Redlining and Black Voter Turnout: The Modern Legacy of Historical Discrimination and Racist Policies

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1 Introduction

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Abstract

In the 1930s, the Home Owners' Loan Corporation (HOLC) created a series of maps categorizing neighborhoods into groups based on their perceived lending risk. Many believe that the lowest-rated neighborhoods, which were significantly lower income and more Black than the highest-rated neighborhoods, were systematically denied access to loans and mortgages, in a practice known as redlining. I test the relationship between these map ratings and present-day voter turnout among Black and White voters. Using a regression discontinuity design, I first compare cities just below the population cutoff for the creation of the HOLC maps to cities just above the cutoff, based on 1930 and 2016 characteristics. Although I find that the HOLC map cities had a larger Black share of the population, more racial segregation, and lower economic mobility, the differences at the city level are not significant. At the neighborhood level, I find that higher HOLC grades are associated with higher White voter turnout, but not with higher Black voter turnout. Furthermore, when I use a lasso regression model to impute HOLC grades for both redlined and non-redlined neighborhoods, I find that this difference in the relationship between predicted HOLC grade and voter turnout for Black and White voters is only present in high-density neighborhoods that were *not* designated as redlined. This implies a significant relationship between the HOLC maps and the difference in Black and White voter turnout across neighborhoods.

Throughout the history of the United States, racial oppression and discrimination have fostered an economic landscape that looks very different for White Americans and Black Americans. Today, the household wealth of the median White family is nearly ten times greater than that of the median Black family, and the percentage of Black adults with less than a high-school degree is 15%, nearly double that of White adults (McIntosh et al. 2020; NCES 2019). Arguably one of the most important divides comes in the form of political participation, particularly voter turnout, which determines political representation, and in turn, can impact everything from the distribution of state aid to trust in government (Cascio and Washington 2012; Shingles 1981). Estimates of the exact gap between White and Black voter turnout vary by year and data source, but the difference is almost always substantial – White voter turnout in the 2016 presidential election was estimated to be anywhere from 3.7 to 10.8 percentage points higher than Black voter turnout (Ansolabehere, Fraga, and Schaffner 2021). Although much work has been dedicated to showing that these variations can be explained by factors like income, educational attainment, age, and sex, there are still aspects of the relationship between voter turnout and race that have not been thoroughly explored.

While it is widely understood that historic practices, from school segregation to state-sanctioned voter disenfranchisement, contributed to racial inequality at the time, the present-day effects of such practices are far less clear. In this paper, I look at patterns of voter turnout through the lens of redlining in the 1930s, a practice under which certain communities were systematically denied access to credit and other financial services, in order to better understand how systemic racism nearly a century ago relates to inequality today. To gain a baseline understanding of redlining and the resulting demographic and economic patterns, I first exploit a city-level discontinuity in redlining to examine the present-day differences between cities that were formally designated to be redlined by federal lending agencies, and those that were not. The results, while not conclusive, indicate that the "redlined" cities may have experienced a larger growth in the Black share of the population between 1930 and 2016, and may today have higher levels of racial segregation and lower economic mobility on average when compared to "non-redlined" cities.

I also use precinct-level voter file data and American Community Survey (ACS) population data to estimate voter turnout and voter registration rates in the 2016 presidential election. I find that among cities designated as redlined, neighborhoods that were graded more highly (and were thought to experience more favorable lending practices) experienced much higher White voter turnout than neighborhoods that were graded lower (and were thought to experience some financial discrimination), while Black voter turnout stayed relatively constant in differently graded neighborhoods. Furthermore, I find that this trend was not present in high-density neighborhoods that were *not* designated as redlined, suggesting that there may be a causal relationship between redlining and differences in Black and White voter turnout across different neighborhoods.

In Section 2, I present historical background on both redlining and voter turnout, and summarize existing literature on racial inequality, redlining, and political participation. In

Section 3, I discuss my data sources and methodology, both at the city level and for voting outcomes. Finally, Sections 4 and 5 present empirical results for city-level analysis and voting analysis, respectively, and Section 6 concludes.

2 Background and Literature Review

Voting In a country built on the demand for fair political representation, it is especially devastating that the right to vote has never been equally guaranteed to all Americans. Even after the ratification of the fourteenth and nineteenth amendments (which respectively gave Black men and all women the right to vote), many states continued to openly exclude Black Americans from voting, through disenfranchisement devices like literacy tests, poll taxes, and even outright violence (Brown-Dean et al. 2015).[1] 1965 marked the passage of the Voting Rights Act, which removed many barriers to voting for Black Americans in certain states by prohibiting limitations of voting rights on the basis of race. In the years that followed, Black voter turnout and registration rates shot up – by 1968, growth in non-white voter turnout had doubled since 1960, and Black voter registration in the southern states most impacted by the Voting Rights Act had increased by 67% on average (Filer, Kenny, and Morton 1991; Cascio and Washington 2012). In turn, Black political representation also increased dramatically – by 1980, the number of Black elected officials had more than tripled. Despite huge advances in political engagement and representation, however, voter suppression re-emerged with a vengeance in 2013, after the Supreme Court ruled that key sections of the Voting Rights Act were unconstitutional, in Shelby County v. Holder. Within months, several states had already passed stricter voter ID laws, and in the 2014 elections, jurisdictions that had been the most strictly regulated prior to the ruling were found to have significantly increased the rate of voter purges (Feder and Miller 2020).[2]

While voting rights legislation, historic oppression, and policy are key determinants of voter turnout, particularly among Black Americans, there is an enormous body of work on numerous other factors that also contribute to political participation. Studies have shown that

1. Many states had a literacy requirement when registering to vote, which was usually administered by a White official. Voters would be judged subjectively on their ability to read and interpret complicated technical passages, which resulted primarily in the disenfranchisement of Black voters. Poll taxes were also levied in some states prior to casting a ballot, preventing poor Black men and women from voting, while often allowing poor White voters to use the “grandfather clause”, which exempted those whose fathers or grandfathers had voted.

2. Voter purging, often disguised as registration list maintenance, is a practice in which eligible voters are incorrectly removed from voter lists. While there is some debate as to the legality of voter purging, it overwhelmingly affects minority voters.

education and income both have a causal effect on voter turnout (Filer, Kenny, and Morton 1993) – for instance, in the case of education, (Sondheimer and Green 2010) estimate that randomly inducing a high school dropout to graduate high school would increase their probability of voting by nearly 50 percentage points. Race and segregation also play a role: (Oberholzer-Gee and Waldfogel 2001) show that the likelihood of voting increases when living amongst people who share the same political preferences, and (Fraga 2016) shows that Black Americans are more likely to vote when located in districts with Black representation on the ballot. Income inequality and Black share of the population, on the other hand, are both negative predictors of voter turnout (Hill and Leighley 1999; Galbraith and Hale 2008). Redlining is a particularly interesting independent variable, because it is not only an old practice (allowing us to analyze longitudinal patterns and make observations about the impact of historical policies), but it is also very closely tied to many of the other causal variables of voter turnout, such as income, race, and education. To get a better sense of the historical context surrounding redlining, I next give a brief overview of the history and literature on redlining, particularly in relation to the 1930s HOLC maps.

HOLC Maps In 1933, in an effort to protect homeowners against foreclosure in the midst of the Great Depression, the federal government created the Home Owners' Loan Corporation (HOLC). As part of its City Survey Program, the HOLC created a series of "Residential Security" maps for cities across the country, with systematic grades assigned to neighborhoods based on their perceived lending risk. The maps were constructed based on input from local banks, realtors, and city officials, based on factors including the quality of housing, the economic class of residents, access to amenities, and, most egregiously, the racial composition of the neighborhood. The lowest rated neighborhoods, marked as "Hazardous", were largely inhabited by residents of color, especially when compared to highly rated and mostly White neighborhoods, marked as "Best" (Mitchell and Franco 2018). In particular, it has been theorized that "Hazardous" neighborhoods were systematically denied access to loans and mortgages, in a practice known as redlining. Although the extent to which these maps directly impacted lending and mortgage refinancing practices has been debated, they were constructed based on input from lending decision makers, and so it is unmistakable that these maps are at the very least a partial reflection of lending practices in the 1930s (Hillier 2005). But while redlining has been heavily studied, in many different contexts, it is still poorly understood, and much of the existing research on redlining has failed even to establish the existence of discriminatory lending practices (Berkovec et al. 1994; Tootell 1996). Consequently, despite some evidence that the HOLC maps did influence the lending behavior of private lending institutions (Jackson 1980), it is difficult to conclusively identify any patterns of economic outcomes as causal effects of the HOLC maps.

Recently, the HOLC maps have been digitized, allowing researchers to analyze their modern-day implications. Even setting aside the question of whether HOLC maps are a measure of redlining, recent research on the HOLC maps is mixed. Some studies have found evidence that the HOLC maps contributed to lower present-day house prices, credit scores, and home ownership rates (Aaronson, Hartley, and Mazumder 2017; Appel and Nickerson 2016), while others have suggested that these patterns stem from other factors (Fishback et al. 2020). This paper does not attempt to definitively validate either of these two theories, but instead presents observations based on new empirical evidence and discusses the possible implications. Although this paper does not evaluate whether the HOLC maps themselves caused, represent, or were a result of redlining, for simplicity of notation, the HOLC maps are often referred to as "redlining" throughout.

Socioeconomic Outcomes Before looking at empirical evidence, it is worth considering some potential mechanisms by which redlining may impact present-day voter turnout. Panel (a) of Figure 1 displays the HOLC maps for the cities of San Francisco and Oakland, along with the original grade given to each neighborhood. Panels (b) and (c) display present-day data for the same two cities. In comparing panels (a) and (b), it appears that neighborhoods with lower HOLC grades in the 1930s roughly correspond to areas in 2016 with higher present-day concentrations of Black residents.[3] Neighborhoods with larger Black shares have been shown to experience lower house values and higher rates of default, suggesting that racial makeup impacts financial stability (Perry, Rothwell, and Harshbarger 2018). So while an obvious link between redlining and voter turnout would be that redlining causes lower incomes, which in turn lowers voter turnout, a slightly more nuanced addition may be that redlining also affects the racial composition of the neighborhood, increasing the Black share, which reduces average wealth, further depressing voter turnout. On the other hand, these patterns may be evidence of racial segregation, which has been shown to increase voter turnout.

Panels (a) and (c) similarly show a strong correspondence between higher 1930s HOLC grades and higher 2016 median house values, an indication that the same neighborhoods that were perceived as financial liabilities, particularly for home ownership, in the 1930s, have tangibly less valuable houses today. Does this mean that HOLC redlining had a causal effect on median house prices in 2016? Not necessarily, but this pattern is reflective of recent

3. For 2016, data is taken from the American Community Survey, which uses 'block groups' as the smallest geographic unit. Note that these units are different from the 1930s HOLC neighborhoods.

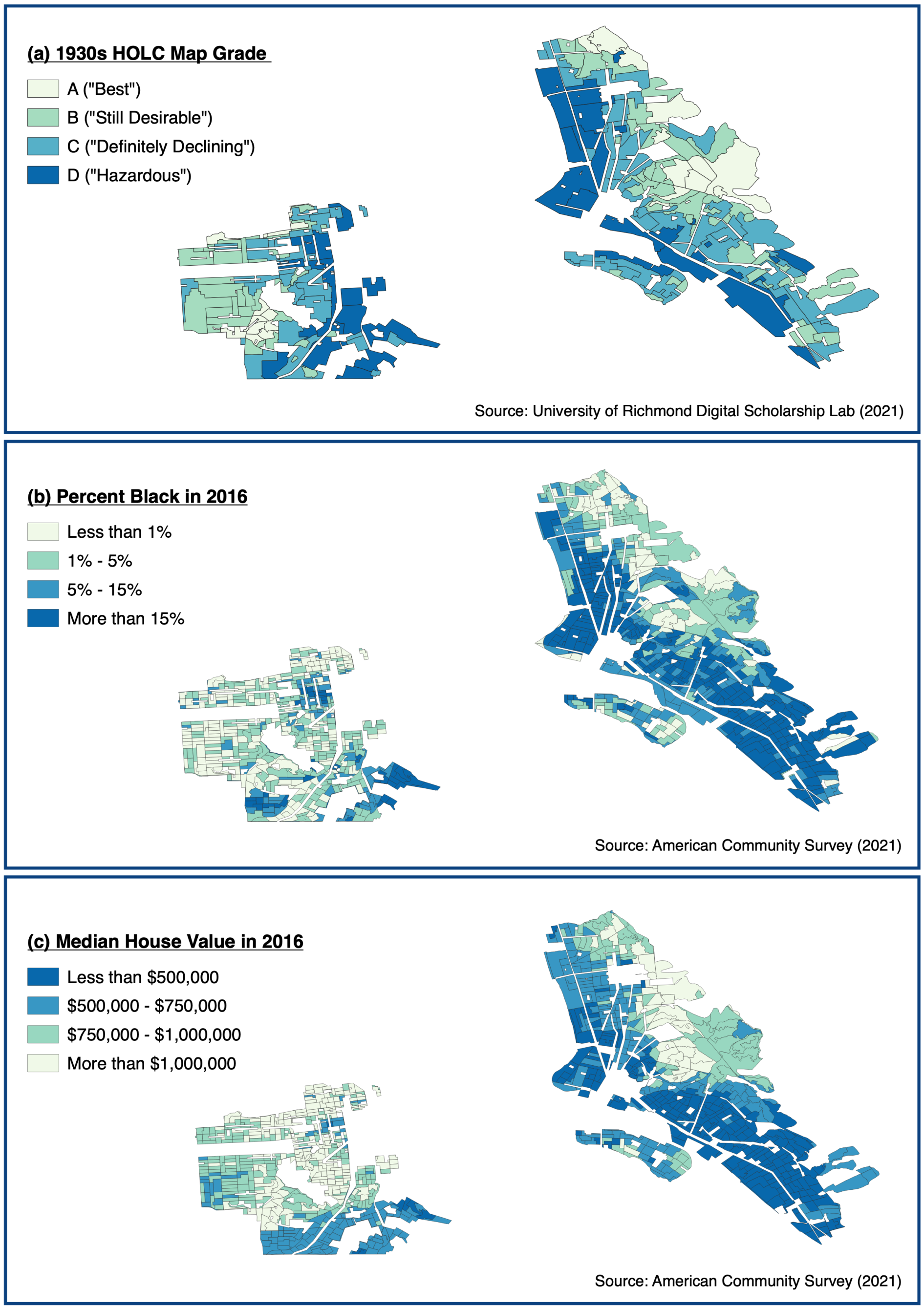

Figure 1: A comparison of neighborhoods in San Francisco and Oakland over time, from (a) HOLC neighborhood grades in the 1930s to (b) the percentage of the block group that was Black or African American Alone in 2016 and (c) the median house value by block group in 2016. Observe that areas that were marked as ”Hazardous” or ”Definitely Declining” by the HOLC maps in the 1930s now contain a disproportionately high Black population, and have consistently lower house values.

findings on the importance of place, particularly in relation to economic outcomes. While neighborhood-level variations in everything from economic mobility to infant mortality have been documented for some time, the effect of the neighborhood itself is often obscured by the effect of the characteristics of the people living in that neighborhood (Sampson, Morenoff, and Gannon-Rowley 2002). A growing body of literature, however, has provided evidence that even after accounting for the characteristics of residents, neighborhoods have causal effects on outcomes like intergenerational mobility, academic performance, and even one's own sense of wellbeing (Chetty and Hendren 2018a; Rothwell and Massey 2015; Ludwig et al. 2012). Furthermore, these effects (known as "neighborhood effects" or "place effects") impact Black residents and White residents differently. (Chetty and Hendren 2018b) show that neighborhood effects are generally correlated with Black share, which creates a compounding effect where neighborhood effects can amplify racial inequality. This effect is illustrated in (Lopez Turley 2003), which shows that increases in neighborhood income significantly improve test scores among White students in all neighborhoods, but that the effect of an increase in neighborhood income on test scores among Black students is only significantly positive in neighborhoods where at least 85% of the residents are Black. A possible mechanism may be that redlining itself contributed to creating a place effect across neighborhoods in some cities, which affect these various outcomes, which in turn affect voting. Although there are an endless number of links between all of these different variables, it is useful to begin analysis armed with some idea of what we might expect.

