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The long-run effects of the 1930s HOLC "redlining" maps on place-based measures of economic opportunity and socioeconomic success[☆]

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ABSTRACT

We estimate the long-run effects of the 1930s Home Owners Loan Corporation (HOLC) redlining maps on census tract-level measures of socioeconomic status and economic opportunity from the Opportunity Atlas (Chetty et al., 2018). We use two identification strategies to identify the long-run effects of differential access to credit along HOLC boundaries. The first compares cross-boundary differences along actual HOLC boundaries to a comparison group of boundaries that had similar pre-existing differences as the actual boundaries. A second approach uses a statistical model to identify boundaries that were least likely to have been chosen by the HOLC. We find that the maps had large and statistically significant causal effects on a wide variety of outcomes measured at the census tract level for cohorts born in the late 1970s and early 1980s.

1. Introduction

There is compelling evidence of substantial variation in the long-term socioeconomic success of children who grew up in neighborhoods near each other during the 1980s and 1990s (Chetty et al., 2018). However, we know little about *how* these geographic differences arose. In this study, we attempt to connect these contemporary geographic differences in economic opportunity with the historical "redlining" maps produced by the Home Owners Loan Corporation (HOLC), a Federal housing agency, during the 1930s. We hypothesize that the lack of access to credit in certain neighborhoods deemed risky at the time, could have led to substantial financial disinvestment and the resorting of families, resulting in significant place-based differences in the life-course consequences of children growing up generations later.

We build upon previous work by Aaronson et al. (2020), hereafter AHM, who develop methods to identify the causal effects of the HOLC maps on neighborhood trajectories with respect to segregation and housing. We combine their methodology with rich data from the Opportunity Atlas (Chetty et al., 2018), which offers measures on a broad range of socioeconomic outcomes including national income rank, family structure, incarceration, and geographic mobility. Overall, we find that growing up on the lower-graded side of a HOLC border had an economically large and statistically significant effect on the life chances of cohorts born several decades after the maps were drawn. The magnitude of the effects are typically about 4–12 percent of an outcome's respective sample mean. We also find that the estimates are larger along "yellow-lined" borders (borders that compare neighborhoods receiving a "C" grade to those that received a "B" grade) than "redlined" borders (borders that compare "D" graded neighborhoods to "C" graded neighborhoods), a finding consistent with AHM.[1] We confirm the economic significance of these results on an entirely different dataset covering modern day credit outcomes. The mean Equifax Risk Score™ is lower by

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[1] As we discuss below, neighborhoods were graded on a color-coded A to D scale with the highest graded A neighborhoods coded green, B neighborhoods coded blue, C neighborhoods coded yellow, and the lowest graded D neighborhoods coded red.

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about 8–9 points, and the share of borrowers that are subprime is about 3 percentage points higher, in neighborhoods that are on the lower graded side of HOLC borders.

Our study contributes to a growing body of work that has exploited newly accessible digitized versions of the HOLC maps. Previous work by AHM has examined the effects on racial segregation and housing outcomes (home ownership, house values and rents) over the 1940 to 2010 period. Related findings on racial segregation and housing outcomes can be found in Faber (2020), Appel and Nickerson (2016), and Krimmel (2017), and on crime in Anders (2019). Our analysis, however, is the first to demonstrate that there was a meaningful effect of this New Deal era housing policy on how neighborhoods impact labor market outcomes, family structure, incarceration, and credit scores.

These results provide new and striking evidence of how the impact of a federal intervention can have broad and long-lasting consequences, affecting economic activity and sorting into and out of communities, and ultimately creating areas of greater or lesser opportunity. It is therefore a reminder that to understand the landscape of urban inequality that exists today, we must look to the past and examine the unfolding consequences of social policies implemented many decades ago.

2. Background and prior evidence on the effects of HOLC maps

The Home Owners Loan Corporation (HOLC) was created in 1933 under the direction of the Federal Home Loan Bank Board (FHLBB) to help stem the tide of foreclosures caused by the Great Depression. The HOLC was primarily tasked with refinancing loans to homeowners at risk of foreclosure, and by 1936, they had refinanced roughly 10 percent of non-farm mortgages (Jackson 1985; Fishback et al., 2011; Nelson et al., 2019). Through this program, the HOLC played an important role in shifting housing finance from short duration loans with balloon payments to fully amortized higher loan-to-value mortgages with 15 to 20-year durations that are more akin to the modern housing finance system. This unprecedented federal investment in homeownership was succeeded by two even larger programs: the Federal Housing Administration (FHA) and the GI Bill (Dreier et al., 2005).[2] The combined influence of these policies made homeownership cheaper than renting in much of the country, helping to drive the homeownership rate from 44 percent in 1934 to 63 percent in 1972 (Jackson 1985).

The HOLC was also instructed by the FHLBB to introduce a systematic appraisal process that included neighborhood-level characteristics when evaluating residential properties. This directive was motivated by concerns over the health of the lending industry, which was devastated by the foreclosure crisis (Hillier 2005; Nicholas and Scherbina 2013), coupled with the Federal government's new, large stake in the value of residential real estate. The FHLBB wanted to ensure the continued stability of property values throughout the nation and was looking for a mechanism that would solve the coordination problem between the Federal government and private lenders (Hillier 2005).

The HOLC's practice of lending risk assessment included an important spatial component. Appraisers and other real estate professionals were hired to grade neighborhoods based on housing quality, proximity to industry, and the characteristics of a neighborhood's residents. The presence of immigrants, poor households, and non-White racial groups were considered detrimental to a neighborhood's assessment (Connolly 2014; Jackson 1985).[3] Grades were on a scale from A to D, with A indicating the lowest lending risk and D indicating an area in decline. The HOLC created color coded "Residential Security Maps" for appraised cities, in which A neighborhoods were colored green, B were colored blue, C were colored yellow, and D were colored red. The origin of the term "redlining" is likely due to the difficulty of securing a mortgage if one lived in a D graded neighborhood. Ultimately, the HOLC drew residential "security" maps for 239 cities between 1935 and 1940 and completed more than 5 million appraisals.

The HOLC grades and associated maps were subsequently shared with the FHA, who drew their own maps that influenced the provision of mortgage insurance, as well as other government agencies. There is also anecdotal evidence that the maps likely filtered out to private lenders, though this is an area of dispute among researchers, since the HOLC only made a limited number of maps which were, as a matter of policy, not supposed to be shared (e.g. Connolly 2014; Jackson 1980; Hillier 2003; Greer 2012; Aaronson et al. 2020).

In any event, over subsequent decades, billions of dollars of affordable loans flowed to predominantly white and suburban communities, while urban communities of color were mostly left out (Rothstein 2017). By conflating race and mortgage risk, the HOLC and FHA policies may have contributed to subsidizing suburbanization among whites while leading to financial disinvestment in many urban areas. This has led some observers to argue that the practices of these Federal agencies played a role in the high levels of segregation during the middle of the twentieth century (Hirsch 1983; Massey and Denton 1993; Sugrue 1996; Logan 2016; Rothstein 2017). Other researchers note that the acceleration of urban segregation pre-dates 1930s government housing and credit policies and therefore has broader roots (e.g. Cutler et al. 1999; Logan and Parman, 2017; Shertzer and Walsh 2019).

Research on the impact of HOLC maps is not designed to settle this debate, but rather to identify the causal effect of redlining on the long-run outcomes of neighborhoods and the individuals who have resided in them over time. Previous research has largely focused on the trajectories of neighborhoods in decades following the HOLC maps with respect to housing outcomes and segregation. This analysis focuses on a broad set of socioeconomic outcomes of residents who grew up in the neighborhoods many decades after the maps were drawn.

3. Data

Our goal is to estimate the causal long-run effect of the 1930s HOLC maps on the economic mobility of cohorts born decades later. We primarily consider a number of outcomes developed in the Chetty et al. (2018) Opportunity Atlas, which have been used recently in many contexts (e.g. Kearney and Levine 2014; Goodman and Isen, 2015; Bailey et al., 2017; Sharkey and Torrats-Espinosa 2017; Derenoncourt 2018; Figlio et al., 2019; Rothstein 2019; Card et al. 2019; and Davis et al., 2019). We begin with a brief description of the underlying data.

3.1. HOLC maps

We obtained geocoded renderings of the original HOLC maps from the Digital Scholarship Lab (DSL) at the University of Richmond. While the maps for 149 of the 239 redlined cities have been digitized by DSL, as we discuss below, the geographic scale of the Opportunity Atlas data leaves us with only 30 useable cities for our analysis.[4] Each city contains many graded neighborhoods, and in some cases adjacent neighborhoods may receive different grades. We assign an ID to each straight line

[2] In addition, the Federal National Mortgage Agency (FNMA) was introduced in the late 1930s, which created a secondary home loan market.

[3] This can be seen in the area description files associated with the maps that have a free text field where there are many examples of how race and ethnicity were decisive factors in a neighborhood grade.

