Discussion of:

"Pockets of Poverty: The Long-Term Effects of Redlining"

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Atlanta Fed/Georgia State Real Estate Finance Conference, November 30, 2017

Overview

- I have a working paper on the same topic with Dan Aaronson and Dan Hartley
  (first presented in Spring 2016 at Fed System Applied Micro mtg. in Cleveland)

Federal Reserve Bank of Chicago

The Effects of the 1930s HOLC "Redlining" Maps

Daniel Aaronson, Daniel Hartley, and Bhashkar Mazumder

Overview

- I have a working paper on the same topic with Dan Aaronson and Dan Hartley
  (1st presented in Spring 2016 at System Applied Micro mtg. in Cleveland)
- Rather than say that "*they should have done what we did*", I'll just show you what we did
  - But, obviously just a 10 minute version
- Along the way I will try to compare and contrast
  - Different data, time periods
  - Different methodologies
  - Different outcomes
- Should shed light on some key issues

Our Key Findings

- HOLC maps led to increased segregation, reduced home ownership, lowered home values and credit scores, and decreased upward mobility
  - Effects peak around 1970 to 1980 and then wane
  - Boundaries drawn 80 years ago are reflected in measures of financial well-being today
- Long-run effects differ by border type and by city
  - Housing and credit market effects in “yellow-lined” areas bigger and more persistent than redlined areas. Potentially important for thinking about channels.
  - Work in progress explores heterogeneity by city.

Data

HOLC Maps and Data:

- Originally drawn for 239 cities with a population of 40,000 or more. We obtained geocoded maps of 149 cities from the University of Richmond Digital Scholarship Lab.
- We have also done textual analysis of detailed area description files

Census Data

- 1910 - 1940 100% count of geocoded address-level data
- 1950-1980: Census tract aggregate data
- 1990, 2000, 2010: Block-level aggregate data

NY Fed Consumer Credit Panel/Equifax, 1999-2016

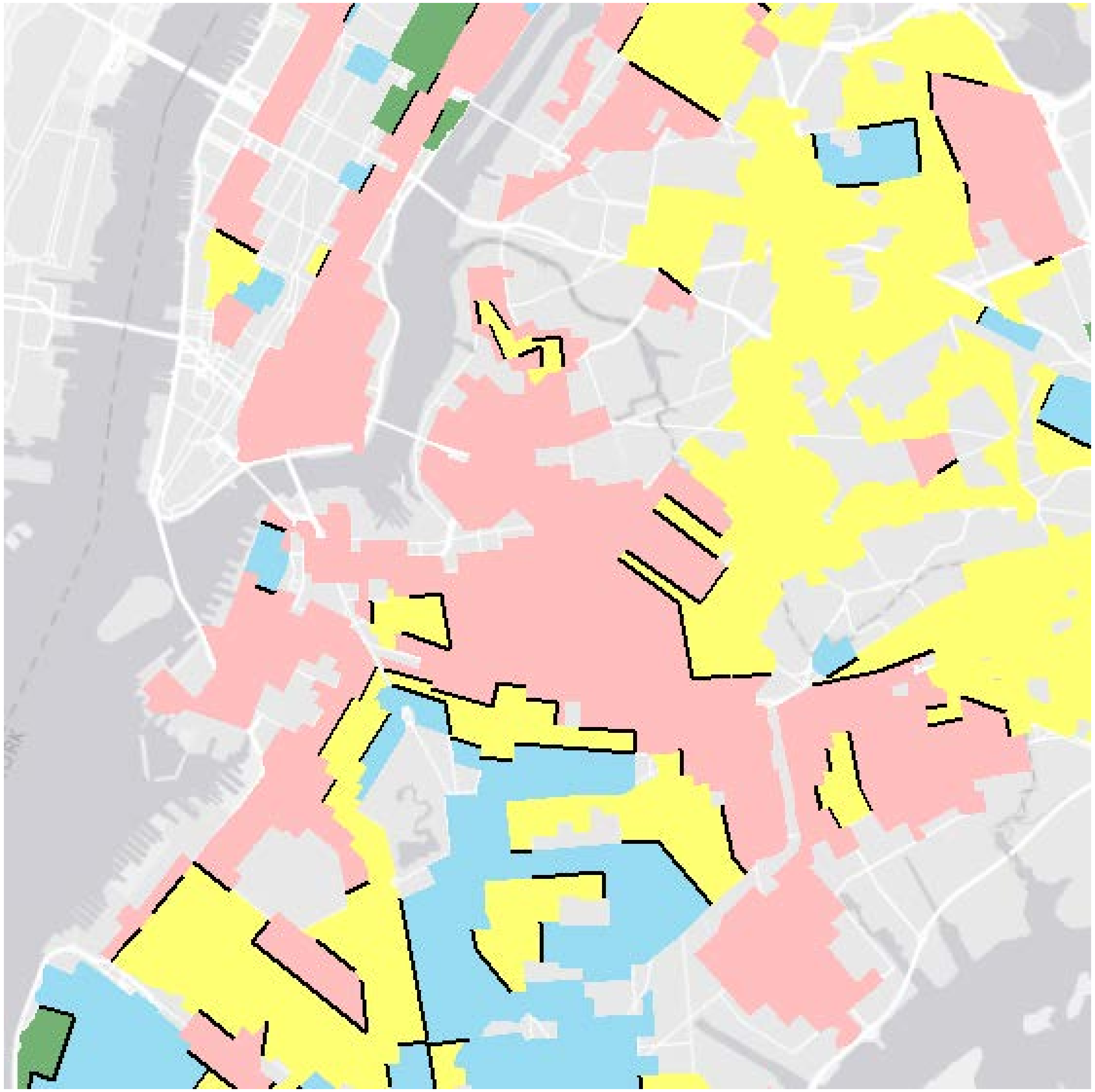
- ~20% sample
- Block-level
- Credit scores, indicator for subprime

Methodology: Border Design

- We *differentiate D-C borders from C-B borders*
- Create 1/8, 1/4 mile buffer zone along borders