3 Data and Methodology

3.1 City-Level Data and Methods

Before looking at voting outcomes, I first use city-level data to assess the relationship between the HOLC maps and various outcome variables, which presents an interesting variation on the problem of identifying the causal effect of redlining. Did the presence of redlining through HOLC maps in the 1930s have an impact on the demographic and economic characteristics of the city as a whole, even decades later? While neighborhood-level discrimination has been explored to some extent, the city-level effects of discrimination are far less well-understood, since discrimination, while always at the expense of one community, is often to the benefit of another. Using methodology based on work by (Aaronson, Hartley, and Mazumder 2017) and (Anders 2019), I exploit a unique feature of the HOLC maps to attempt to gain some insight into how redlining has affected cities as a whole today.

In the 1930s, the HOLC only drew "Residential Security" maps for cities with a population of at least 40,000. This natural cutoff allows for the comparison of outcome variables such as income, demographic makeup, and house prices between cities with 1930 populations just below 40,000 and cities with 1930 populations just above 40,000. The key identification assumption here is that cities near this cutoff do not differ significantly, at least as it pertains to economic and demographic outcome variables.

Using data from the 1930 Census,[4] I identify 117 cities with populations between 30,000 and 50,000. Of these, any cities within 40 miles of a (different) redlined city are excluded, to avoid capturing the effects of a larger nearby city. The result is a control group of 30 cities with a 1930 population between 30,000 and 40,000, and a treatment group of 23 cities with a 1930 population between 40,000 and 50,000.[5] 1930s outcome variables are calculated using the IPUMS 5% Census Sample, and are matched at the city level with 2016 outcome variables from the NHGIS 2012-2016 5-Year American Community Survey. Additionally, data on income inequality, segregation, and economic mobility are taken from Online Table 4 of (Chetty and Hendren 2018b). Since this data is not available at the city level, it is matched to city data by county – since the cities in the sample are specifically chosen to not be close to redlined cities, each county contains only one of either the control or treatment cities. The key assumption, however, is that this county-wide data is attributable to the city in our sample, which may not necessarily be true. Further details on methodology for city and county matching and distance calculations, and a complete list of the control and treatment cities are presented in Appendix A.

3.2 ZCTA-Level Data and Methods

Following discussion of city-level analysis, I present results on voting outcomes. The main causal variable in this section is "redlining score", or HOLC score, which is constructed using data on HOLC neighborhood grades and boundaries from the Digital Scholarship Lab at the University of Richmond (Nelson et al. 2021). The main outcome variable is an estimate of voter turnout, constructed using data from Catalist, a private data utility firm, and data from the 5-Year 2012-2016 American Community Survey (ACS), retrieved from the National Historical Geographic Information System (NHGIS) – data on other covariates is

4. While I use the 5% sample for all other data, IPUMS provides the city population for all cities with populations greater than 10,000, so the city-level populations are exact.

5. There are 2 cities with 1930 populations between 40,000 and 50,000 that do not have associated HOLC maps, as determined through Mapping Inequality (Nelson et al. 2021) and (Fishback et al. 2020). These cities are not counted in the 23 treatment cities.

also retreived from the same source (Manson et al. 2019). Finally, analysis is also performed using predicted HOLC score, which is computed using a combination of the HOLC data and the ACS data. All data is aggregated at the Zip Code Tabulation Area (ZCTA) level. See Appendix B for further details on the reason for aggregation to the ZCTA level.

Redlining Score I first construct a ZCTA-level measure of redlining, based on the average HOLC grade of a given ZCTA. HOLC neighborhoods are generally smaller than ZCTAs, so I calculate an area-weighted average of the grades of the HOLC neighborhoods contained within a given ZCTA.[6] To do this, I use Geographic Information System (GIS) software to map ZCTA boundaries on top of the HOLC maps, and assign each HOLC grade a numeric score, with score 4 assigned to "A" (Best), score 3 assigned to "B" (Still Desirable), score 2 assigned to "C" (Definitely Declining) and score 1 assigned to "D" (Hazardous).[7] Figure 2 illustrates the conversion of HOLC neighborhood scores to ZCTA-level HOLC scores for the city of Los Angeles.

Note that this may result in a ZCTA that barely overlaps with a single HOLC neighborhood being assigned a HOLC score. To avoid this problem, I exclude any ZCTA with less than 20% of its area covered by HOLC neighborhood(s).[8] There are a total of 2,925 ZCTAs that overlap at least partially with HOLC neighborhoods and 1,842 ZCTAs that overlap at least 20% with HOLC neighborhoods.

Summary statistics for the 20% cutoff sample of ZCTAs are presented in Table 1. On average, ZCTAs with lower HOLC scores (corresponding to lower original HOLC grades) are more Black, less educated, more impoverished, have lower household incomes, and have lower house values, while population and area do not appear to vary significantly across different grades. Inequality, measured by the Gini Index, a measure of income distribution used to represent wealth and income inequality,[9] and the Black/White Income gap, however, is not

6. Note the distinction between the HOLC grades on the original map, which are given as letter grades, and the scores computed here, which are numeric.

7. For instance, a ZCTA that is comprised of one A-grade neighborhood (10% of ZCTA area), two B-grade neighborhoods (each 15% of ZCTA area), and one D-grade neighborhood (40% of ZCTA area), with the rest of the area not graded on the HOLC map, would be assigned a score of $4 \times (0.1)/(0.8) + 3 \times (0.3)/(0.8) + 1 \times (0.4/0.8) \approx 2.125$.

8. I test this cutoff in Appendix Table A3 – while the mean HOLC score is consistent between different cutoffs, the 20% cutoff has a significantly higher percentage of the ZCTA area covered by HOLC neighborhoods than the 10% or 0% cutoff, but retains more observations than a 30% or 40% cutoff.

9. A Gini Index of 0% signifies perfect equality (i.e. everyone has the same income), while a Gini Index of 100% signifies complete inequality (i.e. a single person has all of the income for a given region). The average Gini Index across all counties is 37.7, much smaller than the Gini Index among the sample counties. This is likely since the sample consists of larger cities, where wealth and income inequality tend to be higher (Holmes and Berube 2016).

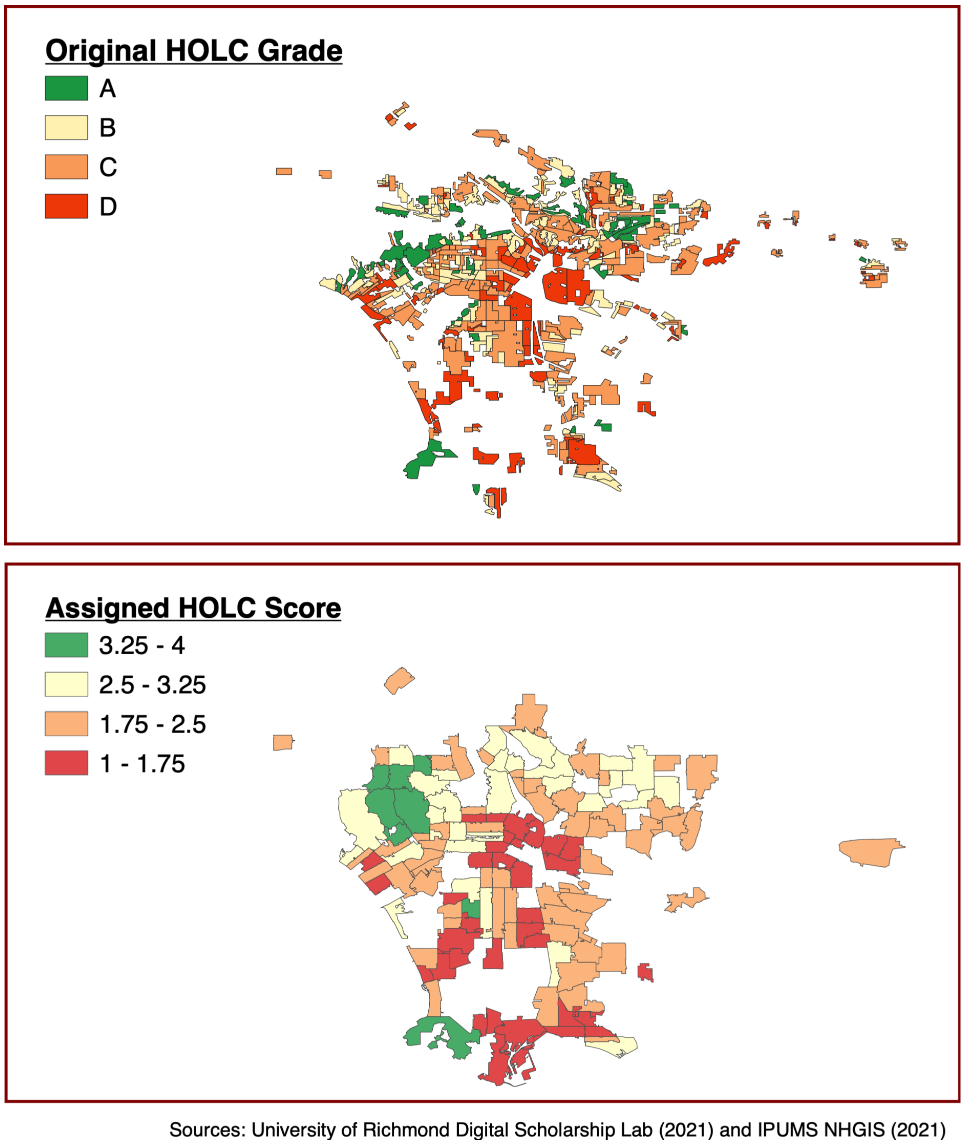

Figure 2: A comparison of HOLC neighborhoods and zip code tabulation areas (ZCTAs) in Los Angeles. The top panel shows the original HOLC map neighborhoods and their associated grades, while the bottom panel shows the imputed redlining score (or "HOLC Score") for each ZCTA that overlaps with HOLC neighborhoods.

linearly increasing or decreasing in HOLC score – it appears instead that the neighborhoods with the lowest and highest HOLC scores have the highest inequality on average, implying that the discriminatory effects of redlining, if present, may have primarily disadvantaged the lowest rated neighborhoods, while benefiting the highest rated neighborhoods.

Voting Outcomes Although voter turnout data is widely available through many well-documented, open-sourced or freely available projects such as the MIT Election Data and Science Lab or OpenElections,[10] there is very little information on voter turnout by race, mainly due to the fact that race data is not directly collected during voting, and thus in almost every state, there is no official record of turnout by race.[11] One widely-used source of voter turnout data by race (or other demographic cross-sections) is the Current Population Survey (CPS) Voter Supplement, which has collected data on voting and registration every year since 1964. The CPS, however, is only administered to a very small sample of households (surveying roughly 60,000 households for every release), among which not every household responds to the voter supplement, resulting in non-response bias. Additionally, since the responses are self-reported, the voter turnout as calculated from the CPS also suffers from vote over-report bias.[12] Since these two biases actually counteract each other, the resulting discrepancy is small, and many studies have corrected for this bias using methodology from (Hur and Achen 2013), which adjusts CPS turnout rates for individual groups using official turnout numbers.

However, recent studies have increasingly relied on more detailed voter file data, compiled by private companies, due to mounting evidence that the CPS and other surveys, even with bias correction, are inaccurate. In fact, a recent paper by (Ansolabehere, Fraga, and Schaffner 2021) shows that the CPS consistently understates the turnout gap between white and minority voters, by overestimating voter turnout among Black and Hispanic voters, and at times even underestimating voter turnout among White voters. With this in mind, for this paper I have obtained the number of voters of each race in 2016 and the number of registered persons of each race in 2020, both at the precinct level, from Catalist, a company with a known track record of producing accurate and unbiased voter turnout estimates. Catalist uses official voter registration records, and imputes race and vote probability based on a wide range of other data sources, to estimate voting numbers for each precinct. Additionally, I

10. Available via https://electionlab.mit.edu/data and http://openelections.net respectively.

11. One notable exception to this is Georgia, which publishes official voter turnout by race for every precinct.

12. Note that this is not unique to the CPS – all survey based accounts of voter turnouts suffer from over-report bias to some extent.