[4] These cities are Baltimore (MD); Bay City (MI); Boston (MA); Bronx (NY); Brooklyn (NY); Buffalo (NY); Cambridge (MA); Chicago (IL); Cleveland (OH); Detroit (MI); Erie (PA); Evansville (IN); Hudson County (NJ); Indianapolis (IN); Manchester (NH); Minneapolis (MN); New Britain (CT); New Haven (CT); New Orleans (LA); New York (NY); Oakland (CA); Philadelphia (PA); Pittsburgh (PA); Rochester (NY); San Diego (CA); San Francisco (CA); Somerville (MA); St. Louis (MO); Staten Island (NY); Toledo (OH). Not every city has useable D-C and C–B boundaries. Cities are defined based on the Census 2000 place boundary shape file. This restriction primarily discards suburbs.

Table 1
Census Characteristics of Boundaries in Our Sample vs. AHM (2020).

1910–1930 Census characteristics	D-C			C–B		
	Our sample	AHM sample	Difference p-value	Our sample	AHM sample	Difference p-value
Share African-American gap, 1930	0.040	0.061	0.243	0.004	0.006	0.830
Share African-American gap, 1920	0.021	0.030	0.506	−0.008	0.004	0.181
Share African-American gap, 1910	0.030	0.025	0.757	−0.013	0.000	0.350
Home ownership gap, 1930	−0.026	−0.032	0.736	−0.060	−0.056	0.855
Log house value gap, 1930	−0.151	−0.153	0.975	−0.219	−0.182	0.499
Log rent gap, 1930	−0.109	−0.124	0.633	−0.169	−0.127	0.381
Population density gap, 1930	2594.2	91.0	0.001	1214.7	401.7	0.357
African American pop density gap, 1930	841.5	448.8	0.035	28.0	36.7	0.838
White population density gap, 1930	1752.7	−357.9	0.003	1186.7	365.0	0.348
Sample size	91	1133		42	736	

segment of an HOLC boundary that is at least a quarter mile in length and where grades differ by one letter between neighborhoods on each side.[5] We then draw rectangular areas that extend a quarter of a mile on each side of a boundary. We refer to these areas as boundary buffer zones or simply buffers. Each boundary has two such buffers – the lower graded side (LGS) and higher graded side (HGS). We also refer to boundaries that divide a D neighborhood from a C neighborhood as "D-C" and those separating B and C areas as "C–B."[6]

3.2. The Opportunity Atlas and decennial censuses

Two sets of data are fit to the quarter mile or longer rectangular buffer zones: characteristics from the 1910 to 1930 decennial censuses and outcomes from the Opportunity Atlas. On the former, we use the 1910 to 1930 100 percent Census population counts from Minnesota Population Center and Ancestry.com (2013). We are able to match roughly 50 to 80 percent of respondents to HOLC neighborhoods.[7] We aggregate census measures to the buffer zone by taking the mean of all observations which fall inside of a buffer zone so long as it contains at least 3 households.

The Opportunity Atlas provides census-tract level estimates of a rich set of socioeconomic outcomes pertaining to cohorts born between 1978 and 1983. The measures are derived from a combination of administrative records, such as IRS tax filings, and Census Bureau surveys, such as the decennial Census and the American Community Survey.[8] Those records allow the Opportunity Insights researchers to compute an exposure-weighted average of the census tracts these birth cohorts lived in from age 0 through age 23, and thus to estimate the effect of growing up in a particular census tract on outcomes later in life. In turn, we assign Opportunity Atlas outcomes to boundary buffer areas using the outcomes of any census tract where at least 15 percent of the tract's area lies within a buffer zone. We take the population-weighted mean outcome if multiple census tracts overlap with a buffer zone.[9]

Unfortunately, we lose many boundaries because of the 15 percent overlap requirement, which trades-off accurate representation of buffer zone populations with statistical power for estimation.[10] Related, and as discussed in the next section, our identification strategy relies on boundary fixed effects, which requires that *both sides* of a boundary contain separate census tracts that reach the 15 percent minimum threshold. Ultimately, these assignment rules result in samples that utilize 91 HOLC and 136 comparison D-C boundaries and 42 HOLC and 69 comparison C–B boundaries that meet our criteria.

One concern is that these rules induce sample selection bias. In particular, the useable buffer zones may over-represent more densely populated, compact land area tracts and therefore compromise external validity.[11] To address this issue, Table 1 compares differences in 1910 through 1930 Census characteristics across the sample of D-C and C–B HOLC boundaries used in this paper to the larger set of D-C and C–B boundaries used in AHM. Columns 1, 2, 4, and 6 reveal roughly similar buffer zone gaps in African American share, homeownership rate, home values, and rents in our selected sample as compared to the full sample from AHM. As expected, however, there is a large difference between our sample and the AHM full sample in terms of population density differences along D-C boundaries. This is reflected in the p-values shown in column 3. For C–B boundaries, however, Column 6 shows there is no statistically significant differences between our sample and the full AHM sample, even for population density.

We use a number of Opportunity Atlas measures, most of which capture adult outcomes that occurred in the late 2000s and early 2010s. With respect to intergenerational economic mobility, these include:

1) expected household income rank in adulthood
2) expected household income rank at age 29
3) probability of reaching the top quintile in the income distribution in adulthood
4) fraction living in a low poverty (<10 percent) neighborhood in adulthood
5) fraction working during adulthood.[12]

Other measures include incarceration, marriage, and geographic mobility:

6) probability of incarceration in adulthood
7) fraction married during adulthood
8) fraction living in the same census tract.[13]

We also explore several family structure measures that are directly tied to the childhood or teenage experience of the Opportunity Atlas

[5] In the spirit of analyzing similar neighbors separated by a boundary, we do not look at boundaries separated by more than one grade (e.g. D versus B).

[6] There are not enough A neighborhoods to estimate effects along A-B boundaries.

[7] In the 1910, 1920, and 1930 censuses, 73, 72, and 99 percent of household heads have a street address. Of those, we are able to successfully geocode 63, 68, and 79 percent to modern street locations. Most of those are then assignable to HOLC neighborhoods. See AHM for a detailed discussion of the sample and possible selection issues.

[8] See Chetty et al. (2018) for more detail.

[9] If a tract overlaps both sides of a boundary's buffers, it gets included in the average of the side where it has the greatest overlap.

[10] Reasonable alternative overlap thresholds, such as 10 and 20 percent, do not change any of our inferences.

[11] Census draws tracts so that they contain about 4000 people on average, thus tracts with higher population density typically cover less land area.

[12] The first four measures come from 2014 or 2015 IRS tax filings. The fraction working during adulthood comes from whether an individual has positive 2015 W2 income or self-reported weeks worked in the ACS.

[13] Incarceration is measured from the 2010 decennial Census. Marriage is from filing a joint tax return in 2015. Fraction living in the same tract or commuting zone is based on an individual and their parent's addresses from 2015 1040 or W2 records.

cohorts:

9) fraction living with a male tax claimer during childhood
10) fraction with two adult tax claimers during childhood
11) teenage birthrate of women.

We concentrate primarily on six measures—2, 3, 4, 6, 10, and 11—which we believe capture the range of important dimensions of long-run socioeconomic success available in the Atlas. The remaining five measures are referenced in the results section but, for the sake of brevity, are relegated to the Appendix.[14]

3.3. Credit bureau data

We supplement the Opportunity Atlas with credit bureau data from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (CCP). The CCP covers roughly 5 percent of the population and provides block-level credit data between 1999 and 2016. We use two measures: a) mean of the Equifax Risk Score™ and b) the share of borrowers that are subprime, traditionally measured by Equifax as a score below 620.[15]

3.4. Summary statistics

Table 2 provides summary statistics of the Opportunity Atlas and credit score measures by HOLC neighborhood (left panel) and boundary buffer zones (right panel). Unsurprisingly, the neighborhood-level statistics show that children who grew up in higher graded neighborhoods have higher levels of success. For example, children who grew up in D-graded neighborhoods had about an 11 percent chance of reaching the top income quintile while the comparable statistic for children who grew up in A-graded neighborhoods is 23 percent. Most of the outcomes improve monotonically with HOLC grade. The boundary buffer-level statistics on the right-hand side of the table reveal similar, though slightly muted, differences when moving from the lower-graded side of a boundary buffer to the higher-graded side.

4. Methodology

Our strategy is guided by the historical narrative that the creators of the HOLC maps explicitly considered neighborhood characteristics and their trends when drawing borders. This means that a simple strategy of using cross-boundary differences (or a regression-discontinuity design) would be insufficient. Indeed, AHM show that there were sharp differences in racial composition, homeownership rate, home values, and rents that existed along the borders prior to the creation of the maps in the 1930s. We also do not have a set of outcomes that are equivalent to the Opportunity Atlas measures from a pre-HOLC map period. This means that we cannot make pre-vs post-map comparisons, or implement a simple difference-in-difference strategy.

Instead, we follow two identification strategies used in our previous work. In the first approach, we start with a standard boundary-based design where we make comparisons across actual HOLC boundaries separating one grade difference neighborhoods, i.e. either D versus C (the D-C border) or C vs B (the C–B border). Fig. 1 provides a visual example from New York City. The black lines in the map represent the segments of relevant borders. Our strategy compares nearby neighbors that live within a 1/4 mile (1320 feet) from these boundaries. In particular, for each border segment, we difference the characteristics of households living on the higher-graded side to the lower-graded side. By concentrating on these nearby neighbors, we can remove potentially important, but typically hard to measure, confounding factors, such as nearby amenities and labor market opportunities, which influence residents on both sides of a border.