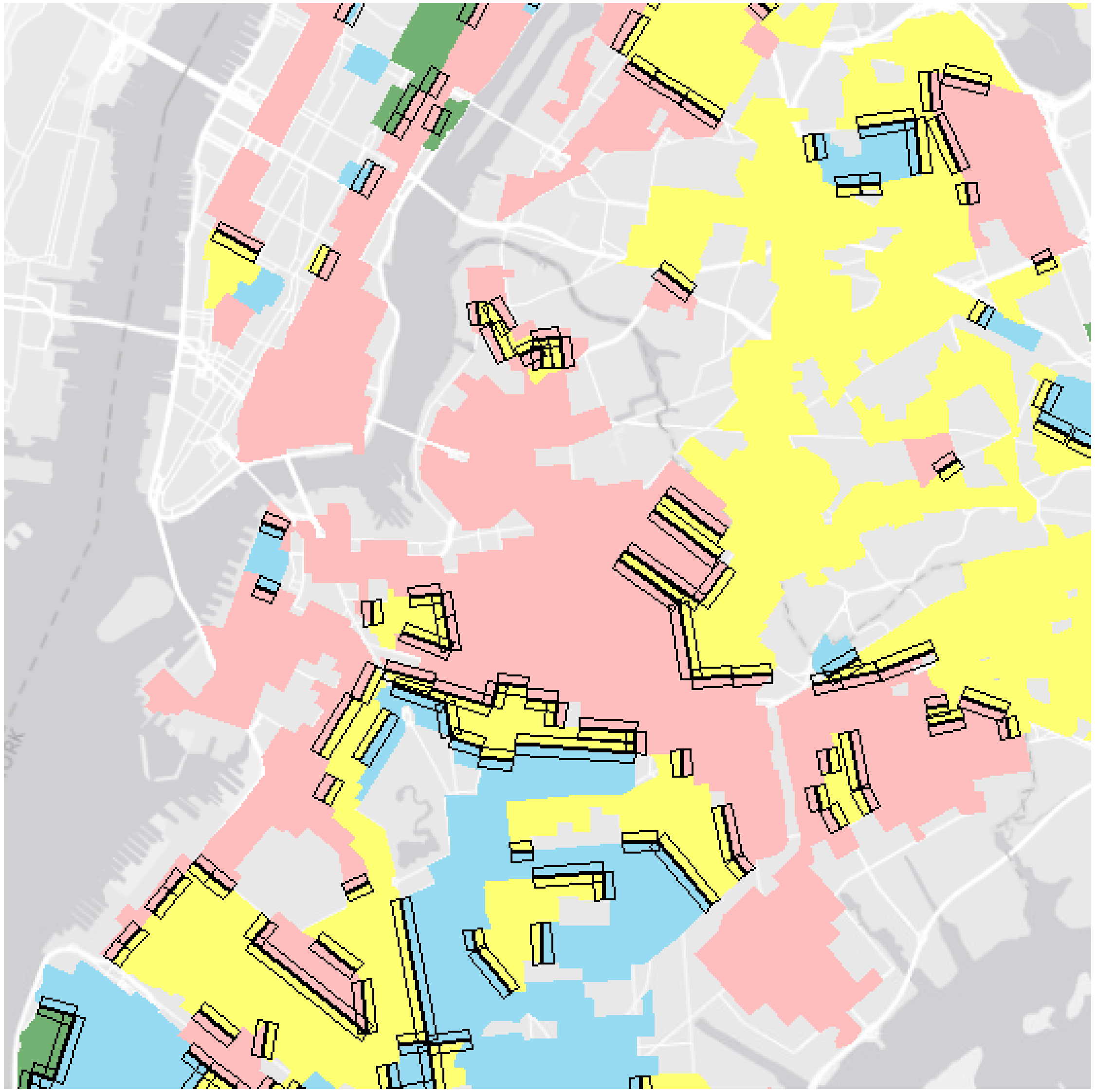
1) Identify Different Grade Boundaries

Example: New York City



2) Create Boundary Buffer Zones

(1/8 mile buffer around HOLC boundaries that are over ¼ mile in length)



Methodology: Border Design

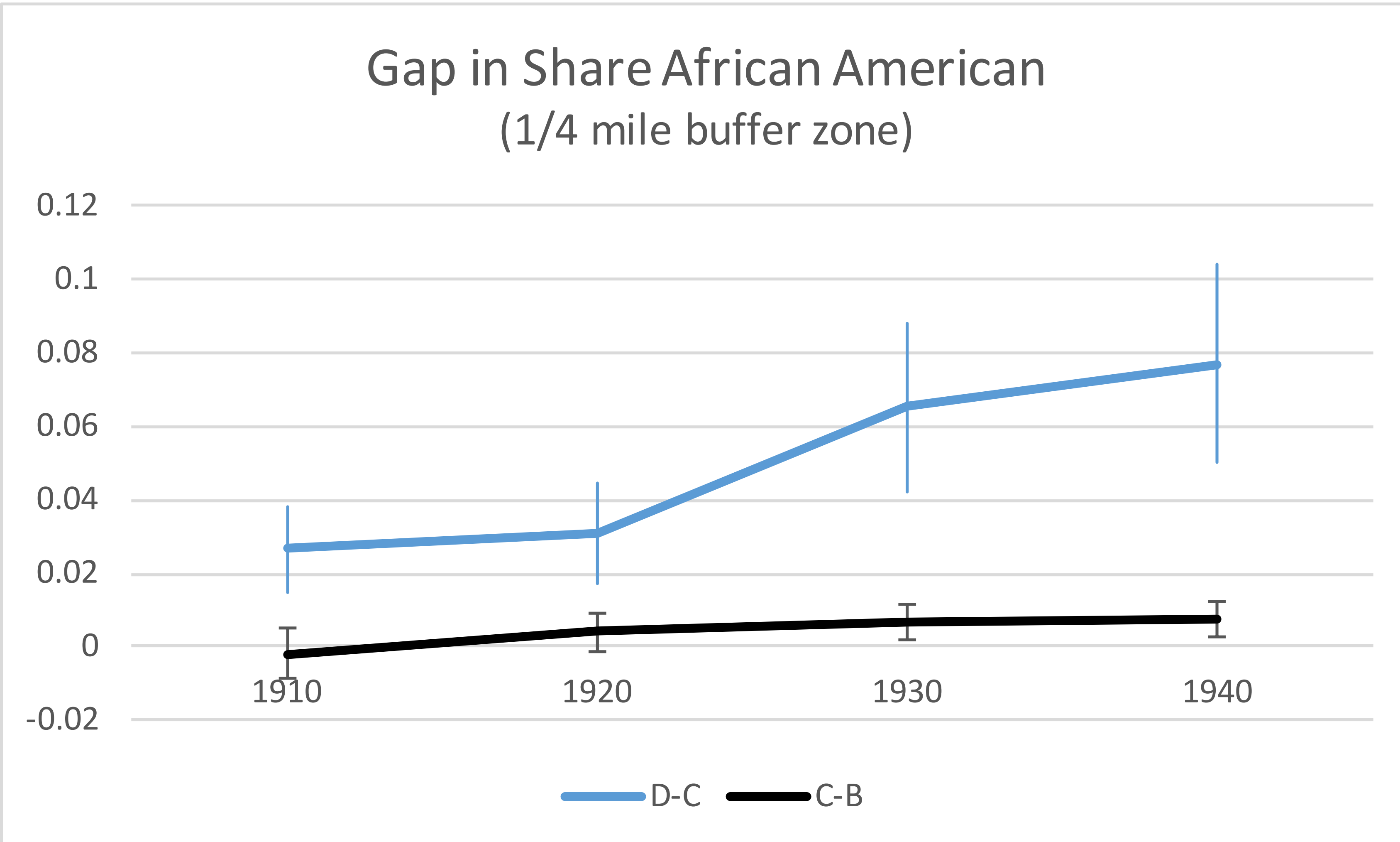
- We *differentiate D-C borders from C-B borders*
- Create 1/8, 1/4 mile buffer zone along borders
- Using address level micro data from 1910-1930, we show that:

  1) Border Diff in Diff sometimes fails parallel trends assumption

  2) RD assumption of discontinuity along the border fails

  - Pre-trends in gaps are growing along D-C borders from 1910-1930
  - Clear pre-map discontinuities using fine grain cells (15 meters)

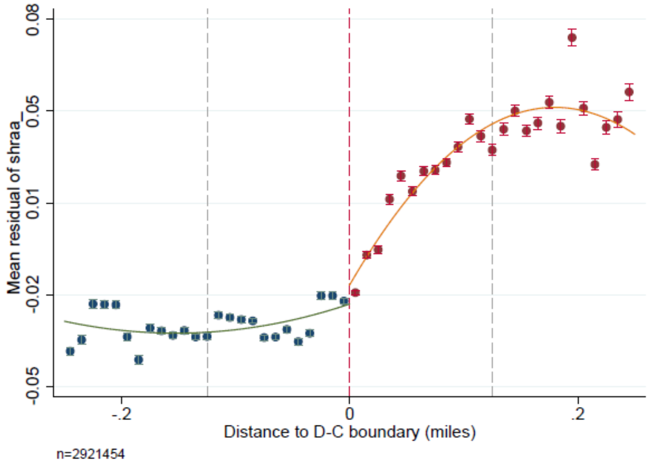
Parallel Trends Holds for C-B … but not for D-C



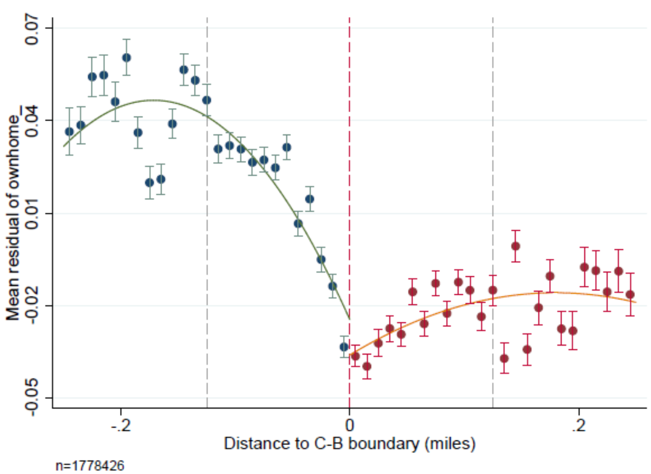
RD Assumption of Continuity Violated

Appendix Figure A2: Distance plots around HOLC Borders

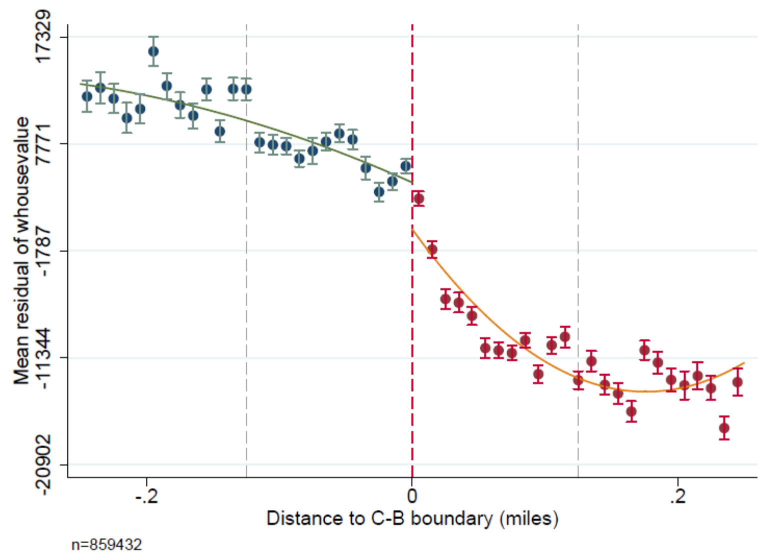
Panel A: African American Share, 1930, C-D boundaries