Mean and Std. Dev. – All ZCTAs with $> 20\%$ HOLC Overlap

		By HOLC Score Quartile			
	Overall	Quartile 1	Quartile 2	Quartile 3	Quartile 4
HOLC Score	**2.11**	1.22	1.86	2.29	3.09
	(0.72)	(0.20)	(0.14)	(0.17)	(0.37)
2016 Population	**26.1**	24.7	28.3	28.6	23.0
(Thous.)	(19.1)	(21.5)	(20.6)	(18.6)	(14.3)
Area (mi^2)	**6.74**	7.24	7.26	5.46	7.02
	(19.6)	(21.8)	(19.4)	(12.6)	(22.9)
Percent Black	**23.9**	32.6	25.8	21.2	16.1
	(26.5)	(28.3)	(27.2)	(25.0)	(22.6)
Percent HS Grad	**84.4**	78.7	81.5	85.6	91.7
	(11.2)	(12.0)	(10.7)	(10.1)	(6.7)
Percent Below Pov.	**21.9**	29.7	23.8	20.6	13.4
	(13.2)	(13.1)	(13.4)	(10.9)	(9.2)
Med. HH Income	**53.7**	41.4	47.4	52.3	73.5
(Thous. 2016$)	(29.6)	(22.5)	(22.3)	(23.5)	(36.9)
Med. House Val.	**293**	245	265	273	390
(Thous. 2016$)	(261)	(228)	(221)	(240)	(317)
Gini Index	**47.4**	48.6	46.5	46.6	47.9
	(5.5)	(5.9)	(5.4)	(5.0)	(5.3)
B-W Inc Gap	**20.6**	23.5	16.7	18.7	23.8
(Thous. 2016$)	(24.9)	(25.1)	(21.7)	(22.5)	(29.5)
Observations	1842	461	460	460	461

Table 1: A comparison of key variables across the ZCTA sample, among the primary ZCTA sample – containing only ZCTAs that overlap with HOLC neighborhoods by at least 20%. Summary statistics are presented for all ZCTAs in the sample, and by quartile of HOLC score. Note that overall HOLC scores are lower than 2.5 (the midpoint of the lowest and highest grades), likely because lower-graded HOLC neighborhoods, as marked on the original map, tended to be larger on average than higher graded HOLC neighborhoods. All monetary data is given in thousands of 2016 dollars. HOLC grade data is calculated using geospatial data from (Nelson et al. 2021) and (Manson et al. 2019). All other variables are taken, at the ZCTA level, from the 5-Year 2012-2016 ACS (Manson et al. 2019).

obtain data on the Citizen Voting Age Population by race from the 5-Year 2012-2016 ACS, which, unlike the 1-Year ACS or the CPS, releases data at the ZCTA level, and is also more recent than the 2010 Census.

The Catalist data is only available at the precinct level, so I aggregate it to the ZCTA level, dividing votes from precincts that fall between multiple ZCTAs based on area. Calculating this overlap area requires GIS boundaries for the precincts, which, unfortunately, is not included in the Catalist data. Fortunately, (Voting Election Science Team 2018) provides GIS boundaries for 2016 precincts in most states. Of the 38 states that contain cities with HOLC maps, 24 are successfully matched with the voter file data using this dataset, and an additional two states are matched using more recent GIS data released directly by the state.[13] Once vote totals are matched to GIS data at the precinct level, the ZCTA-wide vote total is calculated. Once again, ZCTAs are generally larger than precincts, so all votes from a precinct that is completely contained within a ZCTA are assigned to that ZCTA. If a precinct is on the border between multiple ZCTAs, the votes are divided based on the fraction of the precinct's area that is contained within each ZCTA, and assigned accordingly.[14] Vote totals are calculated separately by race. Of the 14,662 total ZCTAs that were assigned a vote total, 916 had also been assigned a HOLC score.

I include only ZCTAs comprised only of sufficiently large precinct parts (to avoid including ZCTAs with arbitrarily small vote totals), and with sufficient area covered by precincts (to avoid including ZCTAs with inaccurate precinct matching).[15] Of the 916 ZCTAs assigned both a HOLC score and a vote total, 894 ZCTAs (or 97.6%) meet these criteria. Finally, I divide the imputed vote total by the Citizen Voting Age Population (CVAP), as obtained from the ACS, for each ZCTA to obtain an estimate of voter turnout – see Appendix C for details on the choice of CVAP for the denominator. An identical procedure is used to

13. The 24 states matched through the Voting and Election Science Team database are Arizona, Arkansas, Colorado, Florida, Georgia, Iowa, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Nebraska, New Hampshire, North Carolina, Oklahoma, Oregon, Rhode Island, South Carolina, Texas, Virginia, Washington, and Wisconsin. While data is also available for Illinois and Tennessee, precinct names were inconsistent to the point where matching was impossible. Additionally, data for Pennsylvania was released too late to be included in this analysis. California and Utah were matched using state-released precinct GIS data, bringing the total number of matched states to 26 – *only* ZCTAs from these 26 states are used throughout the Voting Outcomes section.

14. For instance, if a ZCTA contains three whole precincts, each with 1,000 votes, and 1/3 of another precinct with 3,000 votes, then that ZCTA is assigned $1,000 + 1,000 + 1,000 + (1/3)(3,000) = 4,000$ votes. As discussed in Appendix B, area-weighted vote division is feasible because ZCTA boundaries are not dependent on demographic factors, unlike precinct boundaries.

15. I exclude ZCTAs comprised of precinct parts that collectively constitute less than 10% of their respective precincts, and I exclude ZCTAs with less than 80% of their area covered by precincts. All findings are robust to these cutoffs.

calculate percent registered.[16] Finally, I also impose the constraint that all ZCTAs must have turnout figures between 5% and 100%. This restriction excludes roughly 20% of matched ZCTAs, but findings are once again robust to this constraint, as we see in Section 5.1. In total, this gives a sample of 729 HOLC ZCTAs.

Redlining Score Finally, in addition to the "HOLC ZCTAs", I also construct a sample of "non-HOLC ZCTAs" – ZCTAs with similar characteristics to the HOLC ZCTAs, in the same 26 states as the HOLC ZCTAs, but that were *not* redlined. I start with a sample of 7,473 ZCTAs that were successfully matched to precincts and assigned turnout scores, but do not overlap at all with any HOLC neighborhood, as well as the core sample of 729 HOLC ZCTAs. It is reasonable to assume that without any constraints, the non-HOLC sample would primarily consist of rural areas, which differ in many ways from the city centers in which most HOLC neighborhoods reside. To attempt to reduce this effect, I take only the ZCTAs that are sufficiently "urban", by the historical Census definition, which mandates a population density of at least 1,000 people per square mile (ppsm) (U.S. Census Bureau 1994). This leaves 1,996 non-HOLC ZCTAs and 699 HOLC ZCTAs. The top panel of Table 2 presents summary statistics for the full sample and this "urban" sample. The primary problem with using the 1,000 ppsm cutoff is that this definition of urban is usually applied to entire cities or towns. ZCTAs, especially those in urban areas, are smaller subdivisions of cities, intended to more closely mimic neighborhoods. For instance, while the city of Phoenix, AZ has a population density of just over 3,000 ppsm, this area includes both central downtown ZCTAs, with population densities as high as 10,787 ppsm, and suburban or even rural ZCTAs, with population densities as low as 217 ppsm. As a result, Table 2 shows that within the urban sample, the HOLC ZCTAs still have an average population density more than twice that of the non-HOLC ZCTAs, as well as much lower median incomes, and much higher median house values than the non-HOLC ZCTAs – evidence consistent with the idea that many of the non-HOLC ZCTAs are in suburban areas, which likely differ in more ways from the HOLC ZCTAs than in just their redlining status. Additionally, since the most densely populated ZCTAs are in large cities, most of which were redlined (e.g. Boston, Chicago, San Francisco, etc.), the HOLC ZCTAs are likely biased by these population-dense outliers.

In light of this, I designate a "superurban" sample of ZCTAs with population densities of at least 5,000 ppsm but no larger than 20,000 ppsm, which contains approximately equal

16. Note that since our data only contains registration numbers for 2020, while the CVAP is from 2016, the registration percentages are less accurate.

numbers of non-HOLC ZCTAs (374) and HOLC ZCTAs (379). *Even* with this restriction, the average population density of the HOLC ZCTAs is slightly higher than the average population density of the non-HOLC ZCTAs, but the gap is much smaller (and persists no matter what cutoffs are used).

For the Urban and Superurban samples, I then use Lasso Regression to train a predictive model for HOLC score, based on the sample of HOLC ZCTAs, and predict the estimated HOLC score (PHOLC) for both the HOLC and non-HOLC ZCTA samples. I briefly summarize the results in the bottom panel of Table 2. The Root Mean Squared Error and R^2 for both samples is relatively similar – both are fairly low, given the number of variables used in prediction,[17] due to the fact that there is such a high degree of randomness in the HOLC data to begin with. Additionally, for both samples, the average predicted score for the HOLC cities is significantly lower than the average predicted score for the non-HOLC cities.

4 City-Level Economic Outcomes

4.1 Population and Income

This section presents several findings. First, I compare the present-day populations of the treatment and control cities. Figure 3 plots the log of the 2016 population against the 1930 population, for the treatment group of "redlined" cities, with populations just above 40,000 (in red) and the control group of "non-redlined" cities, with populations just below 40,000 (in blue). If the identification assumption – that the two cities did not differ significantly in 1930 aside from the HOLC map treatment – holds, then we would not expect to see any significant differences between the present-day populations of the two groups. Indeed, while the regression lines on either side initially appear to be sloped in opposite directions, this difference is negligible when considering the small sample size and the magnitude of standard error. The identification assumption is difficult to test, given that many of the other variables (racial composition, income, etc.) that could serve as benchmark comparisons may actually themselves be outcome variables of interest, however the lack of a significant difference in present-day populations is promising. While it does not confirm that our identification assumption holds, it indicates that the 40,000 population cutoff was not significantly related to the overall growth of the cities in this sample.

17. I use thirty variables, not counting state dummies, including variables like income, education level, travel time to work, Gini index, median rent, etc.

Mean & SD – HOLC and non-HOLC (NHOLC) ZCTAs by Density Cutoff

	All		Urban*		Superurban**	
	NHOLC	HOLC	NHOLC	HOLC	NHOLC	HOLC
Summary Statistics						
2016 Population	16.6	27.2	33.7	27.0	38.6	31.2
(Thous.)	(17.3)	(16.2)	(17.6)	(16.3)	(18.7)	(17.0)
Pop. Density	1,061	7,568	3,529	7,879	7,145	9,507
(ppl per mi^2)	(1,952)	(6,778)	(2,414)	(6,750)	(2,233)	(3,948)
Pct. Black	11.2	20.0	12.7	20.1	11.0	19.0
	(15.6)	(24.0)	(15.7)	(24.2)	(13.8)	(23.5)
Pct. HS Grad	85.7	82.6	87.7	82.6	82.6	82.2
	(8.9)	(12.7)	(9.3)	(12.9)	(11.2)	(13.3)
Pct. Below Pov.	15.5	22.8	14.4	23.0	18.6	22.3
	(8.9)	(11.7)	(9.4)	(11.7)	(11.1)	(11.4)
Med. HH Inc.	54.1	50.2	63.7	50.3	57.7	52.1
(Thous. $)	(20.8)	(24.5)	(25.0)	(24.9)	(23.0)	(22.8)
Med. House Val	182.6	304.6	269.1	311.6	329.9	366.7
(Thous. $)	(159.0)	(286.7)	(216.1)	(290.6)	(247.1)	(277.6)
Gini Index	42.7	47.7	43.0	47.8	44.1	48.1
	(5.6)	(5.6)	(5.3)	(5.6)	(5.4)	(5.4)
B-W Inc. Gap	13.4	20.9	14.2	21.2	16.1	21.1
(Thous. $)	(21.5)	(24.3)	(20.6)	(24.4)	(20.3)	(25.9)
Observations	7473	729	1996	699	379	374
Predictive Model						
Pred. HOLC Score			2.31	2.09	2.20	2.06
			(0.36)	(0.44)	(0.38)	(0.37)
RMSE			0.498		0.504	
R^2			0.472		0.428	
Observations			1589	607	310	293

Table 2: A comparison of key variables across the HOLC ZCTA (matched to precincts and overlapping at least 20% with HOLC neighborhoods) and non-HOLC ZCTA (matched to precincts and not overlapping with any HOLC neighborhoods) samples. Summary statistics are presented for all ZCTAs in the sample, for ***Urban ZCTAs**, which have a population density of at least 1,000 people per square mile, and for ****Superurban ZCTAs**, which have a population density between 5,000 and 20,000 people per square mile. Note that the number of observations in the top and bottom panels differ – this is because prior to the training of the lasso regression model, any ZCTAs with missing data are removed, and the HOLC and non-HOLC samples are restricted to cover the same set of states. All variables are taken, at the ZCTA level, from the 5-Year 2016 ACS (Manson et al. 2019).