However, this differencing strategy is typically not enough for our context. As an example, the blue line in Panel A of Fig. 2 plots the average gap in share African American along D-C borders using the 1910 to 1930 100 percent Census population counts (Minnesota Population Center and Ancestry.com, 2013). A positive gap shows that the share African American was larger on the D side than the C side of the border as early as 1910 and, if anything, growing in size prior to the drawing of the maps in the 1930s. That is, there is a clear pre-trend.[16] Moreover, the border design will likely not satisfy the assumption of continuity, as exemplified again with share African American along the D-C border as an example in Appendix Figure A1.[17]

To deal with these problems, we construct a set of *comparison boundaries* that mimic the pre-existing characteristics of neighborhoods around HOLC borders. The comparison borders are derived from a randomly placed half-mile by half-mile grid that is overlaid on every HOLC city. An example of this for New York City is shown in Appendix Figure A2. We construct 1/4-mile buffer zones around each line segment that does not overlap with an HOLC boundary. We then pool these line segments with the actual treated HOLC borders and estimate the probability that a line segment is an HOLC border, conditional on observable characteristics as measured in the 1910, 1920, and 1930 decennial censuses. Specifically, we estimate the following probit from a pooled sample of treated HOLC border segments and the control border segments derived from half mile-by-half mile city grids:

$$1\{Treated\}_{b,c} = \alpha_c + \sum_{k=1}^{K} \beta^k_{1910} z^{k,1910}_{b,c} + \beta^k_{1920} z^{k,1920}_{b,c} + \beta^k_{1930} z^{k,1930}_{b,c} + \varepsilon_{b,c} \tag{1}$$

where $1\{Treated\}_{b,c}$ is an indicator variable for whether border b in city c is a treated border (i.e. has an HOLC grade change), α_c is a city fixed effect, and $z^{k,t}_{b,c} = x^{k,t}_{lgs,b,c} - x^{k,t}_{hgs,b,c}$ are the gap between an explanatory variable k on the lower-graded side (*lgs*) and the higher-graded side (*hgs*) at time t = 1910, 1920, and 1930. For the comparison borders, we randomly assign one side of the border to the lower-graded side and the other to the higher-graded side.[18] In parallel to the treatment boundaries, we then construct the difference or gap between the mean of our outcome on the “higher-graded” and “lower-graded” side. When we estimate equation (1) for the D-C borders only, we pool the randomly assigned grid borders that are within D and C HOLC neighborhoods. Similarly, the probit for the C–B borders only uses grid borders from within the C and B HOLC neighborhoods. The variables indexed by k include 1910, 1920, and 1930 Census measures of the gaps in the share African American, African American population density, white population density, share foreign born, the home ownership rate, the share of homeowner

[14] The Opportunity Atlas reports these measures by race. Unfortunately, we do not have enough neighborhoods in our sample to provide the power to find racial differences.

[15] The Equifax Risk Score is a proprietary credit score that estimates the likelihood that an individual will pay his or her debts without defaulting. A variety of factors that relate to loan performance contribute to credit scores, including previous payment history, outstanding debts, length of credit history, new accounts opened, and types of credit used (Avery et al., 2009); delinquency, large increases in one’s debt, and events of public record (e.g., bankruptcy or foreclosure) often lead to low credit scores (Anderson 2007). The scores range from 280 to 850, with higher scores representing greater financial health and advantage.

[16] A related result shows up on the borders of modern school district boundaries (Bayer et al. 2007; Dhar and Ross 2012).

[17] Figure A1 plots binned means of residuals after an address-level regression of household share African American on boundary fixed effects. The bin width is 0.01 miles. Negative distances indicate the C-side of the boundary and positive distances indicate the D-side of the boundary.

[18] Random assignment ensures that the distribution of the within boundary differences in our comparison group is representative of all comparison boundaries and is not skewed toward either tail of the distribution. Note that reweighting of comparison boundaries occurs after the randomization.

Table 2
Summary statistics.

	HOLC grade				Boundary Buffer level			
					D-C		C–B	
	D	C	B	A	D-side	C-side	C-side	B-side
Opportunity Atlas Outcomes								
Household Income Percentile Rank	0.393	0.428	0.479	0.503	0.388	0.416	0.429	0.464
Household Income Percentile Rank at 29	0.395	0.425	0.468	0.484	0.392	0.414	0.425	0.455
Probability of Reaching Top Quintile	0.109	0.143	0.196	0.233	0.102	0.129	0.146	0.177
Fraction Incarcerated	0.031	0.026	0.017	0.018	0.031	0.028	0.023	0.018
Fraction in Tract with Poverty Rate < 10%	0.287	0.338	0.418	0.449	0.267	0.296	0.342	0.389
Fraction living in Childhood Tract	0.216	0.211	0.202	0.186	0.222	0.215	0.217	0.208
Fraction with Male Claimer	0.560	0.618	0.683	0.698	0.553	0.592	0.596	0.651
Fraction Married	0.241	0.292	0.351	0.361	0.228	0.264	0.282	0.318
Fraction of Women with Dependent when Age 13-19	0.327	0.272	0.199	0.190	0.337	0.295	0.255	0.202
Fraction Claimed by Two People	0.380	0.460	0.550	0.595	0.369	0.417	0.420	0.493
Fraction with Positive Earnings	0.725	0.738	0.757	0.759	0.726	0.737	0.730	0.748
Equifax								
Equifax Risk Score™ (2016)	662	671	692	729	662	665	675	682
Fraction Subprime (2016)	0.281	0.232	0.173	0.105	0.257	0.252	0.199	0.190
Sample size	360	594	302	55	91	91	42	42

Notes: Descriptive statistics by HOLC grade and boundaries buffer areas. The Opportunity Atlas (Equifax) statistics are based on census tracts (block groups) that include at least 15 (50) percent of their population within a HOLC neighborhood (buffer zone).

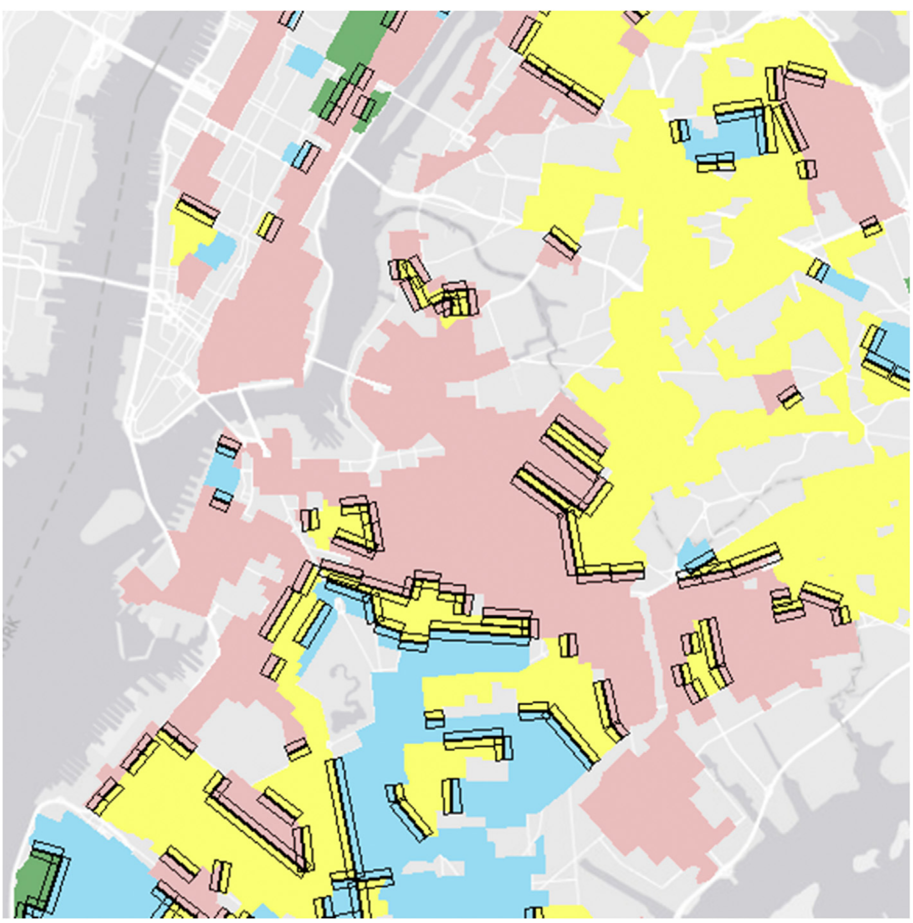


Fig. 1. Boundary Buffer Zones for New York City. *Notes*: This map provides a visual depiction of the "boundary buffer zones" in part of New York City that form the main unit of our analysis. Areas shaded in red, yellow, blue, and green constitute D, C, B, and A graded neighborhoods. The thick black lines denote straight-line neighborhood boundaries that are at least ¼ mile in length. The lighter black lines outline the 1/4-mile buffer zones surrounding each boundary. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

households that have a mortgage, log house value, and log rent. We present the marginal effect estimates from the probits for the D-C and C–B border samples in Appendix Table 1.[19]

As noted in section IIIa, the match between HOLC neighborhoods and Opportunity Atlas census-tract measures forces us to drop many borders from our estimation sample. Using this small sample to estimate equation (1) results in imprecise propensity score estimates. Therefore, we use a larger sample of borders from AHM to estimate equation (1)'s coefficients. For the most part, using the smaller estimation sample at this step results in similar point estimates but standard errors that can be 2 to 3 times larger. Still, in Section V, we provide a brief description of the

[19] Some variables are not available in all years.