Panel B: Home Ownership, 1930, B-C Boundaries



Panel C: House Values, 1930, B-C Boundaries



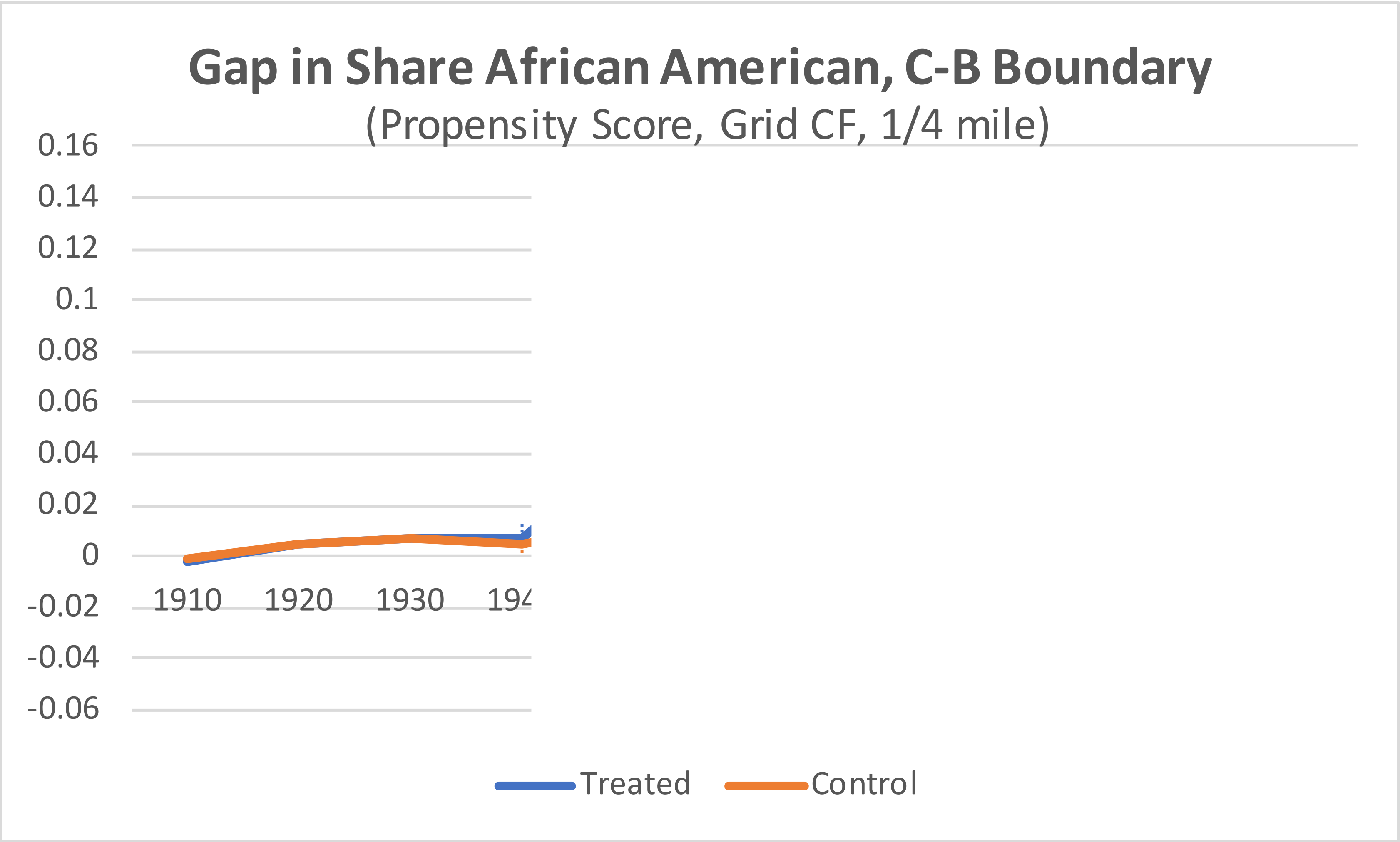
Note: Each dot here is 50ft or 15m

Methodology: Border Design

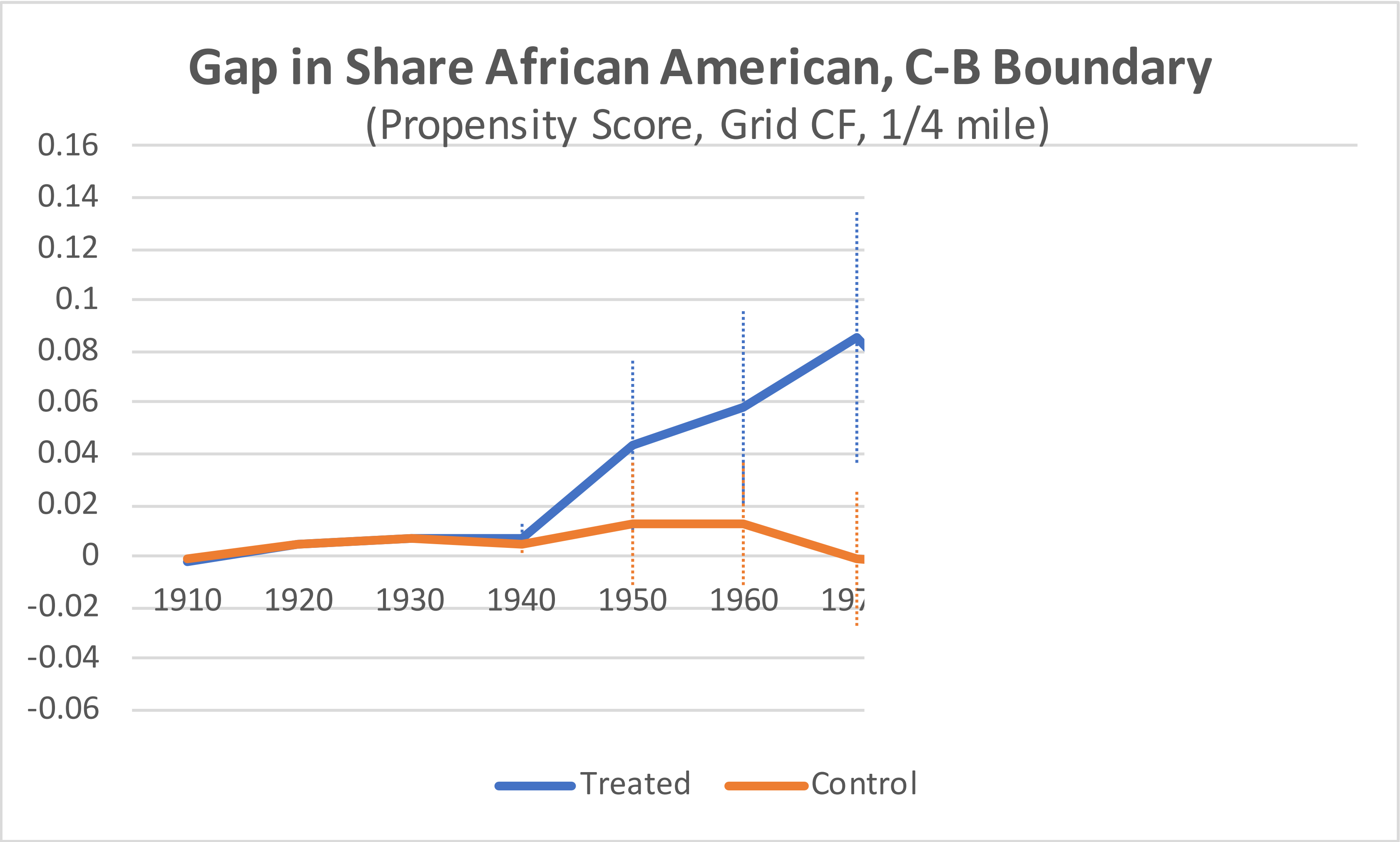
- We *differentiate D-C borders from C-B borders*
- Create 1/8, 1/4 mile buffer zone along borders
- Using address level micro data from 1910-1930, we show that:
  1) Border Diff in Diff sometimes fails parallel trends assumption
  2) RD assumption of discontinuity along the border fails
  - Pre-trends in gaps are growing along D-C borders from 1910-1930
  - Clear pre-map discontinuities using fine grain cells (15 meters)
- **Alternative Approaches:**
  - Highlight C-B where diff in diff assumptions are highly plausible
  - Compare treated borders to a set of counterfactual boundaries we create using propensity score (synthetic control method) on observables. Look for boundaries that could have been drawn based on pre-existing gaps (but weren't)
  - Use only subset of idiosyncratic borders (counterfactual boundaries with lowest likelihood for being drawn based on p-scores --RD assumptions actually hold here)