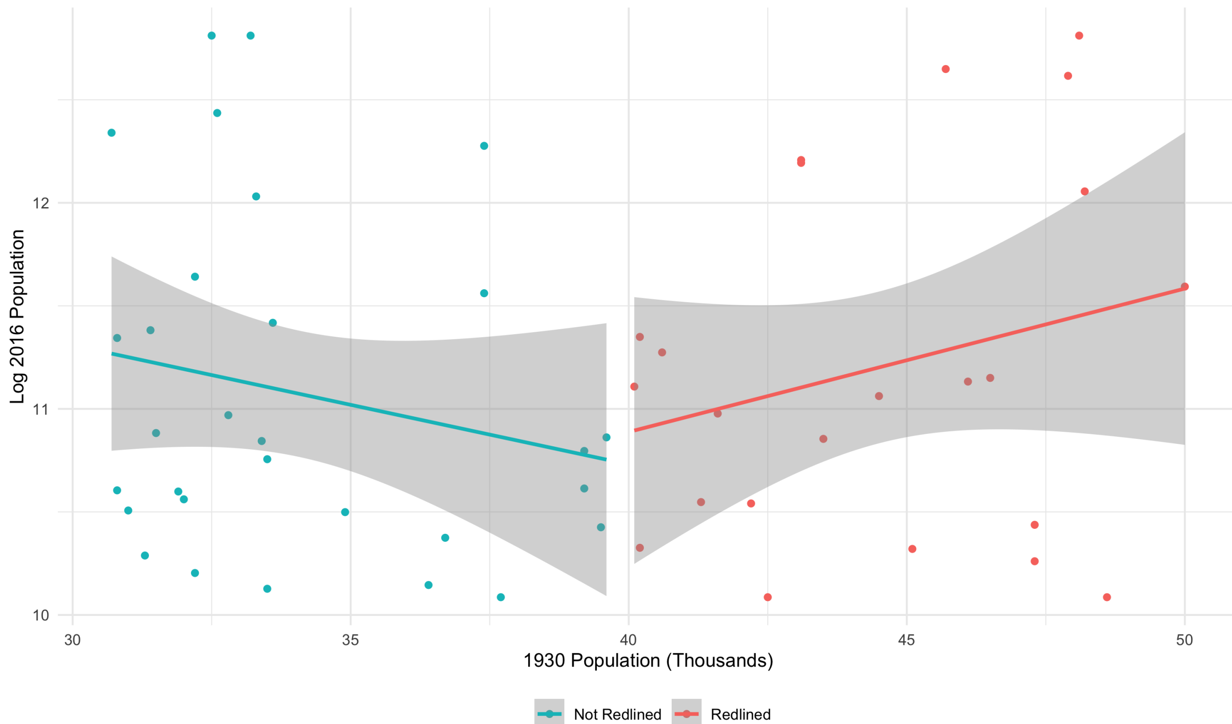

Figure 3: This figure graphs Log 2016 Population against 1930 Population, for the redlined (treatment) cities, on the right in red, and the non-redlined (control) cities, on the left in blue. The 1930s HOLC maps were only drawn for cities with populations of at least 40,000 or above – a natural cutoff that can be used to compare outcomes for *barely* redlined cities, and *barely* not redlined cities. A regression line is plotted for each group of cities, but the relationship between Log 2016 population and 1930 population is not significant for either group. 2016 city population data is taken from the 5-Year 2012-2016 American Community Survey, while 1930 city population data is taken from the 1930 Census (Manson et al. 2019; Ruggles et al. 2020).

Assuming that the cutoff is indeed independent from economic outcome variables of interest, I present further results. Figure 4 plots the percentage of the city that was Black in both 1930 and 2016 against the 1930 population, for redlined and non-redlined cities. The top panel shows that in 1930, the two groups have relatively similar Black shares of population, if slightly different slopes (which is likely due to the cluster of outlier cities in the non-redlined group with a high Black share). By 2016, however, while the pattern of Black share of population for non-redlined cities stays remarkably constant, the same does not hold for the redlined cities, which now have a considerably higher Black share. While the slope of the regression line for redlined cities stays relatively flat, the level increases, creating a noticeable jump at the population cutoff of 40,000. In fact, while the overall percentage Black of the non-redlined population was similar to that of the redlined population in 1930 (8.3 and 8.0% respectively), by 2016, the population of the redlined cities was 17.5% Black, compared to only 12.7% in the non-redlined cities. Although the standard errors are quite large, these results are in line with previous analysis by Aaronson et al., raising the real possibility that redlining has directly impacted the racial composition of cities. The regional variation between these cities is evenly distributed (in fact, a larger percentage of the control cities are in the South, a region with a much larger Black population, than among the treatment cities). And while larger cities tend to have larger Black populations than smaller cities, there is not much of a difference in present-day populations of the two groups, as seen in Figure 3. So why might this pattern appear?

One potential theory is that redlining had an effect on the overall wealth of the city. If a city became wealthier over time, it may have experienced an influx of migrants in search of higher-paying jobs – alternatively, if a city became poorer over time, it may also have experienced an influx of migrants in search of cheaper housing. Both of these theories are examined in Figures 5 and 6. In Figure 5, measures of the median household income in 1930 and 2016 are graphed against the 1930 population. While 1930 income data is not directly available, the IPUMS data set provides the variable `OCCSCORE`, which uses median income and occupation data from 1950 to impute income (in hundreds of 1950 dollars) based on occupation in 1930 (Ruggles et al. 2020).[18] This is compared to the actual median income from 2016, graphed in hundreds of 2016 dollars. As one might expect, the general average income level is considerably higher in 2016. Interestingly, however, while the 1930 incomes of the redlined cities as plotted against their 1930 populations are considerably more sloped, this effect disappears in 2016 – in fact, the regression line for the redlined cities has shifted down relative to the regression line for non-redlined cities. The standard errors, however,

18. This variable, or a similarly constructed variable, is used in several other papers as an imputed measure of pre-1950s income, including (Olivetti et al. 2020) and (Collins and Wanamaker 2017).

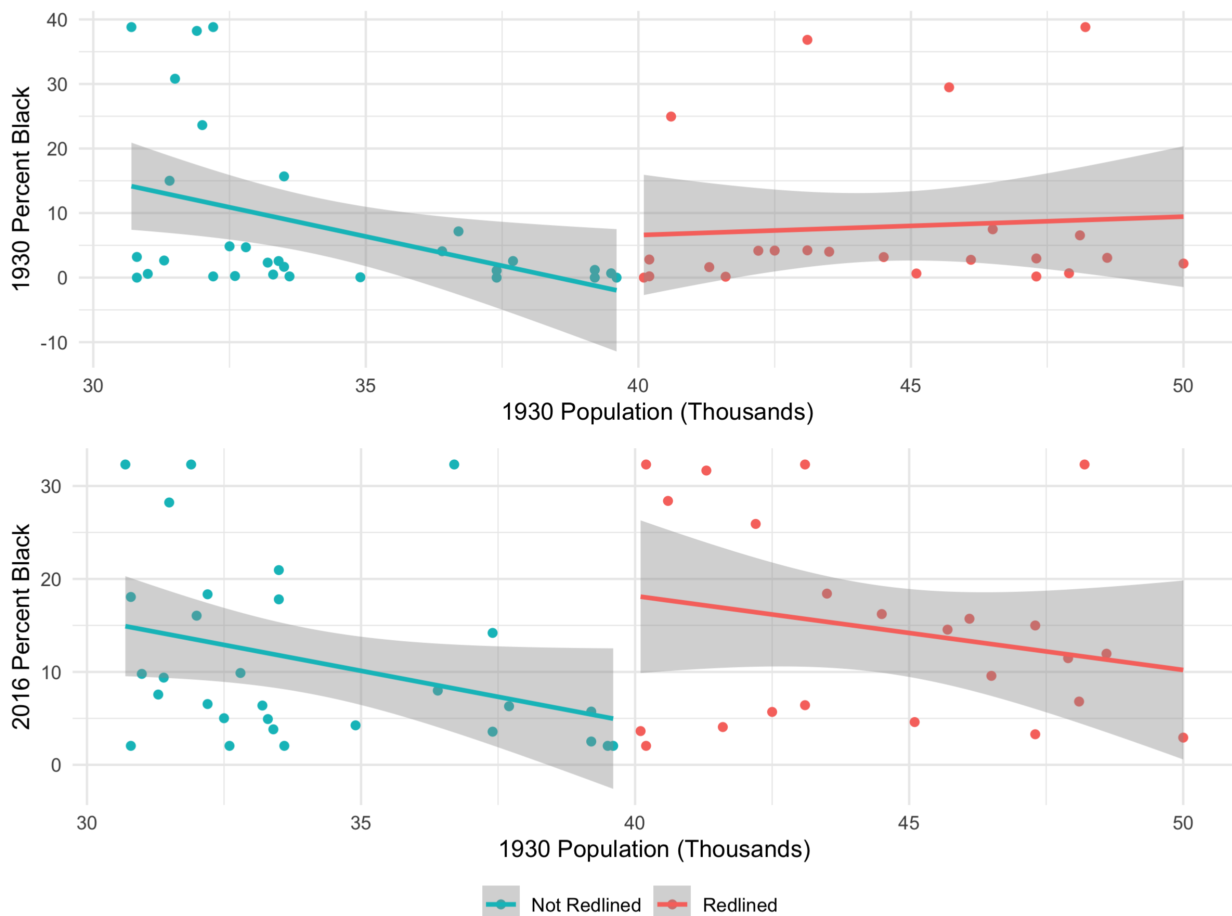

Figure 4: This graph plots the percentage of the population that is Black against the 1930 population, for the control and treatment cities, in both 1930 and in 2016. Data is 10% Winsorized, which removes major outliers. 1930 data is obtained from the 1930 Census while 2016 data is obtained from the 2016 ACS (Ruggles et al. 2020; Manson et al. 2019).

are quite large, so this result does not provide much insight into our theorized mechanism. Additionally, there is a great deal of uncertainty surrounding the accuracy of the `OCCSCORE` variable, particularly in predicting Black incomes, adding more doubt (Collins 2000).

Figure 6 is slightly more striking, but similarly ambiguous. This figure compares the median house values among the redlined and non-redlined groups in 1930 and 2016. While the average median house value is slightly higher in redlined cities in 1930 (although not significantly so), the reverse is true in 2016 (although again, the result is not significant).

4.2 Inequality, Mobility, and Segregation

Although the population and income variables are interesting, since redlining occurs at the neighborhood level, one might expect the potential negative effects of redlining on income in some communities to be cancelled out by the potential positive effects of redlining on income in other communities – the same might apply to house value. This section examines outcome variables that may reflect the effects of redlining *within* cities, between different neighborhoods, rather than the effects on the city as a whole.

Table 3 presents several key statistics. As discussed in section 3, these variables are originally at the county level prior to aggregation. Although each county contains only one city from the sample, since counties contain many smaller cities, the assumption that the characteristics of the entire county are attributable the city may not necessarily hold. Among the control and treatment cities, however, each is the largest city in its respective county, and so it is reasonable to believe that county-level characteristics mostly reflect the characteristics of the main city.

The first variable presented in the table is the Gini Index, which is strikingly similar for the non-redlined and redlined group – additionally, although not shown in the table, other measures of income inequality, such as the share of the population in the middle class[19] or the income share of the top 1%, are also similar between the two groups. Similarly, income segregation (measured by the Theil Index) is virtually identical between the two groups. So there is no evidence that the HOLC maps impacted the spread of income within a city.

There is, however, a slight difference in the racial segregation of the two groups. Racial segregation (again measured by the Theil Index) is four percentage points higher in the counties surrounding redlined cities than in the counties surrounding non-redlined cities. Although

19. This is calculated as the percentage of the population with incomes between the 25th and 75th national income percentiles.

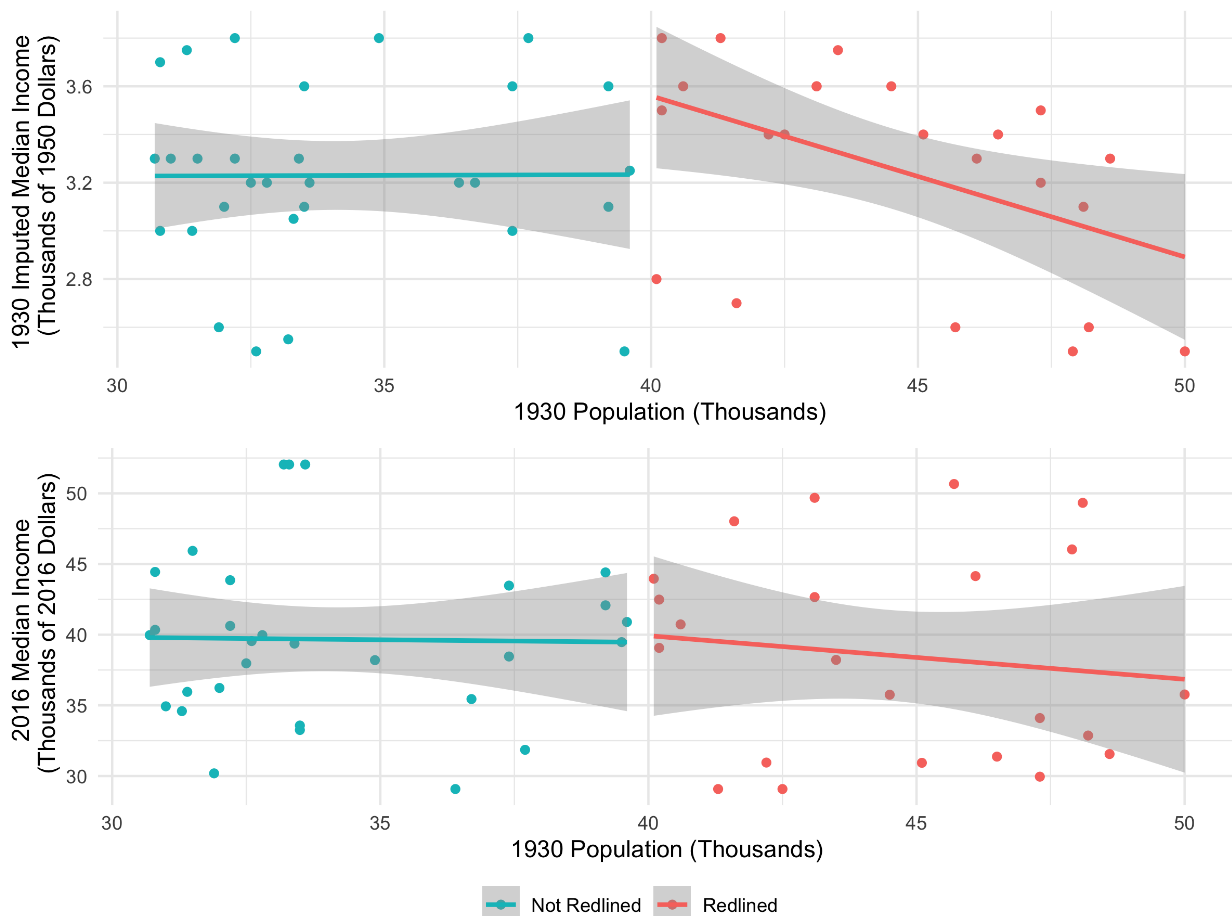

Figure 5: This graph presents the imputed median household income for redlined and non-redlined cities in 1930 in the top panel, in thousands of 1950 dollars, and the median household incomes for both groups in 2016 in the bottom panel, in thousands of 2016 dollars, all against the 1930 population (see Appendix A for details on these variables). Data is 10% Winsorized, which removes major outliers. 1930 data is obtained from the 1930 Census while 2016 data is obtained from the 5-Year 2016 ACS (Ruggles et al. 2020; Manson et al. 2019).