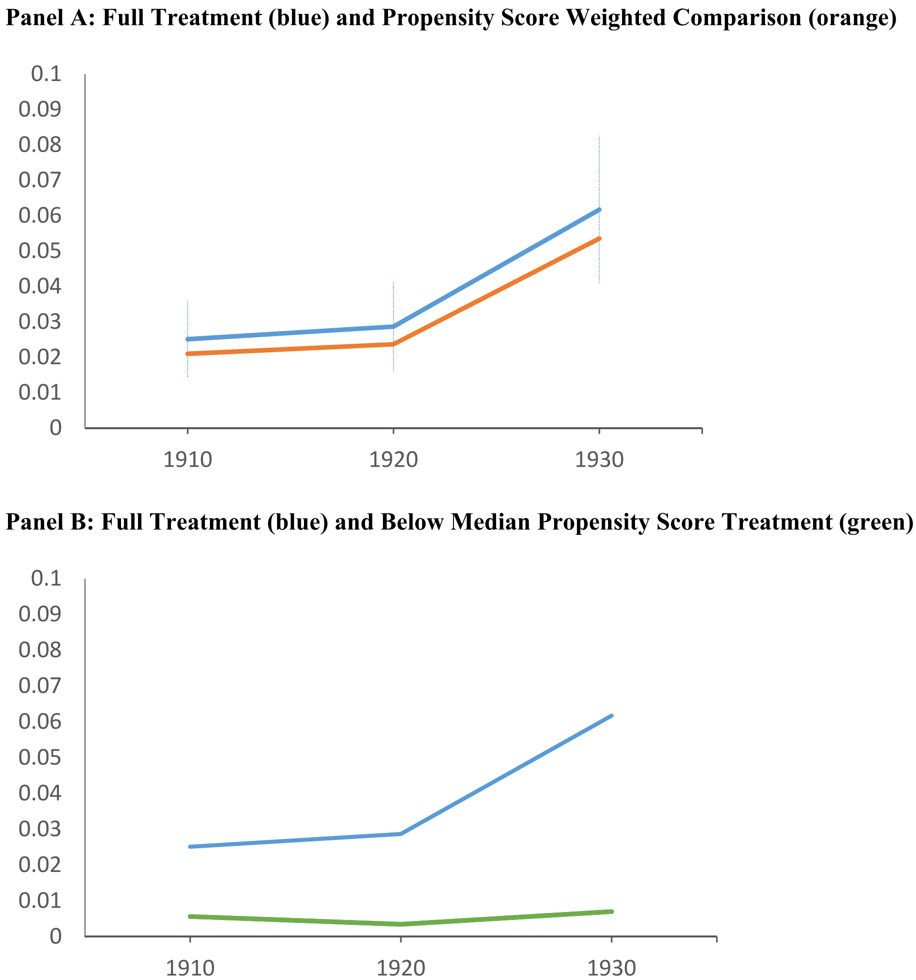


Fig. 2. Pre-trends in Cross-Border Differences in the Share of African Americans. *Notes*: The full treatment estimates (blue lines) are derived from a ¼ mile buffer zone around the D-C boundaries. The comparison boundaries are based on a ¼ mile buffer zone drawn around grids over each city and weighted by propensity scores to mirror pre-map trends (see text for more detail). The green line shows only the treated border segments that have a propensity score below the median. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

results when we use the smaller propensity score sample as well.

The point of estimating propensity scores is that there will be some comparison boundaries where, based on our model, the gaps in the right hand side variables (e.g. the difference in African American share between the lower graded side and higher graded side in 1930) would imply that these would have high likelihood of being given different grades by the HOLC, even though in actuality they had the same grade and no boundary was drawn. We can then use the estimated propensity scores (the predicted values from the probit) to reweight the grid comparison borders such that those with buffer zone differences that look more like the treated border buffer zone differences receive more weight. The weights are constructed for the comparison borders as w = pscore/(1-pscore) and for the "treated" borders as $w = 1$. The orange line in Panel A of Fig. 2 shows the results for share African American along the D-C border; now, the weighted comparison group have almost identical trends as the treated borders. Moreover, we construct these borders to also match the pre-trends in homeownership, home values, and rental prices from 1910 to 1930.

Lastly, we estimate a set of regressions:

$$y_{g,b,c} = \beta_{grid} 1[treated] * 1[lgs] + \beta_{lgs} 1[lgs] + \alpha_b + \varepsilon_{g,b}c \qquad (2)$$

where $y_{g,b,c}$ is an Opportunity Atlas outcome from buffer area g on border b in city c, $1[treated]$ is an indicator that the geographic unit is on an HOLC grade change border, $1[lgs]$ is an indicator that the geographic unit is on the lower-graded side, α_b are boundary fixed effects, and β_{grid} is the coefficient of interest.[20]

The second identification strategy uses the propensity scores to identify a set of treated HOLC borders that do not exhibit pre-existing trends in observable outcomes and therefore could plausibly identify causal effects even without the use of a comparison group. This method is a version of subclassification or stratification (Imbens 2015; Imbens and Rubin 2015), where the sample is partitioned into subclasses based on the estimated propensity score. Within a subclass, differences in covariates are minimized and causal effects can plausibly be inferred since assignment can be viewed as close to random.

In Panel B of Fig. 2 we show that using only treated borders that received a below median propensity score eliminates pre-trends in share African American in the treated group of D-C boundaries.[21] The figure shows that the below median propensity score treatment group (green line) has almost zero cross-border difference in the share of African American. The motivation for this approach is that these low propensity boundaries are more likely drawn idiosyncratically, for example to complete a polygon where the other borders of the neighborhood divide areas with significant pre-trend differences. After taking the set of below median propensity score treated borders, we run the following specification:

[20] The un-interacted treatment indicator is not present in Equation (2) because it is subsumed by the boundary fixed effects.

[21] As noted above we use the full set of boundaries from AHM to estimate the propensity scores not just those available in Opportunity Atlas cities. This method works well for homeownership rates, house values, and rental prices, as well as race, and for both D-C and C–B borders.

$$y_{gbc} = \beta_{low-p} 1[lgs] + \alpha_b + \varepsilon_{gbc}$$

where β_{low-p} is the coefficient of interest and the other terms are defined as above.

5. Results

5.1. D-C boundaries

Fig. 3 illustrates our main results along the D-C boundaries.[22] The six panels highlight representative outcomes on household income (A to C), incarceration (D), and family structure (E and F) using the grid procedure.[23] Each panel contains four lines: the point estimate and 95 percent confidence interval band whiskers for the grid design's a) treated boundaries, b) comparison boundaries, c) their difference (labeled DD), and d) the treated boundaries for the low propensity design.

We find striking differences in the household income percentile ranks of individuals who grew up on the D versus the C sides of HOLC boundaries. Panel A reveals that at age 29 (i.e. between 2007 and 2012), those that grew up on the D side of a redlined boundary have a household income rank that is 2.2 percentile ranks lower (standard error of 1.0) compared to nearby C side residents.[24] By comparison, we find no statistical difference between the lower and higher graded sides of control boundaries. The difference-in-difference estimate is −1.6 (0.8) percentile ranks. This represents 4 percent of the mean income rank in our sample of treatment boundary neighborhoods. The estimate from the low propensity boundaries is similar to the grid difference-in-difference estimate.

Even larger economic differences arise when we examine outcomes that focus on the tails of the income distribution. Panel B shows that the probability of being in the top quintile of the household income distribution is 1.9 (1.2) percentage points lower for those born on the D side of the D-C boundary, or just under 16 percent of the sample mean. Similarly, the share of households living in low (<10 percent) poverty neighborhoods (Panel C) is much lower for those born on the D-side, with a DD effect size of 10 percent. An extreme negative outcome, the probability of being incarcerated at the time of the 2010 Census (Panel D), likewise appears to be more prevalent for those who grew up on the D-side, although since this is a relatively rare event, the effects are imprecisely estimated. With the exception of incarceration, poorer outcomes on the D-side consistently arise when we use our low propensity score method as well.

We also find that family structure outcomes are lower for those on the D-side of the D-C boundary. Specifically, the fraction of households with two adult tax claimers is 4.5 (2.4) percentage points lower on the D-side, roughly 12 percent of the sample mean of 39.3 percent (Panel E). Teen births are 1.8 percentage points higher, or 6 percent of the sample mean, although this estimate is statistically insignificant at conventional levels (Panel F). Other family structure measures, including the fraction of households with a male tax claimer and the fraction of Opportunity Atlas children who are married as adults, likewise suggest a potentially important impact (see Appendix Figures A3 and A4). And, again, the size and direction of the results are the same along low propensity score boundaries.