Results

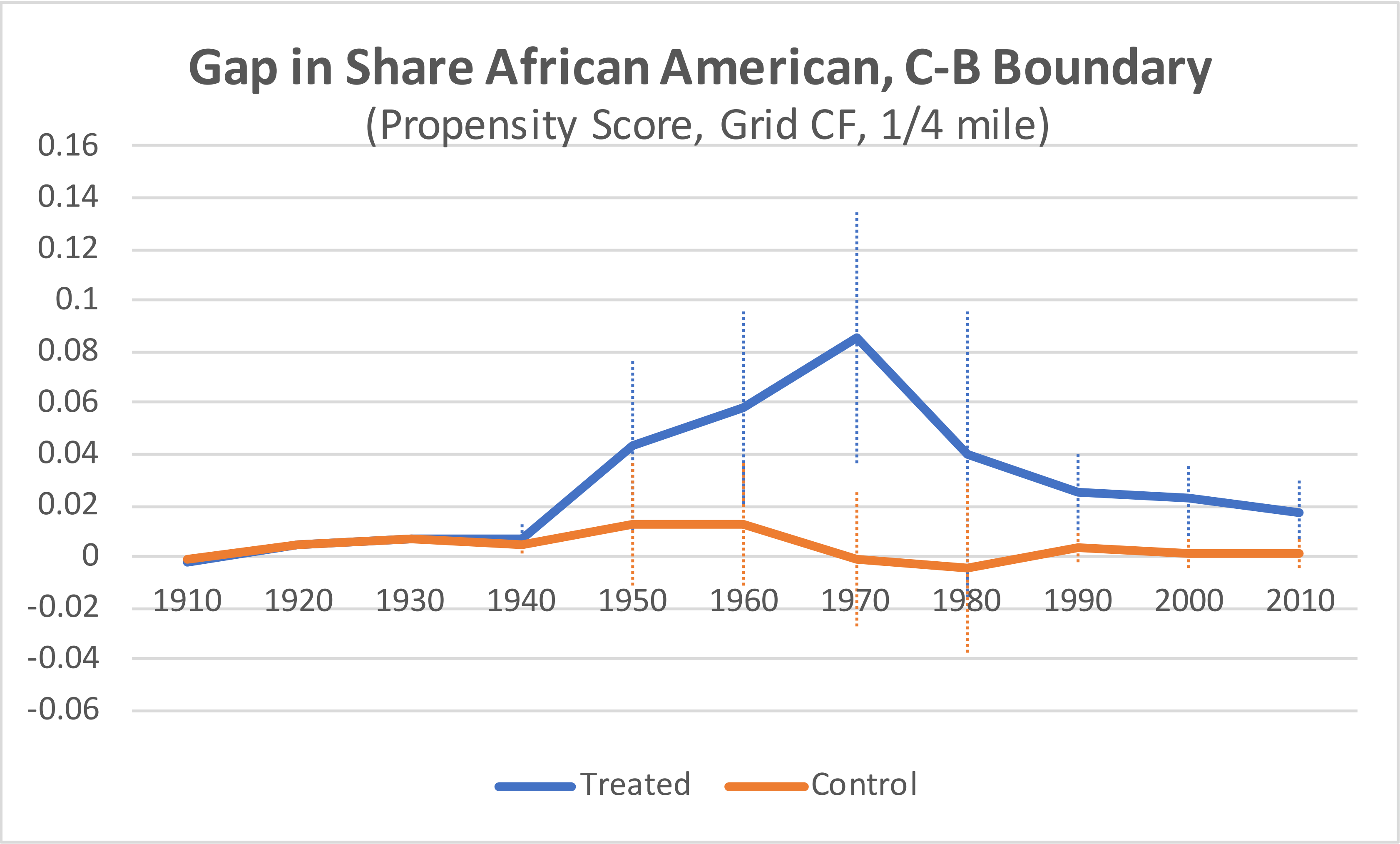
Effects on Segregation (C-B)



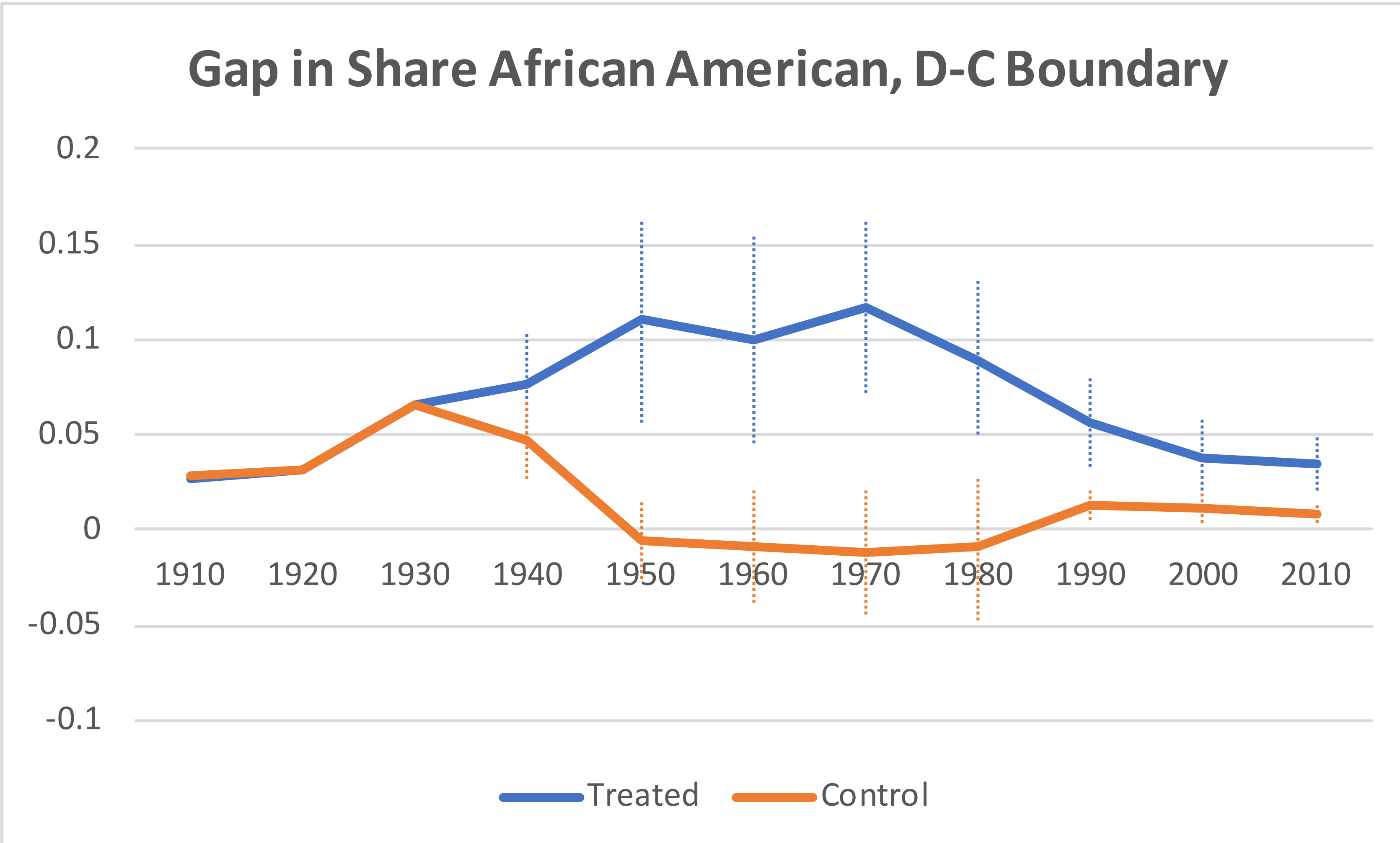
Effects on Segregation (C-B)



