
- Compare redlined cities (pop 40,000 to 50,000) to non-redlined cities (pop 30,000 to 40,000) in 1930.
- Construct transition matrices of visits based on neighborhood income quintiles (defined within city). How likely are visits from lowest quintile to highest quintiles or, reverse?
- Show the difference in transition matrix between redlined and nonredlined cities. Captures outgoing and incoming visits

Neighborhood Income of Destination: 2 3 4 5 Origin: -0.4 -0.4 -0.5 -1.2 2.4 (0.07)(0.07)(0.07)(0.06)(0.06)More outgoing visits to the bottom quintile from the -0.70.5 0.7 0.6 -1.2 2 bottom quintile in redlined (0.07)(0.07)(0.06)(0.06)(0.05)cities (1,1). Fewer 3 2.5 1.5 -3.4 -0.6 -0.1 outgoing visits to higher (0.05)(0.05)(0.06)(0.06)(0.05)quintiles (rest of row 1) -2.7 2.22.6 4 -1.1 -1 (0.05)(0.06)(0.06)(0.05)(0.05)5 -0.8 2.9 2 -2.5 -1.6 (0.05)(0.05)(0.05)(0.05)(0.05)

Table 9: Difference in Neighborhood Income Quintile Mobility, Redlined Minus Non-redlined Cities

Notes: This table shows the difference (redlined cities minus non-redlined cities) in the percent of visits from home census block groups (column) to destination census block groups (row), where home and destination block groups are determined by their income quintile ranking within a city. The sample of redlined cities had a population between 40,000 and 50,000 in 1930. The sample of non-redlined cities had a population between 30,000 and 40,000 in 1930. Standard errors are generated from 100 bootstrap replications, each sampling 10 million visits.

Neighborhood Inco Destin	ome of nation:						
		1	2	3	4	5	
(	Origin:						
	1	2.4 (0.07)	-0.4 (0.07)	-0.4 (0.07)	-0.5 (0.06)	-1.2 (0.06)	
	2	- <i>0.7</i> (0.07)	0.5 (0.07)	0.7 (0.06)	0.6 (0.06)	-1.2 (0.05)	
Fewer incoming visits to the bottom quintile in redlined cities from higher income quintiles	3	- <i>3.4</i> (0.05)	-0.6 (0.06)	2.5 (0.06)	1.5 (0.05)	-0.1 (0.05)	
	4	-2.7 (0.05)	-1.1 (0.06)	2.2 (0.06)	2.6 (0.05)	-1 (0.05)	
	5	-1.6 (0.05)	-0.8 (0.05)	2.9 (0.05)	2 (0.05)	-2.5 (0.05)	

Table 9: Difference in Neighborhood Income Quintile Mobility, Redlined Minus Non-redlined Cities

Notes: This table shows the difference (redlined cities minus non-redlined cities) in the percent of visits from home census block groups (column) to destination census block groups (row), where home and destination block groups are determined by their income quintile ranking within a city. The sample of redlined cities had a population between 40,000 and 50,000 in 1930. The sample of non-redlined cities had a population between 30,000 and 40,000 in 1930. Standard errors are generated from 100 bootstrap replications, each sampling 10 million visits.

## Summary and Discussion

- Institutionalized lending discrimination not only affected the historical trajectories of residential segregation and housing in US cities, but also impacts modern-day "experienced segregation"
- Debate about whether this is causal. Maybe maps just captured pre-existing differences? That is certainly true of naïve estimators, but several research designs suggest a causal effect including using exogenous cutoff in redlining by city size, and a focus on C-B.
- Are these caused by HOLC maps or capturing other mechanisms such as FHA insurance? Future work may be able to better disentangle the relative roles. Results based on HOLC may understate the full effect of overall government policy.

# Extra slides

#### Conclusion

- Redlining has long been suspected to have led to financial disinvestment in neighborhoods, but so far there has been little quantitative evidence of long-run effects
- We find strongly suggestive evidence that maps had causal effects over subsequent decades on segregation, housing markets and economic opportunity

#### Extra Slides

#### Geographic Coverage

![](_page_22_Figure_1.jpeg)

#### Includes 9 of largest 10, 17 of largest 20, and 30 of the 42 cities > 200k in 1940.

# Propensity Score Estimation

Each observation is a border segment. Actual treated borders are pooled with the comparison borders based on the grid.

$$1\{Treated\}_{b,c} = \alpha_c + \sum_{k=1}^{K} \beta_{1910}^k z_{b,c}^{k,1910} + \beta_{1920}^k z_{b,c}^{k,1920} + \beta_{1930}^k z_{b,c}^{k,1930} + \epsilon_{b,c}$$

Back

 $\alpha_c$  is a city fixed effect

 $z_{b,c}^{k,t} = x_{lgs,b,c}^{k,t} - x_{hgs,b,c}^{k,t}$  is gap between variable k on lgs and hgs (lgs = lower graded side)

*k*: share African American, homeownership rate, log house value, log rent, African American population density, white population density, share foreign born, share of homeowner households that have a mortgage

#### Smoother Distance Plots Using Low P-score

![](_page_24_Figure_1.jpeg)

Number of observations = 1102124

![](_page_25_Picture_0.jpeg)

#### Response to Fishback et al (2021)

- Fishback et al claim that the HOLC maps did not have much influence on where the FHA was willing to insure mortgages
- However, there is ample evidence that HOLC shared the maps with FHA (see AHM, 2021).
  - Fishback et al write: "a 1942 document states that the HOLC shared copies of the entre set of maps with the FHA upon completion" (p10).
  - They say this could have been as early as 1937. They also assert that by 1942 the FHA was likely relying on data from the 1940 Census rather than the HOLC maps. This implies a possible 5-year window for the HOLC maps to have had an influence on where the FHA would insure mortgages. This in turn impacts where mortgage lenders were willing to lend and at what terms.
- Their figures 1, 2, and 3 show that from 1935 to 1940 the FHA insured almost no mortgages in the D areas and much fewer mortgages in the C areas than in the A or B areas.
- Their Figure 4 shows that after 1937 (when the HOLC maps may have been shared with the FHA) there are almost no mortgages insured in D areas.
- Suggestive evidence in their own paper: "We found this red line drawn in pencil on one map of the National Archive's FHA collection", It appears to trace out the boundary between the A and B areas in Greensboro and the C and D areas suggesting that an FHA red line may have been drawn based on an HOLC map. But they do not provide the year of the map or other details.