As a way of summarizing multiple outcomes, we formed an average index where we normalized each outcome to a Z-score with mean zero and standard deviation one and then took the average of the Z-scores across all six outcomes in Figs. 3 and 4 and the five outcomes in Panels A through E of Appendix Figures A3 and A4.[25] In Panel F of Appendix Figures A3 and A4, we present these estimates. The average Z-score index results show about a 0.2 standard deviation lower outcome associated with the D-side of D-C boundaries for the treated and the difference-in-differences estimates. Both are statistically different from zero (Panel F of Appendix Figure A3). The low propensity score estimate is smaller, at about 0.1 standard deviations, and not statistically different from zero.

All our measures work in the direction of worse outcomes for those born on the D side, with magnitudes that primarily range between 4 and 12 percent of their respective sample mean. Nevertheless, small sample sizes limit the power for a few of these estimates to pass traditional statistical thresholds of significance. That said, many individual outcomes still do, and together, they easily pass such tests jointly. In particular, we again used our Z-score measures and jointly tested their statistical significance within a seemingly unrelated regression (SUR) framework that allows for a flexible variance-covariance structure for the error terms across equations. We performed this joint test using any of the income measures highlighted in Fig. 3, or all three, along with the remaining three non-income outcomes from that figure. The coefficients from the grid-based design using D-C boundaries are jointly different from zero at least at the 1 percent significant level and in most cases well below that. Expanding the list to include the five outcomes reported in Appendix Figure A3 has little impact. Our difference-in-difference estimates are also jointly statistically different from zero, typically at the 1 to 3 percent level.[26] A joint significance test of the low propensity score D-C boundaries using income, incarceration, and family structure outcomes rejects zero at the 0.2 percent level, and a similar test using all 11 measures rejects that the coefficients are jointly different from zero at the 0.1 percent level. Therefore, the low propensity score results are quite consistent with what we find when using our grid design.

5.2. C–B boundaries

As in AHM, we find the impact of the HOLC maps on the outcomes of the Opportunity Atlas cohorts is especially striking along the C–B boundaries. Panel A in Fig. 4 shows age 29 residents born on the C side of a redline boundary are 2.9 (1.1) percentiles lower in household income percentile rank compared to nearby B side residents, with no statistical difference between the lower and higher graded sides of comparison boundaries.[27] The difference-in-differences estimate of −2.5 (1.6) percentiles is about 50 percent bigger than the same estimate along the D-C boundaries and roughly 6 percent of the mean of 44 percentile points in our sample of treatment and control boundary neighborhoods. Similarly, we find especially large and highly statistically significant effects along the C–B borders with regard to the probability of being in the top quintile (Panel B) and living in a low poverty rate neighborhood (Panel C). Incarceration (Panel D) continues to suffer from imprecision but the point estimate is quite large, at 40 percent of the sample mean. Family structure outcomes are lower on the C side of the C–B boundary as well (Panels E and F). Specifically, the fraction of households with two adult tax claimers is 9.8 (6.6) percentage points lower and teen births among our Opportunity Atlas cohorts is 6.1 (4.0) percentage points higher on the C side. These estimates are roughly 20 and 30 percent of sample means. Jointly, the outcomes in Fig. 4 are highly statistically significant at the 0.1 percent level or better, including when all 11 Atlas measures are used (Appendix Figure A4). As with the D-C boundaries, the results are similar

[22] Appendix Table 2 presents the corresponding point estimates and standard errors illustrated in Fig. 3.

[23] The results for the other Opportunity Atlas outcomes are shown in the Appendix.

[24] The results are unsurprisingly similar without the age 29 restriction. See Appendix Figure A2.

[25] We multiply fraction incarcerated, fraction of women with dependent when ages 13–19, and fraction living in childhood tract by negative one before taking the average of the Z-scores.

[26] The results with all 11 outcomes can be somewhat sensitive to a very small handful of extreme observations. When we winsorize the outcomes at the 1st and 99th percentiles, the joint tests are significant at the 1 percent level.

[27] Appendix Table 3 presents the corresponding point estimates and standard errors illustrated in Fig. 4.

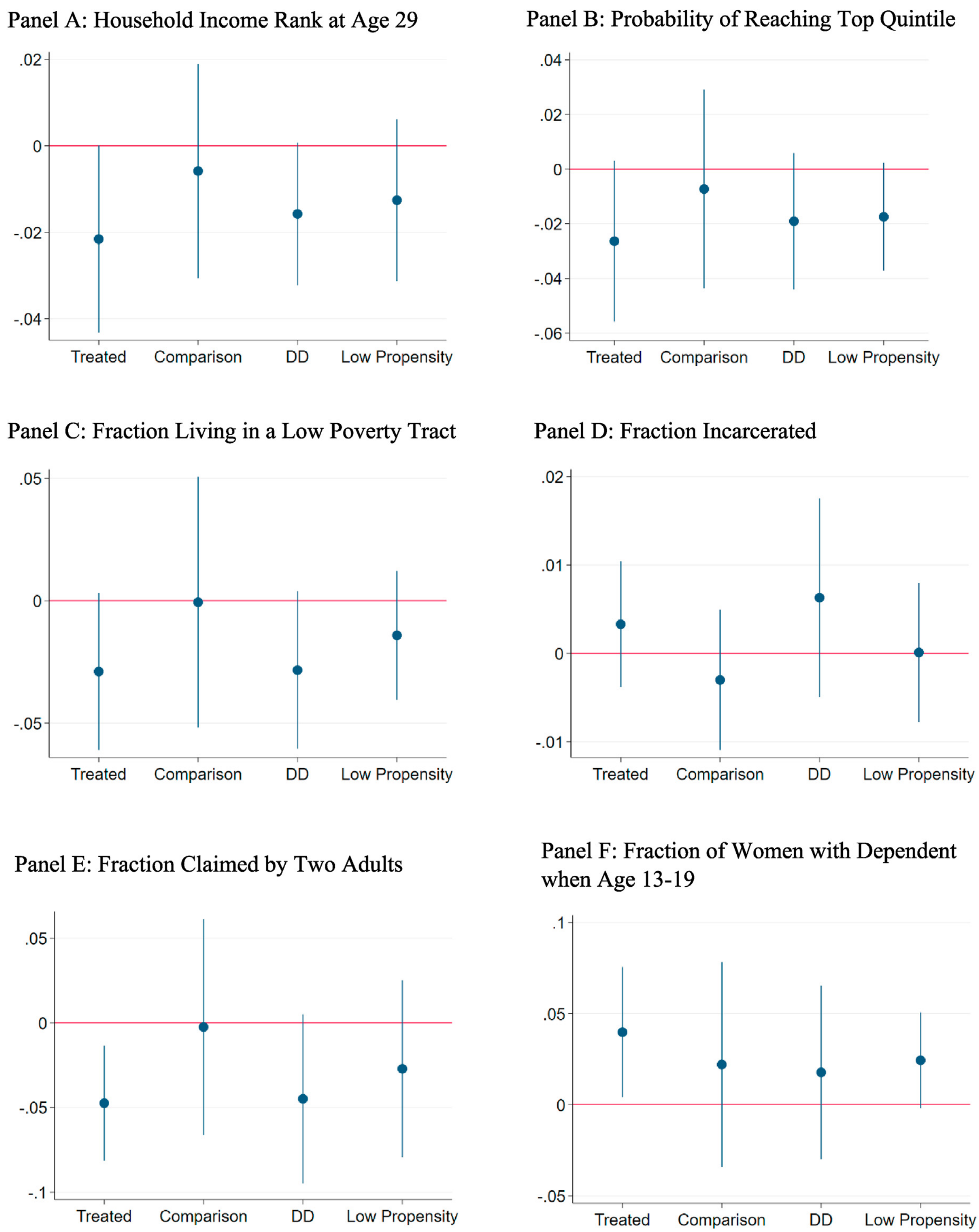


Fig. 3. Main results along D-C boundaries, by outcome.

in magnitude using the low propensity score method.[28]

[28] To improve precision, the results use a larger sample of borders to estimate the propensity score coefficients (equation (1)). We experimented with using the smaller matched HOLC-Opportunity Atlas sample of borders when estimating the propensity score model. For the C–B grid and D-C low propensity score set of results, the point estimates and standard errors are similar. For the C–B low propensity score and D-C grid results, the standard errors 2 to 3 times larger, therefore making any inferences difficult.