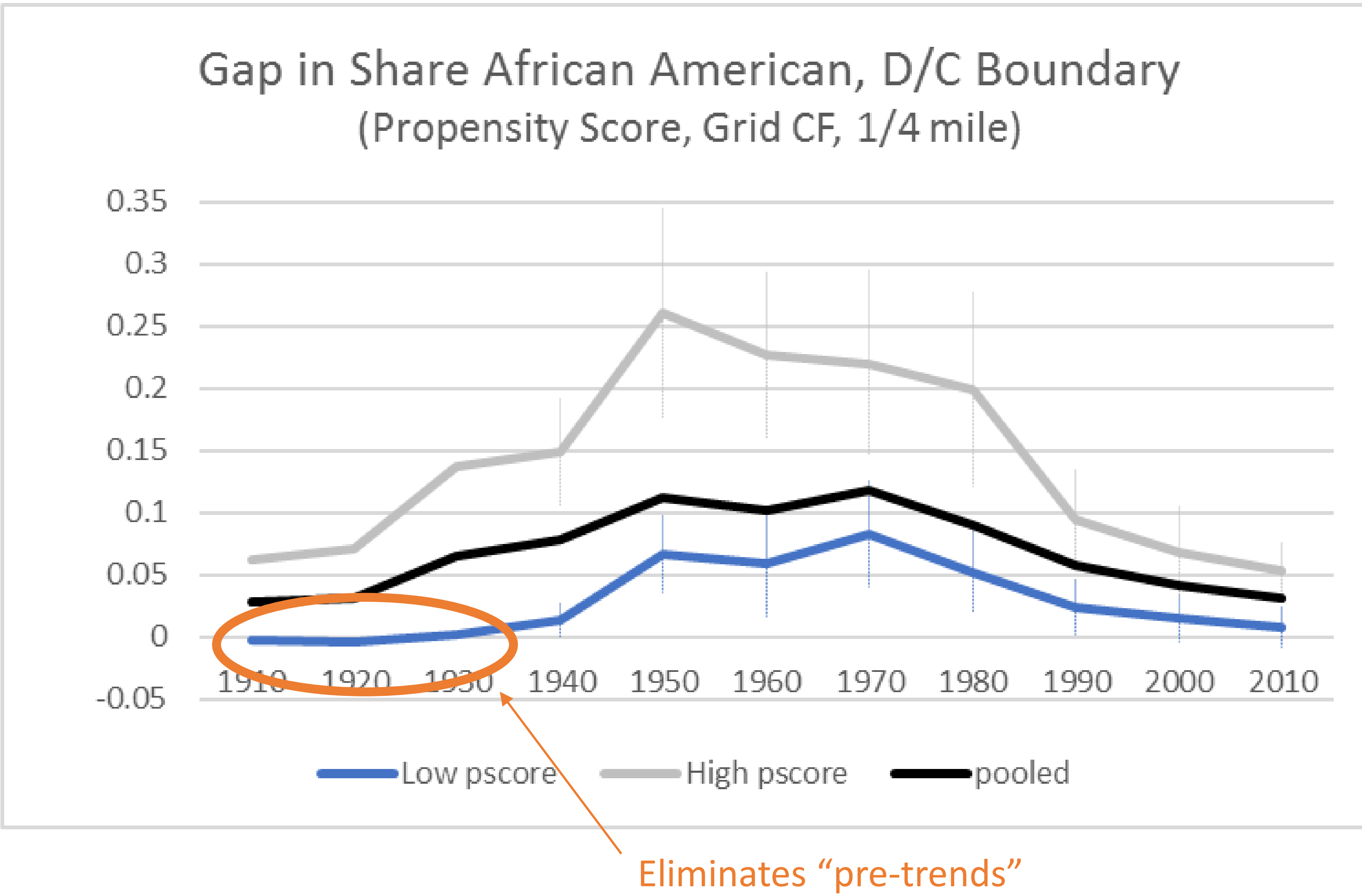
Effects on Segregation (C-B)



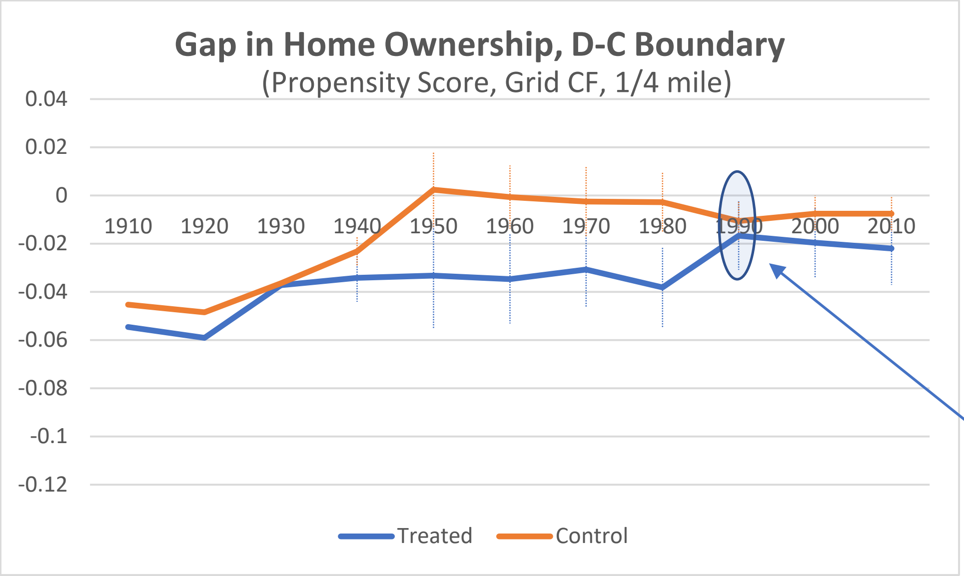
Effects on Segregation (D-C)