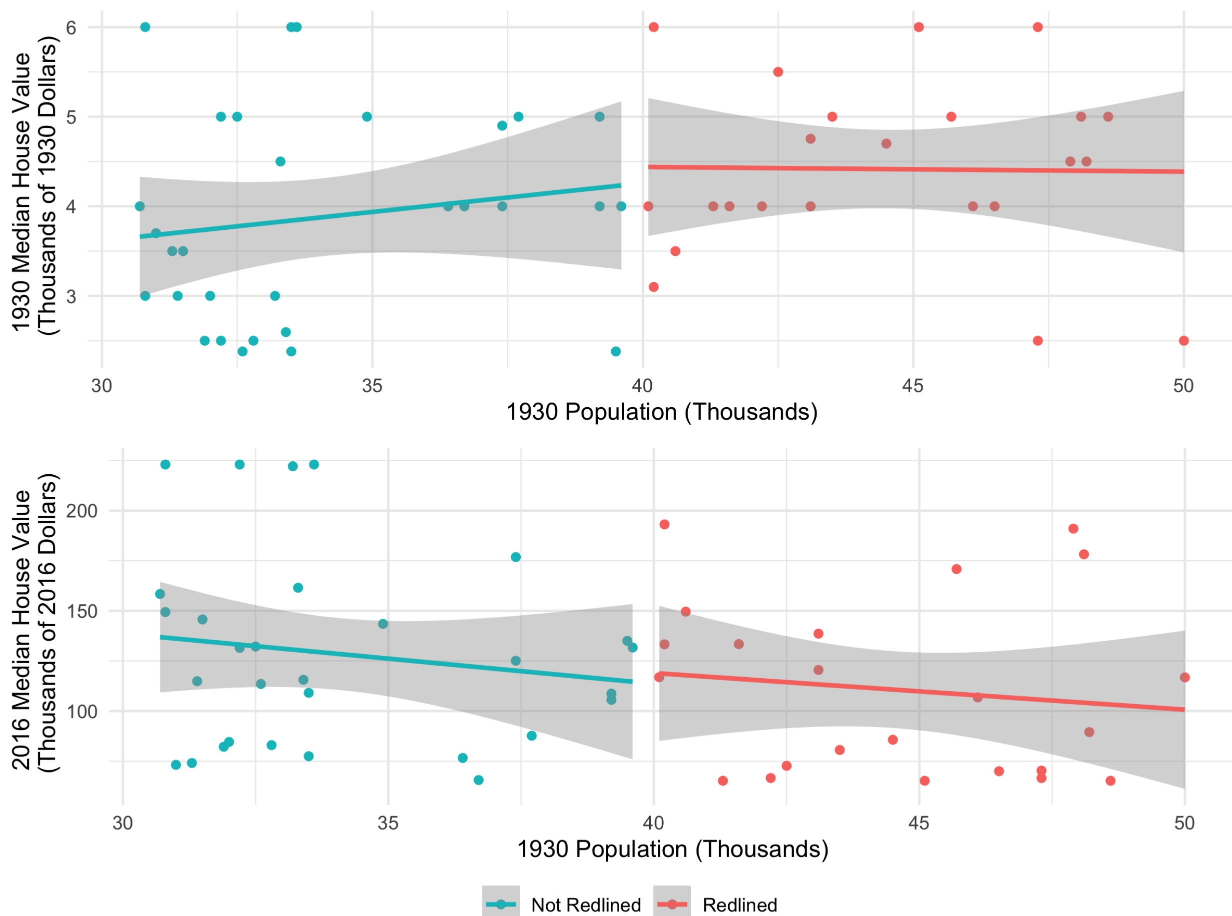

Figure 6: This graph presents the median house values for redlined and non-redlined cities in 1930 in the top panel, in thousands of 1930 dollars, and the median house values for both groups in 2016 in the bottom panel, in thousands of 2016 dollars, all against the 1930 population. Data is 10% Winsorized, which removes major outliers. 1930 data is obtained from the 1930 Census while 2016 data is obtained from the 5-Year 2016 ACS (Ruggles et al. 2020; Manson et al. 2019).

this difference is not significantly different from zero, it suggests that further research on the link between redlining and racial segregation at the city level may be insightful.

Finally, the last two rows of Table 3 reflect the discussion in Section 2 on "place" or "neighborhood" effects. The table entries represent the percentage of household income at age 26 lost from staying in a given county for one extra year of childhood, relative to the national mean – **p25 Place Effect** is the magnitude of this effect for children with parents at the 25th percentile of income nationally, and **p75 Place Effect** is the magnitude of this effect for children with parents at the 75th percentile of income nationally, both averaged across the group. Although the effects are dwarfed by the amount of variation among counties within each group, it is interesting to note that the mean place effect for low income children is 11 percentage points lower in redlined cities than in non-redlined cities – i.e. for a child with parents with income at the 25th percentile, spending a year in one of the redlined cities would decrease household income at age 26 by 15% on average, compared to only 4% on average from spending a year in one of the non-redlined cities. On the other hand, the mean place effect for high income children is actually 3 percentage points higher in redlined cities than in non-redlined cities, potentially indicating that redlining could have a differential effect on economic mobility for high- and low-income children.

It is important to note, of course, that many of these variables are *highly* correlated, such as racial segregation and place effect. Since the sample of cities is so small, much of the variation comes down to individual cities – for instance, removing the six cities with the lowest 2016 Black share of the population (five of which are non-redlined cities) causes the difference in **p75 Place Effect** to all but disappear (although the difference in **p25 Place Effect** remains). So while it is possible that these results are indicative of the effects of redlining, it is also possible that the differences stem from random variation, and are all linked (e.g. the redlined sample may just happen to have highly racially segregated cities, which may also happen to have strongly negative p25 Place Effects, high Black population shares, and lower median incomes). These results, however, are also in line with other work on HOLC maps by (Aaronson, Hartley, and Mazumder 2017) and (Mitchell and Franco 2018), which show worse economic outcomes among redlined cities, and more segregation in cities with higher shares of low redlining grades.

Furthermore, the lack of an observable effect of the HOLC maps on these outcomes does not necessarily imply the lack of an effect of redlining on these outcomes. Although I have been using the terms interchangeably, HOLC maps may not have had a causal effect on redlining in the first place. Suppose that instead of *causing* redlining, the HOLC maps were simply a tangible representation of existing redlining practices, as has been suggested by many. In this case, since our analysis rests on the assumption that the control group and treatment group are similar in all ways aside from the HOLC maps, we would expect the control cities to have had similar redlining practices as the treatment cities, even without the HOLC maps. Then we would not expect to see differences in any of the outcome variables between the two groups. Thus while this section does not present any quantitative effects of redlining, the results indicate that further exploration into the city-level outcomes of redlining, particularly pertaining to racial segregation, and economic mobility, may prove insightful.

5 Voting Outcomes

5.1 Initial Diff-in-Diff Estimation

Having examined redlining and the HOLC maps at the city level, I now use neighborhood-level analysis to examine the relationship between voting and redlining. I start by displaying, in Figure 7, the relationship between the average numeric HOLC grade (the "HOLC Score") and the imputed voter turnout of a ZCTA by race, among the sample of redlined ZCTAs (the "HOLC ZCTAs"). While the total voter turnout and the voter turnout among White voters are both increasing in the ZCTA's HOLC Score, the slope of the line for Black voters is almost completely flat, suggesting that on average, while redlining may be associated with higher White voter turnout, redlining has no effect on Black voter turnout. A similar trend emerges when looking at the percentage of the population registered to vote, with even more dramatic results. In Figure 8, the slope of the regression line for White voters is actually steeper than for the total population, while the regression line for Black voters now has a slightly negative slope. Although the registration results are slightly messier, with much larger error and less accurate data,[20] the trend matches very closely with the results seen in Figure 7.

To further explore the relationship between these variables, I present regression results in Table 4. Column (1) shows the overall positive relationship (across both races) between HOLC score and voter turnout, estimating that an increase in HOLC score by 1 (corresponding to an increase in the HOLC grade by one level), is linked to an increase in voter turnout of 4.7 percentage points on average. This is in line with the observed characteristics of cities with lower and higher HOLC scores (in Table 1), which indicated that ZCTAs with higher HOLC

20. Recall that the registration data is for November of 2020, which means that there is no up-to-date ACS release that allows for accurate calculation of the CVAP, as was done for the 2016 data. Since accurate data is not available, for consistency, I use the 2016 CVAP throughout.

	Mean and Std. Dev.	
Variable	Non-Redlined	Redlined
Gini Index	43.0	42.8
	(8.6)	(8.4)
Income Segregation	0.07	0.07
	(0.03)	(0.03)
Racial Segregation	0.14	0.18
	(0.07)	(0.07)
p25 Place Effect	-0.04	-0.15
	(0.36)	(0.38)
p75 Place Effect	0.02	0.05
	(0.21)	(0.15)
Obs.	30	23

Table 3: A comparison of key variables among the control and treatment groups, at the county level. While treatment is determined at the city level (i.e. each data point represents a redlined or non-redlined city), the outcome variables are by county, so county-level data is used here. Data is obtained from (Chetty and Hendren 2018b) Online Data Table 4.

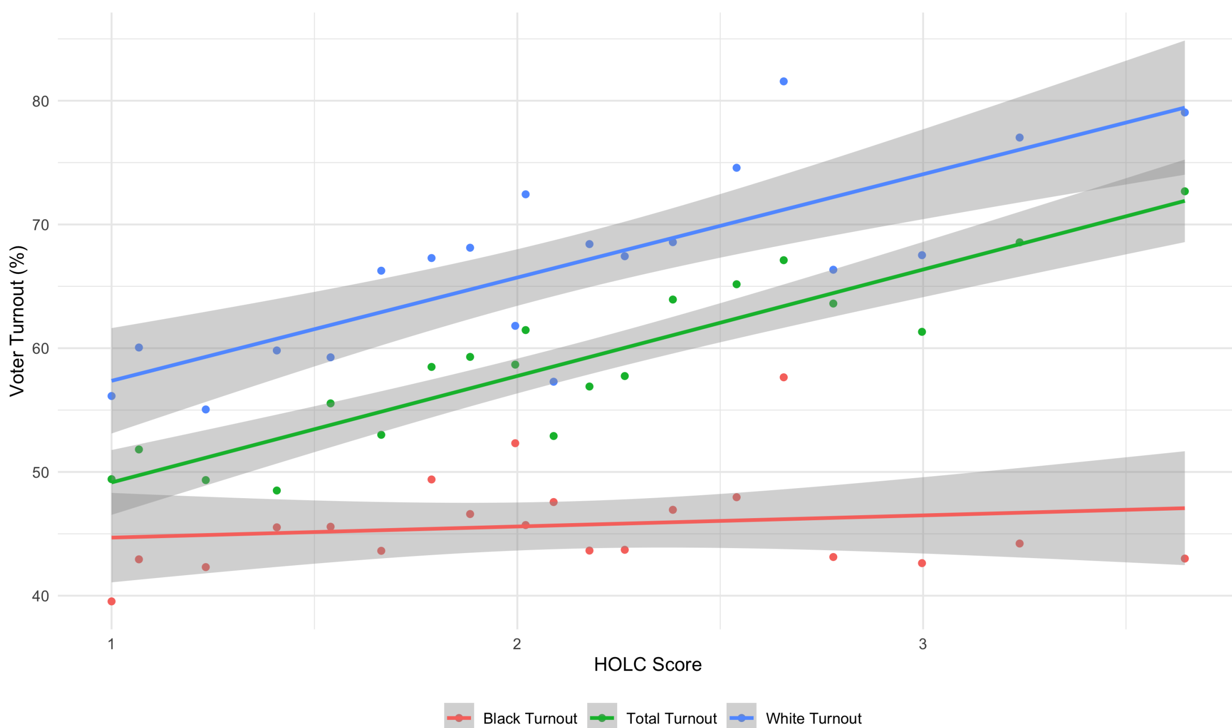

Figure 7: This figure displays a binned scatter plot of Voter Turnout against HOLC Score the for 729 HOLC ZCTAs, across 26 states.

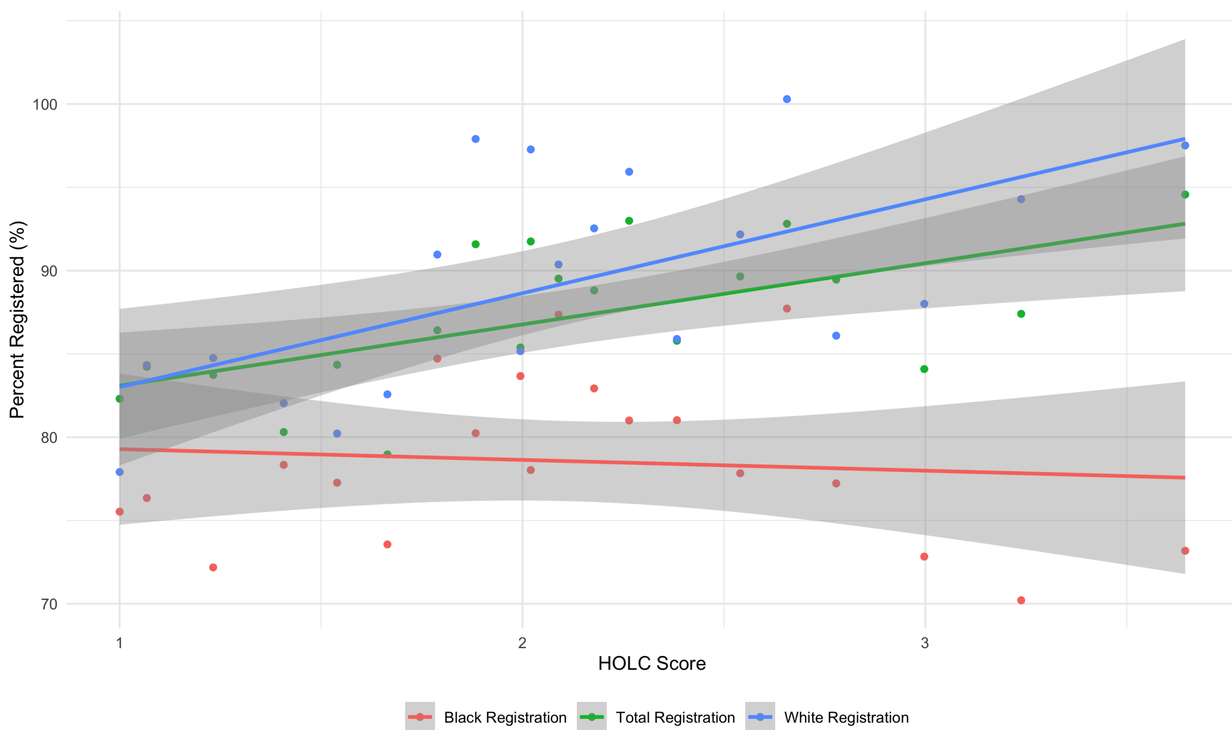

Figure 8: This figure displays a binned scatter plot of Voter Turnout against HOLC Score the for 729 HOLC ZCTAs, across 26 states. Because only current registration data was available, percent registered was calculated by dividing the number of people registered in November of *2020* by the CVAP in 2016.