5.3. *Additional evidence from modern credit scores*

We used the same methods to examine the long run (post-1999) effect of the maps on modern-day credit scores, including the likelihood of being considered "subprime" (Equifax Risk Score<620). For the treated boundaries, we find statistically significant credit score gaps that are always worse on the lower-graded side (Fig. 5). As of 2016, the D-C gap stood at 8.0 (1.9) Equifax Risk Score points and the C–B gap was 9.4 (2.3) points. Similarly, the probability of being subprime is currently just over

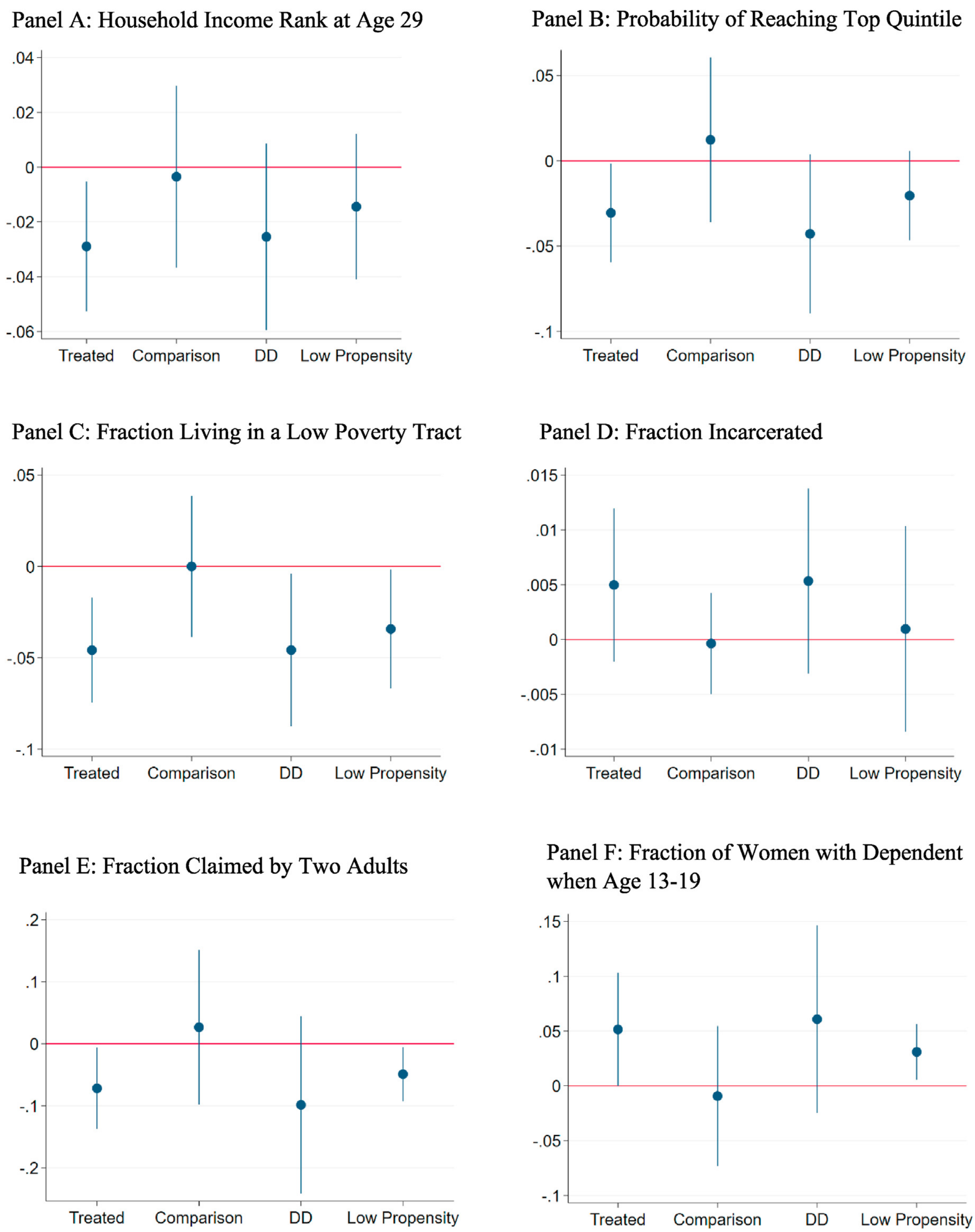


Fig. 4. Main results along C–B boundaries, by outcome.

3 percentage points on the higher graded side of both boundaries. The subprime gap was larger in the 2000s, especially during the Great Recession.

5.4. Limitations

There are some important caveats to our analysis. First our estimated Opportunity Atlas effects only pertain to birth cohorts growing up a half century after the redlining maps were drawn and likely a decade or two removed from the 1970 or so peak of the maps' impact on neighborhoods. Our previous research has shown that while the impact of the maps on neighborhood development faded in the 1980s and 1990s, it remains economically relevant, albeit muted, to the household and housing market composition of neighborhoods today. Using a very different source of data, the Opportunity Atlas measures, allows us to test whether growing up on the lower-graded side of a HOLC border still matters to birth cohorts entering labor markets at the beginning of the 21st century. We believe these results provide compelling evidence to

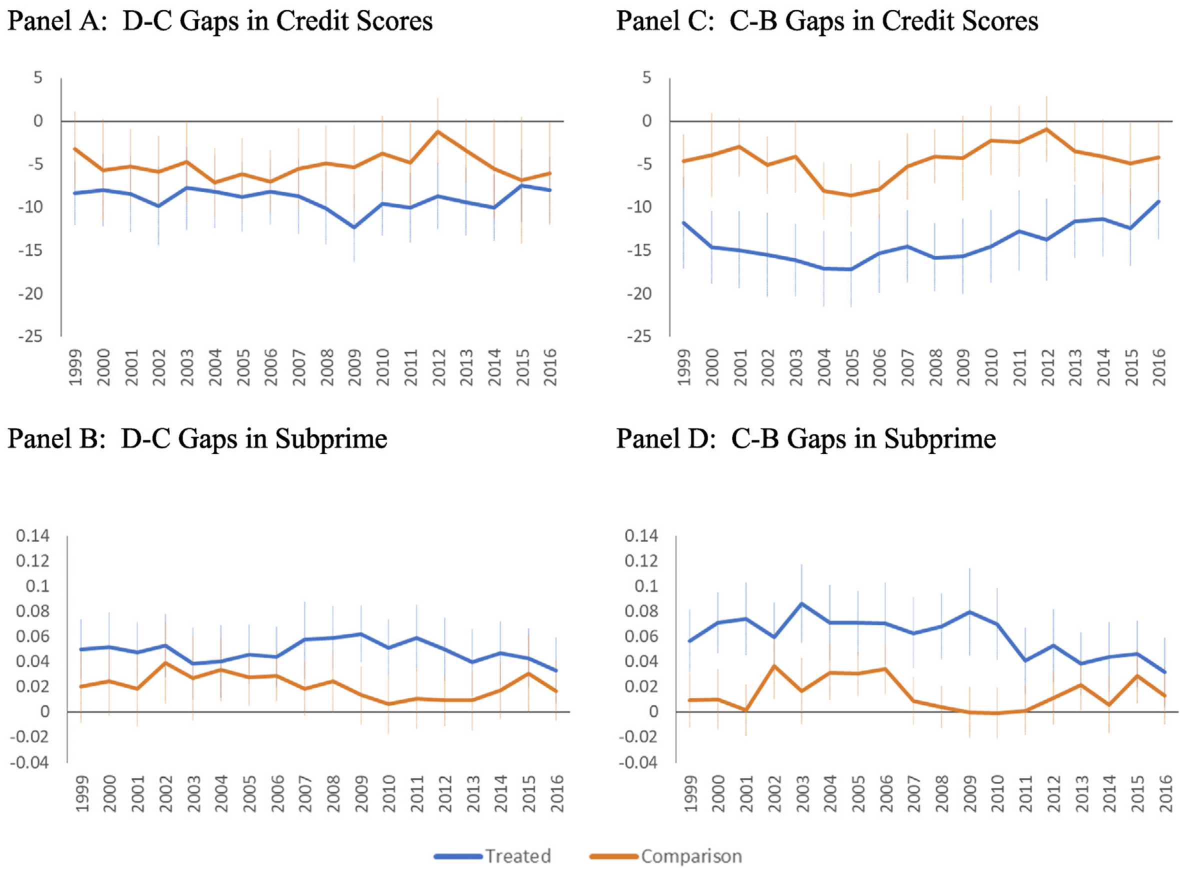


Fig. 5. Impact on Credit Scores, D-C and C–B Boundaries. *Notes*: Credit scores are from the Federal Reserve Bank of NY Consumer Credit Panel. An individual is classified as subprime if her Equifax Risk Score is less than 620. The treatment estimates (blue lines) are derived from a ¼ mile buffer zone around the D-C or C–B boundaries. The comparison boundaries are based on a ¼ mile buffer zone drawn around grids over each city and weighted by propensity scores to mirror pre-map trends (see text for more detail). Vertical bands denote 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

suggest that it does.

A second limitation is that we are unable to provide evidence on which of the many possible mechanisms were critical factors that led to the deterioration of these neighborhoods. We suspect that one major channel is financial disinvestment. Lower access to credit is likely to lead to reduced housing values as has been found by AHM. A deterioration in home values increases the likelihood that some homeowners may face a higher mortgage debt level than the value of their property (Glaeser and Gyourko 2005). Property owners in such circumstances are less likely to maintain or improve their properties (Gyourko and Saiz 2004; Haughwout et al. 2013; Melzer 2017).

In addition, other institutional factors in conjunction with the HOLC grades may have led to even further impetus for financial disinvestment. For example, individuals who were unable to obtain mortgages from banks or other formal lenders, may have instead entered into "contract sales," where one missed payment could result in losing all equity in the house (Satter 2009). Other mid-century government policies such as highway construction (Brinkman and Lin 2017), and urban renewal (Rast 2019) could have exacerbated financial disinvestment in low graded neighborhoods.