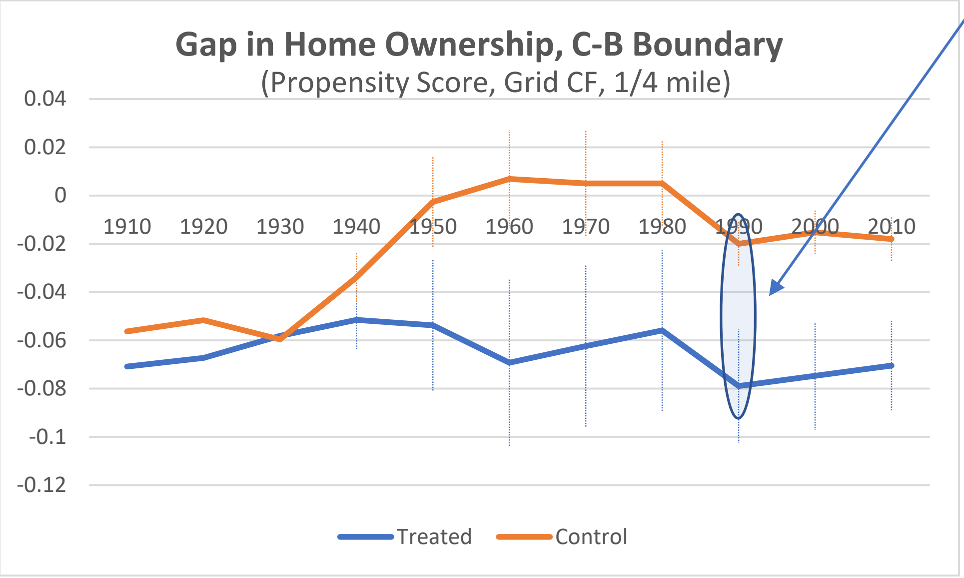


Effects on Segregation (D-C): Comparing Low vs High Propensity for Treatment



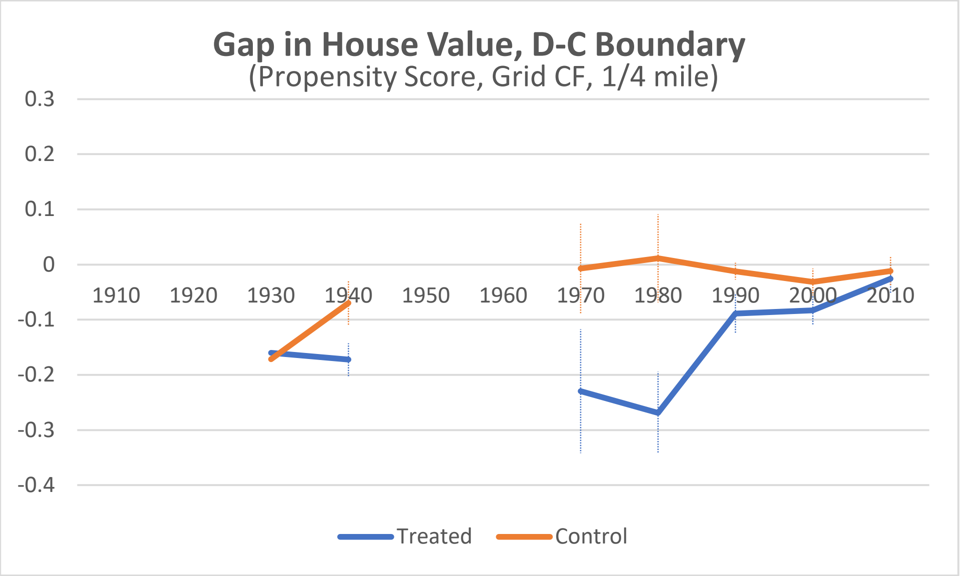
Home Ownership Results

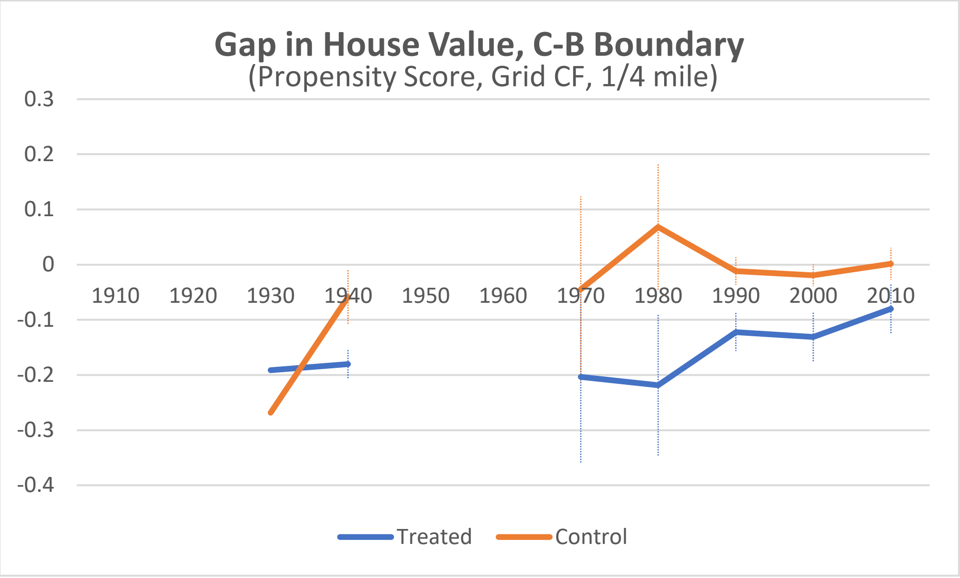




This is 1990

House Value Results

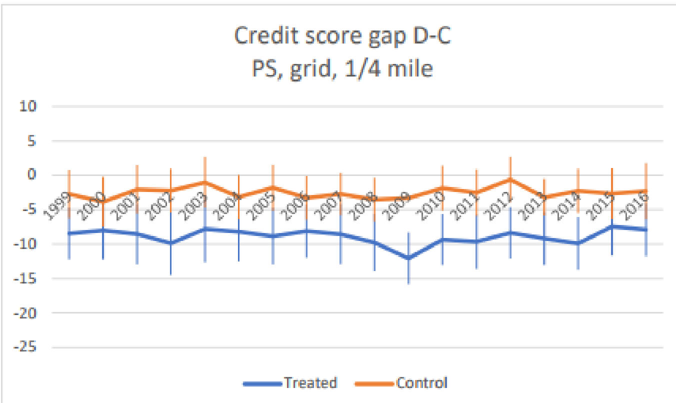




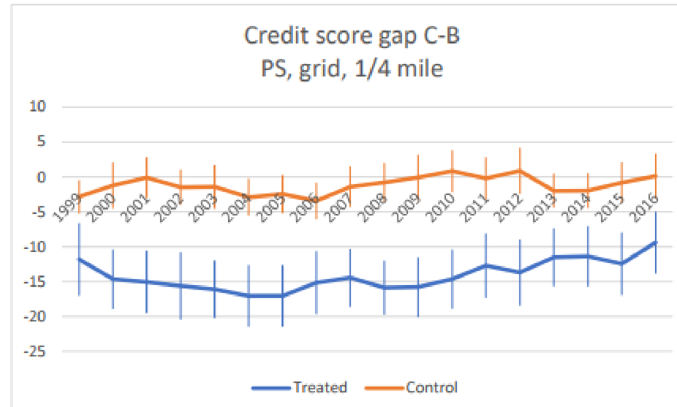
Effects on Modern Credit Scores

Figure 11: Effects on D-C and C-B Gaps in Credit Scores

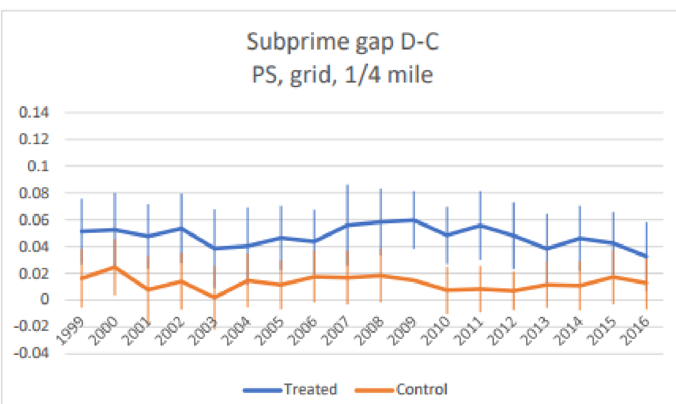
Panel A: D-C Gaps in Credit Scores



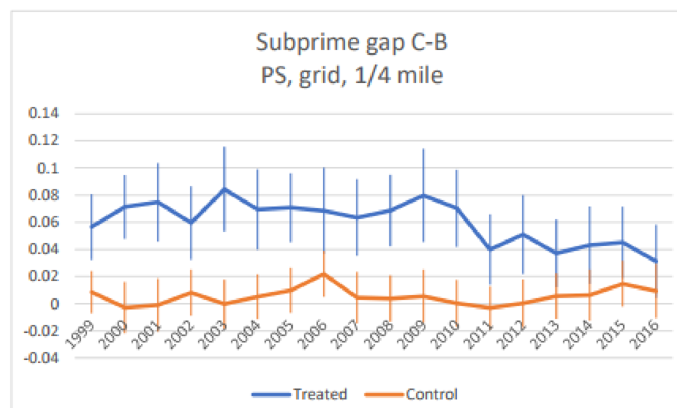
Panel C: C-B Gaps in Credit Scores



Panel B: D-C Gaps in Subprime



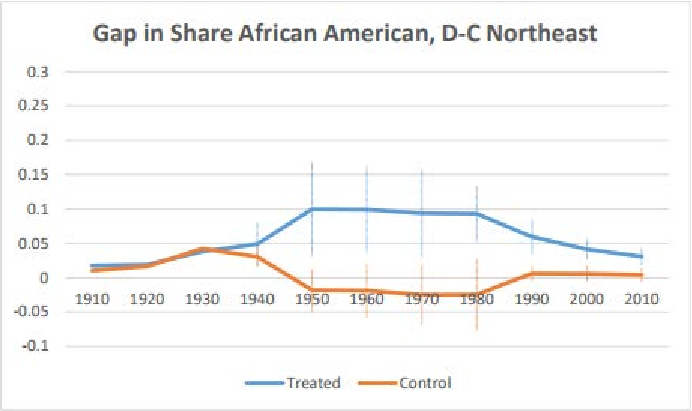
Panel D: C-B Gaps in Subprime



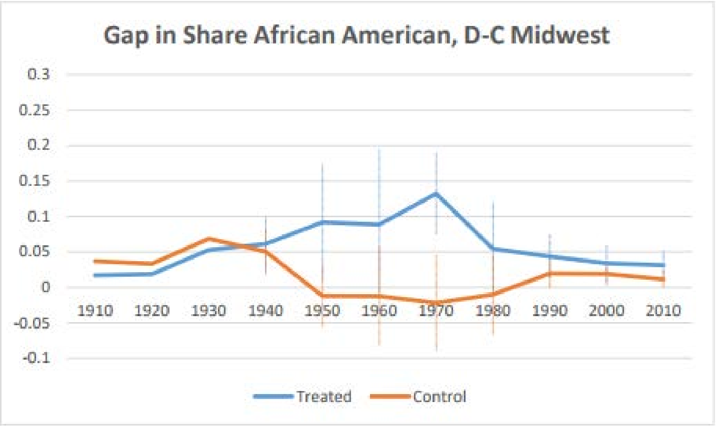
Source: FRBNY Consumer Credit Panel/Equifax

Segregation Effects by Region

Panel A: Northeast



Panel B: Midwest



Panel C: South

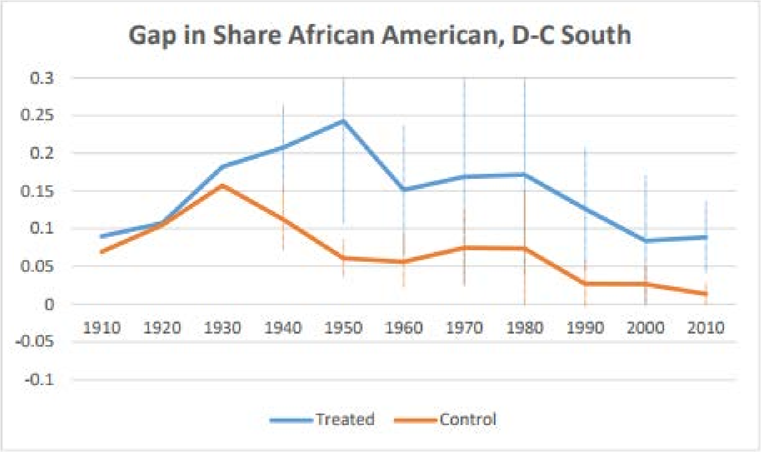
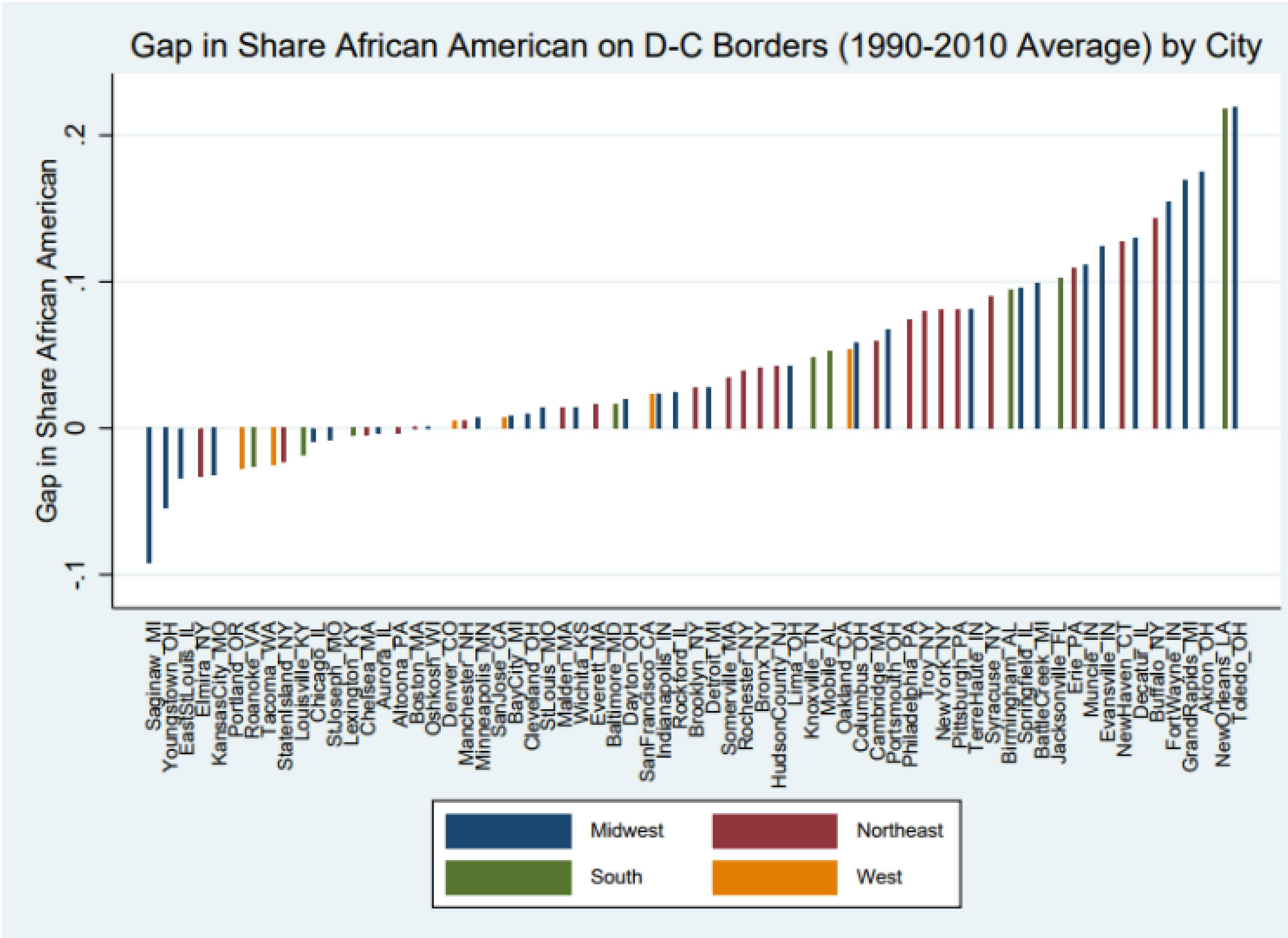


Figure 13: City-specific Gaps Along D-C and C-B Borders

Panel A: D-C Gaps in African American Share by City, Average 1990-2010



Concluding Thoughts

- Strongly suggestive evidence that maps had causal effects over subsequent decades (race, housing markets, credit markets). Account for 15-30 percent of *overall area gap*s in segregation and home ownership over 1950-2010.
- Effects on C-B borders (“yellow-lined”) are typically larger and more persistent. Is this due to policy, information, spatial investment?
- Evidence that effects peaked around 1970 or 1980.
- Fair degree of heterogeneity across regions, cities and neighborhood grades. Useful variation to try to better understand.
- Comparison with Appel and Nickerson
  - o Similar magnitude of effect size on home ownership in 1990
  - o But, many differences in data, research design and overall methodology
  - o Other important points of contrast: we find that border types matter and that neighborhood demographic composition changed dramatically.