scores have higher median incomes and levels of education and lower shares of population; since these variables are also highly correlated with voter turnout, this strong positive relationship is unsurprising. Column (2) looks at race, indicating that average Black voter turnout is 19.8 percentage points lower than average White voter turnout among HOLC ZCTAs. Column (3) combines these two analyses, interacting HOLC score with race:

$$\text{turnout} = \beta_0 + \beta_1 \text{HOLC} + \beta_2 \text{Black} + \beta_3 \text{HOLC} \times \text{Black} \tag{1}$$

The results correspond to Figure 7. First, note that we estimate $\hat{\beta}_1 = 0.071$, indicating that for White voters, a one-unit higher HOLC score corresponds to a 7.1 percentage point increase in turnout. For Black voters, however, we can see that the effect of the HOLC score is much smaller. $\hat{\beta}_1 - \hat{\beta}_3 = 0.071 - 0.049 = 0.022$, indicating that for Black voters, a one-unit higher HOLC score corresponds to only a 2.2 percentage point increase in turnout. Thus while for a ZCTA with a HOLC score of 1 (Grade "D"), White voter turnout is expected to be 14.4 percentage points higher than Black voter turnout, this gap grows to 29.1 percentage points for a ZCTA with a HOLC score of 4 (Grade "A"). This gap remains essentially unchanged even when, in column (4), I control for state fixed effects, ZCTA population, and ZCTA area, variables which did not appear to be related to HOLC score, based on Table 1.

In column (5), I include other covariates, such as the Black share of the population, the percentage of adults who graduated high school, the median household income and house value, and the Black/White income gap, which may be correlated with HOLC score. When these variables are introduced, the positive relationship between HOLC score and White voter turnout ($\hat{\beta}_1$) shrinks to 0.024, suggesting that much of the variation in voter turnout between HOLC neighborhoods among White voters is due to factors like income, house value, and Black share. Crucially, the estimated coefficient on the interaction between race and HOLC score, $\hat{\beta}_3$, remains nearly identical. This means that while the positive effect of HOLC score on White voter turnout is now much smaller, with an increase in HOLC score of 1 corresponding to an increase in turnout of 2.4 percentage points, now the relationship between HOLC score and Black voter turnout is *negative*, with an increase in HOLC score of 1 corresponding to a *decrease* in Black turnout by 2.5 percentage points. If we view this as an isolation of the direct effect of redlining, excluding the effects through income, house value, and racial composition, then the implication is that 1930s redlining benefitted White voters today, at the expense of Black voters today. Columns (4) and (5) are replicated for the full sample of ZCTAs, which are considerably less filtered based on turnout (as discussed in Section 3), in columns (6) and (7). The results are very similar to columns (4) and (5), suggesting that the findings are robust to the selection methodology used.

5.2 Triple Difference Estimation

The primary concern with interpreting this finding as a direct effect of redlining is that we do not have a point of comparison. Although we attempt to control for a variety of economic and demographic characteristics, all that Table 4 shows is that ZCTAs that happened to have been assigned higher HOLC scores in the 1930s have considerably higher White voter turnout than those that were assigned lower scores, while the difference is smaller for Black voters, possibly even negative. However, it is entirely possible that similar neighborhoods in different cities, that were not redlined, also exhibit similar patterns, based on variables unrelated to redlining. To check whether this is the case, I construct a sample of "non-HOLC ZCTAs", as outlined in Section 3, and assign predictive HOLC scores to ZCTAs in both groups, based on a number of socioeconomic, geographic, and demographic variables.

The aim is to estimate the difference between the value of β_3 in equation (1) for HOLC and non-HOLC ZCTAs, using predicted HOLC scores (PHOLC) instead of actual HOLC scores. If the difference in voting outcomes by HOLC score by race is truly due to redlining, then we should see a difference in the effect of PHOLC by race on turnout between HOLC and non-HOLC ZCTAs. As a first look, I graph voter turnout against predicted HOLC score by race among the "urban" sample in Figure 9. The entire graph appears to rotate flatter for the HOLC ZCTAs, suggesting that HOLC ZCTAs *overall* have a weaker relationship between variables like income, education, etc., and voter turnout, compared to non-HOLC ZCTAs. It does not, however, suggest that there is any substantial difference in this effect for White and Black voters. But as noted in Section 3, even with the "urban" cutoff of 1,000 ppsm, the non-HOLC ZCTAs appear to primarily consist of suburban areas, which may affect voter turnout differentially by race. So there is a possibility that the "suburban" effect counteracts any effect of the HOLC maps, which may be why no difference appears in Figure 9.

As a further test, I also graph voter turnout against predicted HOLC score by race among the "superurban" sample in Figure 10, and find a very different pattern. Firstly, the overall level of voter turnout amongst both White and Black voters is higher on average in HOLC cities, by a significant amount. Secondly, and most crucially, while the relationship between predicted HOLC score and voter turnout appears to be nearly identical for White and Black voters in non-HOLC ZCTAs, in HOLC ZCTAs, the relationship is much weaker, nearly flat, among Black voters than among White voters (as we saw in Figure 7). This is quite

Voter Turnout Outcomes by Race and HOLC Score among HOLC ZCTAs

	Dep. Variable: ZCTA-Level Black/White 2016 Voter Turnout						
	Main Sample					Full Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HOLC	0.047		0.071	0.075	0.024	0.072	0.019
	(0.008)		(0.010)	(0.010)	(0.010)	(0.011)	(0.012)
Black		-0.198	-0.095	-0.095	-0.099	-0.158	-0.144
		(0.011)	(0.033)	(0.030)	(0.028)	(0.035)	(0.033)
HOLC × Black			-0.049	-0.049	-0.046	-0.029	-0.035
			(0.015)	(0.013)	(0.013)	(0.016)	(0.015)
Percent Black					0.181		0.289
					(0.027)		(0.030)
Percent HS Grad					0.007		-0.157
					(0.067)		(0.079)
Log Med. HH Inc.					0.108		0.128
					(0.022)		(0.025)
Log Med. House Val.					0.105		0.151
					(0.016)		(0.018)
Log B-W Inc Gap*					0.029		0.026
					(0.009)		(0.011)
Constant	0.451	0.649	0.499	0.517	-2.156	0.786	-2.540
	(0.018)	(0.007)	(0.023)	(0.104)	(0.240)	(0.125)	(0.277)
Population Controls	No	No	No	Yes	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes	Yes	Yes
R^2	0.020	0.196	0.223	0.359	0.455	0.325	0.447
Observations	1458	1458	1458	1458	1458	1758	1758

Table 4: Estimated voter turnout by race among HOLC ZCTAs. The full sample includes all ZCTAs with at least 80% coverage by matched precincts and an estimated voter turnout between 0-200% (total 879 ZCTAs). The main sample includes all ZCTAs with at least 80% coverage by matched precincts and an estimated voter turnout between 5-100% (total 729 ZCTAs). Each sample contains exactly twice the number of observations as ZCTAs, since each ZCTA has one observation for Black voter turnout and one observation for White voter turnout – Black is an indicator variable for Black voter turnout observations. All covariate data is taken from the 5-Year 2016 ACS (Manson et al. 2019). *The B-W Inc Gap variable represents the median White Household Income - the median Black Household Income for the ZCTA. Because roughly 10% of ZCTAs in the sample have a negative value for this Income Gap, a constant is added to the Income gap first, such that the minimum value of the adjusted Income gap is 1, before taking the Log. Population controls include the Log of total population of the ZCTA and the Log of total area of the ZCTA, in square meters.

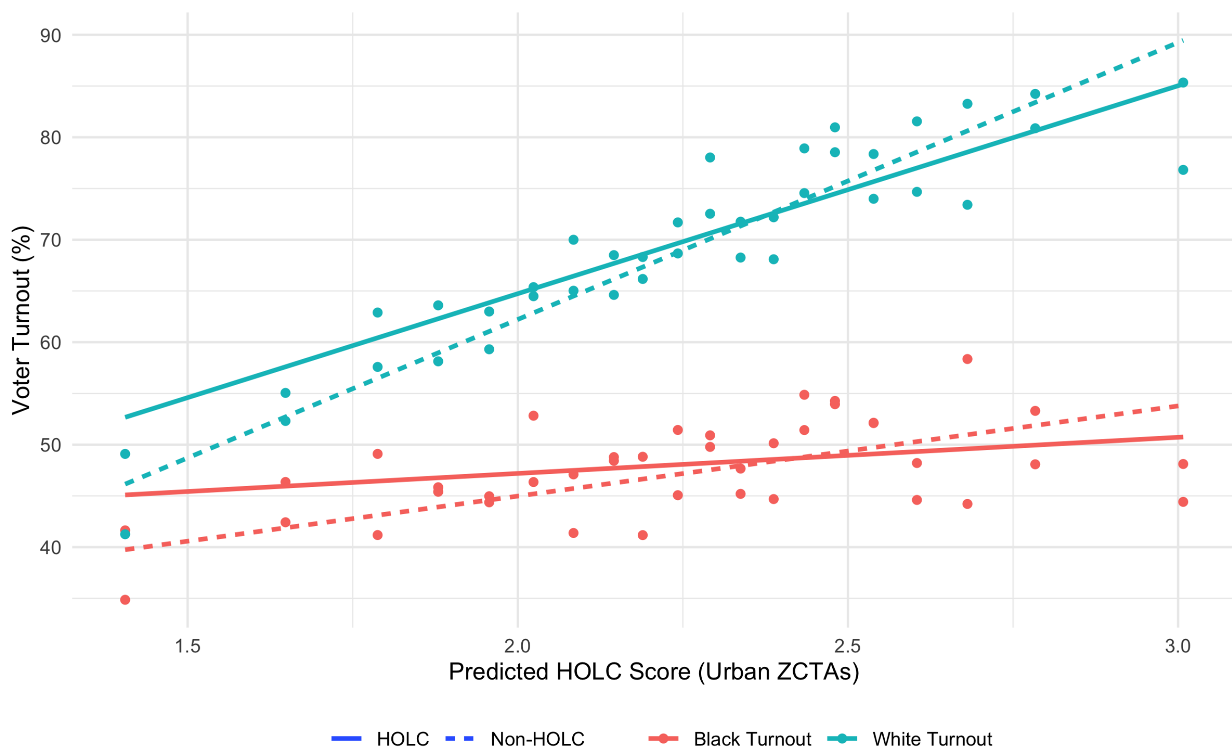

Figure 9: This figure displays a binned scatter plot of Voter Turnout against predicted HOLC Score by race for 2,197 Zip Code Tabulation Areas (ZCTAs) designated as urban (with at least 1,000 ppsm), divided into HOLC (solid line) and non-HOLC (dashed line) ZCTA groups. Data is displayed by treatment group (HOLC or non-HOLC) and race.

striking, since it suggests that there may, in fact, be a causal effect of redlining on voter turnout for Black voters – one that is quite different from the causal effect of redlining on voter turnout for White voters. I present the same graphs with Percent Registered as the Outcome Variable, which show similar results, in Appendix Figures A1 and A2.

To formally test this relationship, I estimate the following equations, denoting HOLC ZCTAs with the indicator variable Treat, where VT and RP represent voter turnout and registration percentage, respectively.

$$\begin{aligned} VT = \beta_0 + \beta_1\text{PHOLC} + \beta_2\text{Black} + \beta_3\text{Treat} + \beta_4\text{PHOLC} \times \text{Black} + \\ \beta_5\text{PHOLC} \times \text{Treat} + \beta_6\text{Black} \times \text{Treat} + \beta_7\text{PHOLC} \times \text{Black} \times \text{Treat} \end{aligned} \quad (2)$$

$$\begin{aligned} RP = \beta_0 + \beta_1\text{PHOLC} + \beta_2\text{Black} + \beta_3\text{Treat} + \beta_4\text{PHOLC} \times \text{Black} + \\ \beta_5\text{PHOLC} \times \text{Treat} + \beta_6\text{Black} \times \text{Treat} + \beta_7\text{PHOLC} \times \text{Black} \times \text{Treat} \end{aligned} \quad (3)$$

The results, which largely reflect the trends observed in Figures 9 and 10, are displayed in Table 5. Columns (1) displays the results for the estimation of equation 2 among the Urban sample. The key result here is that there is **no** significant difference in PHOLC × Black between the treatment and non-treatment groups, suggesting that the relationship between the economic and demographic characteristics of a ZCTA and the voter turnout by race in that ZCTA is not dependent on whether a city was redlined or not. To illustrate this, suppose we pick two identical cities, A and B, except while A was redlined (Treat = 1), B was not (Treat = 0). If we choose two ZCTAs in city A, one with a PHOLC score of 1 and one with a PHOLC score of 3 (and call them A1 and A3 respectively), then we predict White voter turnout ($VT^{W,U}$) and Black voter turnout ($VT^{B,U}$), where the U superscript indicates

Figure 10: This figure displays a binned scatter plot of Voter Turnout against predicted HOLC Score by race for 603 Zip Code Tabulation Areas (ZCTAs) designated as "superurban" (with between 5,000 and 20,000 ppsm), divided into HOLC (solid line) and non-HOLC (dashed line) ZCTA groups. Data is displayed by treatment group (HOLC or non-HOLC) and race.