Other potential mechanisms include the changing demographic composition of these areas as found by AHM. We believe understanding these mechanisms, as well as the historical interplay between various government policies, societal racial residential preferences, and the practices of private institutions in the real estate market remains a critical area of research in the future.

6. Conclusion

Our analysis is motivated by new data and new evidence showing remarkable divergence in the social and economic fortunes of residents in communities that are sometimes less than a mile apart (Chetty et al., 2018; Chetty and Hendren, 2018; Chyn, 2018; Sharkey and Faber, 2014). In Los Angeles, for instance, low-income children raised in Watts during the 1980s and 1990s had much lower income as adults and were substantially more likely to experience a period of incarceration, than children raised just a short distance away in Compton. The availability of data on social and economic outcomes at a fine level of geography represents a major advancement in the study of spatial inequality, but less progress has been made in the effort to understand the sources of divergent economic and social outcomes across communities.

We merge neighborhood level data from the Opportunity Insights project with redlining maps developed in the 1930s to identify the causal effects of neighborhood credit-worthiness ratings. Building on methods and findings in previous work showing that HOLC ratings had a causal impact on the development of neighborhoods that sat on the boundaries of areas rated D instead of C, or C instead of B, we examine whether the boundaries drawn in the 1930s affected the social and economic outcomes of individuals born several decades later.

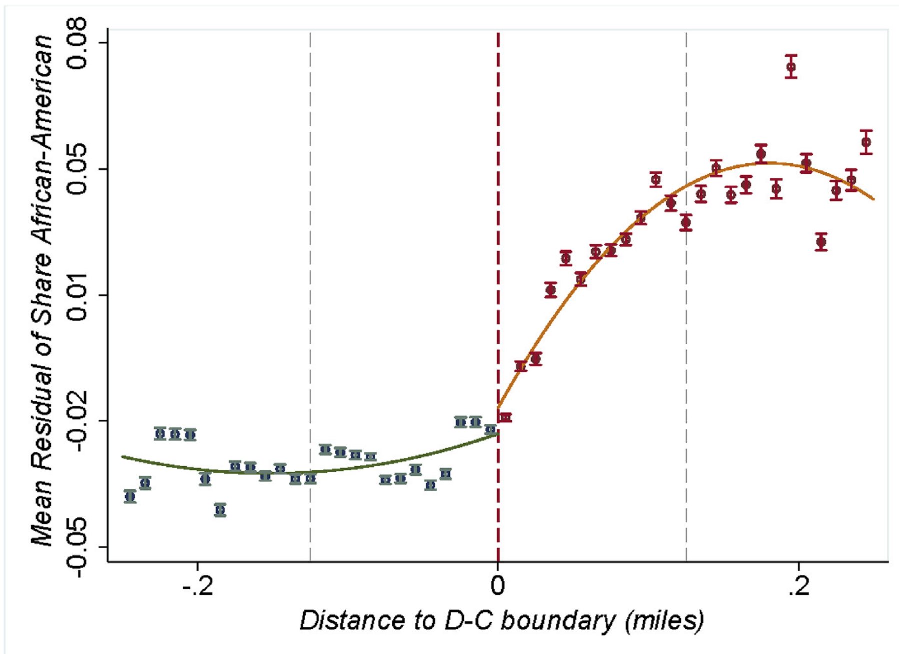
We again find that the ratings have a causal, and an economically meaningful, effect on outcomes like household income during adulthood, the probability of living in a high-poverty census tract, the probability of moving upward toward the top of the income distribution, and modern credit scores. Models of all outcomes show the same direction of effect, even if some are estimated imprecisely. Further, the impact of being raised in neighborhoods rated C instead of B again appears to be greater than the impact of being raised in neighborhoods rated D instead of C. In other words, our results suggest that yellow-lining may have been more consequential than red-lining.

The most striking conclusion from the analysis is the way that government intervention can alter communities for decades to come. The outcomes we studied were measured among cohorts born four decades after the HOLC maps were drawn, and yet the ratings still had visible impacts on many different social and economic outcomes in these communities. Our results provide clear evidence that policy decisions made decades ago can begin a process of investment and disinvestment with long-term consequences for communities and the residents within them.

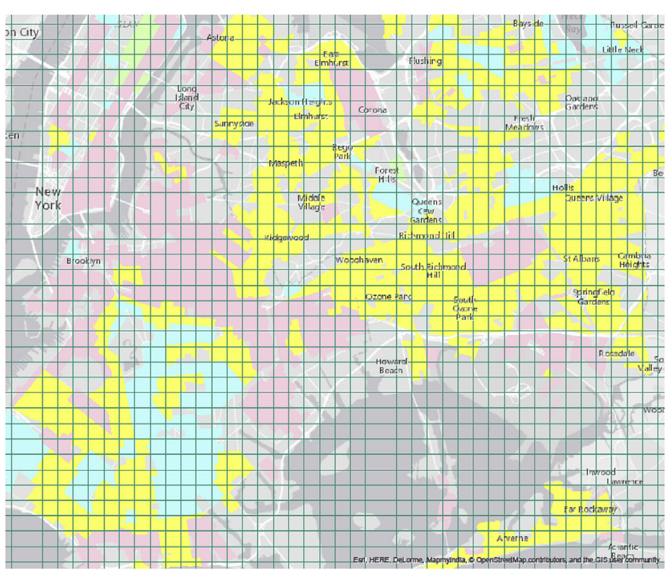
Declaration of competing interest

We have no competing interests to declare.