Extra Slides

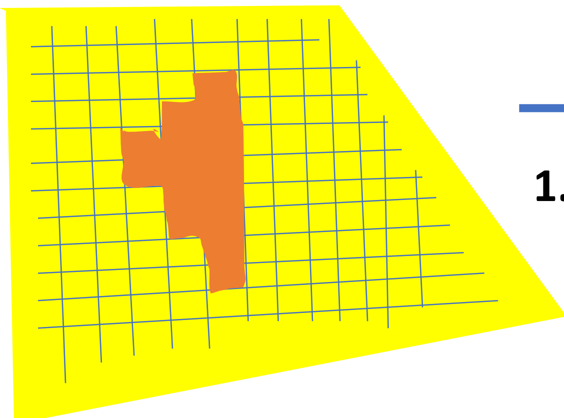
Identification strategy Part 2

- Problem: D-C boundaries were likely drawn where racial gaps were growing and where homeownership gaps existed. There may also be pre-existing trends in unobservables.
- Solutions:
  1. Create control boundaries that had similar characteristics and trends before the maps were drawn.
  2. Use only treated boundaries with minimal gaps pre-maps.

- Key Ideas:
  "Missing Borders" --some borders were not drawn because they were inside a natural neighborhood. These lend themselves to be "controls" (Chicago)
  "Misaligned Borders" --some borders might have been drawn at an arbitrary location, simply to close a polygon.

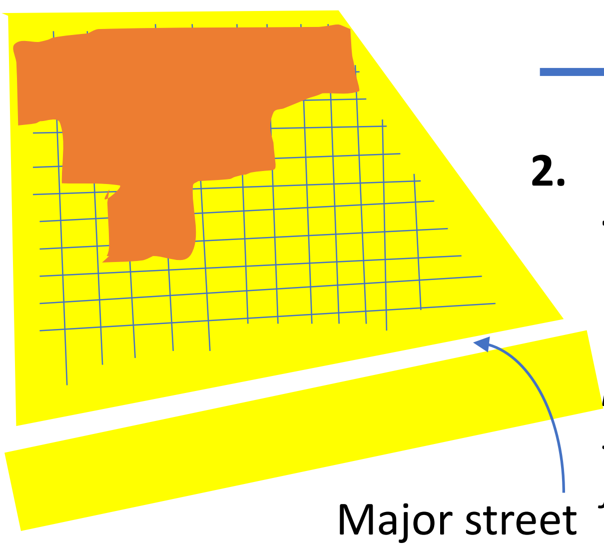
Potential Issues with HOLC Borders

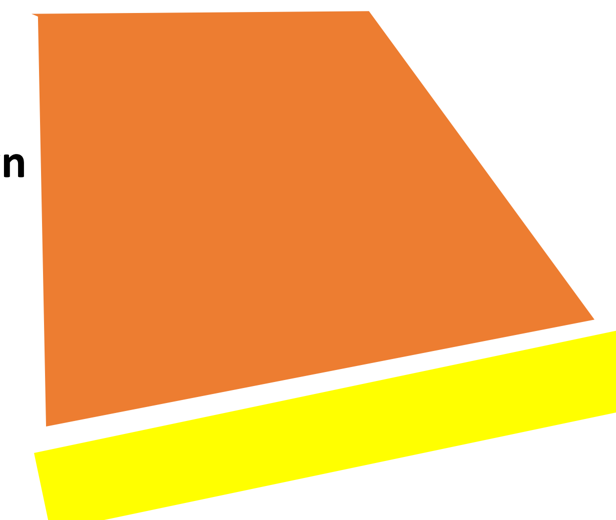
"Latent" Grades within areas



Actual Grades

1. **Missing interior borders**
   (these are potential controls)



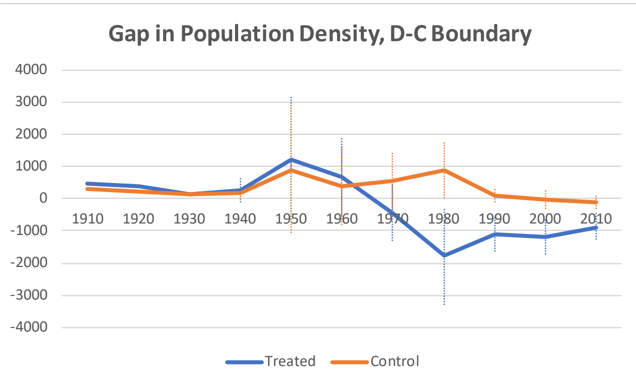


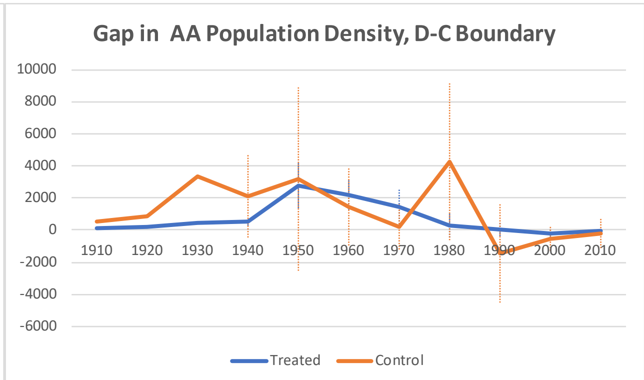
2. **"Misaligned" Borders drawn to close a polygon**

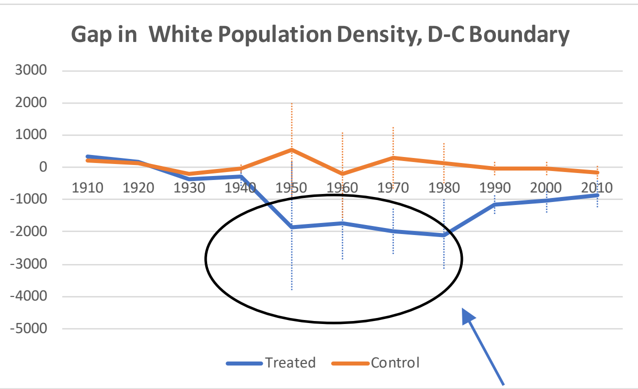
   Ex. Chicago D98: *"The eastern portion of the area is not quite so heavily populated with foreign element."*

Population by Race Dynamics Differ between D-C and C-B

D-C Boundaries

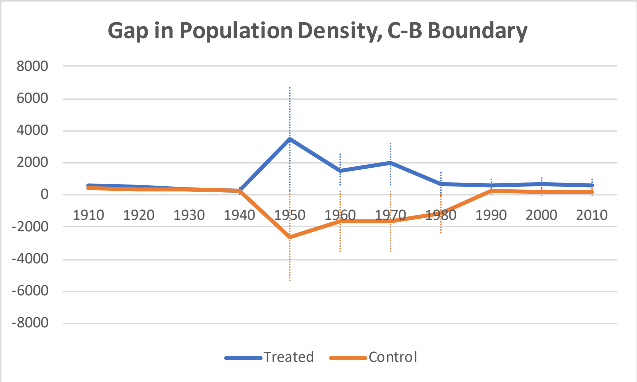


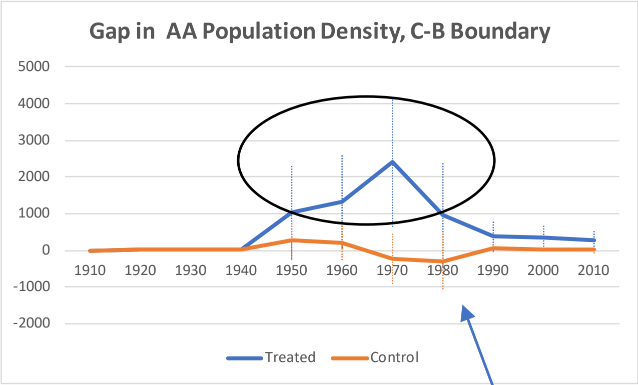


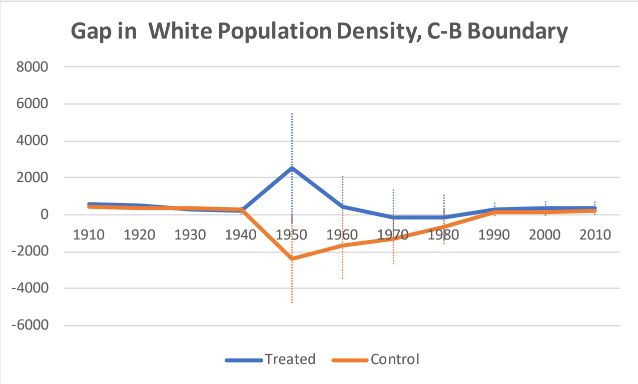


White flight

C-B Boundaries







Black in-flow

Note: a little less robust to methods.

Figure A5: Distance plot of AA Share Using Low Propensity Treated