Voting Outcomes by Race, Pred. HOLC Score, and HOLC Status

	Dep. Var.: % **Vote**		Dep. Var.: % **Reg.**	
	Urban	Superurban	Urban	Superurban
	(1)	(2)	(3)	(4)
($\hat{\beta}_1$) PHOLC	0.271	0.153	0.236	0.165
	(0.014)	(0.025)	(0.020)	(0.034)
($\hat{\beta}_2$) Black	0.179	-0.265	0.409	-0.117
	(0.046)	(0.078)	(0.065)	(0.108)
($\hat{\beta}_3$) Treat	0.188	0.022	0.378	0.236
	(0.051)	(0.080)	(0.072)	(0.111)
($\hat{\beta}_4$) PHOLC $\times$ Black	-0.158	0.042	-0.197	0.042
	(0.020)	(0.035)	(0.028)	(0.048)
($\hat{\beta}_5$) PHOLC $\times$ Treat	-0.074	0.019	-0.147	-0.063
	(0.023)	(0.037)	(0.033)	(0.051)
($\hat{\beta}_6$) Black $\times$ Treat	-0.097	0.264	-0.249	0.295
	(0.072)	(0.113)	(0.102)	(0.157)
($\hat{\beta}_7$) PHOLC $\times$ Black $\times$ Treat	0.029	-0.121	0.088	-0.143
	(0.033)	(0.052)	(0.046)	(0.072)
($\hat{\beta}_0$) Constant	0.047	0.268	0.292	0.382
	(0.032)	(0.055)	(0.046)	(0.076)
R^2	0.272	0.248	0.043	0.07
Observations	4394	1206	4394	1206

Table 5: Estimated voter turnout and people registered (in 2020) as a percentage of CVAP (in 2016) by race and by treatment group. Results are displayed for the Urban sample (which includes ZCTAs with a population density of at least 1,000 ppsm) and the Superurban sample (which includes ZCTAs with a population density between 5,000 and 20,000 ppsm). Each sample contains exactly twice the number of observations as ZCTAs, since each ZCTA has one observation for Black voter turnout and one observation for White voter turnout. Black is an indicator variable for Black voter turnout observations, while Treat is an indicator variable for voter turnout observations among the HOLC ZCTAs (as opposed to the non-HOLC ZCTAs). The PHOLC variable is the predicted HOLC score, based on a lasso regression model trained on characteristics of the HOLC ZCTA data.

that this estimation uses the Urban sample, as follows:

$$\begin{aligned}
\widehat{VT}^{W,U}_{A1} &= \hat{\beta}^U_0 + \hat{\beta}^U_1\text{PHOLC} + \hat{\beta}^U_3 + \hat{\beta}^U_5\text{PHOLC} \\
&= 0.047 + 0.271(1) + 0.188 - 0.074(1) \\
&= 0.432 \\
\widehat{VT}^{B,U}_{A1} &= \hat{\beta}^U_0 + \hat{\beta}^U_1\text{PHOLC} + \hat{\beta}^U_2 + \hat{\beta}^U_3 + \hat{\beta}^U_4\text{PHOLC} + \hat{\beta}^U_5\text{PHOLC} + \hat{\beta}^U_6 + \hat{\beta}^U_7\text{PHOLC} \\
&= 0.047 + 0.271(1) + 0.179 + 0.188 - 0.158(1) - 0.074(1) - 0.097 + 0.029(1) \\
&= 0.385 \\
\widehat{VT}^{W,U}_{A3} &= 0.047 + 0.271(3) + 0.188 - 0.074(3) = 0.826 \\
\widehat{VT}^{B,U}_{A3} &= 0.047 + 0.271(3) + 0.179 + 0.188 - 0.158(3) - 0.074(3) - 0.097 + 0.029(3) = 0.521
\end{aligned}$$

So in the redlined city, the White-Black voter turnout gap is approximately 4.7 percentage points in a low graded neighborhood, but 30.5 percentage points in a high graded neighborhood – roughly on par with findings in Section 5.1. Now, suppose we choose two ZCTAs in city B, with the same PHOLC scores of 1 and 3 (and call them B1 and B3 respectively). Then we predict:

$$\widehat{VT}^{W,U}_{B1} = 0.318; \;\; \widehat{VT}^{B,U}_{B1} = 0.339$$
$$\widehat{VT}^{W,U}_{B1} = 0.86; \;\; \widehat{VT}^{B,U}_{B1} = 0.565$$

For the non-redlined city, in the low graded neighborhood predicted Black voter turnout is actually slightly *higher* than predicted White voter turnout, giving a gap of -0.2 percentage points. In the high graded neighborhood, the gap is 29.5 percentage points. So while the sizes of the gaps are slightly smaller in the non-redlined city across all neighborhoods, and the *difference* in the White-Black voter turnout gap across different neighborhoods is slightly larger in non-redlined cities, neither of these differences are significant, implying that redlining did not have a differential effect on voter turnout by race. In this analysis, however, the key assumption is that ZCTAs A1 and B1 and ZCTAs A3 and B3 do not differ in any way other than that A1 and A3 were redlined. What if instead, ZCTAs B1 and B3 are both located in suburban areas, while A1 and A3 are located in densely packed city centers? The effects of surburbanization on voter turnout have been widely studied but are largely inconclusive, and analysis by race is much less common and even less conclusive. For instance, there is mixed evidence as to whether suburbs are more or less racially segregated than city centers. Since racial segregation has been linked to higher voter turnout, if Black voters are less segregated in suburbs, this could imply that Black voter turnout in non-HOLC ZCTAs was understated. On the other hand, suburbs have also been linked to lower income inequality compared to urban centers, suggesting that voter turnout overall in non-HOLC ZCTAs was overstated. The potential causes and effects of this "suburbs" problem are numerous. To attempt to isolate the actual effects of redlining from the effect of suburbanization, column (2) presents the results for the estimation of equation 2 among the superurban sample. The first striking result is that voter turnout overall, for both White and Black voters, is higher in HOLC ZCTAs than in non-HOLC ZCTAs. The second is that the gaps in turnout between low and high grade neighborhoods are much smaller than in the urban sample, suggesting that turnout may have been understated among low-grade ZCTAs (which are generally lower income and more Black), and may have been overstated among high-grade ZCTAs. Finally, the key result here is the significance of the coefficient on the PHOLC × Black × Treat term. To illustrate this, I repeat the exercise from above, predicting White ($VT^{W,S}$) and Black voter ($VT^{B,S}$) turnout, where the S superscript indicates that this estimation uses the superurban sample.

$$\widehat{VT}^{W,S}_{A1} = 0.462; \;\; \widehat{VT}^{B,S}_{A1} = 0.382$$
$$\widehat{VT}^{W,S}_{A3} = 0.806; \;\; \widehat{VT}^{B,S}_{A3} = 0.568$$
$$\widehat{VT}^{W,S}_{B1} = 0.421; \;\; \widehat{VT}^{B,S}_{B1} = 0.198$$
$$\widehat{VT}^{W,S}_{B3} = 0.727; \;\; \widehat{VT}^{B,S}_{B3} = 0.588$$

Now, in a redlined city the White-Black turnout gap is approximately 8 percentage points in a low graded neighborhood and 23.8 percentage points in a high graded neighborhood. In a non-redlined city, the White-Black turnout gap is approximately 22.3 percentage points in a low graded neighborhood and 13.9 percentage points in a high graded neighborhood.[21] So while the redlined city shows a moderate increase in turnout gap by 14.3 percentage points, the non-redlined city actually shows a slight *decrease* in turnout gap, by 8.4 percentage points (although this decrease is not significant). Columns (3) and (4) show similar results for Percent Registered in 2020, with slightly less precision. The fact that the estimated coefficient on the PHOLC × Black × Treat term is *significantly negative* suggests that while voter turnout as a function of predicted HOLC score increases at roughly the same rate for White voters in non-HOLC ZCTAs, Black voters in non-HOLC ZCTAs, and White voters in HOLC ZCTAs, the rate of increase for Black voters in HOLC ZCTAs is significantly lower.

21. Note that Figure 10 does not show this decrease in the White-Black turnout gap as HOLC score increases as clearly, because it graphs the regression line for the binned scatterplot, and not the full dataset.

This leads to two primary theories as to why this pattern is observed.

The first is a demographic theory: that neighborhoods with low HOLC grades in redlined cities became more segregated than similar neighborhoods in non-redlined cities, which resulted in *higher* voter turnout among Black voters (given evidence that segregation increases voter turnout). The main drawback to this theory is that White voter turnout in these same neighborhoods did not also increase, which could potentially be explained by an increase in the Black share of the population (and therefore a smaller White share of the population, which may have led to lower political efficacy, and therefore reduced political engagement). The other potential mechanism for this pattern would be that due to the economic effects of redlining, Black people in low HOLC grade neighborhoods of redlined cities saw reductions in income, education, house value, economic mobility etc., directly resulting in a lower voter turnout. While this may explain the flattening of the relationship between predicted HOLC Score and Voter Turnout, this does not explain why the overall level of Black voter turnout increased in redlined cities, across all neighborhoods.

Of course, if redlining did have a causal effect on Black voter turnout, it is likely that the actual mechanism was some combination of demographic effects and economic effects. In fact, this supports the evidence well – perhaps redlined cities overall became more segregated, leading to higher voter turnout overall, but simultaneously, redlined neighborhoods also saw economic effects, which reduced economic mobility and flattened the relationship between voter turnout and income, house price, etc. among Black residents.

6 Conclusion

This analysis, while insufficient to prove causation, does highlight several interesting paths forward in this area of research. Firstly, at the city level, I do not find any significant differences in economic or demographic variables, although there is evidence of interesting patterns in certain variables. In particular the Black population as a share of the city's population (which grew more in redlined cities than in non-redlined cities), present-day racial segregation (which was generally slightly stronger in redlined cities than in non-redlined cities), and present-day economic mobility (which was slightly lower in redlined counties than in non-redlined counties) all suggest that further exploration, with a larger dataset or a more precise identification strategy, may yield more significant results.

Then, in Section 5, I explore the relationship between redlining and voting outcomes. First, I find that while neighborhoods with higher HOLC scores had significantly higher White voter turnout than neighborhoods with lower HOLC scores, this effect was negligible among Black voters, suggesting that redlining may have had positive effects on White voter turnout in highly graded HOLC neighborhoods, at the expense of Black voters. The difference-in-difference estimate was significant, a finding that was robust to the inclusion of other control variables, and the specification of the sample of HOLC neighborhoods. To further explore this relationship, I used a sample of "non-HOLC" neighborhoods as a control group, and used a predictive model and the resulting predicted HOLC scores to perform a triple-difference analysis. While the results were counterintuitive and not significant for the baseline sample of non-rural ZCTAs, restricting this sample to only "superurban" ZCTAs (with sufficiently high population density that suburban ZCTAs were largely excluded) showed a significantly negative triple-difference estimate, suggesting that the pattern of differential effects of predicted HOLC score on voter turnout by race was unique to HOLC ZCTAs.

While this is not proof of a causal relationship, it suggests that further exploration into the feasibility of several possible mechanisms may be worthwhile. For instance, could this disparity be due to the effects of racial segregation in some cities, or even some neighborhoods? Could this disparity be due to differences in economic mobility by race in different cities? Could it be some combination of the two, or even some other unexplained factor? Redlining has proven to be a difficult area of study in which to prove causality, but many of the linked effects are still indicative of larger patterns. The study of "place effects" indicates that specific places can potentially have very large effects on everything from economic mobility to educational attainment. The question that naturally emerges, is what causes these place effects? Even beyond redlining, are the economic and political effects of living in certain places due to chance, or can they in part be attributed to historic policies and practices? While this paper shows some evidence that some of the effects of place on voting may be attributable to redlining, it also paves the way more generally for future research on the link between historic oppression and modern-day inequality.

Appendices

A City-Level Outcomes

Detailed Description of Control and Treatment Cities While the methodology used to determine the control and treatment cities in this paper is similar to the methodology used in (Aaronson, Hartley, and Mazumder 2017), the actual cities may differ, primarily due to the difference in determining distances between cities. Here, all cities with 1930 populations between 30,000 and 50,000 are first geolocated using the Google Maps API tool. Once latitude and longitude have been determined for all cities, the data set of all cities is merged with the dataset of only redlined cities. Merging is done by distance – i.e. only cities within a straight-line distance of 40 miles are matched. All cities matched with a redlined city are discarded (*including redlined cities that are matched with other redlined cities*), resulting in the list of cities presented in Tables A1 and A2.

City Matching and Outcome Variables The IPUMS 5% Sample for the 1930 Census includes detailed city identifiers (`CITY`), which allows for easy identification of HOLC cities based on city name and state. I use the (exact) variable `CITYPOP` to identify the city population for the purpose of the control/treatment cutoffs, however when calculating the Percent Black, I use the IPUMS person-level weights (`PERWT`) and race identifiers to impute the share of the population that is "Black Alone". Although income data is not available in the 1930 census (or the 1940 census), IPUMS provides the harmonized variable `OCCSCORE`. This variable indicates the median 1950s income of a given occupation, in 1950 dollars. Although it is not directly comparable to present-day median income, because the same measure is used for all cities, it still provides a relative understanding of median incomes across different cities. These imputed incomes are summed at the household level, then the median (weighted by IPUMS household-level weights) is computed at the city level. House values are available as a continuous variable in the 1930 Census (`VALUEH`), but are heavily concentrated at multiples of 50, which is why the house value data appears nearly in levels in the top panel of Figure 6. House values are again computed by taking the household-weighted median across each city.

IPUMS does not have detailed city-level identifiers for the 5-Year 2012-2016 ACS,[22] however

22. While the `CITY` variable is still available in later years, only large cities are identified, which excludes many of the cities in the sample.