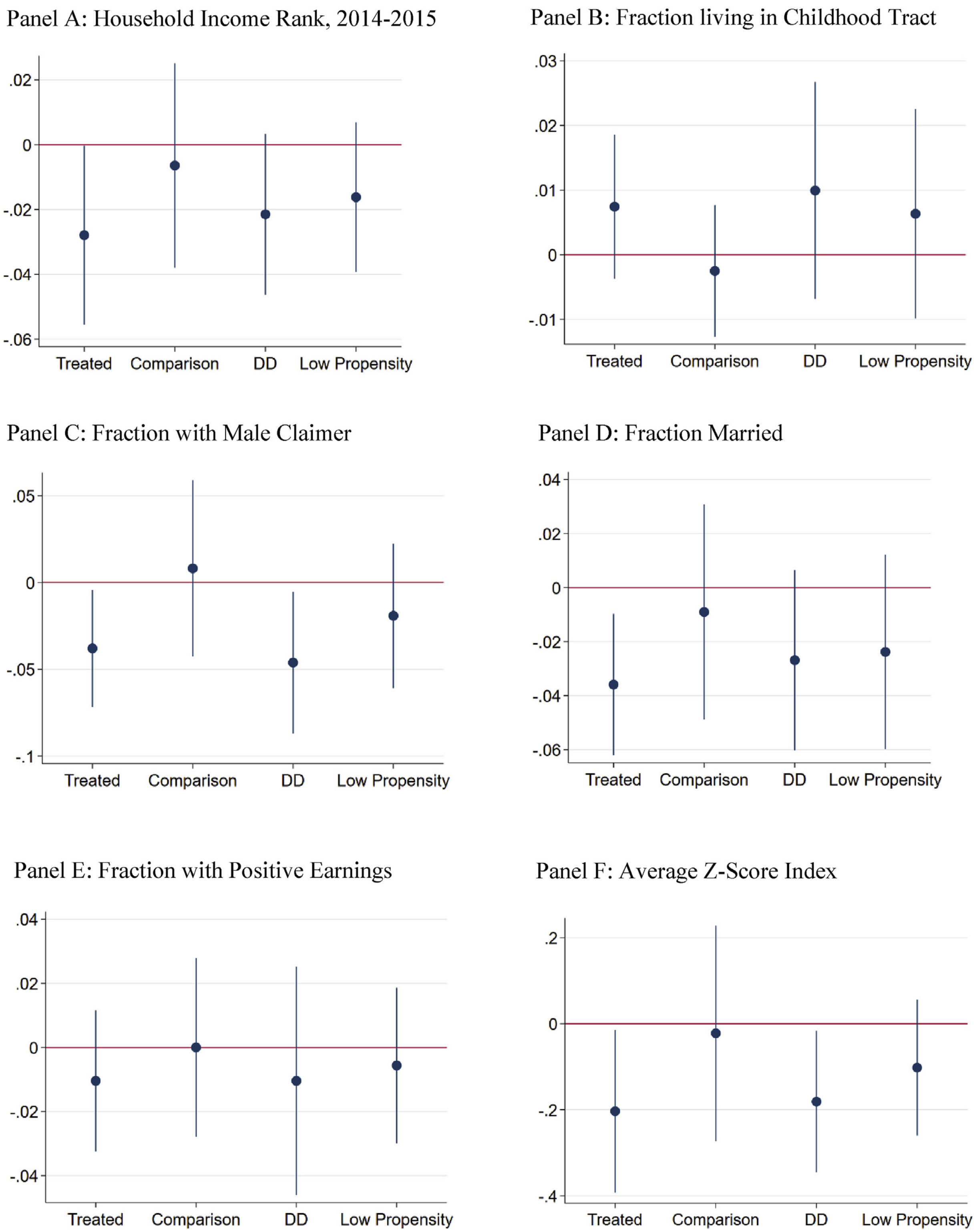
Appendix



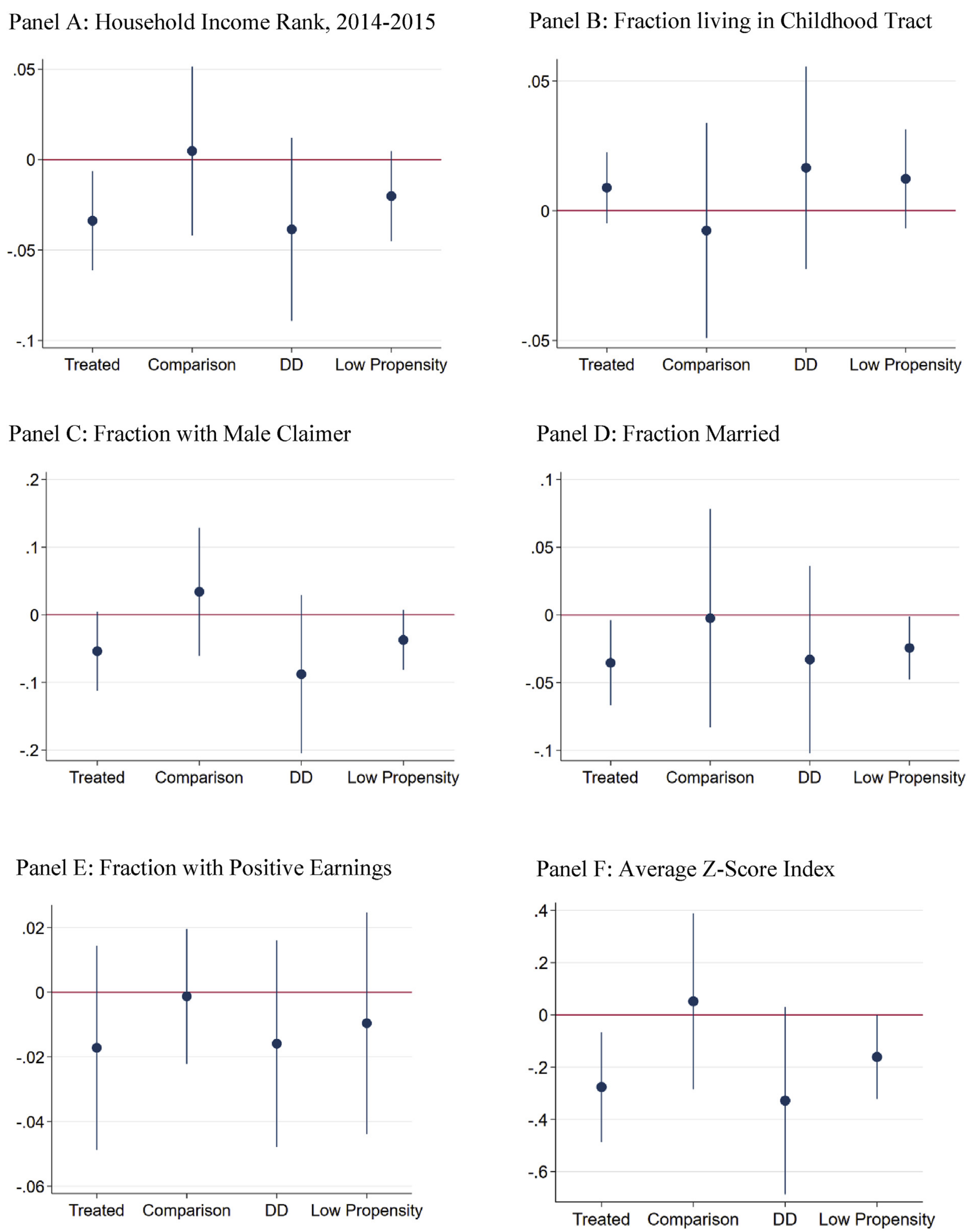
Appendix Fig. A1. : Share African American vs. Distance to D-C HOLC Borders, 1930



Appendix Fig. A2. Example of Grid Placed over New York City. *Notes*: The above map of NYC depicts the initial step in the construction of a set of non-HOLC "grid" comparison boundaries that are weighted to resemble our treated HOLC boundaries before the maps were drawn. To construct our grid boundaries, we drew 1/2-mile by 1/2-mile grids over HOLC cities. We then constructed 1/4-mile buffer zones around each line segment that did not overlap with an HOLC boundary. See Fig. 1 for an illustration of actual boundary buffer zones. .



Appendix Fig. A3. Further Results Along D-C Boundaries, by Outcome



Appendix Fig. A4. Further Results Along C–B Boundaries, by Outcome

Appendix Table 1
Propensity Score Probit Estimates

	D-C	C–B
Mortgage gap, 1910	−0.034*	0.028
	(0.018)	(0.021)
Mortgage gap, 1920	0.050**	−0.011
	(0.021)	(0.025)
Share African American gap, 1910	−0.077	−0.001
	(0.053)	(0.073)
Share African American gap, 1920	−0.057	0.031
	(0.066)	(0132)
Share African American gap, 1930	0.188***	−0.218*
	(0.051)	(0.131)
Radio gap, 1930	−0.224***	−0.134
	(0.035)	(0.040)
Homeownership gap, 1910	−0.046**	−0.056**
	(0.023)	(0.024)
Homeownership gap, 1920	−0.074**	−0.012
	(0.030)	(0.032)
Homeownership gap, 1930	−0.087**	−0.227***
	(0.036)	(0.040)
Foreign born gap, 1910	0.020	−0.000
	(0.046)	(0.044)
Foreign born gap, 1920	0.246***	−0.037
	(0.058)	(0.070)
Foreign born gap, 1930	−0.012	0.235**
	(0.085)	(0.102)
African American population density gap, 1910	0.00001	−0.00023**
	(0.00002)	(0.00009)
African American population density gap, 1920	0.00003	0.00002
	(0.00002)	(0.00007)
African American population density gap, 1930	0.00002***	0.00009**
	(0.00001)	(0.00004)
White population density gap, 1910	0.00001*	0.00003***
	(0.00000)	(0.00001)
White population density gap, 1920	−0.000001	0.00000
	(0.000004)	(0.00001)
White population density gap, 1930	−0.00001**	−0.00000*
	(0.00000)	(0.00000)
Literacy gap, 1910	−0.037	0.082
	(0.081)	(0.115)
Literacy gap, 1920	−0.337***	0.101
	(0.110)	(0.173)
Literacy gap, 1930	−0.065	0.242
	(0.145)	(0.249)
Log(house value gap), 1930	−0.093***	−0.182***
	(0.015)	(0.021)
Log(rent gap), 1930	−0.082***	−0.098***
	(0.019)	(0.024)
Sample size	5451	3764
Pseudo R^2	0.166	0.186

Note: Regression includes missing indicator variables for all covariates.

Appendix Table 2
Main results along D-C boundaries, by outcome

	HH income rank, age 29	Prob top quintile	Fraction in low poverty tract	Fraction incarcerated	Fraction Claimed by 2 adults	Fraction teen births
Treated	−0.022*	−0.026*	−0.029*	0.003	−0.047***	0.040**
	(0.010)	(0.014)	(0.015)	(0.003)	(0.016)	(0.017)
Comparison	−0.006	−0.007	−0.001	−0.003	−0.003	0.022
	(0.011)	(0.016)	(0.023)	(0.004)	(0.029)	(0.025)
D-in-D	−0.016*	−0.019	−0.028*	0.006	−0.045*	0.018
	(0.008)	(0.012)	(0.015)	(0.005)	(0.024)	(0.023)
Low propensity	−0.013	−0.017*	−0.014	0.000	−0.027	0.024*
	(0.009)	(0.009)	(0.012)	(0.004)	(0.025)	(0.012)

Note: These estimates are plotted in Fig. 3. Each cell represents a separate regression. Sample sizes are: Treated = 182, Comparison = 272, D-in-D = 454, and Low Propensity = 120.

Appendix Table 3
Main results along C–B boundaries, by outcome

	HH income rank, age 29	Prob top quintile	Fraction in low poverty tract	Fraction incarcerated	Fraction Claimed by 2 adults	Fraction teen births
Treated	−0.029**	−0.031**	−0.046***	0.005	−0.071**	0.052*
	(0.011)	(0.013)	(0.013)	(0.003)	(0.031)	(0.024)
Comparison	−0.004	0.012	−0.000	−0.000	0.027	−0.009
	(0.013)	(0.019)	(0.015)	(0.002)	(0.048)	(0.025)
D-in-D	−0.025	−0.043*	−0.046**	0.005	−0.098	0.061
	(0.016)	(0.022)	(0.019)	(0.004)	(0.066)	(0.040)
Low propensity	−0.014	−0.020	−0.034**	0.001	−0.049**	0.031**
	(0.012)	(0.011)	(0.014)	(0.004)	(0.019)	(0.011)

Note: These estimates are plotted in Fig. 4. Each cell represents a separate regression. Sample sizes are: Treated = 84, Comparison = 138, D-in-D = 222, and Low Propensity = 44.

Author statement

All authors contributed to this paper.

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