“Control” Cities

	Population		% Black	
City	*1930*	*2016*	*1930*	*2016*
Baton Rouge, LA	30,700	228,694	39.7	55.2
Bellingham, WA	30,800	84,462	0.0	1.4
Hagerstown, MD	30,800	40,325	3.2	18.1
Marion, OH	31,000	36,568	0.6	9.8
Port Huron, MI	31,300	29,388	2.6	7.6
Fort Smith, AR	31,400	87,712	15.0	9.4
Pensacola, FL	31,500	53,250	30.8	28.2
Meridian, MS	31,900	40,094	38.2	61.1
Muskogee, OK	32,000	38,605	23.6	16.0
Watertown, NY	32,200	26,997	0.2	6.5
Wilmington, NC	32,200	113,724	44.7	18.3
Tucson, AZ	32,500	527,586	4.8	5.0
Laredo, TX	32,600	251,671	0.2	0.4
Kokomo, IN	32,800	58,075	4.7	9.9
Colorado Springs, CO	33,200	448,759	2.3	6.4
Sioux Falls, SD	33,300	167,884	0.5	4.9
Joplin, MO	33,400	51,231	2.6	3.8
Mansfield, OH	33,500	46,902	1.7	17.8
Paducah, KY	33,500	25,010	15.7	21.0
Santa Barbara, CA	33,600	90,922	0.2	1.5
Lewiston, ME	34,900	36,277	0.0	4.3
Zanesville, OH	36,400	25,467	4.1	8.0
Danville, IL	36,700	32,030	7.2	32.3
Green Bay, WI	37,400	104,951	0.0	3.6
San Bernardino, CA	37,400	214,581	1.1	14.2
Cumberland, MD	37,700	20,290	2.6	6.3
Quincy, IL	39,200	40,689	1.2	5.7
Sheboygan, WI	39,200	48,813	0.0	2.5
Butte, MT	39,500	33,708	0.7	0.6
LaCrosse, WI	39,600	52,140	0.0	1.9
Mean		**101,894**	**8.3**	**12.7**
Median		**50,022**	**2.4**	**7.1**

Table A1: Population and Share of Population Black, in 1930 and 2016, for cities with 1930 populations between 30,000 and 40,000, are not within 40 miles of a redlined city, and which do not have associated HOLC maps.

“Treatment” Cities

	Population		% Black	
City	*1930*	*2016*	*1930*	*2016*
Oshkosh, WI	40,100	66,713	0.0	3.6
Ogden, UT	40,200	84,900	0.2	1.8
Poughkeepsie, NY	40,200	30,511	2.8	37.4
Lynchburg, VA	40,600	78,755	25.0	28.4
Muskegon, MI	41,300	38,086	1.6	31.7
Dubuque, IA	41,600	58,535	0.1	4.1
Lima, OH	42,200	37,836	4.2	25.9
Portsmouth, OH	42,500	20,393	4.2	5.7
Amarillo, TX	43,100	197,570	4.2	6.4
Columbus, GA	43,100	200,303	36.8	45.1
Battle Creek, MI	43,500	51,763	4.0	18.4
Lorain, OH	44,500	63,714	3.2	16.2
Jamestown, NY	45,100	30,345	0.6	4.6
Lexington, KY	45,700	311,529	29.5	14.5
Waterloo, IA	46,100	68,357	2.8	15.7
Muncie, IN	46,500	69,583	7.5	9.6
Bay City, MI	47,300	34,110	0.2	3.3
Elmira, NY	47,300	28,583	3.0	15.0
Stockton, CA	47,900	301,443	0.7	11.5
Phoenix, AZ	48,100	1,555,324	6.5	6.8
Jackson, MS	48,200	172,039	40.7	81.2
New Castle, PA	48,600	22,500	3.1	12.0
Pueblo, CO	50,000	108,385	2.2	2.9
Mean		**113,197***	**8.0**	**17.5**
Median		**66,713**	**3.1**	**12.0**

Table A2: Population and Share of Population Black, in 1930 and 2016, for cities with 1930 populations between 40,000 and 50,000, are not within 40 miles of another redlined city, and which have associated HOLC maps. (*) Note that the 2016 population of Phoenix (1,555,324), which is over twice as large as the other redlined cities combined, is replaced with the 2016 population of Tucson (527,586), the largest non redlined city, for the purpose of this calculation.

NHGIS does release 5-Year ACS summary tables at the `PLACE` level, which includes all cities, townships, and municipalities. I use Median Household Income and Median House Value data at the place level, matching each 1930 `CITY` with its corresponding 2016 NHGIS `PLACE`. All cities were matched successfully.

B Aggregation to Zip Code Tabulation Area (ZCTA)

I use three primary data sources in this paper, all of which are available at different geographic levels. The HOLC data is taken from manually drawn maps, and so the neighborhoods used in this data are not used anywhere else, but since the original data source is the maps themselves, it is relatively easy to impute HOLC grades for other geographic units based on area. The voter turnout data is available at the precinct level, which is a significantly smaller unit than the HOLC neighborhood (there are over 186,000 precincts in the raw Catalist voter file data). Finally, the Citizen Voting Age Population (CVAP) estimates are available at multiple geographic levels, from block groups, which are slightly smaller than precincts, to zip code tabluation areas (ZCTAs), which are larger than precincts, to cities, counties, etc, but are not available at the precinct level. The main challenge in calculating voter turnout was to determine the correct geographic unit: either estimating CVAP by precinct, using block group data, or estimating votes by ZCTA, using precinct data.

Although smaller geographic units are obviously preferable, as they allow for more granular analysis, the major drawback from aggregating to the precinct level is that while block groups are drawn by the US Census to be consistent and uniform (often based on boundaries such as major roads, rivers, etc.), precincts are often drawn by elected officials, and therefore may suffer from gerrymandering. Therefore the precinct boundaries themselves are often drawn based on factors such as race and class, and so imputing CVAP by race by precinct is very inaccurate. ZCTAs are collections of block groups, also drawn by the census, and so ZCTA boundaries generally are not biased, allowing estimation of votes by ZCTA with relative accuracy. Therefore all major analysis in this paper is done at the ZCTA level.

C Choosing a Denominator for Voter Turnout

There are a wide variety of ways to calculate voter turnout, once given the number of voters. One common denominator is the Voting Age Population (VAP), which counts the entire population over the age of 18. The main drawback of this method is that the VAP also includes ineligible voters, such as felons (in some states), and non-citizens, while excluding eligible overseas voters. To remedy this, many calculations of voter turnout use the Voting Eligible Population, which counts all eligible voters, as the denominator. For this paper, I land somewhere in the middle, using the Citizen Voting Age Population (CVAP), which excludes non-citizens, but also excludes overseas citizens and includes institutionalized persons.

I use the CVAP for two reasons: the first is due to the inclusion of the institutionalized population. The exclusion of felons and other disenfranchised groups from voting is heavily biased against Black voters – in 2016, one in every thirteen Black adults was disenfranchised, nearly four times the rate of disenfranchisement for non-Black adults. Laws on felon voting also differ dramatically from state to state – in Maine and Vermont (states that are 2.4 and 2.1% Black, respectively), felons in prison are allowed to vote, while in twelve states, including four states that are over 20% Black, some felons lose the right to vote permanently, even after serving their sentence, parole, and probation.[23] Since the percentage of the population that is disenfranchised due to imprisonment is very closely tied to racial discrimination and racial composition of a state, we do not exclude the institutionalized population from our voter turnout denominator. The second reason for using the CVAP is simply due to data availability – for instance, data on the overseas voting-eligible population is not available at the granular geographic levels that we are using, let alone by race.[24]

23. These states, with their respective Black population percentages, are Alabama (27.8 %), Arizona (6.0%), Delaware (24.4%), Florida (17.6%), Iowa (5.2%), Kentucky (9.5%), Mississippi (38.9%), Nebraska (6.1%), Tennessee (18.0%), Virginia (21.3%), and Wyoming (2.1%). In 2016, Nevada (11.3%) was also included on this list, but has since rolled back their restrictions to allow felons to vote after being released from prison.

24. The total number of overseas voters in 2016 was just over 200,000, out of nearly 137 million votes cast (Federal Voting Assistance Program 2018).

Summary of Outcomes from Varying HOLC Area Cutoff

Area Cutoff	ZCTAs	Mean HOLC Score	Std. Dev.	% Area Covered
No Cutoff	2925	2.12	0.76	20.0%
10%	2153	2.11	0.72	40.8%
20%	1842	2.11	0.72	50.9%
30%	1583	2.11	0.71	59.5%
40%	1350	2.11	0.71	66.5%

Table A3: Summary of the number of ZCTAs, the average HOLC score, and the total percentage of the ZCTAs that are covered by HOLC neighborhoods.

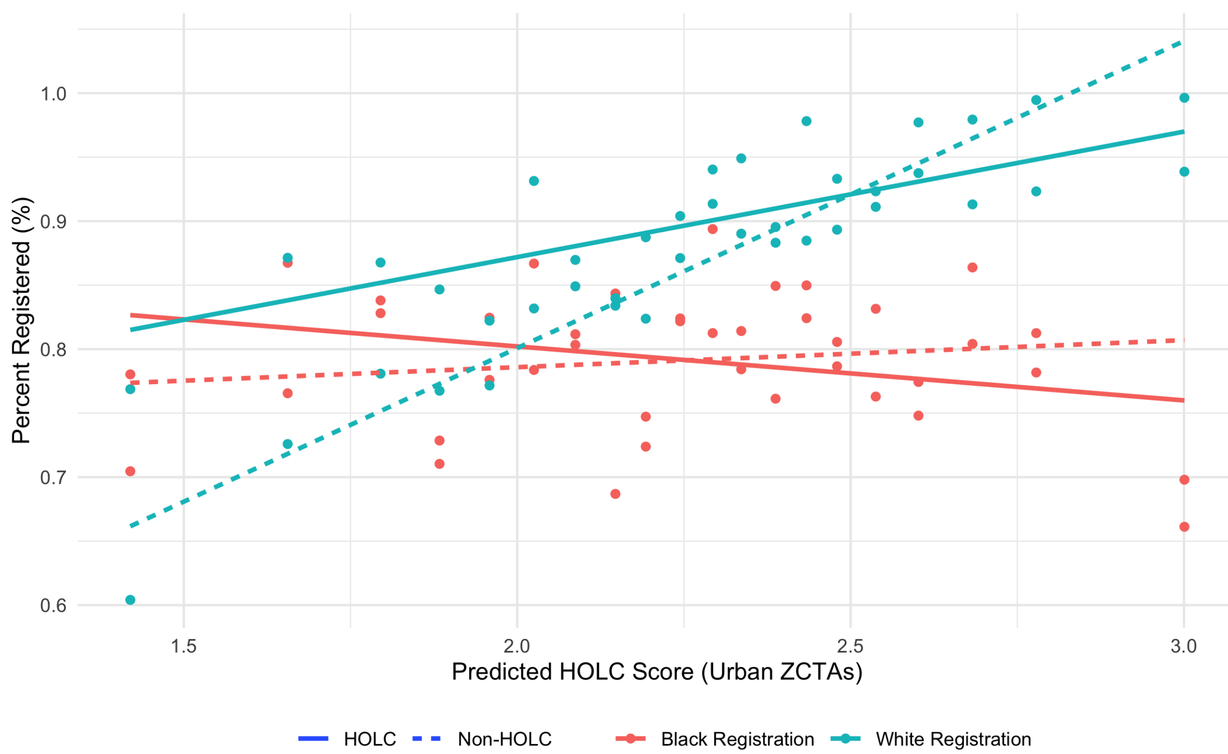

Figure A1: This figure displays a binned scatter plot of the Number of People Registered (in 2020) as a percentage of CVAP (in 2016) against predicted HOLC Score for 2,197 Zip Code Tabulation Areas (ZCTAs) designated as "urban" (with at least 1,000 ppsm), divided into HOLC and non-HOLC ZCTA groups. Data is displayed by treatment group (HOLC or non-HOLC) and race.

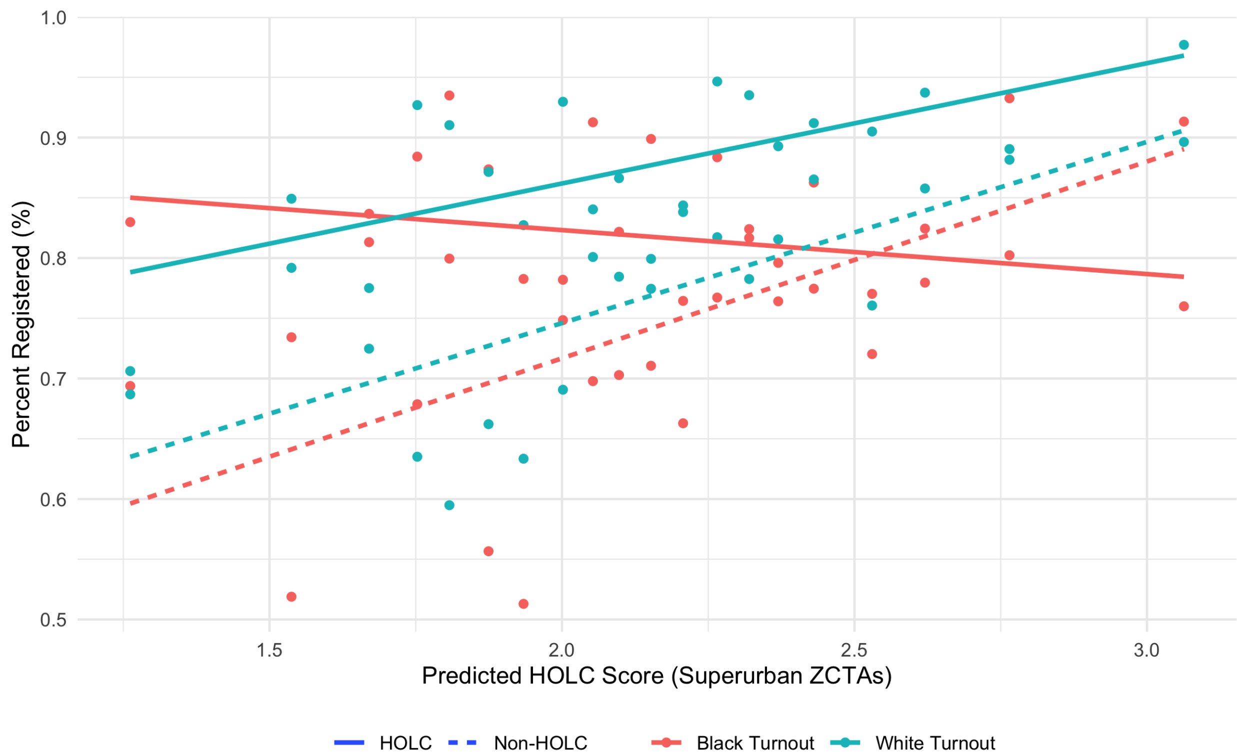

Figure A2: This figure displays a binned scatter plot of the Number of People Registered (in 2020) as a percentage of CVAP (in 2016) against predicted HOLC Score for 603 Zip Code Tabulation Areas (ZCTAs) designated as "superurban" (with between 5,000 and 20,000 ppsm), divided into HOLC and non-HOLC ZCTA groups. Data is displayed by treatment group (HOLC or non-HOLC) and race.

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